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Abstract

U.S. trading in non-U.S. stocks has grown dramatically. Round-the-clock, these stocks trade in the home market, in the U.S. market and, potentially, in both markets simultaneously. We develop a general methodology based on a state space model to study 24-hour price discovery in a multiple markets setting. As opposed to the standard variance ratio approach, this model deals naturally with (i) simultaneous quotes in an overlap, (ii) missing observations in a non-overlap, (iii) noise due to transitory microstructure effects, and (iv) contemporaneous correlation in returns due to market-wide factors. We provide an application of our model to Dutch-U.S. stocks. Our findings suggest a minor role for the NYSE in price discovery for Dutch shares, in spite of its non-trivial and growing market share. The results differ significantly from the variance ratio approach.

Some Keywords: Efficient price; Financial markets; High-frequency data; Kalman filter; Unobserved components time series models.

JEL classification: C33; G14.

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1 Introduction

In the last decade, international firms have increasingly sought a U.S. listing, oftentimes achieved through cross-listing their shares at either the New York Stock Exchange (NYSE) or at the NASDAQ. At the end of 2002, 467 non-U.S. firms were listed at the NYSE and generated approximately 10% of total volume that year (numbers are taken from the 2003 annual report). The NASDAQ lists even more non-U.S. firms. This trend has prompted many academic studies. Most of them focus on the benefits of cross-listings, such as reduced cost of capital and enhanced liquidity of a firm's stock.[1]

A relatively unexplored question is how much U.S. trading contributes to round-the-clock price discovery over and above domestic trading. Reasoning could go both ways. On the one hand, the home market being closest to the company's headquarters and, therefore, closest to where information is produced, may be most important (see, e.g., Bacidore and Sofianos (2002), Hau (2001), and Solnik (1996)). On the other hand, U.S. stock exchanges being the largest and most liquid exchanges in the world may imply an important role in price discovery also for non-U.S. stocks, particularly now that their share in total U.S. volume is rapidly increasing. Chan, Hameed, and Lau (2003), for example, find that trading location matters irrespective of business location for a group of companies that changed listing from Hong Kong to Singapore.

Our objective is to develop a general methology to determine how informative trading is for round-the-clock price discovery in a multiple markets setting. It enables the analysis of the questions raised for U.S. trading in non-U.S. stocks, but applies more generally to securities trading in multiple venues and, possibly, multiple time zones. Examples include securities trading on multiple trading platforms or through multiple broker-dealers, oftentimes referred to as fragmented trading (see Stoll (2001a)), London and Tokyo trading in U.S. treasury securities (see, e.g., Fleming and Lopez (2003)), and foreign listings at European exchanges.[2]

The empirical literature on round-the-clock price discovery dates back to *single* market studies comparing variance ratios of open-to-close and close-to-open returns. They generally find trading periods to produce more information than non-trading periods (see e.g. Oldfield and Rogalski (1980), French and Roll (1986), Harvey and Huang (1991), and Jones, Kaul, and Lipson (1994)). A natural extension of this approach to our multiple-markets setting is to single out economically relevant timepoints in the day and compare return variances across time, averaged across all stocks. This approach fails for three reasons. First, in our setting, calculating returns involves arbitrary choices for prices in overlapping periods, as we observe prices in multiple markets. Second, midquotes and transaction prices are potentially noisy

[1]See, e.g., Alexander, Eun, and Janakiramanan (1987, 1988), Foerster and Karolyi (1999), Karolyi (1998), Domowitz, Glen, and Madhavan (1998), Pagano, Roëll, and Zechner (2002), and Miller (1999)

[2]Pagano, Randl, Roëll, and Zechner (2001) report a non-trivial number of listings at the European exchanges are foreign, up to 50% for Amsterdam, Brussels, Frankfurt, and Switzerland.

proxies for the unobserved efficient price due to microstructure effects such as the market making mechanism and minimum tick sizes (see, e.g., Stoll (2001b)). Such noise is negligible for weekly, monthly, or annual returns, but not for intraday returns. This is illustrated by studies that find that 24-hour returns based on opening prices are, on average, up to 20% more volatile than those based on closing prices (see Forster and George (1996), Gerety and Mulherin (1994), Amihud and Mendelson (1987), and Stoll and Whaley (1990)). Market microstructure noise is potentially distorting because it artificially inflates price discovery within a trading day. Third, Ronen (1997) criticizes the standard variance ratio approach as it does not account for contemporaneous correlation.

In this paper, we develop a methodology based on a state space model to account for the three main criticisms of the standard variance ratio approach. Such a model arises naturally after characterizing the (unobserved) efficient price process. Consistent with modern finance, we model the efficient price as a random walk (see, e.g., Campbell, Lo, and MacKinlay (1997)). To study round-the-clock price discovery, we endow this random walk with deterministic, time-varying volatility. To account for transitory price changes, we model the observed midquote as the unobserved efficient price plus short-term "microstructure" noise and we allow for potential market under- or overreaction to information (see, e.g., Amihud and Mendelson (1987)). In the overlap, both midquotes are functions of the same unobserved efficient price plus idiosyncratic noise. To account for cross-correlation in returns, we model returns as the sum of a common and an idiosyncratic factor in the spirit of Hasbrouck and Seppi (2001).[3]. The model is estimated using maximum likelihood. The Kalman filter is used to calculate the likelihood at each step in the optimization. A major advantage of the Kalman filter in our setting is that it deals naturally with missing values in the non-overlap trading periods. Moreover, the model-based smoother allows for decomposition of an observed price change into a transitory and a permanent component based on the entire sample, that is past as well as future observations (see Durbin and Koopman (2001)).

For partially overlapping markets, the state space approach compares favorably to alternative methodologies. In related work, Hasbrouck (1995) proposes a vector error-correction model to measure "information shares" of exchanges for price discovery during the period when both exchanges are open. Although this approach accounts for transitory price changes, it does not extend to our setting as it cannot deal with missing values in one of the markets in the non-overlap. Barclay and Hendershott (2003) use weighted price contribution (WPC) to study how informative after-hours trading is. The WPC approach, however, does not explicitly allow for transitory effects. In their pioneering study, Barclay and Warner (2003, p. 300) develop WPC and acknowledge "it is not clear how any bias from ignoring temporary price-change

[3]The common factor represents macro-economic information or portfolio-wide liquidity shocks (see Subrahmanyam (1991), Chowdhry and Nanda (1991), Kumar and Seppi (1994), and Caballe and Krishnan (1994))

components could drive our results."

The state space model is estimated on a 1997-1998 sample of Dutch blue chips cross-listed in New York. The U.K. excluded, Dutch stocks are the European stocks that generate most volume in New York. The dataset is rich, since it includes all trades and quotes on both sides of the Atlantic, as well as intraday quotes on the exchange rate and intraday prices on the major Dutch index and the S&P500.

The results demonstrate the empirical relevance of the model, as the estimated variance pattern of the efficient price innovations differs significantly from the pattern based on the standard variance ratio approach. Such an approach was pursued in earlier papers on British and Dutch cross-listed stocks (see Werner and Kleidon (1996) and Hupperets and Menkveld (2002), respectively). The major difference is that the variance ratio approach finds that continued trading in New York after the Amsterdam close is *significantly* more informative than the overnight period, whereas the state space model does not.[4] This difference is primarily due to significant noise in New York midquotes, which is, implicitly, assumed to be absent in the variance ratio approach.[5] Interestingly, such noise is insignificant for Amsterdam midquotes outside the overlap. We quantify price discovery consistent with existing literature and find that price discovery in Amsterdam is a factor three higher than in New York or the overnight period. These numbers compare to a factor seven reported for NYSE stocks comparing daytime and overnight price discovery (see George and Hwang (2001)). These results survive a number of robustness tests, including potential non-zero correlation between transient, microstructure noise and efficient price innovations (see, e.g., Hasbrouck (1993) and George and Hwang (2001)).

The rest of the paper is structured as follows. Section 2 presents and discusses a multivariate state space model for midquotes of securities that are traded in different markets. Section 3 elaborates on trading Dutch securities in Amsterdam and New York. Section 4 presents the model estimates and contains robustness tests. Section 5 summarizes the main conclusions.

2 Model

The principles of the analysis in this paper are based on an unobserved "efficient" price and observed midquotes in two markets that trade the same security. State space models are a natural tool in this setting as the efficient price can be modeled as an unobservable state variable and the midquotes as observations of this variable with measurement error to reflect transitory microstructure effects.

[4]This is consistent with Barclay, Litzenberger, and Warner (1990) who find, for U.S. stocks cross-listed in Japan, that Japanese trading does not increase the level of return variance.

[5]This finding is consistent with Barclay and Hendershott (2003) who find less efficient price discovery in after-hours trading at the NASDAQ.

2.1 The unobserved efficient price model

Consistent with modern finance, we model the efficient price as a random walk. We include a deterministic linear trend to account for positive expected returns. For the purpose of studying round-the-clock price discovery we pick T economically interesting time points in the day. The efficient price process is subject to deterministic, time-varying volatility depending on the time of day. The efficient price innovation is decomposed into a common factor and an idiosyncratic innovation. The common factor is associated with a macro-economic or portfolio-wide liquidity shock (see Subrahmanyam (1991) and Caballe and Krishnan (1994)). The process for a multiple of n stock prices, T intraday timepoints and D trading days can therefore be described as

$$\alpha_{t,\tau+1} = \alpha_{t,\tau} + \beta\xi_{t,\tau} + \eta_{t,\tau}, \qquad \xi_{t,\tau} \sim \mathrm{N}(0, \sigma^2_{\xi,\tau}), \qquad \eta_{t,\tau} \sim \mathrm{N}(\mu_\tau, \sigma^2_{\eta,\tau}C), \tag{1}$$

for $t = 1, \ldots, D$, $\tau = 1, \ldots, T$ and with $\alpha_{t+1,1} = \alpha_{t,T+1}$. The $n \times 1$ state vector $\alpha_{t,\tau}$ contains the unobserved efficient prices of n stocks at day t and timepoint τ. The scalar variable $\xi_{t,\tau}$ is the unobserved common factor and the $n \times 1$ vector β is fixed and contains unknown coefficients or factor loadings. The common factor is a zero mean random variable with a deterministic intraday dependent variance structure. The idiosyncratic disturbance vector $\eta_{t,\tau}$ is normally and independently distributed with intraday varying $n \times 1$ mean vector μ_τ and $n \times n$ diagonal variance matrix $\sigma^2_{\eta,\tau}C$. The mean vector μ_τ represents the intraday seasonality of expected returns whereas the scaling variance $\sigma^2_{\eta,\tau}$ is for the intraday seasonality in the volatility of returns. The scaled variance matrix $C = \mathrm{diag}(c_1, \ldots, c_n)$ captures inter-stock volatility differences. The common and idiosyncratic shocks are mutually and serially uncorrelated at all time points.

The model (1) can also be represented using a single disturbance term, that is

$$\alpha_{t,\tau+1} = \alpha_{t,\tau} + \zeta_{t,\tau}, \qquad \zeta_{t,\tau} \sim \mathrm{N}(0, \Sigma_{\zeta,\tau}), \qquad \Sigma_{\zeta,\tau} = \sigma^2_{\xi,\tau}\beta\beta' + \sigma^2_{\eta,\tau}C, \tag{2}$$

where $\zeta_{t,\tau} = \beta\xi_{t,\tau} + \eta_{t,\tau}$. To ensure identification of the model, we impose the parameter restrictions

$$\frac{1}{n}\sum_{i=1}^{n}\beta_i^2 = 1, \qquad \frac{1}{n}\sum_{i=1}^{n} c_i = 1. \tag{3}$$

where β_i is the ith element of vector β for $i = 1, \ldots, n$. These two restrictions allow $\sigma^2_{\xi,\tau}$ and $\sigma^2_{\eta,\tau}$ to be interpretated as the average (over n stock prices) systematic and idiosyncratic variance, respectively. Round-the-clock price discovery in the sample is then determined by

$$\sigma^2_{E,\tau} = \sigma^2_{\xi,\tau} + \sigma^2_{\eta,\tau}, \tag{4}$$

where $\sigma^2_{E,\tau}$ is defined as the average variance of the efficient price innovations.

2.2 The observation model

Although we do not observe the efficient price, midquotes in either or both markets at day t and time τ are the best proxies as they do not suffer from the bid-ask bounce in transaction prices (see e.g. Roll (1986)). They are, nevertheless, noisy as they suffer from transient microstructure effects, such as rounding errors due to discrete price grids, temporary liquidity shocks, or inventory-management by market makers. The model for n midquotes observed during T intraday timepoints and D days and for K different markets is specified as

$$p_{k,t,\tau} = \alpha_{t,\tau} + \varepsilon_{k,t,\tau}, \qquad \varepsilon_{k,t,\tau} \sim \mathrm{N}(0, \sigma^2_{\varepsilon,k,\tau} \cdot I_n), \tag{5}$$

where $p_{k,t,\tau}$ contains midquotes for n stocks traded at market k with $k = 1, \ldots, K$, $t = 1, \ldots, D$ and $\tau = 1, \ldots, T$. The transitory error $\varepsilon_{k,t,\tau}$ is solely due to microstructure effects. The observation error variances depend on the time-of-day and on the market but they are assumed to be equal across all stocks, an assumption that will be relaxed at a later stage.

2.3 The observation model with price reaction

The basic observation equation (5) is extended to allow for market under- or overreaction to information, which cannot be excluded ex-ante in high frequency analysis (see, e.g., Amihud and Mendelson (1987)). A natural way to do this is to include the efficient price change $\alpha_{t,\tau} - \alpha_{t,\tau-1}$ in the observation equation. We obtain

$$\begin{aligned} p_{k,t,\tau} &= \alpha_{t,\tau} + \theta(\alpha_{t,\tau} - \alpha_{t,\tau-1}) + \varepsilon_{k,t,\tau} \\ &= \alpha_{t,\tau} + \theta\zeta_{t,\tau-1} + \varepsilon_{k,t,\tau} \\ &= \alpha_{t,\tau} + \theta\beta\xi_{t,\tau-1} + \theta\eta_{t,\tau-1} + \varepsilon_{k,t,\tau}, \end{aligned} \tag{6}$$

where scalar coefficient θ measures the price reaction to information. This specification, however, does not distinguish between, for example, underreaction to firm-specific or common factor information. Further, coefficient θ may vary within the day. To allow for these generalizations, we consider the specification

$$p_{k,t,\tau} = \alpha_{t,\tau} + \theta_{\xi,\tau}\beta\xi_{t,\tau-1} + \theta_{\eta,\tau}\eta_{t,\tau-1} + \varepsilon_{k,t,\tau}, \tag{7}$$

where $\theta_{\xi,\tau}$ and $\theta_{\eta,\tau}$ are scalar coefficients for $\tau = 1, \ldots, T$. The common factor (firm-specific) efficient price innovation at time τ is pre-multiplied by $\theta_{\xi,\tau}$ ($\theta_{\eta,\tau}$) to indicate that midquotes underreact (negative θ's) or overreact (positive θ's) to the innovation. The modelling framework allows us to determine whether these effects exist by testing the null hypothesis that θ's are equal to zero.

2.4 State space representation

The standard state space model is formulated for a vector of time series y_s with a single time index s and is given by

$$y_s = Z_s\delta_s + \nu_s, \qquad \delta_{s+1} = T_s\delta_s + R_s\chi_s, \qquad s = 1, \ldots, M, \tag{8}$$

where disturbances $\nu_s \sim \mathrm{N}(0, H_s)$ and $\chi_s \sim \mathrm{N}(0, Q_s)$ are mutually and serially uncorrelated. The initial state vector $\delta_1 \sim \mathrm{N}(a, P)$ is uncorrelated with the disturbances. In the case elements of the state vector follow nonstationary processes, the initial state vector cannot be specified properly and is regarded as being partially diffuse. The system matrices or vectors Z_s, T_s, R_s, H_s and Q_s, together with the initial mean a and variance P, are assumed as fixed and known for $s = 1, \ldots, M$. This general state space model is explored further in textbooks of Harvey (1989) and Durbin and Koopman (2001), amongst others.

The basic model (2) and (5) can be represented as a state space model (8) by choosing

$$y_s = \left(p'_{1,t,\tau}, \ldots, p'_{K,t,\tau}\right)', \qquad \delta_s = \alpha_{t,\tau}, \qquad s = (t-1)\cdot T + \tau,$$

with $nK \times 1$ observation vector y_s, $n \times 1$ state vector δ_s and $M = TD$. The state space disturbance vectors are specified as

$$\nu_s = \left(\varepsilon'_{1,t,\tau}, \ldots, \varepsilon'_{K,t,\tau}\right)', \qquad \chi_s = \zeta_{t,\tau}.$$

The state space matrices are then given by

$$Z_s = \ell'_K \otimes I_n, \quad T_s = R_s = I_n, \quad H_s = \mathrm{diag}(\sigma^2_{\varepsilon,1,\tau}, \ldots, \sigma^2_{\varepsilon,K,\tau}) \otimes I_n, \quad Q_s = \Sigma_{\zeta,\tau},$$

where ℓ_K is the $K \times 1$ vector of ones and I_n is the $n \times n$ unity matrix. We notice that H_s and Q_s only vary within a trading day t for $t = 1, \ldots, D$.

The model of interest (1) and (7) can also be casted in state space form. The state vector needs to be extended to include the lagged disturbances $\xi_{t,\tau-1}$ and $\eta_{t,\tau-1}$ in the model. The $(2n+1) \times 1$ state vector δ_s and the $(n+1) \times 1$ state disturbance vector are then defined as

$$\delta_s = \left(\alpha'_{t,\tau}, \eta'_{t,\tau-1}, \xi_{t,\tau-1}\right)', \qquad \chi_s = \left(\eta'_{t,\tau}, \xi_{t,\tau}\right)',$$

while observation vector y_s remains as defined. The state space matrices are

$$Z_s = \ell'_K \otimes [I_n, \theta_{\eta,\tau} I_n, \theta_{\xi,\tau}\beta], \quad T_s = \begin{bmatrix} I_n & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}, \quad R_s = \begin{bmatrix} I_n & \beta \\ I_n & 0 \\ 0 & 1 \end{bmatrix}, \quad Q_s = \begin{bmatrix} \sigma^2_{\eta,\tau} C & 0 \\ 0 & \sigma^2_{\xi,\tau} \end{bmatrix},$$

while H_s remains as defined.

2.5 Estimation and signal extraction

The Kalman filter and associated algorithms can be used for inference and signal extraction (see, e.g., Durbin and Koopman (2001)). The Kalman filter evaluates the conditional mean and variance of the state vector δ_s given the past observations $Y_{s-1} = \{y_1, \ldots, y_{s-1}\}$, that is

$$a_{s|s-1} = \mathrm{E}(\delta_s | Y_{s-1}), \qquad P_{s|s-1} = \mathrm{var}(\delta_s | Y_{s-1}), \qquad s = 1, \ldots, M,$$

where $a_{1|Y_0} = a$ and $P_{1|Y_0} = P$. The recursive equations are given by

$$a_{s+1|s} = T_s a_{s|s-1} + K_s v_s, \qquad P_{s+1|s} = T_s P_{s|s-1} T_s' + R_s Q_s R_s' - K_s F_s^{-1} K_s',$$

with one-step ahead prediction error vector $v_s = y_s - Z_s a_{s|s-1}$, its variance matrix $F_s = Z_s P_{s|s-1} Z_s' + H_s$ and Kalman gain matrix $K_s = T_s P_{s|s-1} Z_s' F_s^{-1}$ for $s = 1, \ldots, M$. The recursions need various adjustments when the initial state is partially diffuse. Further it can be shown that when the model is correctly specified the standardized prediction errors are normally and independently distributed with a unit variance.

An important feature of state space methods is their ability to deal with missing values, which are paramount in our dataset, since no observations are available on one of the exchanges during the non-overlap. When all elements in y_s are missing, the recursive equation for example reduces to

$$a_{s+1|s} = T_s a_{s|s-1}, \qquad P_{s+1|s} = T_s P_{s|s-1} T_s' + R_s Q_s R_s'.$$

The parameters in the state space model are estimated by maximizing the loglikelihood that can be evaluated by the Kalman filter as a result of the prediction error decompostion. The loglikelihood function is given by

$$l = -\frac{nKM}{2} \log 2\pi - \frac{1}{2} \sum_{s=1}^{M} \log |F_s| - \frac{1}{2} \sum_{s=1}^{M} v_s' F_s^{-1} v_s.$$

For the application of round-the-clock price discovery, the observation vector y_s is of a high dimension. It follows that the variance matrix F_s is of a high dimension which is inconvenient since it needs to be inverted and its determinant needs to be computed for each s. Consequently, the computations are relatively slow for a single loglikelihood evaluation. During the process of loglikelihood maximization, the Kalman filter is carried out repeatedly many times. A more computational efficient implementation of the Kalman filter for vector observations is based on updating y_s element by element. This reduces the computational load considerably because inversions of large matrices are no longer required, see Durbin and Koopman (2001, section 6.3) for more details and for computational comparisons.

Signal extraction refers to the estimation of the unobserved efficient price given all observations Y_M. The conditional mean vector $\hat{\delta}_s = \mathrm{E}(\delta_s | Y_M)$ and conditional variance matrix

$V_s = \mathrm{var}(\delta_s|Y_M)$ can be computed by a smoothing algorithm. Estimation and signal extraction were done in `Ox` (see Doornik (2001)) using the `SsfPack` state space routines (see Koopman, Shephard, and Doornik (1999), `www.ssfpack.com`). A recent version of `SsfPack` has implemented the Kalman filter with exact diffuse initializations and with an element by element treatment of y_s.

3 Data from Amsterdam and New York markets

The volume of non-U.S. shares grew to approximately 10% of total NYSE volume in 2002. European shares accounted for most of this volume—approximately one-third. Not surprisingly, U.K. shares accounted for most European volume, followed by Dutch shares that generated more volume than French and German shares combined. The cross-listed Dutch shares studied in this paper are NY Registered Shares as opposed to the more common American Depositary Receipts (ADRs). These are, however, not regarded as materially different in the eyes of investors, according to Citibank, one of the key players in the Depositary Services industry. Most important is that both the NY Registered Share and the ADR can be changed for the underlying common share at a small fee of approximately 15 basis points.

In our sample, Dutch shares traded from the Amsterdam open, 3:30 EST, to the New York close, 16:00 EST, with a one-hour trade overlap as is depicted in Figure 1. To study round-the-clock price discovery, we select 6 economically relevant timepoints inspired by the variance patterns reported in earlier studies (Werner and Kleidon (1996) and Hupperets and Menkveld (2002)). The first timepoint is 4:00, which is half an hour after the Amsterdam open. We choose not to take the actual open as trading might not start directly, creating a missing observation. Subsequent time points in the Amsterdam trading period are 8:00, 9:00, and 10:00. These are, purposefully, located around the economically interesting event times 8:30 and 9:30, since at these times U.S. macro-announcements are published and the NYSE opens, respectively. In the U.S. trading period we further select 11:00 to incorporate the Amsterdam close and 15:30 to study price discovery during the remainder of the trading day. We choose to stay half an hour ahead of the close to minimize disturbance due to last minute trading.

The Amsterdam and the New York Stock Exchange are both continuous, consolidated auction markets in the terminology proposed by Madhavan (2000). Both exchanges release trade and quote information in real time. The main difference is that New York is a hybrid market, because orders can arrive at the floor through both brokers and the electronic Superdot system. Amsterdam is a pure electronic market in which orders are routed to a consolidated limit order book and are executed according to price-time priority. In our sample period, a market maker ("hoekman") was assigned to each book with the obligation to "smooth price discovery" by inserting limit orders at times of illiquidity. For the blue chip stocks we study, however, they rarely intervened. And, for our sample period, tick sizes were comparable across both exchanges: US$ 1/16 at the NYSE and NLG 0.1 ($\approx$US$ 0.05) at the Amsterdam Stock Exchange.

The dataset used in this study consists of trade and quote data from Euronext-Amsterdam and the NYSE for July 1, 1997 through June 30, 1998. Seven Dutch blue chip stocks cross-listed in New York have been selected for the current study: Aegon (AEG), Ahold (AHO), KLM, KPN, Philips (PHG), Royal Dutch (RD) and Unilever (UN). These firms are multinationals in different industry groups and represent more than 50% of the local index in terms of market capitalization.

Summary statistics for trading in the seven Dutch stocks are tabulated in Table 1. They are very diverse as is apparent from trade variable averages such as volatility, volume, and spread.[6] A closer look reveals that they are similar in two important ways. First, for none of the stocks has New York been able to generate more volume than Amsterdam. Second, quoted spreads are larger in New York, up to almost 300%. This is most likely due to the different market structure in New York, where many orders receive price improvement from the floor. The effective spread, in this case, is a more appropriate measure, as it is based on actual trades. Changing to this measure, we find that differences shrink and for some stocks New York spreads are lower. This result should be interpreted with care, since average trade size is higher in Amsterdam (see Hupperets and Menkveld (2002)). Hence, the average Amsterdam trade potentially bites deeper into the limit order book and, therefore, suffers a higher effective spread. Although finding the most competitive exchange is beyond the scope of this paper, effective spread results show that exchanges are very competitive, which is a promising result in view of the price discovery questions addressed in this study. Comparing Amsterdam to New York based on statistics for the overlapping hour yields a similar picture. The main difference is that average values for all variables are higher during the overlap.

4 Empirical Results

4.1 Variance ratio estimates

As a preliminary analysis we follow the standard variance ratio approach and calculate the variance pattern of intraday and overnight returns. The intraday returns are calculated based on the six identified timepoints τ_i, where we arbitrarily choose the average midquote as a proxy for the price during the overlap.[7] Table 2 reports the variance estimates, which are translated

[6] You find the definition of these variables are described in the caption of the table.

[7] For all estimates reported in this paper "outliers" were removed for different reasons. First, in 1998 the change to daylight savings time in the Netherlands happened one week before the U.S. As a result, there was

into hourly equivalents to enable comparisons. For the three intervals in the Amsterdam trading period, the average variance equals $3.6 \cdot 10^{-5}$, which corresponds to a standard deviation of 60 basispoints per hour or an annualized volatility of 47%.[8] Variance for the hour containing the Amsterdam close is a significant 48% higher. Consistent with existing literature, we translate this finding into stating that price discovery—the information flow per unit of time—in this hour is a factor 1.5 higher (see, e.g., Jones, Kaul, and Lipson (1994), French and Roll (1986), Ronen (1997), and George and Hwang (2001)). Additionally, the Amsterdam non-overlap is a significant factor 2.4 more informative than the NYSE non-overlap, which, in turn, is a significant factor 1.3 more informative than the overnight hours.

To motivate the state space model advocated in this paper, Table 3 reports the autocorrelations for intraday returns. If measurement errors exist and if they are economically significant, we should find negative first order autocorrelation. Most of these autocorrelations are indeed negative and two of them are significant. We find a significantly positive autocorrelation for the period containing the Amsterdam close. Apparently, markets underreact to information in the New York open, causing persistence in returns for the subsequent Amsterdam close period. Higher order autocorrelations are insignificant, except for the Amsterdam close period, but this appeared to be entirely caused by a specific day in the sample as the autocorrelation turns insignificant after removing that day from the analysis.

4.2 Estimation results

We proceed by re-estimating the intraday variance pattern using the state space model advocated in this paper. We test for significance of parameters at a 95% level and leave out the insignificant ones. The results are in Tables 4 and Table 5. The first table is organized in two different panels. Panel A features the estimate of the variance pattern, which is plotted in Figure 2 along with the variance pattern based on the direct variance ratio approach reported

no trading overlap from March 30 to April 3, 1998. This period was removed from the sample as it is not representative. Second, at the end of the trading day on October 27, New York prices collapsed by 7%. They fully recovered at the New York open the next day. This overnight period was removed from the sample as it was a clear temporary distortion. Third, on a Unilever quarterly announcement on May 1, 1998, the share price jumped by roughly 8% on the Amsterdam open. This jump was removed as it clearly was a one-time event and not representative for regular round-the-clock price discovery.

[8] We do realize, however, that for the first interval from 4:00 to 8:00, variance is skewed towards the first two hours after the opening, consistent with the stylized fact of an intraday U-shape in volatility. We still aggregate these trading hours into one period, as we are primarily interested in the role of both markets in round-the-clock price discovery, which motivates the proposed time periods. This is consistent with existing literature that studies average hourly price discovery for trading and non-trading periods by aggregating the full trading period and studying variances of open-to-close returns and close-to-open returns (see, e.g., Oldfield and Rogalski (1980), French and Roll (1986), Harvey and Huang (1991), and Jones, Kaul, and Lipson (1994))

in Table 2. The state space model estimates differ in two important ways. First, trading in New York after the Amsterdam close is *not* significantly more informative than the overnight non-trading hours. The main reasons are that the New York midquotes contain significant noise and that the New York market appears to overreact significantly (87%) to firm-specific information. At the same time, the market underreacts to common-factor information, but this effect is much smaller (16%) and, as we will show later, is not robust. Second, most information is attributed to the New York open period, instead of the Amsterdam close period. The reason is market underreaction to both common-factor and firm-specific information (35% and 34%, respectively) in the New York open period. In other words, the information present in the New York open period is not yet fully revealed in midquotes halfway through the overlapping period. This is consistent with the hypothesized behavior of institutional and informed investors, who strategically split their orders both through time and across markets in the presence of noise traders (see, e.g., Kyle (1985), Chowdhry and Nanda (1991)). The intuition is that this enables them to hide their orders more easily and suffer less market impact. We attribute the firm-specific underreaction to informed investors and the common-factor underreaction to institutional investors, who, by trading portfolios, are likely to cause commonality in order flow.[9] This is shown to be the major cause of commonality in returns (see Hasbrouck and Seppi (2001)). For partially overlapping markets, it is optimal for these two types of investors to concentrate their orders in the overlap (see Menkveld (2003)). Similarly, the market underreaction (30%) to firm-specific information in the Amsterdam close period can be interpreted as continued trading in New York by informed investors, who did not yet fully exploit their information in the overlap.

To further characterize round-the-clock price discovery, we decompose information into firm-specific and common-factor information by time of day. Figure 3 illustrates this decomposition and leads to three important observations. First, the significantly larger innovations in the efficient price during the overlap are due to increased firm-specific rather than common-factor information. Apparently, the hypothesized order-splitting is primarily carried out by privately informed traders, as opposed to portfolio-trading institutional investors. Second, the New York preopening period is characterized by common-factor rather than firm-specific information. Although this period is not significantly more informative than the preceding Amsterdam trading hours, its common-factor component is significantly higher and its firm-specific component is significantly lower. This is consistent with U.S. macro-announcements in this period or, alternatively, with earnings releases by major U.S. companies[10] that potentially affect market

[9]We do not claim that these two investor types do not overlap. On the contrary, privately informed investors are oftentimes institutional investors.

[10]These releases are typically published before the market opens, so as to give investors time to read and analyze them.

sentiment for the oncoming U.S. trading day. Third, the "New York only" period is neither significantly more informative on the firm-specific component, nor on the common-factor component.[11]

Panel B of Table 4 reports the estimates of the observation error variance. In the optimization, they converge to zero for all timepoints in Amsterdam outside the overlap. We cannot reject the null of no observation error for these midquotes. For New York midquotes outside the overlap, however, we do reject the null of no observation error. During the overlap both the Amsterdam and the New York midquotes are significantly noisy. The non-zero pricing errors are interesting for two reasons. First, New York midquotes in the overlap are significantly noisier than Amsterdam midquotes. The estimates imply a 33 basispoint standard deviation for New York errors, which is 26% higher than Amsterdam. This, together with the non-overlap results, is yet another sign of Amsterdam's dominance in price discovery. The errors are economically significant as they are of the same magnitude as hourly efficient price innovations. The New York midquote at 15:30, just ahead of the close, is noisiest and economically significant, since the error's standard deviation is more than half the standard deviation of the efficient price innovation over the *entire* NYSE non-overlap, from 11:00 to 15:30. The next morning, just prior to the market open, one should realize that the last New York midquote, although the most recent observation, also bears significant noise.

Figure 4 illustrates price discovery as it plots the estimate of the efficient price and the midquote observations for Royal Dutch. In the three-days-plot (lower panel), we see that midquotes at the timepoints with non-zero noise differ from the efficient price estimate. Particularly interesting is that the efficient price in the overlap is closer to the Amsterdam midquote than the New York midquote. This illustrates our finding that the midquote in New York is noisier.

Tables 5 reports the stock-specific parameter estimates of the vector of loadings β and the scaled variance matrix C in the price model (1). For five out of seven stocks the estimate of β differs significantly from one. Casual comparison of these estimates with the "true" β weights, as reported in, for example, the Bloomberg system, we find a correlation of 0.82. The correlation is not perfect, since β measures different exposures—high- versus low-frequency exposures to market-wide "shocks" or macro factors. Cross-sectional variation is even higher for inter-stock variance differences measured by C as for every stock this parameter differs significantly from one. This heterogeneity in β and in the variance matrix C makes decomposition of the total variance of efficient price innovations into an idiosyncratic and a common factor component, stock-specific. The general pattern reported in Figure 3 should be interpreted carefully. Whereas it is informative on how both components, *irrespective* of each other, behave

[11] This is consistent with Craig, Dravid, and Richardson (1995) who find that only a small portion of overnight volatility in the Nikkei index occurs during U.S. trading hours.

through time, it is not informative on how important they are for the total variance of a specific stock. To study how this decomposition is affected, we have to inflate the common-factor-variance to idiosyncratic-factor-variance ratio for stock i by β_i^2/c_i. These factors are reported in panel C and, not unexpectedly, vary significantly across stocks. Interestingly, the common-factor component is highest for Aegon, Royal Dutch, and Unilever. This is probably due to these stocks' high exposure to the U.S. market in our sample period, as Aegon just took over the U.S. company Transamerica, while Royal Dutch and Unilever were members of the S&P500.

Finally, the state space approach provides us with an estimate of the common factor conditional on the observations, which we can compare with local market indices—the AEX and the S&P500—for each time of day. In Table 6 we report the correlation between the smoothed common factor estimate and index returns. The correlation is highest, 0.57, and significant for the start of the trading day in Amsterdam. This is not surprising as our stocks represent more than 50% of total market capitalization of the index stocks in the sample period.[12] It drops significantly to 0.38 in the New York preopening, indicating that the cross-listed stocks, *collectively*, start price discovery less related to the remainder of the Dutch market. This effect is particularly strong for the hour containing the NYSE open, as correlation with the AEX now drops to an insignificant 0.08. For the remainder of the trading day, the common factor significantly correlates with the S&P500 with correlation coefficients of 0.21 and 0.28. These levels are lower than the Amsterdam non-overlap, as these stocks, obviously, do not make up a significant part of the S&P500. Interestingly, the correlation with the local market is higher outside the overlap than during the overlap. This reinforces the finding in Chan, Hameed, and Lau (2003) that "price fluctations are affected by country-specific investor sentiment."

4.3 Checking robustness

In this section we validate our findings for robustness and perform diagnostic analysis on filtered state innovations. We also discuss the model assumption that measurement error is independent of the efficient price innovation, as microstructure papers indicate this might be too strong an assumption. Although all results are discussed in this section, we only report the most important results in tables and figures to conserve space. The results not reported here are available through an appendix that is accessible through the corresponding author's website.

As our primary interest in the paper is round-the-clock price discovery, we test robustness of the estimated intraday variance pattern in two ways. First, we split the sample in two subperiods and estimate the model for each period. Second, we allow for stock-specific measurement error variances. The results, reported in panels B and C of Table 7, show that the main results

[12] The weight these stocks have in the Dutch market index (AEX), however, is far less as the index is not weighted by market capitalization.

are largely unaffected, i.e., the round-the-clock information pattern, the market under- and overreaction parameters, and the significantly noisier NYSE prices in the overlap. The only difference is that the common-factor underreaction during New York only trading vanishes in the second subperiod.

We base our diagnostic analysis on the scaled filtered state innovations, which should be white noise if the model is specified correctly. Figure 5 shows a plot of (i) the innovations with all stocks in consecutive order, (ii) their empirical distribution against the standard normal, (iii) autocorrelations up to the tenth lag, and (iv) autocorrelations of the squared innovations up to the tenth lag. Innovations are heavy-tailed, a standard phenomenon in empirical finance. Autocorrelations are insignificant. The autocorrelations of squared returns are positive, indicating GARCH effects, but small. Further inspection using scatterplots, however, shows that this may be spurious as they seem to be driven by a few relatively large observations. Though accounting for stochastic volatility might affect the estimates of the confidence intervals, it is unlikely to change the deterministic intraday variance pattern (see Andersen, Bollerslev, and Das (2001)).

The assumed independence of the efficient price innovation and the measurement error seems at odds with common microstructure models. In a standard structural model, the transaction price at time t equals the sum of an efficient price and a linear expression in signed volume of the previous two trades (see, e.g., George and Hwang (2001)). Since the innovation in the efficient price is a linear function of the same signed volumes (plus additional terms), the independence assumption for $\varepsilon_{k,t,\tau}$ and $\eta_{t,\tau}$ in our state space model could be violated. Ideally, we would relax the assumption to test the robustness of our results, but this is, econometrically, not possible as the model would become underidentified (see Hasbrouck (1993)). Instead, we argue it is unlikely that the issue impacts our main results for three reasons. First, we model midquotes instead of transaction prices, which eliminates one of the signed volume terms in the "transaction price" equation. Second, the remaining signed volume term relates to the cost for a single market maker to carry inventory through time. This is not an issue for the Amsterdam market as it is fully electronic and highly liquid, so that virtually all trades are executed without the intervention of the designated market maker ("hoekman").[13] In New York, the market maker ("specialist") is an active intermediary, but Madhavan and Sofianos (1998) document that market makers "control their inventory positions by selectively timing the size and direction of their trades rather than by adjusting their quotes".[14] Third, panel D in Table 7 shows that the main results are not affected by pre-setting the correlation to 0.175, which is our best guess based on George and Hwang (2001)).[15]

[13]This was confirmed by an exchange official.

[14]This explains the weak inventory effects documented for the NYSE in Madhavan and Smidt (1993) and Hasbrouck and Sofianos (1993)

[15]George and Hwang (2001) report that 9% of the transitory component ("measurement error") variance and

5 Conclusion

This paper studies round-the-clock price discovery for cross-listed stocks in markets that do not fully overlap. We propose a state space model for multiple stocks with an efficient price as the unobserved state and midquotes as observations. Compared to other approaches, the model's appeal lies in its ability to deal naturally with (i) simultaneous quotes in an overlapping period, (ii) missing observations in the non-overlap, (iii) noise due to short-term microstructure effects, and (iv) contemporaneous correlation in returns due to common market-wide factors. As a matter of fact, our specification enables us to estimate the common factor return, conditional on the data. We compare it to the return on the local market indices to find out to what extent the common factor mirrors these indices.

We exploit a rich dataset on Dutch stocks cross-listed at the NYSE with tick data on trades, quotes, exchange rates, and both local market indices. We find that the overlapping period is the most important period in 24-hour price discovery, followed by the "Amsterdam only" period. Least important are the "New York only" and the overnight period, which, perhaps surprisingly, are equally informative. Further evidence of the NYSE's minor role in price discovery is the significant noise in midquotes throughout the trading day. Amsterdam midquotes, however, are not noisy outside the overlap and significantly less noisy during the overlap. The round-the-clock price discovery process can be further analyzed by decomposing the information by time-of-day into a firm-specific and a common-factor component. We find that it is firm-specific information that causes the overlap to be relatively more informative. Interestingly, we also find that the NYSE preopening period is characterized by common-factor information, consistent with U.S. macro-announcements that are published in this period. Further study of the common-factor estimate reveals that it correlates highly with the Dutch market index in early Amsterdam hours, but this correlation decreases substantially in the course of the day, as

34% of the permanent component ("efficient price innovation") is due to signed volume. Following microstructure theory, we assume all correlation between the two components is caused by signed volume. Based on these observations, we estimate the correlation at 0.175. This is easily seen by writing down a simultaneous model of the transitory (t) and the permanent (p) component:

$$
\begin{aligned}
t &= c + \varepsilon, \quad \varepsilon \perp c, \\
p &= \alpha c + \eta, \quad \eta \perp c, \quad \eta \perp \varepsilon.
\end{aligned}
$$

The correlation between t and p is now easily calculated as:

$$
\rho_{t,p} = \frac{cov(t,p)}{\sigma_t \sigma_p} = \frac{\alpha \sigma_c^2}{\sqrt{\frac{1}{0.34}}\sigma_c \sqrt{\frac{1}{0.09}}\alpha\sigma_c} = \sqrt{0.09 \cdot 0.34} \approx \pm 0.175.
$$

As we can exclude a negative signed volume effect, because we use midquotes and *not* transaction prices, the remaining signed volume effect for "inventory reasons" suggests a positive sign, i.e. +0.175.

we get closer to the start of trading in New York. The correlation is low and insignificant around the New York open, indicating that the cross-listed stocks exhibit common price discovery independent of the rest of the home market. During New York trading hours, the common factor significantly correlates with the S&P500. Again, this correlation is lower during the overlap than outside the overlap. These findings suggest that efficient price innovations are driven by country-specific investor sentiment (see, e.g., Chan, Hameed, and Lau (2003)).

Incidentally, the empirical results for the overlap — most information, strongest market underreaction, and significant noise — are consistent with theoretical studies that predict that, in the presence of noise traders, privately-informed traders should split their orders across markets (see, e.g., Chowdhry and Nanda (1991), Menkveld (2003)) and through time (see, e.g., Kyle (1985)) to minimize market impact. The decomposition of information reconfirms this claim as the increase in information in the overlap is firm-specific rather than common.

References

Alexander, G. J., C. S. Eun, and S. Janakiramanan (1987). Asset pricing and dual listing on foreign capital markets: A note. *Journal of Finance 42*, 151–158.

Alexander, G. J., C. S. Eun, and S. Janakiramanan (1988). International listings and stock returns: Some empirical evidence. *Journal of Financial and Quantitative Analysis 23*, 135–151.

Amihud, Y. and H. Mendelson (1987). Trading mechanisms and stock returns: An empirical investigation. *Journal of Finance 42*, 533–553.

Andersen, T. G., T. Bollerslev, and A. Das (2001). Variance-ratio statistics and high-frequency data: Testing for changes in intraday volatility patterns. *Journal of Finance 56*(1), 305–327.

Bacidore, J. and G. Sofianos (2002). Liquidity provision and specialist trading in NYSE-listed non-U.S. stocks. *Journal of Financial Economics 63*, 133–158.

Barclay, M. J. and T. Hendershott (2003). Price discovery and after trading hours. *Review of Financial Studies 16(4)*, 1041–1073.

Barclay, M. J., R. H. Litzenberger, and J. B. Warner (1990). Private information, trading volume, and stock-return variances. *Review of Financial Studies 3(2)*, 233–253.

Barclay, M. J. and J. B. Warner (2003). Stealth trading and volatility: Which trade moves prices? *Journal of Financial Economics 34*, 281–305.

Caballe, J. and M. Krishnan (1994). Imperferct competition in a multi-security market with risk neutrality. *Econometrica 62*, 695–704.

Campbell, J. Y., A. W. Lo, and A. C. MacKinlay (1997). *The Econometrics of Financial Markets*. Princeton, New Jersey: Princeton University Press.

Chan, K. A., A. Hameed, and S. T. Lau (2003). What if trading location is different from business location? Evidence from the jardine group. *Journal of Finance 58(3)*, 1221–1246.

Chowdhry, B. and V. Nanda (1991). Multimarket trading and market liquidity. *Review of Financial Studies 4*, 483–511.

Craig, A., A. Dravid, and M. Richardson (1995). Market efficiency around the clock: Some supporting evidence using foreign-based derivatives. *Journal of Financial Economics 39*, 161–180.

Domowitz, I., J. Glen, and A. Madhavan (1998). International cross-listing and order flow migration: Evidence from an emerging market. *Journal of Finance 53*(6), 2001–2027.

Doornik, J. A. (2001). *Object-Oriented Matrix Programming using Ox 3.0*. London: Timberlake Consultants Press.

Durbin, J. and S. J. Koopman (2001). *Time Series Analysis by State Space Models*. Oxford: Oxford University Press.

Fleming, M. J. and J. A. Lopez (2003). Heat waves, meteor showers, and trading volume: An analysis of volatility spillovers in the U.S. treasury market. Discussion paper, Federal Reserve Bank of New York.

Foerster, S. and A. Karolyi (1999). The effects of segmentation and investor recognition on asset prices: Evidence from foreign stocks listings in the U.S. *Journal of Finance 54*, 981–1013.

Forster, M. M. and T. J. George (1996). Pricing errors at the NYSE open and close: Evidence from internationally cross-listed stocks. *Journal of Financial Intermediation 5*, 95–126.

French, K. and R. Roll (1986). Stock return variances, the arrival of information and the reaction of traders. *Journal of Financial Economics 17*, 5–26.

George, T. J. and C. Y. Hwang (2001). Information flow and pricing errors: A unified approach to estimation and testing. *Review of Financial Studies 14*(4), 979–1020.

Gerety, M. S. and J. H. Mulherin (1994). Price formation on stock exchanges: The evolution of trading within the day. *Review of Financial Studies 7*(3), 609–629.

Harvey, A. C. (1989). *Forecasting, Structural Time Series Models and the Kalman filter*. Cambridge: Cambridge University Press.

Harvey, C. and R. D. Huang (1991). Volatility in foreign currency futures markets. *Review of Financial Studies 4*, 543–569.

Hasbrouck, J. (1993). Assessing the quality of a security market: A new approach to transaction-cost measurement. *Review of Financial Studies 6*(1), 191–212.

Hasbrouck, J. (1995). One security, many markets: Determining the contributions to price discovery. *Journal of Finance 50*, 1175–1199.

Hasbrouck, J. and D. J. Seppi (2001). Common factors in prices, order flows, and liquidity. *Journal of Financial Economics 59*, 383–411.

Hasbrouck, J. and G. Sofianos (1993). The trades of market makers: An empirical analysis of NYSE specialists. *Journal of Finance 48*, 1565–1593.

Hau, H. (2001). Location matters: An examination of trading profits. *Journal of Finance 56(5)*, 1959–1983.

Hupperets, E. and A. J. Menkveld (2002). Intraday analysis of market integration: Dutch blue chips traded in amsterdam and new york. *Journal of Financial Markets 5*(1), 57–82.

Jones, C. M., G. Kaul, and M. L. Lipson (1994). Information, trading, and volatility. *Journal of Financial Economics 36*, 127–153.

Karolyi, A. G. (1998). Why do companies list abroad? a survey of the evidence and its managerial implications. *Financial Markets, Institutions, and Instruments 7*, 1–60.

Koopman, S. J., N. Shephard, and J. A. Doornik (1999). Statistical algorithms for models in state space using SsfPack 2.2. *Econometrics Journal 2*, 113–166.

Kumar, P. and D. J. Seppi (1994). Information and index arbitrage. *Journal of Business 69*, 481–509.

Kyle, A. (1985). Continuous auctions and insider trading. *Econometrica 53*, 1315–1335.

Madhavan, A. (2000). Market microstructure: A survey. *Journal of Financial Markets 3*(3), 205–258.

Madhavan, A. and S. Smidt (1993). An analysis of changes in specialist inventories and quotations. *Journal of Finance 48*, 1595–1628.

Madhavan, A. and G. Sofianos (1998). An empirical analysis of NYSE specialist trading. *Journal of Finance 48*, 189–210.

Menkveld, A. J. (2003). Splitting orders in overlapping markets: Theory and U.S.-Dutch evidence. Discussion paper, AFA 2002 Annual Conference Paper `www.ssrn.com/abstract=286986`.

Miller, D. P. (1999). The market reaction to international cross-listings: Evidence from depository receipts. *Journal of Financial Economics 51*, 103–123.

Oldfield, G. S. and R. J. Rogalski (1980). A theory of common stock returns over trading and non-trading periods. *Journal of Finance 35*, 729–751.

Pagano, M., O. Randl, A. A. Roëll, and J. Zechner (2001). What makes stock exchanges succeed? Evidence from cross-listing decisions. *European Economic Review 45(4-6)*, 770–782.

Pagano, M., A. A. Roëll, and J. Zechner (2002). The geography of equity listing: Why do companies list abroad? *Journal of Finance 57(6)*, 2651–2694.

Roll, R. (1986). A simple model of the implicit bid-ask spread in an efficient market. *Journal of Finance 39*, 1127–1139.

Ronen, T. (1997). Tests and properties of variance ratios in microstructure studies. *Journal of Financial and Quantitative Analysis 32*(2), 183–203.

Solnik, B. H. (1996). *International Investments*. Reading, MA: Addison-Wesley.

Stoll, H. R. (2001a). Market fragmentation. *Financial Analysts Journal 57(4)*, 16–21.

Stoll, H. R. (2001b). Market microstructure. Discussion Paper 16, Owen Graduate School of Management, Vanderbilt University.

Stoll, H. R. and R. E. Whaley (1990). Stock market structure and volatility. *Review of Financial Studies 3*, 37–71.

Subrahmanyam, A. (1991). A theory of trading in stock index futures. *Review of Financial Studies 4*, 17–51.

Werner, I. M. and A. W. Kleidon (1996). U.K. and U.S. trading of British cross-listed stocks: An intraday analysis of market integration. *Review of Financial Studies 9*(2), 619–664.

Table 1: Summary Statistics Trading Amsterdam and New York

This table contains summary statistics for trading in Amsterdam and New York from July 1, 1997, through June 30, 1998. Panel A contains averages for the full trading day; panel B for the overlapping hour. All variables are 15-minute averages. *Trade Price Volatility* is calculated as the variance of the 15-minute squared returns based on transaction prices and measured in basispoints. *Midquote Volatility* is calculated the same way, but based on midquotes. *Quoted Spread* is calculated as the time-weighted average of all prevailing quoted spreads in a 15-minute interval. *Effective Spread* is calculated as the time-weighted average of twice the difference between the transaction price and the prevailing midquote. Both spreads are measured in basispoints. *Volume* is the 15-minute average number of shares traded.

Panel A: Trading Statistics Full Day (15-minute averages)

		Share						
		AEG	AHO	KLM	KPN	PHG	RD	UN
Trade Price	AMS	922	1,360	1,284	1,005	1,412	730	581
Volatility (bp^2)	NY	336	1,214	753	376	808	859	493
Midquote	AMS	544	1,076	929	642	1,118	600	438
Volatility (bp^2)	NY	274	799	686	390	743	914	533
Quoted	AMS	23	40	37	32	25	20	18
Spread (bp)	NY	51	106	66	90	38	44	19
Effective	AMS	18	26	28	25	18	15	14
Spread (bp)	NY	19	49	32	35	15	15	13
Volume	AMS	34	89	20	53	77	139	57
(1,000 *shares*)	NY	3	1	6	1	24	72	20

Panel B: Trading Statistics Overlapping Hour (15-minute averages)

		Share						
		AEG	AHO	KLM	KPN	PHG	RD	UN
Trade Price	AMS	1,437	2,116	2,321	1,779	2,096	1,017	966
Volatility (bp^2)	NY	933	2,007	1,840	733	1,508	1,291	619
Midquote	AMS	1,038	1,708	1,949	1,325	1,783	897	827
Volatility (bp^2)	NY	888	1,466	1,679	815	1,553	1,284	710
Quoted	AMS	23	41	36	31	25	21	20
Spread (bp)	NY	61	120	83	90	44	47	20
Effective	AMS	20	28	32	28	20	17	16
Spread (bp)	NY	51	82	58	83	33	17	21
Volume	AMS	53	124	33	81	123	232	95
(1,000 *shares*)	NY	5	3	11	2	38	120	34

Table 2: Hourly Variance for Intraday and Overnight Returns

This table contains estimates of the midquote return variance for different intraday time intervals based on July 1, 1997, through June 30, 1998. All stocks are included. Midquote returns for are first demeaned by subtracting the time-proportional average mean over the entire sample and then scaled to correct for inter-stock volatility differences. Standard deviations are in parentheses.

	Time Intervals, $\tau_i - \tau_{i+1}$					
Event	Start AMS	NY PreOpen	NY Open	AMS Close	NY Only	Over-night
Start (EST)	4:00	8:00	9:00	10:00	11:00	15:30
End	8:00	9:00	10:00	11:00	15:30	4:00
σ^2_τ	0.36	0.36	0.36	0.53	0.15	0.12
$(\times 10,000)$	(0.01)	(0.05)	(0.05)	(0.05)	(0.01)	(0.00)

Table 3: Intraday Return Autocorrelations

This table presents the raw return autocorrelations up to the second lag of intraday and overnight midquote returns. The midquote in the overlapping interval was arbitrarily fixed at the average of the Amsterdam and New York midquote. The autocorrelations are calculated for the full sample period, from July 1, 1997, through June 30, 1998, and averaged across all stocks. We explicitly account for commonality in returns when determining confidence intervals.

Time Interval	Event	Lag 1		Lag 2	
4:00-8:00	AMS Only	-0.077			
8:00-9:00	NY PreOpen	0.056		-0.020	
9:00-10:00	NY Open	-0.125	*	-0.005	
10:00-11:00	AMS Close	0.251	*	-0.170	*
11:00-15:30	NY Only	-0.050		0.039	
15:30-4:00(+1)	Overnight	-0.165	*	-0.022	

*: Significant at a 95% confidence level.

Table 4: Estimation results for efficient price and observation models

This table contains maximum likelihood estimates of the state space model (1) and (7) based on intraday midquotes for the period from July 1, 1997, through June 30, 1998. The model is for observation vector $p_{k,t,\tau}$ that contains the midquotes for all stocks traded in market k at day t and timepoint τ. In Panel A estimates are presented for the efficient price innovation variance $\sigma^2_{E,\tau}$, the common price variance $\sigma^2_{\xi,\tau}$, the price reaction to a common innovation $\theta_{\xi,\tau}$, the firm-specific price variance $\sigma^2_{\eta,\tau}$ and the price reaction to a firm-specific innovation $\theta_{\eta,\tau}$. Note that $\sigma^2_{E,\tau} = \sigma^2_{\xi,\tau} + \sigma^2_{\eta,\tau}$. In Panel B estimates are presented for the variance of the measurement error in both markets, $\sigma^2_{\varepsilon,k,\tau}$ with $k \in \{\mathrm{A}, \mathrm{NY}\}$. Standard deviations are in parentheses.

Panel A: Variance Efficient Price Innovation ($\times 10,000$, Hourly)

	Time Intervals, $\tau_i - \tau_{i+1}$					
Event	Start AMS	NY PreOpen	NY Open	AMS Close	NY Only	Over-night
Start (EST)	4:00	8:00	9:00	10:00	11:00	15:30
End	8:00	9:00	10:00	11:00	15:30	4:00
$\sigma^2_{E,\tau}$	0.35	0.33	0.43	0.38	0.09	0.10
	(0.02)	(0.02)	(0.02)	(0.03)	(0.01)	(0.01)
$\sigma^2_{\xi,\tau}$	0.13	0.18	0.16	0.15	0.05	0.05
	(0.01)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)
$\theta_{\xi,\tau}$			-0.35		-0.16	
			(0.04)		(0.04)	
$\sigma^2_{\eta,\tau}$	0.22	0.15	0.27	0.23	0.05	0.05
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.00)
$\theta_{\eta,\tau}$			-0.34	-0.30	0.87	
			(0.02)	(0.08)	(0.13)	

Panel B: Variance Measurement Error ($\times 10,000$)

	Time Points, τ_i, (EST)					
Start (EST)	4:00	8:00	9:00	10:00	11:00	15:30
$\sigma^2_{\varepsilon,A,\tau}$	0.00	0.00	0.00	0.07		
	(0.00)	(0.00)	(0.00)	(0.01)		
$\sigma^2_{\varepsilon,NY,\tau}$				0.11	0.07	0.14
				(0.01)	(0.02)	(0.00)

Table 5: Estimation results for decomposition parameters

This table contains maximum likelihood estimates of the state space model (1) and (7) based on intraday midquotes for the period from July 1, 1997, through June 30, 1998. The model is for observation vector $p_{k,t,\tau}$ that contains the midquotes for all stocks traded in market k at day t and timepoint τ. Estimates are presented for the common factor loading vector β and diagonal variance matrix of firm-specific innovations. For ease of interpretation, the common factor variation relative to firm-specific variation is signalled by β_i^2/c_i for $i = 1, \ldots, n$. Standard deviations are in parentheses.

	Share						
	AEG	AHO	KLM	KPN	PHG	RD	UN
β_i	0.98	1.23	0.87	0.87	1.11	1.00	0.88
	(0.03)	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)	(0.04)
c_i	0.55	1.21	1.54	0.67	1.83	0.75	0.46
	(0.03)	(0.06)	(0.06)	(0.03)	(0.07)	(0.04)	(0.03)
β_i^2/c_i	1.75	1.25	0.49	1.12	0.68	1.34	1.68
	(0.16)	(0.10)	(0.05)	(0.10)	(0.06)	(0.11)	(0.15)

Table 6: Correlation Common Factor and Market Index

This table contains the correlations between the (smoothed) common factor estimate of the state space model and intraday returns on the AEX index and the S&P500 indices for different intraday time intervals. Standard deviations are in parentheses.

	Time Intervals, $\tau_i - \tau_{i+1}$				
Event	Start AMS	NY PreOpen	NY Open	AMS Close	NY Only
Start (EST)	4:00	8:00	9:00	10:00	11:00
End	8:00	9:00	10:00	11:00	15:30
ρ(Common Factor, AEX)	0.57	0.38	0.08		
	(0.07)	(0.07)	(0.07)		
ρ(Common Factor, S&P500)				0.21	0.28
				(0.07)	(0.07)

Table 7: Robustness Checks

This table contains estimates of the efficient-price-innovation variance and other parameters for various models. They represent robustness checks of the main results of Table 4. Panel A repeats the estimates of Table 4. Panel B splits the sample in two sub-periods: (i) July 1, 1997, through December 31, 1997, and (ii), January 1, 1998, through June 30, 1998. Panel C allows for stock-specific measurement error variances $\sigma^2_{\varepsilon,k,\tau}$. Panel D sets the correlation $\rho(\eta_{t,\tau-1}, \varepsilon_{k,t,\tau})$ between the efficent price innovation and the subsequent measurement error equal to 0.175, inspired by microstructure theory and empirical work by George and Hwang (2001). Standard deviations are in parentheses.

	$\sigma^2_{E,\tau}$						$\theta_{\xi,\tau}$		$\theta_{\eta,\tau}$			$\sigma^2_{\varepsilon,A,\tau}$	$\sigma^2_{\varepsilon,NY,\tau}$
	Start AMS	NY Pre-Open	NY Open	AMS Close	NY Only	Over-night	NY Open	NY Only	NY Open	AMS Close	NY Only		
	4:00	8:00	9:00	10:00	11:00	15:30	9:00	11:00	9:00	10:00	11:00		
	8:00	9:00	10:00	11:00	15:30	4:00	10:00	12:00	10:00	11:00	15:30	10:00	10:00
A: Basic Model													
	0.35	0.33	0.43	0.38	0.09	0.10	-0.35	-0.16	-0.34	-0.30	0.87	0.07	0.11
	(0.02)	(0.07)	(0.02)	(0.01)	(0.01)	(0.00)	(0.04)	(0.04)	(0.02)	(0.08)	(0.13)	(0.01)	(0.01)
B:Sub-Periods													
First	0.41	0.48	0.51	0.43	0.11	0.09	-0.40	-0.25	-0.39	-0.36	1.13	0.08	0.12
	(0.03)	(0.04)	(0.04)	(0.04)	(0.01)	(0.01)	(0.05)	(0.04)	(0.03)	(0.10)	(0.24)	(0.00)	(0.01)
Second	0.28	0.18	0.39	0.31	0.08	0.10	-0.23	0.00	-0.31	-0.17	0.66	0.06	0.09
	(0.02)	(0.01)	(0.03)	(0.03)	(0.01)	(0.01)	(0.09)	(0.00)	(0.03)	(0.15)	(0.14)	(0.00)	(0.01)
C: Stock-Specific													
	0.35	0.33	0.42	0.39	0.08	0.10	-0.34	-0.16	-0.34	-0.48	1.03	0.06	0.09
	(0.02)	(0.02)	(0.02)	(0.03)	(0.01)	(0.01)	(0.05)	(0.04)	(0.02)	(0.08)	(0.15)	(0.00)	(0.01)
D: $\rho = 0.175$													
	0.35	0.33	0.41	0.32	0.08	0.10	-0.32	-0.16	-0.31	-0.31	0.63	0.07	0.11
	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.04)	(0.04)	(0.02)	(0.07)	(0.09)	(0.00)	(0.01)

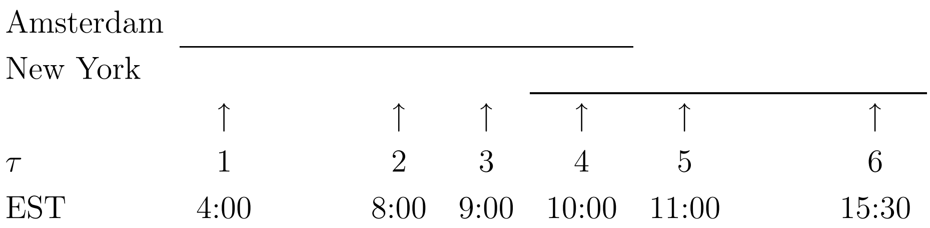

Figure 1: **Time line.** This figure illustrates the time line for trading in Amsterdam and New York using Eastern Standard Time. The economically interesting timepoints modelled in this paper are indicated with arrows. Most are self-explanatory, except for the 8:00 timepoint, which was introduced to pick up the potential effect of U.S. macro-announcements and pre-market-open press releases of rival U.S. firms.

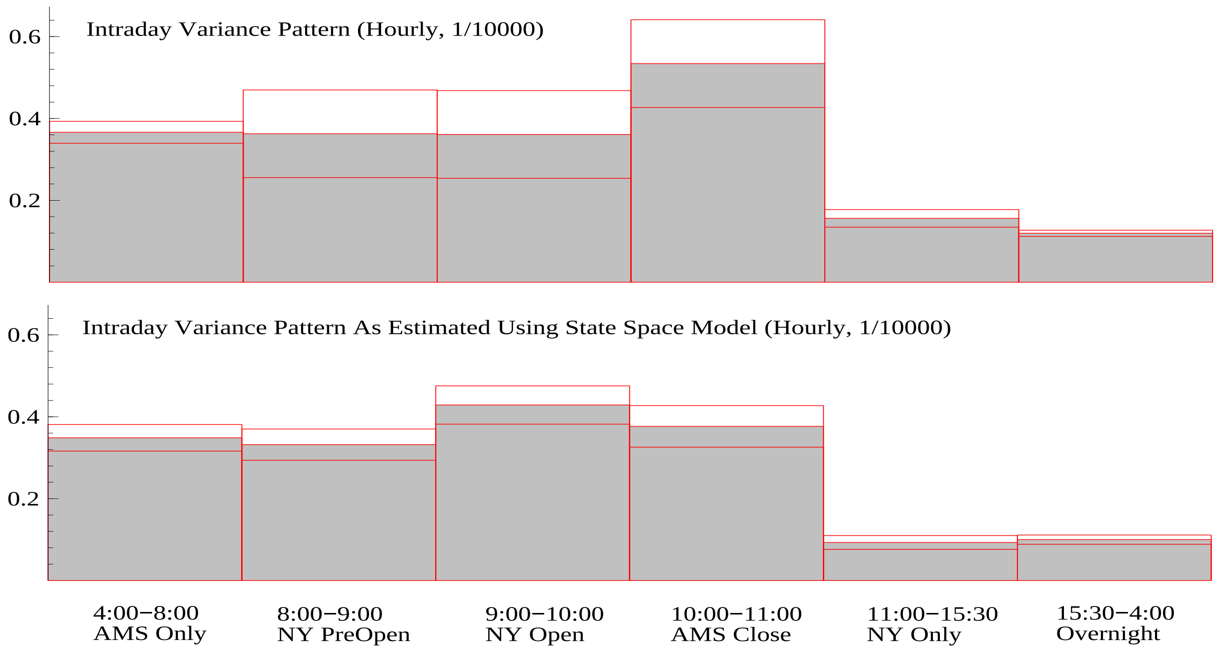

Figure 2: **Variance Pattern Raw Returns vs. Variance Pattern State Space Model**. The top figure illustrates the estimate of the intraday variance pattern based on raw returns of all stocks taking into account inter-stock volatility differences. It is presented on an hourly basis to enhance comparability. The bottom figure represents the variance pattern based on the returns of the unobserved efficient price as estimated by the state space model. The bars represent point estimates; the dotted lines 95% confidence intervals.

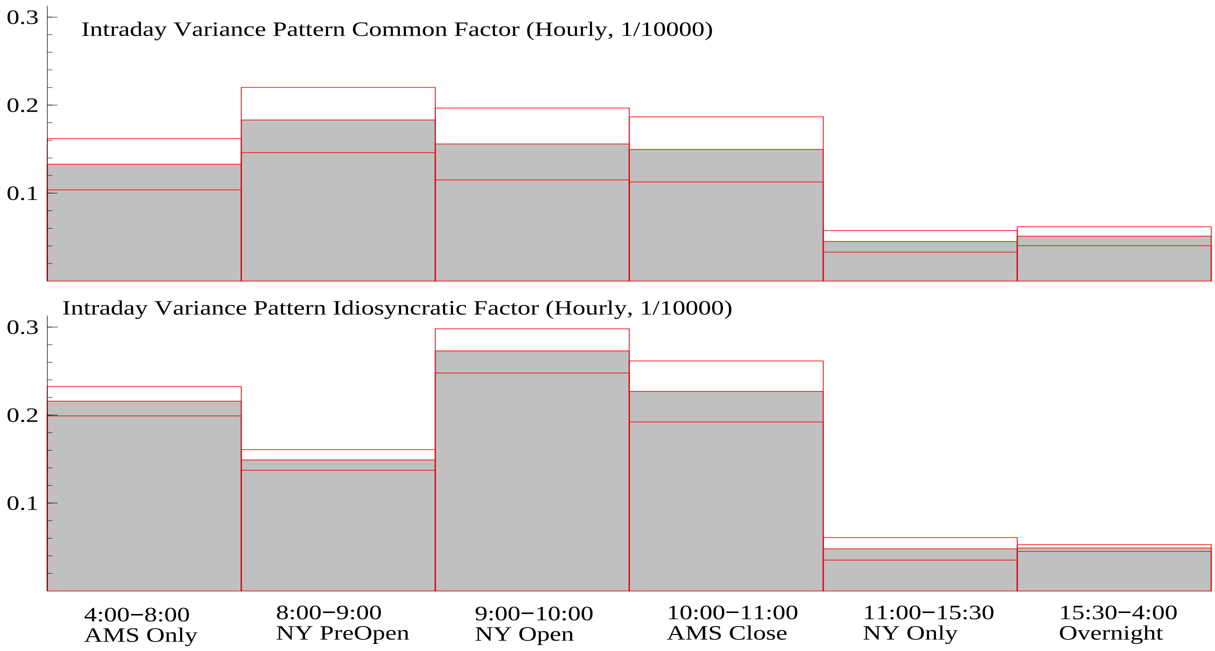

Figure 3: **Variance Decomposition into Common and Idiosyncratic Component**. The state space model specification allows for decomposition of the efficient-price returns into two components: a common component due to a common (market-wide or macro) factor driving the returns across all stocks and an idiosyncratic component due to firm-specific returns. Hence, the variance can be decomposed by time of day. The efficient-price variance pattern, as depicted in Figure 2, is therefore the sum of two components: the top figure represents the common factor component, the bottom figure the stock-specific or idiosyncratic component. The bars represent point estimates; the dotted lines 95% confidence intervals.

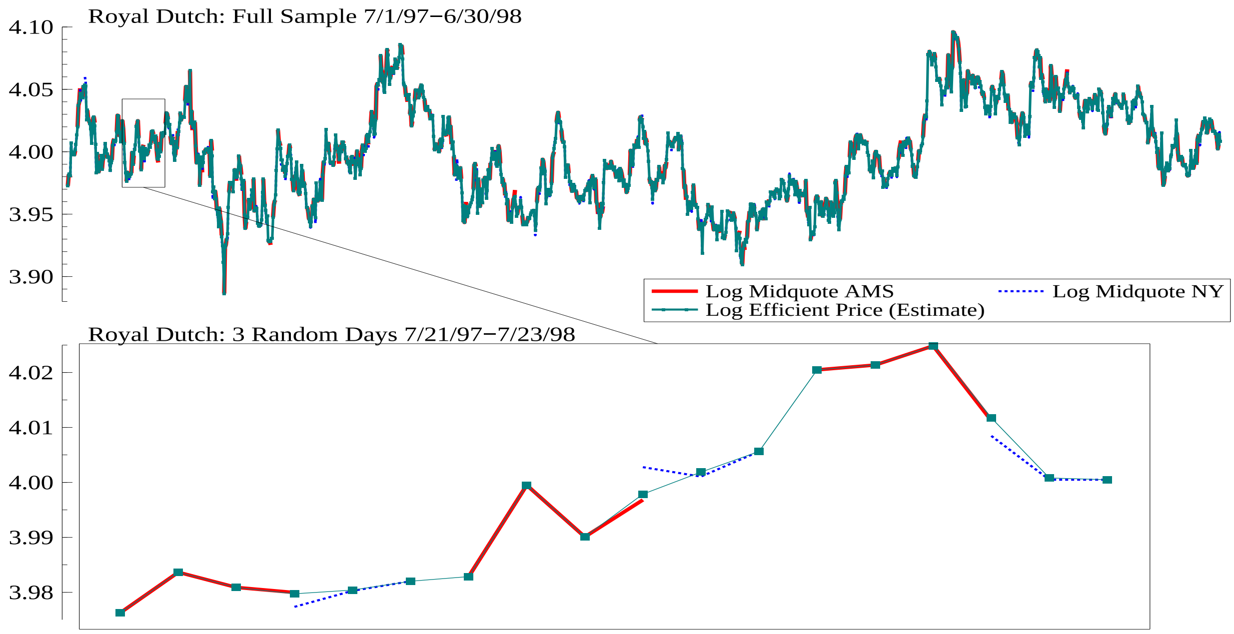

Figure 4: **Midquotes and Efficient Price Estimates for Royal Dutch**. This figure illustrates the model estimates by plotting for Royal Dutch the estimate of the efficient price against the observed midquote in Amsterdam and New York. The upper panel shows the full sample from July, 1, 1997, through June 30, 1998; the lower panel a random sample of three consecutive days: July 21, 22, and 23, 1997.

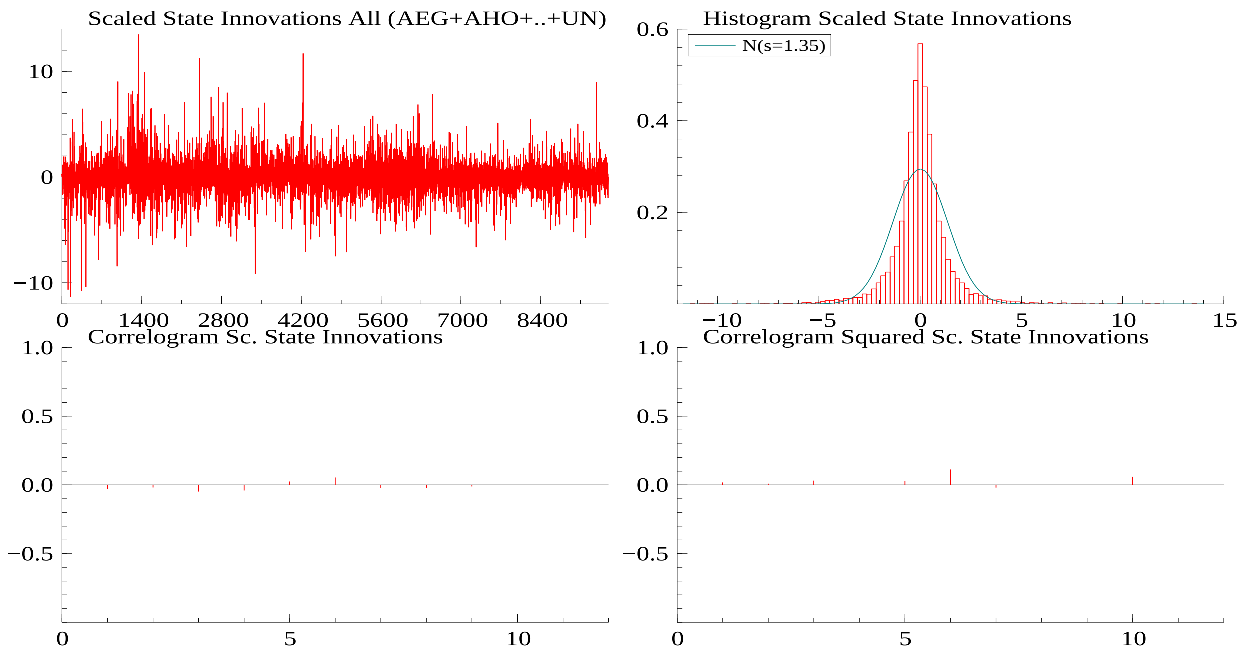

Figure 5: **Diagnostic Analysis of Filtered Innovations**. This figure contains four graphs to illustrate the model's performance. The top left figure plots the scaled filtered state innovations, i.e. the difference between the predicted state conditional on all observations through $t-1$ and the observation, scaled by the standard deviation estimate based on all observations through $t-1$. It plots all stocks in consecutive order. The top right figure shows the empirical density and the bottom left figure shows the correlogram of these innovations. The bottom right figure shows the correlogram of the squared innovations.