Housewives of Tokyo versus the Gnomes of Zurich: Measuring Price Discovery in Sequential Markets

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May 2008

Abstract

This paper proposes a model to compare price discovery across sequential markets. Existing models are based on parallel markets where a common efficient price leads to a no-arbitrage relationship among multiple price series at any point in time. In our model, the changes in the efficient price are embedded in the sequential price changes across markets defined by time zones. We use a structural VAR to identify market-specific shocks to the efficient price and to measure a market's contribution to price discovery. The model is applied to the 24-hour trading of AUD, JPY, EUR, and GBP against USD over an eight-year sample period. We estimate the information shares, in the sense of Hasbrouck (1995), of four sequential markets around the world. Although Europe remains highly significant for the pricing of all four exchange rates, there is evidence of equalizing information shares between Asia and Europe, with Asia gaining information shares in EUR and GBP but losing information shares in AUD and JPY. We do not find evidence that the Asia/Japan trading hours are gaining information share in JPY trading.

Key words: price discovery, information share, sequential markets, Beverage-Nelson decomposition, efficient price, variance ratio, foreign exchange rate.

JEL classification: G14, G15, C32

We thank Douglas Foster, Frederick Harris, S. Ghon Rhee, and Shuji Watanabe for helpful comments and the Securities Industry Research Centre of Asia-Pacific (SIRCA) for providing the foreign exchange data. Jianxin Wang's email is jx.wang@unsw.edu.au, and Minxian Yang's email is m.yang@unsw.edu.au.

> "Years ago, it was the gnomes of Zurich who shook the foreign exchange markets. They have now been replaced by the housewives of Tokyo, who speculate in various currencies. However, whereas the gnomes of Zurich were accused in their day of destabilizing markets, the housewives of Tokyo are apparently acting to stabilize them. Their presence seems to lie behind the marked decline in (perceived) volatility in yen-dollar exchange rates ····. The housewives are betting against professional investors in the IMM, and seem to be profiting from their trading so far."
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> Dr Kiyohiko Nishimura, Bank of Japan, in a speech at the Brookings Institution on July 2, 2007.[1]

I. Introduction

The above speech created the metaphorical "Mrs Watanabe", whose currency trading and market impact captured the imagination of financial and popular press: "On her shoulders may lie responsibility for some of the stability of the global financial system," says the Economist (2007). If indeed "the housewives of Tokyo" are winning against futures traders in Chicago and possibly "the gnomes of Zurich", it would suggest that Japanese retail investors know more about the yen than the rest of the world, and Tokyo trading contains greater information about the value of the yen than anywhere else. On the other hand, the BIS survey shows that U.K. and U.S. account for 34% and 16.6% of global currency transactions respectively. Japan's share of currency transactions has declined from 9.1% in 2001 to 6% in 2007 and is similar to that of Switzerland (6.1%) and Singapore (5.8%). For yen-related transactions, Japan's market share is 25%, compared to 28.3% for U.K. and 16.5% for U.S. (BIS, 2007, Tables B.2 and E.4). The survey indicates that Japan is not the leading hub for currency trading, even for yen-related transactions.

This paper proposes an econometric model to measure the contributions of markets around the world to the pricing of major exchange rates. In particular we compare the information share of currency trading during Japanese business hours against trading during European and U.S. business hours. The information share, in the sense of Hasbrouck (1995),

[1] Dr Nishimura is currently the Deputy Governor, Bank of Japan. His speech is published as Nishimura (2007).

measures the contribution of a particular market to the price discovery of an asset traded in multiple markets. Studies have shown that the information share of a market may not be proportional to its share of trading volume. Dr Nishimura's observations raise the possibility that trading by Japanese retail investors has a significant impact on currency values and Japan plays a greater role than other markets in determining the value of the Japanese yen (JPY).

Over the past twenty years, financial liberalization and integration, together with advances in information technology, have led to a significant increase in the number of assets being traded in multiple markets around the world. Hasbrouck (1995) is the first to develop a model to compare price discovery across markets. It has been adopted by many studies comparing price discovery of cross-listed stocks or between spot and derivative trading. Several studies, e.g. Booth et al. (1999), Chu et al. (1999), and Harris et al. (2002), adopted an alternative approach proposed by Gonzalo and Granger (1995). Indeed cross-market comparisons of price discovery have spawned into "a mid-sized cottage industry" (Lemann, 2002). A special issue of the Journal of Financial Markets in 2002 was devoted to the comparison between the Hasbrouck model and the Gonzalo-Granger model. Recent studies provide further applications (Chakravarty, et al. 2004; Covrig, et al. 2004; Figuerola-Ferretti and Gonzalo, 2007; Harris, et al. 2008), extension (Pascual, et al. 2006), and comparison of the two methodologies (Yan and Zivot, 2008).

These studies have significantly enhanced our understanding of the institutional and behavioural aspects of the price discovery process. However the existing methodologies are constrained to parallel markets where trading takes place simultaneously. They can not be used to compare global markets without overlapping trading hours, e.g. Tokyo versus London or New York. [2] This paper makes two methodological contributions to the literature on cross-

[2] We are aware of two studies that compare cross-market price impact of non-overlapping markets. Lieberman, et al. (1999) examine six stocks traded in Israel and the United States and Agarwal, et al. (2007) study 17 stocks traded in Hong Kong and London. Both studies show greater price impact from the home market to the foreign market than in the opposite direction.

market comparison of price discovery. First, we develop a model for comparing price discovery in sequential markets, where trading takes place across geographical locations and time zones. An important feature of parallel markets is that the law of one price leads to a no-arbitrage equilibrium for prices from different markets. However for sequential markets, there is only one market open at any time; prices at different points in time do not form a co-integrating relationship. We use a structural VAR to identify the permanent component of price changes and compare the contributions of sequential markets to the efficient price. Our model makes it feasible to compare the relative importance of non-overlapping markets such as Tokyo and New York. It also can be used to improve studies of international markets with small overlapping hours, e.g. Hupperets et al. (2002), Grammig et al. (2005), and Pascual et al. (2006).[3] Second, existing methodologies are based on reduced-form equations where price innovations are inherently correlated across-markets. As pointed out by Lehmann (2002), because of cross-market correlation, price innovations cannot be allocated to specific markets cleanly. A natural solution to this problem is to use a structural model where any contemporaneous return correlation is captured by the structural coefficients. By construction, price innovations in the structural model are uncorrelated across markets, thus provide a clean measure for information flow in a specific market. Yan and Zivot (2008) use a structural VAR to address this problem for parallel markets. We propose a structural model for sequential markets. Our model is based on the open-to-close return of each market and does not require intraday sampling. In contrast, for models of parallel markets, the choice of intraday sampling frequency often has a significant impact on the empirical outcomes.[4]

[3] The small overlapping hours, e.g. 2 hours or less, may lead to bias against the newly opened market as newly arrived traders learn from past price movements (see Hsieh and Kleidon, 1996). When two markets are partially overlapping, they can be divided into three periods with the overlapping period in the middle. Our model can be used to estimate price discovery in the three sequential periods and may improve the cross-market comparison by examining returns over the non-overlapping periods.

[4] Hasbrouck (1995) uses 1-second sampling and reports a narrow range of information share for the NYSE. Huang (2002) uses 1-minute sampling and reports a wide range of information share for the same market, e.g. from 30% to 80%. Booth, et al. (2002) uses an average of 30-minute sampling and reports 13% to 99% information share for the same market.

Our model is applied to the foreign exchange markets, which trade continuously around the clock. By estimating the information shares across markets and time zones, we provide new evidence on exchange rate price discovery and dynamics. There is indirect evidence that some markets are more important than others in currency trading. Ito et al. (1998) and Covrig and Melvin (2002) provide evidence of private information in currency trading and suggest that Tokyo may know more about the yen than other markets. However the findings are disputed by Andersen et al. (2001). Andersen, Bollerslev, Diebold, and Vega (2003) show that U.S. macroeconomic news has much greater price impact than German macro news, suggesting that U.S. has a greater information share than Germany in the Deutsche Mark-U.S. Dollar (USD) market. This study is not based on specific events, e.g. “the Tokyo experiment” or macroeconomic announcements. Instead we estimate a market’s contribution to the permanent price changes over a trading day. We compare the “home markets” of an exchange rate, e.g. Japan and U.S. for the JPY/USD rate, as well as non-home markets, e.g. Europe for the Australian dollar (AUD). Non-home markets are important as hedging and other portfolio needs may cause permanent shifts in demand and supply independent of the macro fundamentals of the home markets.

We compare price discovery across global markets for AUD, JPY, the Euro (EUR), and the British pound (GBP), all against USD, from January 1996 to December 2003. These are the top-four currency pairs in terms of trading value and represent 58% of global currency trading (BIS, 2007, Table B.5). A 24-hour day is divided into four sequential periods: the Asian market (8 hours), the European market (6 hours), the overlap between London and New York (2 hours), and the U.S. market (8 hours). The percentage contributions to price discovery from these markets are estimated and compared to their contributions to trading volume, return, and volatility. Sub-period analyses provide evidence on changes in the contribution of each market over the eight-year. The findings are summarized below:

- On average, Asia has the highest information shares for AUD and JPY at 31~33% and lowest information shares for EUR and GBP at 8~14%. Over the sample period, Asia lost information shares in AUD and JPY, but gained information share in EUR. Our definition of the Asian market covers the entire trading hours in Japan. Asia's declining information share in JPY trading suggests that it is unlikely that retail investors in Japan have greater market power than the "gnomes of Zurich" or professional investors in the futures market in Chicago. The price impact of Mrs Watanabe may have been overstated.
- The information shares of the European market, excluding the London-New York overlapping hours, are around 40% for EUR and GBP and close to 30% for AUD and JPY. Over the sample period, its information shares in AUD and JPY increased significantly but its share in EUR dropped significantly. There is some evidence of equalizing information shares between Asia and Europe over time: Asia gains importance in European currencies and vice versa for Europe. In other words, non-home markets are gaining importance relative to home markets.
- The 2-hour overlapping period between London and New York is highly significant for all exchange rates. Its information shares are relatively stable over the sample period. For the EUR and GBP, this two-hour overlapping period has greater information shares than the eight-hour Asian trading period.
- The U.S. market, excluding the London-New York over-lapping hours, has higher information shares in EUR and GBP than in AUD and JPY. It has lower information shares than Europe for all four currencies.[5] Its information share in AUD declined over time but remained stable in the other currencies.

[5] This appears to be in contrast to the large price reactions to U.S. macro news reported by Andersen, Bollerslev, Diebold, and Vega (2003). Twenty two of the twenty eight U.S. macroeconomic announcements in their study are made during the London-New York overlapping hours. This may explain the relatively low information share during the rest of the U.S. trading hours.

- Although a market's information share can differ significantly from its shares of daily return and return variance, the rank correlations among them are generally over 0.8 across four markets. On a per-trading hour basis, the rank correlations are perfect for JPY, EUR, and GBP. This indicates that our structural model and the estimated information shares capture the information process that drives the observed daily return and volatility. If it is not feasible to estimate a structural model, one can use a market's share of the return variance as a proxy for its information share when the serial and cross-market correlations of returns are small.

Although we do not provide evidence on what affects a market's information share, evidence from microstructure studies of the foreign exchange markets offers some clues. Since the trading platform is the same, the difference between markets is in the number and characteristics of market participants. Studies have shown that private order flows are the critical link between exchange rate changes and economic fundamentals (Evans and Lyons, 2002a, 2005, 2007, and 2008); order flows from financial institutions have greater information content than other investors (Bjonnes, et a. 2005; Carpenter and Wang, 2007); and information flows from major to minor currencies (Evans and Lyons, 2002b; Danielsson, et al. 2002). Therefore a market's information share depends critically on the quantity and the quality of its order flow. Having substantial order flows, particularly in major currencies, is a necessary (but not sufficient) condition for a market to have a significant information share. Having large financial institutions with large client base and substantial research ability will also enhance the information content of order flows.

The paper is organized as follows. Section II explains the sample and presents some analyses of trading value, return, and volatility in each market. Section III presents the model for comparing price discovery in sequential markets. Empirical findings for the foreign exchange markets are discussed in section IV. Some final remarks are contained in section V.

II. Data and Preliminary Analysis

A. Sample Construction

Our primary data source is the Reuters' foreign exchange quotes for AUD, JPY, EUR, and GBP against USD from 1 January 1996 (1 January 1999 for EUR) to 31 December 2003. Weekends are removed because of thin trading. We also remove days with large gaps (over 4 hours) in quote arrivals, which can be the result of system stoppage or holidays in parts of the world. On October 7 and 8, 1998, JPY had "once-in-a-generation" volatility, and both AUD and GBP experienced high volatility.[6] These days are treaded as outliers and are removed from our analyses. This leaves us with 1884 days for AUD, 1902 days for JPY, 1189 days for EUR, and 1879 days for GBP.

Table 1 depicts the local time relative to the Greenwich Mean Time (GMT). The bold letters are local trading hours from 9 am to 4 pm local time.[7] A 24-hour calendar day is divided into four trading periods corresponding to four markets. Period 1 is the Asian trading hours from 23 GMT to the next day's 6 GMT, and is labelled as the Asian market. Period 2 is the European trading from 7 GMT to 12 GMT. It covers most of the trading hours in Frankfurt and Zurich and is labelled as the European market. Period 3 is the overlap of London afternoon and New York morning trading from 13 GMT to 14 GMT and is labelled as the London-NYC market. Period 4 is from 15 GMT to 22 GMT. It covers trading in North and South America excluding the London-NYC period and is labelled as the U.S. market.

For each trading day, the midpoint of the bid-ask quotes is calculated and is sampled at the end of each trading period defined above. If there is not a quote posted exactly at the end of the trading period, the weighted average is calculated from the mid-quote immediately before and after the sample point, with weights being inversely proportional to the distance

[6] On October 7, 1998, JPY jumped from around 130 to 120 per USD in one day. See Cai, et al. (2001) for events surrounding these days.
[7] Both the Reserve Bank of Australia and the Bank of England publish daily exchange rates at 4 pm local time.

from the sample point. The percentage return over the trading period is then calculated. Note this is the same-day open-to-close return, not close-to-close return across trading days.

Table 2 reports the summary statistics of open-to-close returns in the four markets, defined as $100*[\ln(P_{close})–\ln(P_{open})]$. AUD and JPY have the highest volatility during the Asian market while EUR and GBP have the highest volatility during the European market. Asia and Europe generally have opposite direction of skewness except for GBP. EUR and GBP show highest levels of skewness and kurtosis during the Asian market. The Ljung-Box statistic shows that JPY and EUR have strong autocorrelation at 10 lags while GBP shows no autocorrelation. For most currencies, returns during the London-NYC overlapping period are negatively correlated with returns in Europe and positively correlated with returns in the U.S. Interestingly JPY returns during Asia trading have strong autocorrelation but no cross-market correlation. It seems that price movements during Asia trading are either ignored or reversed during the subsequent European market.

B. Preliminary Analyses

Before we estimate the information shares, we present evidence on trading value, return, and volatility over these periods. Table 3 reports the average daily trading value of the four currencies against USD in top-10 foreign exchange markets. It is constructed from the triennial survey conducted by the BIS (2007, Table E.5). Five of the top 10 are in Europe and four are in Asia. AUD trading is more concentrated in Asia (51%), particularly in Australia (33.4%). There is more JPY-USD trading in U.K. (28.6%) than in Japan (25.8%), as in the case of all JPY-related transactions. JPY trades are more evenly split between Asia (39.4%) and Europe (36.9%). EUR and GBP trading is dominated by Europe, and U.K. in particular. Asia's trading shares in EUR and GBP are much lower than those of U.S. These ten markets account for over 93% of world trading of AUD, JPY, and GBP, and 84.9% of world trading of EUR.

To measure a market's contribution to the observed price changes, we calculate its shares of daily return and volatility. Let r_{it} be the open-to-close return of market i on day t and $R_t = \sum_{i=1}^{4} r_{it}$ be the 24-hour return. Market i's share of daily return is measured by its Weighted Price Contribution: $WPC_i = \sum_{t=1}^{T} w_t \times \frac{r_{it}}{R_t}$ where $w_t = |R_t| \Big/ \sum_{t=1}^{T} |R_t|$ is the weight of day t. The term r_{it}/R_t is the relative contribution of market i to the total return R_t. It can be very large when $|R_t|$ is small. The impact of small $|R_t|$ is balanced by the weight of day t.[8] A market's contribution to volatility is measured by its share of the daily realized variance measured over 24 hours. Prices at 30-minute intervals are constructed from the interpolation of the mid-quotes immediately before and after the 30-minute mark. Market i's realized variance, RV_i, is the sum of the squared 30-minute returns over its trading hours.[9] Its share of daily realized variance is $RV_i \Big/ \sum_{i=1}^{4} RV_i$.

The average contributions of each market to daily return and volatility[10] are presented in Table 4. Even though Asia accounts for 51% of the AUD trading volume, its shares of the daily return and volatility are around 30%. While the United States accounts for only 13.5% of the AUD volume, its trading, *excluding the London-NYC overlapping hours,* has greater return and volatility shares than Asia! Therefore higher trading volume does not always lead to greater price impact. Asia has the largest shares of return and volatility for JPY while Europe has the largest shares of return and volatility for EUR and GBP. Europe has greater shares of return and volatility of Asian currencies than vice versa. Overall the average return and volatility shares of a market are similar. The cross-market mean absolute difference

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[8] WPC was first proposed by Barclay and Warner (1993) and has been used by Cao, et al. (2000), Huang (2002), Agarwal, et al. (2007), among others.
[9] Andersen, Bollerslev, Diebold, and Labys (2003) argue that the use of 30-minute returns strikes a balance between the accuracy of the continuous price changes and microstructure frictions.
[10] We use the terms volatility and realized variance interchangeably in this paper.

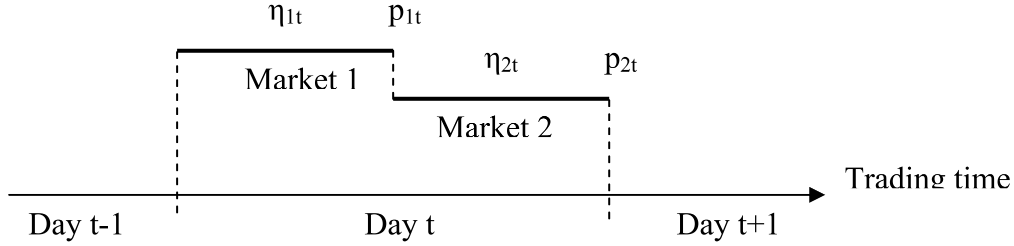
(MAD) between return and volatility shares are very small. Spearman's rank correlations between return and volatility shares are over 0.8 for AUD, JPY, and GBP.

The observed price change and volatility in each market are subject to microstructure noise as well as short-term changes in market conditions. They often have serial and cross-market correlations and do not necessarily reflect market-specific innovations to the underlying currency values. Therefore percentage contributions to return and volatility cannot generally be used to compare price discovery across markets. In the next section, we identify the permanent price changes in the observed returns for the different markets. The variance of permanent price changes is used to construct the information share for each market.

III. Measuring Price Discovery in Sequential Markets

Our approach is in the same spirit as Hasbrouck (1995). While Hasbrouck employs a reduced-form error-correction model, we use a structural VAR and the Beverage-Nelson (1981) decomposition to measure permanent price changes in sequential markets. For simplicity, we use two markets to demonstrate the methodology and note that it can be easily generalized to any number of markets.

Consider a single asset traded in two non-overlapping markets. Let p_{1t} and p_{2t} be the daily closing log prices of market 1 and market 2 respectively, and $r_t = [r_{1t}, r_{2t}]'$ be the vector of daily open-to-close returns of the two markets, i.e., $r_{1t} = p_{1t} - p_{2t-1}$ and $r_{2t} = p_{2t} - p_{1t}$. Let $\eta_t = [\eta_{1t}, \eta_{2t}]'$ be a vector of the independent structural shocks to market 1 and market 2, capturing market-specific information. The scenario is depicted in the diagram below.



We model the return vector r_t using a structural VAR model with K lags:

(1) $$B_0 r_t = B_1 r_{t-1} + B_2 r_{t-2} + \ldots + B_K r_{t-K} + \eta_t = \sum_{k=1}^{K} B_k r_{t-k} + \eta_t$$

The structural shock vector η_t is characterised by $E(\eta_t)=0$; $E(\eta_t \eta_{t-k}^{\prime})=0$ for $k\neq 0$; $E(\eta_t \eta_t^{\prime}) = I$, a 2x2 identity matrix.[11] B_0 is a lower triangular matrix because the markets are sequential and r_{1t} influences r_{2t} but not vice versa. Equation (1) can be written in the reduced form:

(2) $$r_t = \sum_{k=1}^{K} A_k r_{t-k} + \varepsilon_t, \quad \text{or} \quad A(L) r_t = \varepsilon_t,$$

where $A_k = B_0^{-1} B_k$; $\varepsilon_t = B_0^{-1} \eta_t$, $E(\varepsilon_t)=0$, $E(\varepsilon_t \varepsilon_{t-k}^{\prime})=0$ for $k\neq 0$, $E(\varepsilon_t \varepsilon_t^{\prime}) = E[B_0^{-1} \eta_t \eta_t^{\prime} (B_0^{-1})^{\prime}] = (B_0^{\prime} B_0)^{-1} = \Omega$; $A(L)=I-A_1L-\ldots-A_KL^K$; L is the lag operator. The parameters A_k and the covariance matrix Ω in (2) can be estimated using least squares. Since B_0 is lower triangular and Ω is symmetric, the elements of B_0 are exactly identified by $(B_0^{\prime} B_0)^{-1} = \Omega$ and can be estimated by using the lower triangular Cholesky factor of the least squares estimator of Ω.

The reduced-form VAR in (2) has a moving average representation in the form of Beverage-Nelson (1981) decomposition

(3) $$r_t = A(L)^{-1} \varepsilon_t = A(1)^{-1} \varepsilon_t + C(L)(\varepsilon_t - \varepsilon_{t-1}) \quad \text{with} \quad C(L) = \sum_{j=0}^{\infty} C_j L^j,$$

where $A(1) = I-A_1-\ldots-A_K$, $C(L) = [A(L)^{-1} - A(1)^{-1}]/(1-L)$ and C_j converges to zero exponentially as j increases. The daily return (over 24 hours) is obviously $r_{1t} + r_{2t} = \iota' r_t$, where ι is a vector of ones. The log price at the end of day t is the accumulation of $\iota' r_i$ over $i = 1,\ldots,t$ and may be written as

(4) $$p_t = \bar{p}_0 + \iota' A(1)^{-1} \sum_{i=1}^{t} \varepsilon_i + u_t = \bar{p}_0 + \iota' A(1)^{-1} B_0^{-1} \sum_{i=1}^{t} \eta_i + u_t,$$

$$u_t = \iota' C(L) \varepsilon_t = \iota' \sum_{j=0}^{\infty} C_j \varepsilon_{t-j} = \iota' \sum_{j=0}^{\infty} C_j B_0^{-1} \eta_{t-j},$$

[11] An alternative and equivalent parameterisation is to normalise the diagonal elements of B_0 as unity and specify the variance of η_t as a positive diagonal matrix.

where $\overline{p}_0$ is determined by the initial conditions at t = 0. The efficient price is defined as

(5) $$m_t = \lim_{\tau\to\infty} E(p_{t+\tau} \mid F_t) = \overline{p}_0 + \iota' A(1)^{-1} B_0^{-1} \sum_{i=1}^{t} \eta_i ,$$

where F_t is the information set available at the end of day t. The term u_t represents pricing errors and is stationary. The daily change in the efficient price

(6) $$\Delta m_t = m_t - m_{t-1} = \iota' A(1)^{-1} B_0^{-1} \eta_t = h'\eta_t = h_1\eta_{1t} + h_2\eta_{2t} ,$$

is a combination of the structural shocks in two markets, where $h' = [h_1, h_2] = \iota' A(1)^{-1} B_0^{-1}$ is the vector of the impact coefficients of the two shocks. Similar to Hasbrouck (1995), we measure the information share (IS) of market i as

(7) $$IS_i = \frac{var(h_i \eta_{it})}{var(\Delta m_t)} = \frac{h_i^2}{h_1^2 + h_2^2}, \quad i = 1, 2.$$

An alternative measure, termed the component share (CS) or the common-factor share, is often used by studies based on the Gonzalo-Granger (1995) model; e.g. Booth et al. (1999), Chu et al. (1999), and Harris et al. (2002). A similar measure for our structural model is

(8) $$CS_i = \frac{h_i}{h_1 + h_2}, \; i = 1, 2.$$

Note that in our CS measure, the h-coefficients incorporate dynamic effects A(1) and cross-market effects B_0. The existing CS measures based on Gonzalo and Granger (1995) reflects only the contemporaneous impact of reduced-form shocks from different markets on the efficient price.

The reduced-form shocks ε_{1t} and ε_{2t} can be expressed in terms of the independent structural shocks: $\varepsilon_{1t} = \overline{b}_{11}\eta_{1t}$ and $\varepsilon_{2t} = \overline{b}_{21}\eta_{1t} + \overline{b}_{22}\eta_{2t}$ where $\overline{b}_{ij}$ are the elements of B_0^{-1}. The contribution to Δm_t of the reduced-form shock in market 2, ε_{2t}, is given by $(\partial \Delta m_t / \partial \varepsilon_{it})^2 var(\varepsilon_{it})$ with $var(\varepsilon_{2t}) = \overline{b}_{21}^2 + \overline{b}_{22}^2$. When B_0 is not diagonal, i.e. $\overline{b}_{21}$ is not zero, the impact of the reduced-form shock ε_{2t} involves the contribution from market 1, $\overline{b}_{21}^2$. This demonstrates the point made by Lehmann (2002) that price innovations cannot be allocated to specific market cleanly when cross-market correlation is present. The same problem affects the existing component-share measure. Using reduced-form shocks is appropriate only in the case where B_0 is diagonal and structural and reduced-form shocks are equivalent.

While the model in (1) and the information shares in (7) can be easily estimated, the uncertainty in the estimates needs to be quantified. In the price-discovery literature, the information share estimates are usually reported as point estimates without associated standard errors, because the information share measures are complicated functions of the parameters of the underlying VAR models and the "delta method" for computing the standard errors becomes impractical. In this paper, we use a bootstrap to estimate the standard errors of the information share estimates. The bootstrap procedure is outlined below:

S1 Determine the lag length K by AIC, estimated the reduced-form VAR in (2), estimate the information shares in (7), save the estimated polynomial $\hat{A}(L)$ and the residual series $\{\hat{\varepsilon}_{K+1},...,\hat{\varepsilon}_n\}$ from (2);

S2. Generate artificial return vectors $\{r^*_{K+1},...,r^*_n\}$ from (2) by using $\hat{A}(L)$ and random draws from $\{\hat{\varepsilon}_{K+1},...,\hat{\varepsilon}_n\}$;

S3. Estimate the reduced form VAR in (2) and the corresponding information shares in (7) with the artificial data $\{r^*_1,...,r^*_n\}$;

S4. Repeat S2 and S3 many times to construct an empirical distribution, hence the standard errors, for the estimated information shares.

The initial values for r_t^* in S2 can be obtained by randomly drawing a K-block from the original series $\{r_1,...,r_n\}$. Given that our sample size is quite large, the above bootstrap procedure is adequate for estimating standard errors of information shares (see Berkowitz and Kilian (2000) for a review of time series bootstrapping).

IV. Information Shares in Currency Trading

The model developed in section III is applied to the trading of AUD, JPY, EUR, and GBP against USD in four sequential markets: Asia, Europe, London-NYC, and America. Returns of each market are calculated based on the time period defined in section II. The number of lags is determined by the AIC criterion, and is 1 for AUD and GBP, 5 for JPY, and 2 for EUR. The reduced-form VAR of equation (2) is estimated via least squares. The structural coefficient B_0^{-1} is obtained from the Cholesky factorization of covariance matrix Ω. The price impact coefficients are $h' = [h_1, h_2, h_3, h_4] = \iota' A(1)^{-1} B_0^{-1}$. The information share and the component share of a market are given by equations (7) & (8). Standard errors are based on bootstraps with 1000 replications.

The estimated results are presented in four segments in Table 5 for AUD, JPY, EUR, and GBP, respectively. The top panel of each segment presents the estimated structural coefficients matrix B_0^{-1}. For all four exchange rates, at least one of the off-diagonal elements of B_0^{-1} is statistically different from zero.[12] Therefore the covariance matrix Ω is not diagonal, and the reduced-form shocks ε_t in equation (2) are correlated across markets. In this case the structural model of equation (1) is critical to separate price innovations in each market. The next panel reports the estimated price impact coefficients h along with the corresponding information shares and component shares. For example, Asia's information share in AUD is given by $0.377^2/(0.377^2 + 0.357^2 + 0.237^2 + 0.324^2) = 33.1\%$. The component share of Asia is given by $0.377/(0.377 + 0.357 + 0.237 + 0.324) = 29.1\%$.

The third panel presents the results from the bootstrap procedure with 1000 replications. Even though some of the estimated information shares are small, e.g. 8.1% for EUR in Asia, all of them are significantly greater than zero. Information shares of Asia have

[12] The standard errors of B_0^{-1} coefficients are not reported here to conserve space.

greater skewness than those of other markets. Information shares for AUD and JPY have greater skewness than EUR and GBP. The 90% confidence intervals are narrow enough to allow for statistical comparisons between information shares of different markets. For example, for EUR, the lower bound of the 90% confidence interval for Europe is higher than the upper bound for U.S.; the lower bound for U.S. is higher than the upper bound for Asia. Therefore the information share of Europe is higher than that of the U.S. market, which in turn is higher than that of Asia.

Table 6 reports information shares of different markets in each of the eight years in the sample. The number of lags in each year K is determined by the AIC criterion and is generally different from the number of lags for the full sample. Not only the information share of a given market varies across currencies, it also varies substantially over time. At this point, it is unclear what determines a market's information share and what drive its year-to-year changes. Comparisons between the four years in the 1990s and the four years in the new century show the following trend. Asia has lost some of its shares in Asian currencies, i.e. AUD and JPY, but gained in European currencies, particularly EUR. The opposite is true for Europe: its information shares have risen in Asian currencies and fell in European currencies, particularly EUR. So there is some evidence of equalizing information shares between Asia and Europe. The significance of the London-NYC overlapping hours remains steady over the eight years. So is the U.S. market, except for AUD where its share fell.

Since the efficient price and its changes are not observable, one cannot directly verify the estimated information share of a market. We try to shed some light on this issue by comparing the estimated information share of a market with its long-term average contributions to daily return and volatility. Under the conditions that returns of each market do not have serial and cross-market correlations, the structural coefficient matrix B_0 is diagonal and A(L) in equation (2) is an identity matrix. The diagonal elements of B_0^{-1} are the standard deviations of daily returns of each market. The information share of a market, defined in equation (7), is the same as its share of daily volatility reported in Table 4. In this case, the structural and reduced-form shocks are the same and represent changes in the efficient price. As shown in Tables 2 and 5, these conditions generally do not hold in the data: most currencies have significant serial and/or cross-market correlations and B_0^{-1} is not diagonal. However when both serial and cross-market correlations are small, as in the case of GBP, the numerical values and the cross-market rankings of Volatility Share and information share should be similar.

Table 7 compares the information share of a market with its contributions to daily return and volatility. Panel A presents the mean absolute difference (MAD) and Spearman's rank correlation between the information share of a market in Table 5 and its shares of daily return and volatility in Table 4. Except for EUR, the MADs are quite small at around 3%. This is broadly consistent with the low serial and cross-market correlations in Table 2. GBP has no serial correlation and indeed has the lowest MAD at less than 2%. For JPY, EUR, and GBP, Spearman's rank correlations are very high at 0.8 or above. Conceptually all three measures reflect the price impact of a market. There is a long history of using volatility as a proxy for information flow, e.g. Ross (1989), Engle, et al. (1990). When serial and cross-market correlations are small, the volatility share of a market can be used to approximate its information share. The return share is too noisy as shown in Table 4. On the other hand, AUD and EUR both have three off-diagonal elements of B_0^{-1} that are statistically significant. Their return and volatility shares have either high MAD or low rank correlation with the estimated information shares.

Since the number of trading hours varies from 2 for the London-NYC period to 8 for the Asian and U.S. markets, the information share of a market is likely to be affected by its number of trading hours. We compare the per-hour contributions to return, volatility, and information from each market in Panel B of Table 7. The London-NYC overlapping hours have the highest per-hour contributions to all three measures for all four exchange rates. For EUR, the per-hour impact of London-NYC trading is 2 to 10 times larger than the impact from U.S. and Asia trading. On a per-hour basis, the return, volatility, and information shares have low MAD and high rank correlations.

V. Final Remarks

This paper proposes a simple model to compare price discovery in sequential markets. It is applied to the 24-hour foreign exchange trading. We present new evidence on the information shares across markets in different time zones, and how the information shares have changed over the eight-year sample period. Our model for sequential markets can be used in conjunction with models for parallel markets to compare price discovery in partially overlapping markets. It can also be used to compare the information shares of intraday trading hours and explore related microstructure issues. Future research should explore what determines the information share of a market and what drive its changes.

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Table 1: Local Standard Time Relative to GMT

This table divides a 24-hour calendar day into four sequential markets: "Asia" from 23 to 6 GMT, "Europe" from 7 to 12 GMT, "London-NYC" from 13 to 14 GMT, and "U.S." from 15 to 22 GMT. The bold letters denote local trading hours.

Markets	GMT	Sydney	Tokyo	Hong Kong/ Singapore	Frankfort/ Zurich	London	New York	San Francisco
	0	**10**	**9**	8	2	1	20	17
A	1	**11**	**10**	**9**	3	2	21	18
S	2	**12**	**11**	**10**	4	3	22	19
I	3	**13**	**12**	**11**	5	4	23	20
A	4	**14**	**13**	**12**	6	5	0	21
	5	**15**	**14**	**13**	7	6	1	22
	6	16	**15**	**14**	8	7	2	23
E	7	17	16	**15**	**9**	8	3	0
U	8	18	17	16	**10**	**9**	4	1
R	9	19	18	17	**11**	**10**	5	2
O	10	20	19	18	**12**	**11**	6	3
P	11	21	20	19	**13**	**12**	7	4
E	12	22	21	20	**14**	**13**	8	5
London	13	23	22	21	**15**	**14**	**9**	6
- NYC	14	0	23	22	16	**15**	**10**	7
	15	1	0	23	17	16	**11**	8
	16	2	1	0	18	17	**12**	**9**
U	17	3	2	1	19	18	**13**	**10**
S	18	4	3	2	20	19	**14**	**11**
	19	5	4	3	21	20	**15**	**12**
	20	6	5	4	22	21	16	**13**
	21	7	6	5	23	22	17	**14**
	22	8	7	6	0	23	18	**15**
ASIA	23	**9**	8	7	1	0	19	16

Table 2: Summary Statistics of Market Returns

Open-to-close returns in the four markets, defined as $100*[\ln(P_{close})-\ln(P_{open})]$. The asterisk * indicates significant at 5% level.

	Asia	Europe	London-NYC	U.S.
AUD				
Mean	-0.007	-0.006	0.001	0.005
St Dev	0.361	0.360	0.254	0.348
Skewness	-0.246	0.270	-0.117	-0.395
Kurtosis	7.60	11.44	6.90	5.82
$Q_{LB}(10)$	11.09	13.64	4.80	23.20*
Correlation				
Europe	0.010			
LDN-NYC	-0.068*	-0.073*		
U.S.	0.061*	-0.029	-0.007	
JPY				
Mean	-0.006	-0.009	-0.002	0.018
St Dev	0.424	0.392	0.262	0.323
Skewness	0.034	-0.640	-0.503	-0.048
Kurtosis	8.95	8.70	11.40	7.16
$Q_{LB}(10)$	31.03*	13.33	24.29*	13.54
Correlation				
Europe	-0.018			
LDN-NYC	-0.017	0.0006		
U.S.	0.005	-0.084*	0.015	
EUR				
Mean	0.006	-0.040	0.016	0.029
St Dev	0.260	0.415	0.283	0.373
Skewness	-0.646	0.579	0.019	-0.051
Kurtosis	8.45	7.12	4.83	5.52
$Q_{LB}(10)$	13.64	10.30	18.50*	21.56*
Correlation				
Europe	-0.068*			
LDN-NYC	-0.003	-0.081*		
U.S.	0.027	-0.012	0.091*	
GBP				
Mean	-0.006	-0.019	0.016	0.020
St Dev	0.178	0.299	0.197	0.264
Skewness	-0.287	-0.065	0.035	-0.118
Kurtosis	8.42	5.07	4.90	6.15
$Q_{LB}(10)$	5.54	13.65	5.04	10.66
Correlation				
Europe	-0.064*			
LDN-NYC	-0.003	-0.042*		
U.S.	0.031	-0.004	0.073*	

Table 3: Average Daily Transactions

This table reports the average daily transactions in April 2007 in top 10 foreign exchange markets. It is constructed from BIS (2007, Table E.5). Transactions include spot, outright forward, and swap transactions against USD and are measured in billion USD.

	AUD		JPY		EUR		GBP	
	Value	Percent	Value	Percent	Value	Percent	Value	Percent
Australia	76.7	33.4%	13.5	2.5%	23.5	2.2%	13.5	3.0%
Denmark	0.46	0.2%	1.89	0.4%	20.9	1.9%	1.74	0.4%
France	5.89	2.6%	13.0	2.4%	48.2	4.4%	9.92	2.2%
Germany	1.25	0.5%	9.29	1.7%	43.0	3.9%	7.03	1.6%
Hong Kong	14.0	6.1%	16.4	3.1%	20.2	1.9%	12.6	2.8%
Japan	10.6	4.6%	138.8	25.8%	25.7	2.4%	7.62	1.7%
Singapore	15.7	6.8%	43.1	8.0%	47.9	4.4%	21.2	4.7%
Switzerland	6.12	2.7%	20.7	3.9%	74.0	6.8%	28.6	6.3%
United Kingdom	55.9	24.3%	153.6	28.6%	443.6	40.7%	240.3	53.3%
United States	30.9	13.5%	94.0	17.5%	179.1	16.4%	77.1	17.1%
Top 10 Asia	117.0	51.0%	211.8	39.4%	117.3	10.7%	54.9	12.2%
Top 10 Europe	69.6	30.3%	198.5	36.9%	629.7	57.7%	287.6	63.8%
Top 10	217.5	94.7%	504.3	93.8%	926.1	84.9%	419.6	93.1%
Global Total	229.6	100%	537.5	100%	1091.2	100%	450.8	100%

Table 4: Return and Volatility Shares

Return and Volatility Shares are defined in section II. “MAD” is the mean absolute difference between return and Volatility Shares across four markets. “Rank Cor” is Spearman’s rank correlation between return and Volatility Shares across four markets. The asterisk * indicates significant at 5% level.

	Asia	Europe	London -NYC	U.S.	MAD	Rank Cor
AUD						
Return Share	30.4%	25.0%	14.0%	30.6%	1.7%	1.0
Volatility Share	28.6%	28.5%	12.2%	30.6%		
JPY						
Return Share	35.3%	29.0%	15.0%	20.7%	2.7%	1.0
Volatility Share	30.7%	29.7%	13.8%	25.8%		
EUR						
Return Share	13.8%	33.6%	18.5%	34.2%	1.8%	0.6
Volatility Share	17.4%	34.3%	16.4%	31.9%		
GBP						
Return Share	13.6%	36.2%	17.5%	32.8%	2.1%	0.8
Volatility Share	16.3%	37.5%	15.1%	31.1%		

Table 5: Information Share

	Asia	Europe	London-NYC	U.S.
AUD with K = 1 lag				
Structural Coefficients B_0^{-1}				
Asia	0.359*			
Europe	0.003	0.360*		
London-NYC	-0.016*	-0.018*	0.253*	
America	0.021*	-0.009	-0.003	0.346*
Price Impact (h)	0.377	0.357	0.237	0.324
Information Share	33.1%	29.6%	13.1%	24.3%
Component Share	29.1%	27.6%	18.3%	25.0%
Bootstrap on Information Share with 1000 Replications				
Mean	0.331	0.295	0.132	0.242
St Dev	0.029	0.032	0.019	0.023
Skewness	0.134	0.074	0.258	0.099
Kurtosis	2.894	2.947	3.141	2.834
Lower 5%	0.284	0.244	0.103	0.206
Upper 5%	0.381	0.345	0.166	0.281
JPY with K = 5 lags				
Structural Coefficients B_0^{-1}				
Asia	0.416*			
Europe	-0.004	0.386*		
London-NYC	-0.005	-0.001	0.259*	
U.S.	0.006	-0.026*	0.005	0.319*
Price Impact (h)	0.369	0.350	0.299	0.302
Information Share	30.9%	27.9%	20.3%	20.9%
Component Share	28.0%	26.5%	22.7%	22.9%
Bootstrap on Information Share with 1000 Replications				
Mean	0.309	0.278	0.205	0.209
St Dev	0.048	0.048	0.045	0.044
Skewness	0.259	0.107	0.181	0.187
Kurtosis	3.189	2.897	2.948	2.808
Lower 5%	0.233	0.206	0.130	0.137
Upper 5%	0.392	0.358	0.285	0.287

Table 5: Information Share - Continued

	Asia	Europe	London-NYC	U.S.
EUR with K = 2 lags				
Structural Coefficients B_0^{-1}				
Asia	0.256^*			
Europe	-0.026^*	0.412^*		
London-NYC	-0.001	-0.023^*	0.281^*	
U.S.	0.007	-0.002	0.029^*	0.365^*
Price Impact (h)	0.180	0.420	0.290	0.325
Information Share	8.1%	44.3%	21.0%	26.6%
Component Share	14.8%	34.6%	23.9%	26.7%
Bootstrap on Information Share with 1000 Replications				
Mean	0.084	0.440	0.213	0.263
St Dev	0.028	0.043	0.037	0.038
Skewness	0.322	-0.038	0.161	0.067
Kurtosis	2.959	3.064	2.866	2.797
Lower 5%	0.040	0.370	0.154	0.202
Upper 5%	0.135	0.508	0.276	0.327
GBP with K = 1 lag				
Structural Coefficients B_0^{-1}				
Asia	0.176^*			
Europe	-0.017^*	0.297^*		
London-NYC	-0.001	-0.008	0.196^*	
U.S.	0.009	-0.001	0.020^*	0.263^*
Price Impact (h)	0.176	0.297	0.199	0.262
Information Share	13.6%	38.8%	17.3%	30.2%
Component Share	18.8%	31.8%	21.3%	28.1%
Bootstrap on Information Share with 1000 Replications				
Mean	0.137	0.389	0.172	0.302
St Dev	0.023	0.028	0.022	0.026
Skewness	0.131	0.088	0.091	-0.042
Kurtosis	3.117	3.270	2.994	2.858
Lower 5%	0.101	0.346	0.140	0.259
Upper 5%	0.176	0.437	0.208	0.344

Table 6: Sub-Period Information Share

K is the number of lags for the structural VAR. N is the number of observations in each year.

	Asia	Europe	London-NYC	U.S.	K	N
AUD						
1996	41.9%	24.2%	9.5%	24.5%	0	240
1997	39.6%	16.1%	11.1%	33.3%	0	232
1998	29.6%	21.2%	15.8%	33.3%	0	237
1999	24.9%	26.2%	19.9%	29.0%	0	249
Average	*34.0%*	*21.9%*	*14.1%*	*30.0%*		
2000	35.1%	20.9%	14.9%	29.2%	0	247
2001	33.5%	31.8%	12.1%	22.7%	0	229
2002	29.1%	36.9%	11.0%	23.1%	0	228
2003	24.0%	33.1%	19.6%	23.3%	0	222
Average	*30.4%*	*30.7%*	*14.4%*	*24.6%*		
JPY						
1996	29.4%	29.9%	25.4%	15.3%	1	243
1997	47.6%	21.4%	10.3%	20.7%	0	242
1998	25.1%	24.6%	16.7%	33.5%	1	240
1999	40.6%	36.9%	8.7%	13.9%	1	250
Average	*35.7%*	*28.2%*	*15.3%*	*20.9%*		
2000	27.4%	35.6%	17.9%	19.1%	0	245
2001	35.4%	32.0%	14.0%	18.6%	0	228
2002	29.3%	29.7%	22.8%	18.3%	0	232
2003	23.3%	29.3%	20.7%	26.7%	0	222
Average	*28.8%*	*31.6%*	*18.9%*	*20.7%*		
EUR						
1999	7.8%	39.3%	19.3%	33.6%	0	252
2000	0.2%	52.0%	21.0%	26.7%	2	247
2001	14.9%	37.1%	21.2%	26.8%	0	233
Average	*7.6%*	*42.8%*	*20.5%*	*29.0%*		
2002	15.1%	33.5%	16.9%	34.5%	1	233
2003	24.6%	28.9%	21.4%	25.2%	0	224
Average	*19.9%*	*31.2%*	*19.1%*	*29.8%*		
GBP						
1996	11.0%	33.3%	26.9%	28.8%	0	236
1997	12.1%	44.6%	11.4%	32.0%	0	229
1998	17.1%	30.2%	17.1%	35.6%	1	237
1999	9.7%	41.1%	23.9%	25.4%	1	245
Average	*12.5%*	*37.3%*	*19.8%*	*30.4%*		
2000	12.0%	38.6%	21.0%	28.4%	0	245
2001	7.0%	37.6%	28.1%	27.3%	0	231
2002	18.9%	29.0%	19.3%	32.8%	0	229
2003	14.9%	39.2%	19.1%	26.9%	0	227
Average	*13.2%*	*36.1%*	*21.9%*	*28.8%*		

Table 7: Comparison between Return, Volatility, and Information Shares

Return and volatility shares are defined in section II. "MAD" is the mean absolute difference with information share for each currency across four markets. "Rank Cor" is Spearman's rank correlation with information share for each currency across four markets. Panel A compares return and volatility shares in Table 4 with information shares in Table 5. Panel B compares return, volatility, and information shares per trading hour.

Panel A:

	AUD	JPY	EUR	GBP
Return Share				
MAD	3.6%	2.8%	6.6%	1.4%
Rank Cor	0.4	1.0	0.8	1.0
Volatility Share				
MAD	3.2%	3.4%	7.3%	1.8%
Rank Cor	0.4	1.0	0.8	0.8

Panel B:

	Asia	Europe	London -NYC	U.S.	MAD	Rank Cor
AUD						
Return Share	3.8%	4.2%	7.0%	3.8%	0.6%	0.8
Volatility Share	3.6%	4.8%	6.1%	3.8%	0.5%	0.8
Information Share	4.1%	4.9%	6.5%	3.0%		
JPY						
Return Share	4.4%	4.8%	7.5%	2.6%	0.9%	1.0
Volatility Share	3.8%	5.0%	6.9%	3.2%	1.1%	1.0
Information Share	3.9%	4.6%	10.2%	2.6%		
EUR						
Return Share	1.7%	5.6%	9.2%	4.3%	1.2%	1.0
Volatility Share	2.2%	5.7%	8.2%	4.0%	1.5%	1.0
Information Share	1.0%	7.4%	10.5%	3.3%		
GBP						
Return Share	1.7%	6.0%	8.7%	4.1%	0.2%	1.0
Volatility Share	2.0%	6.2%	7.6%	3.9%	0.5%	1.0
Information Share	1.7%	6.5%	8.7%	3.8%		