II. ASYMMETRIC INFORMATION AND EXCHANGE RATES


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1998: Most volatile year since early 1970s

- Asian crisis, Russian bond default, interventions, near-collapse of LTCM
- Shifting macroeconomic fundamentals
- “Hedge funds and panic trading”
- Yen carry-trade
- Liquidity crunch
- Herding to unwind positions

1998: Laboratory to assess determinants of exchange rates

- Public information via macroeconomic news

- Private information via order flow
Data

• Yen/dollar quotes for 1998

• bid & ask and time stamp to nearest second

• use log mid-price weighted by inverse distance to 5-min. endpoint

• n = 1,2,...288 obs per day, t = 1,2,...260 days → 74,880 obs

• delete 21:00 Friday - 21:00 Sunday
Intradaily Patterns

- Returns are random but volatility has predictable components
- business hours open and close
- lunch
- daylight saving time shift
- scheduled government announcements

Calendar Effects

- Holiday dummies
- Tokyo opening
- Summer U.S. afternoon
- Winter Asian Monday morning
- Friday afternoon in America
- Lunch in Tokyo & Europe
- Day-of-week
**Estimation strategy for 5-minute returns:**

\[ R_{t,n} = s_{t,n} \cdot \sigma_{t,n} \cdot Z_{t,n} \]

\( \sigma_{t,n} \) is daily volatility factor

\( Z_{t,n} \) is i.i.d. (0,1) innovation

\( s_{t,n} \) is seasonal component
Estimate logarithmic seasonal component \( \ln(S^2_{t,n}) \) using FFF regression:

\[
2 \ln \frac{|R_{t,n} - \bar{R}|}{\hat{\sigma}_t / N^{1/2}} = c + \beta O_{t,n} + \sum_{k=1}^{D} \lambda_k \cdot I_k(t,n) + \delta_{0,1} \frac{n}{N_1} + \delta_{0,2} \frac{n^2}{N_2}
\]

\[
+ \sum_{p=1}^{P} \left( \delta_{c,p} \cdot \cos \frac{2\pi p}{N} n + \delta_{s,p} \cdot \sin \frac{2\pi p}{N} n \right) + \varepsilon_{t,n},
\]

\(\varepsilon\)M. Melvin, 2002.
Regression Variables:

$\bar{R} = \text{sample mean}$

$\hat{\sigma}_t = \text{a priori estimate of daily volatility component}$

$O = \text{order flow of large institutions}$

$I_k = \text{indicator for calendar & news events}$

$N_1, N_2 = \text{normalizing constants}$

$P = \text{tuning parameter for expansion order}$
Macroeconomic Announcements

- 32 U.S. news releases from Reuters
- 33 Japanese news releases from Bloomberg

- due to 5-minute frequency, use 3rd order polynomial and estimate effect of each event “loading onto” the pattern
- reported results for significant announcements
- identified by using each release in turn with separate “all other news” variable

- Employment reports most important

- 9 U.S. & 6 Japanese “major announcements”
Intervention Effects

-Dummy variables for:

-April 10: BOJ supported weak yen

-June 17: First Clinton Ad. intervention supporting weak yen

-Despite rumors of intervention in 4th qtr., only 2 actual interventions

-Positive & significant effect on volatility
Order Flow

• Order flow reveals private info. regarding position switches
• unwinding yen carry-trade learned through trades
• may be orthogonal to public info.

• No market-wide data exist

• U.S. Treasury requires weekly position data from big participants

  • purchases & sales of spot, forward, & futures contracts

  • Purchases $\rightarrow$ $\uparrow$ volatility  Sales $\rightarrow$ $\downarrow$ volatility

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Relative Importance of Components

- Construct forecasts containing day-of-the-week & holiday effects

- Omit or include each of 4 components

- Ascending order of importance, daily cumulative absolute returns
  - calendar, announcement, intervention, & order flow effects

- Ascending order of importance, 5 minute absolute returns
  - with time-varying daily volatility factor
  - order flow, announcements, intervention, & calendar effects

  - with constant daily volatility factor
  - announcements, intervention, calendar, & order flow effects
Concluding Remarks

- Independent role for order flow
  - account for announcement, intervention, & calendar effects

- Portfolio shifts responsible for much of 1998 yen volatility

- A step toward moving beyond exchange rate models based on “fundamentals”

- Practitioners have long stated that order flow was major source of price changes

  - With lack of transparency & asymmetrically-informed traders we might expect that order flow contains independent info.

ASYMMETRIC INFORMATION AND PRICE DISCOVERY IN THE FX MARKET:
Does Tokyo Know More About the Yen?

Vincentiu Covrig and Michael Melvin
I. INTRODUCTION

**Microstructure theory** ⇒ **informed trader presence affects market dynamics**

**Empirical problem:**

identifying informed

**Suggested experiment:**

Tokyo pre- and post-Dec. 22, 1994


*Informed trader concentration in pre-lunch **BEFORE** period*
Some initial stylized facts:

U-shaped volatility for Japan BEFORE
no U-shape for non-Japan BEFORE
no U-shape for either AFTER

What kind of private information?

customer order flow
early knowledge of government action
inventory positions

GOAL: Test implications of microstructure theories regarding market dynamics with many informed traders present
II. IMPLICATIONS OF INFORMED TRADER CONCENTRATION

A. A Representative Theory

(1) $F = F + \delta$.

(2) $P = F + \lambda \omega$.

Informed trader demand: $\beta(\delta + u)$

(3) $\beta = 1 / \{(1 + \phi)\lambda(k + 1) + A[\phi + \lambda^2 \sigma_Z^2 (1 + \phi)]\}$.

(4) $\lambda[k^2 (1 + \phi) + \sigma_Z^2 \alpha^2] = k \alpha$.

$\alpha = \beta^{-1} = A[\phi + \lambda^2 (1 + \phi) \sigma_Z^2] + (k + 1) \lambda (1 + \phi)$.

informational efficiency, $Q = [\text{var}(\delta | \omega)]^{-1}$

(5) $Q = 1 + \{1 / \phi + (\sigma_Z^2 / k^2 \beta^2)\}$.

**IMPLICATION:** Prices are more informative and converge more quickly to full information levels when there are many informed traders in the market.
B. **Estimating Speed of Adjustment**

Sample
*10:30-12noon Tokyo*  
*20 days BEFORE and AFTER*  
*Reuters quotes on yen/dollar*  
*1-minute returns*

MA(1)-GARCH(1,1)

\[ r_t = \alpha_0 + \varepsilon_t + \alpha_1 \varepsilon_{t-1} \]

\[ h_t = \gamma_0 + \gamma_1 h_{t-1} + \gamma_2 \varepsilon^2_{t-1} + \gamma_3 \text{dum}*h_{t-1} + \gamma_4 \text{dum}^* \varepsilon^2_{t-1} \]

**Estimated half-life of shock to volatility:**

2 ½ minutes **BEFORE**  
14 minutes **AFTER**
III. JAPANESE AND NON-JAPANESE BANK DYNAMICS

If Tokyo knows more, then Japanese quotes should lead non-Japanese?

Causality tests:

\( r_t^d = a + b r_{t-1}^i + c r_{t-1}^d + e_t \)

Sample:
* 20 days BEFORE and AFTER
* early-morning, late-morning, and afternoon
* filter tick-by-tick \( r^i \) returns \( \geq 2.5 \) basis points
* construct \( r^d \) returns around \( r^i \)

FINDINGS:
* 2-way causality in all periods but one
* Japan causes non-Japan in late-morning BEFORE
Nonsynchronous Quoting and Cross Correlations

Difference between 2 observed quotes equals sums of returns of underlying unobserved quote process

(i) \[ q_{t_{i+1}} - q_{t_i} = \sum_{t=t_{i+1}}^{t_{i+1}} \Delta q_t \]

(ii) \[ E(y_{ij}) = E[(q_{t_{i+1}}^J - q_{t_i}^J)(q_{t_{j+1}}^N - q_{t_j}^N)] \]

\[ = E \left[ \sum_{t=t_{i+1}}^{t_{i+1}} \Delta q_t^J \cdot \sum_{k=k_{j+1}}^{k_{j+1}} \Delta q_s^N \right] = \sum_{t=t_{i+1}}^{t_{j+1}} \sum_{k=t_{j+1}}^{t_{j+1}} \gamma_{t-k} \]

(iii) \[ \chi_{ij}(k) = \max[0, \min(t_{i+1}, t_{j+1} + k) - \max(t_i, t_j + k)] \]

(iv) \[ E(y_{ij} | \chi_{ij}) = \sum_{k=-k}^{k} \chi_{ij}(l_c) \gamma_k \]

(v) \[ y_{ij} = \chi_{ij}' \gamma + e_{ij} \]

for \( k = 5 \), Wald test for lead/lag:

<table>
<thead>
<tr>
<th>( q^J ) lead ( q^N )</th>
<th>BEFORE</th>
<th>AFTER</th>
</tr>
</thead>
<tbody>
<tr>
<td>( q^N ) lead ( q^J )</td>
<td>16.2</td>
<td>12.6</td>
</tr>
<tr>
<td>8.3</td>
<td>15.7</td>
<td></td>
</tr>
</tbody>
</table>
IV. Price Discovery in Japan and Elsewhere

Follow Hasbrouck (1995) to estimate contribution of Japanese and non-Japanese quotes to price discovery

\( r_t = \Psi(L)e_t \)

\( r_t = \alpha(\beta'q_{t-1} - E\beta'q_t) + \Gamma_1 r_{t-1} + \Gamma_2 r_{t-2} + \ldots + \Gamma_{k-1} r_{t-k+1} + e_t \)

\( e_t = Fz_t, \quad Ez_t = 0, \quad \text{Var}(z_t) = I \)

\( S_j = ([\psi^F]_j)^2 \frac{1}{l(\psi^\Omega \psi')} \)
<table>
<thead>
<tr>
<th></th>
<th>BEFORE</th>
<th>AFTER</th>
</tr>
</thead>
<tbody>
<tr>
<td>Japanese/non-Japanese info.</td>
<td>96%</td>
<td>89%</td>
</tr>
<tr>
<td>share:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Japanese/Hong Kong info.</td>
<td>128%</td>
<td>111%</td>
</tr>
<tr>
<td>share:</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Japanese contribution to price discovery higher BEFORE than AFTER
V. CONCLUSIONS

Market dynamics differ depending upon the presence of informed traders

*greater the number of informed traders the faster price adjusts to full-information value

*informed-trader quotes lead the rest of the market when high concentration of informed traders

*informed traders’ contribution to price discovery peaks when informed cluster

“Does Tokyo Know More About the Yen?”

*qualified yes ..........

Reference: Covrig & Melvin, JEF, forthcoming; or http://www.public.asu.edu/~mmelvin/
Figure 1: Variance of Yen/Dollar Quotes in Asian Morning -- BEFORE

Figure 2: Variance of Yen/Dollar Quotes in Asian Morning -- AFTER
INTERNATIONALLY CROSS-LISTED STOCK PRICES DURING OVERLAPPING TRADING HOURS: 
price discovery and exchange rate effects

by

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TWO QUESTIONS

1. Where does price discovery occur for firms traded internationally?

2. Given an exchange rate shock, how do stock prices adjust in the home market and the derivative market?
TOPIC ORDER

1. Institutional Details

2. Equilibrium Relationships

3. Framework for Analysis

4. Data and Estimation Results

5. Conclusions
INSTITUTIONAL DETAILS

American Depositary Receipts (ADRs)

*Deutsche Telekom (DT)

*SAP

Global Registered Shares (GRSs)

*DaimlerChrysler (DCX)

XETRA and NYSE
A SIMPLE MODEL OF INTERNATIONAL EQUITY TRADING

\[ E_t = E_{t-1} + u_t \]

\[ P^h_t = P^h_{t-1} + v_t \]

\[ P^u_t = E_{t-1} + P^h_{t-1} + w_t \]

\[ E_t + P^h_t - P^u_t = E_{t-1} + u_t + P^h_{t-1} + v_t - E_{t-1} - P^h_{t-1} - w_t = u_t + v_t - w_t \]

Expect cointegration among the 3 variables

Two stock prices will differ by the exchange rate plus random terms

Have 1 cointegrating vector and 2 common trends:

*exchange rate innovations

*home market price
INFORMATION SHARES BASED ON VECM

By Granger representation theorem can write system as VECM:

$$\Delta P_t = \alpha + BZ_{t-1} + \delta_1 \Delta P_{t-1} + \delta_2 \Delta P_{t-2} + \ldots + \Delta P_{t-q+1} + \epsilon_t$$

where

$$P_t = \begin{bmatrix} E_t \\ P_t^h \\ P_t^u \end{bmatrix}$$

and the cointegrating vector is $A'$ such that $Z_t = A'P_t$ or

$$Z_{t-1} = (\alpha_1 E_{t-1} + \alpha_2 P_{t-1}^h + \alpha_3 P_{t-1}^u)$$
GRANGER REPRESENTATION THEOREM

a) If the level of prices and the exchange rate can be represented by a nonstationary vector autoregression like:

\[ P_t = \partial + \phi_1 P_{t-1} + \phi_2 P_{t-2} + \ldots + \phi_q P_{t-q} + \varepsilon_t \]

b) and \( \Delta P \) has the Wold representation:

\[ (1 - L)P_t = \delta + \psi(L)\varepsilon_t \]

{note: Wold’s decomposition for any zero-mean cov.-stationary process \( y_t \) can be written as a function of the past white-noise errors \( \varepsilon \) one would make in forecasting \( y_t \) as a linear function of lagged \( y_t \)}

c) and there is a cointegrating vector \( A' \) such that

\[ Z_t = A'P_t \]

is stationary where

\[ A'\Psi(1) = 0 \]

then there exists a vector error correction (VEC) model:

\[ \Delta P_t = \alpha + BZ_{t-1} + \delta_1 \Delta P_{t-1} + \delta_2 \Delta P_{t-2} + \ldots + \Delta P_{t-q} + 1 + \varepsilon_t \]
Johansen’s Cointegration Estimation Method

1) Estimate VAR for \(\Delta P_t\)
\[
\Delta P_t = \alpha + \delta_1 \Delta P_{t-1} + \delta_2 \Delta P_{t-2} + \ldots + \delta_q \Delta P_{t-q+1} + u_t
\]

2) Estimate lagged \(P\) regression on lagged \(\Delta P\)
\[
P_{t-1} = b + \phi_1 \Delta P_{t-1} + \phi_2 \Delta P_{t-2} + \ldots + \phi_q \Delta P_{t-q+1} + v_t
\]

3) Calculate Var-Cov matrices of residuals
\[
\Sigma_{uu} = \frac{1}{T} \sum_{t=1}^{T} u_t u_t' \\
\Sigma_{vv} = \frac{1}{T} \sum_{t=1}^{T} v_t v_t'
\]
\[
\Sigma_{uv} = \frac{1}{T} \sum_{t=1}^{T} u_t v_t' \\
\Sigma_{vu} = \Sigma_{uv}'
\]

find eigenvalues of \(\Sigma_{vv}^{-1} \Sigma_{uu} \Sigma_{uv} \Sigma_{uv}'\) ordered \(\lambda_1 > \lambda_2 \ldots > \lambda_n\)

then max. of log likelihood function s.t. constraint of \(h\) cointegrating relations is:
\[
L = -(Tn/2) \log(2\pi) - (Tn/2) - (T/2) \log |\Sigma_{uu}| - (T/2) \sum_{i=1}^{h} \log(1 - \lambda_i)
\]

then conduct likelihood ratio test for number of cointegrating relations
4) Calculate parameter estimates

\( a_1, a_2, \ldots, a_h \) are eigenvectors associated with the \( h \) largest eigenvalues

any cointegrating vector \( A \) can be written as

\[
A = b_1 a_1 + b_2 a_2 + \ldots + b_h a_h
\]

normalize so that \( A' \Sigma_{yy} A = 1 \)

Then typically normalize so that first element of \( A \) equals 1
INFORMATION SHARES

What is contribution of innovations in each asset price to “price discovery”? 

“Information Share” = proportion of innovation variance in asset $i$ explained by innovations in asset $j$

Since each asset price is $I(1)$ and cov-stationary, our 3 equation system can be expressed as a Vector Moving Average (VMA): 

$$\Delta P_t = \Psi(L) \epsilon_t$$ 

where $\Psi$ is a polynomial in the lag operator and $\epsilon$ is a zero-mean vector of random disturbances with covariance matrix $\Omega$

Granger Representation Theorem included cointegration restriction that $A' \Psi(1) = 0$ where $\Psi(1)$ is the matrix polynomial evaluated at $L=1$
Note on VMA

\[ \Delta E_t = u_t \]

\[ \Delta P^h_t = v_t \]

\[ \Delta P^u_t = a \Delta E_{t-1} + b \Delta P^h_{t-1} + \Delta w_t = au_{t-1} + bv_{t-1} + w_t - w_{t-1} \]

define \( \varepsilon^e_t = u_t \), \( \varepsilon^h_t = v_t \), \( \varepsilon^u_t = w_t + au_{t-1} + bv_{t-1} \)

so \( \Delta P^u_t = \varepsilon^u_t - w_{t-1} = \varepsilon^u_t - \varepsilon^u_{t-1} + a\varepsilon^e_{t-2} + b\varepsilon^h_{t-2} \)

and the system can be written as:

\[ \Delta P_t = \Psi(L)\varepsilon_t \]

or

\[
\begin{bmatrix}
\Delta E_t \\
\Delta P^h_t \\
\Delta P^u_t
\end{bmatrix} =
\begin{bmatrix}
1 & 0 & 0 \\
0 & 1 & 0 \\
aL^2 & bL^2 & (1-L)
\end{bmatrix}
\begin{bmatrix}
\varepsilon^e_t \\
\varepsilon^h_t \\
\varepsilon^u_t
\end{bmatrix}
\]

so \( \Psi(1) = \)

\[
\begin{bmatrix}
1 & 0 & 0 \\
0 & 1 & 0 \\
a & b & 0
\end{bmatrix}
\]

We let data choose actual \( \Psi(1) \)
The restriction $A'\Psi(I) = 0$ means that the matrix operator $\Psi(I)$ is singular

We find the elements numerically by dynamic simulation of the estimated VEC (Hamilton, 1994)
*dynamic multipliers associated with unit shock to innovations in each variable

*write the VEC in VMA representation:

$$
\begin{bmatrix}
\Delta E_t \\
\Delta P_t^h \\
\Delta P_t^u
\end{bmatrix}
= 
\begin{bmatrix}
\varepsilon_t^e \\
\varepsilon_t^h \\
\varepsilon_t^u
\end{bmatrix}
+ \Psi_1 
\begin{bmatrix}
\varepsilon_{t-1}^e \\
\varepsilon_{t-1}^h \\
\varepsilon_{t-1}^u
\end{bmatrix}
+ \Psi_2 
\begin{bmatrix}
\varepsilon_{t-2}^e \\
\varepsilon_{t-2}^h \\
\varepsilon_{t-2}^u
\end{bmatrix}
+ \ldots
$$

where $\Psi = \begin{bmatrix}
\psi_{11} & \psi_{12} & \psi_{13} \\
\psi_{21} & \psi_{22} & \psi_{23} \\
\psi_{31} & \psi_{32} & \psi_{33}
\end{bmatrix} = I + \Psi_1 + \Psi_2 + \ldots$

*so long-run multipliers give:

$$
\begin{bmatrix}
\text{perm. impact on } \Delta E_t \\
\text{perm. impact on } \Delta P_t^h \\
\text{perm. impact on } \Delta P_t^u
\end{bmatrix}
= 
\begin{bmatrix}
\psi_{11} & \psi_{12} & \psi_{13} \\
\psi_{21} & \psi_{22} & \psi_{23} \\
\psi_{31} & \psi_{32} & \psi_{33}
\end{bmatrix}
\begin{bmatrix}
\varepsilon_t^e \\
\varepsilon_t^h \\
\varepsilon_t^u
\end{bmatrix}
$$
Our priors on $\Psi$:
With cointegrating vector of essentially $A'=[1\ 1\ -1]$

We expect:

$*\psi_{12} = \psi_{13} = 0$
$*\psi_{22} = \psi_{32}$
$*\psi_{23} = \psi_{33}$

Intuition:

Economic common sense suggests
$*\Delta E$ unaffected by stock price innovations
$*\Delta E$ innovations may have different effect on XETRA & NYSE

Cointegration implies
$*\Delta P^h$ innovations have symmetric effect on XETRA & NYSE
$*\Delta P^u$ innovations have symmetric effect on XETRA & NYSE
Once $\Psi(1)$ is known we can infer the information shares
impact of innovation in price $j$ on price $i$ is

$\Psi_{ij} \in [0, 1]$

Total variance associated with innovations in $i$ is $\psi_{ii}$ diagonal element of $\psi \Omega \psi'$

Since $\Omega$ has off-diagonal elements due to contemporaneous correlation in innovations, to find info. share need a triangularization of $\Omega$

*Cholesky factorization yields matrix $C$ such that $CC' = \Omega$

Information shares found as:

$S_{ij} = (|\Psi C|_{ij})^2 / (\psi \Omega \psi')_{ii}$

this is total innovation variance associated with $i$ explained by innovations in $j$

* $(|\Psi C|_{ij})^2$ is the product of $i^{th}$ row of $\Psi$ matrix and $j^{th}$ column of $C$ matrix

* $(\psi \Omega \psi')_{ii}$ is diagonal element associated with total variance of $i$ innovations

*normalization ensures that info. shares sum to 1 for each asset
DATA

XETRA and NYSE prices on DCX, DT, and SAP
*NYSE TAQ data
*Deutsche Börse A.G. proprietary quotes

USD/EUR from Reuters indicative quoting screen

1 August – 31 October, 1999

Overlap of trading hours
*14:30-16:00 GMT until 19 Sept.
*14:30-16:30 GMT from 20 Sept.

Table 1 summary stats
*SAP trades at 12 to 1 ratio
*mean USD/EUR was 1.0607

Figure 1 plots of logs of variables (avg. of bid & ask)
*level of USD/EUR ranges from 1.0355 to 1.0889
*XETRA & NYSE prices track closely together

Figure 2 plots quoting intensity
*synergies between two markets?
*DT is uniquely “German”

Informal evidence of Frankfurt as “primary” market with New York as “derivative” market
ESTIMATION

Sample at 10 second intervals

*temporal aggregation can dissolve 1-way causality that appears at higher frequency

ADF tests revealed unit roots in log of each price

Johansen cointegration tests support 1 cointegrating vector

*Lag length chosen by Schwarz Info. Criterion (SIC)

\[ \text{SIC} = -2(\log L)/T + n(\log T)/T \]

*start at 18 lags (3 minutes) and estimate VEC for every lag length down to 1

*SIC identifies 3 lags for SAP and DT and 4 lags for DCX
Table 2 VEC estimates

*Johansen stats identify 1 cointegrating vector

* cointegrating vectors are all about \([1 \ 1 \ -1]\) for \([E \ P^h \ P^u]\)

VECs dynamically simulated to find long-run multipliers of unit shock to innovations

(note: set all innovations to zero, then set first observation =1 for one variable and simulate; repeat for other variables)

Table 3 \(\mathcal{P}(I)\) matrices meet priors

*\(E\) unaffected by innovations to stock prices

*long-run impact of shock to 1 stock price is symmetric for itself and the other stock price

Table 3 surprise (or at least diffuse priors)?

*long-run impact of shock to \(P^h\) greater than long-run impact of shock to \(P^u\)

*\(E\) shocks have greater impact on \(P^u\) than \(P^h\)

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Cholesky factorization of $Ω$ yields upper bound on info. share for variable ordered first and lower bound on info. share for variable ordered last

*common problem in VARs with impulse response or variance decompositions

Swanson & Granger propose using the “Directed-Acyclic-Graph” (DAG) approach to choose ordering:

1) specify relationship expected due to prior beliefs based on theory
2) estimate model and calculate all partial correlations among residuals of individual equations
3) construct hypothesis tests of null that some partial correlations equal zero in accord with step 1)
4) if supported by partial correlations, order variables accordingly

DAG for exogenous $E$ that may affect both $P^h$ and $P^u$ while $P^u$ is also affected by $P^h$:

$\Delta E_t \rightarrow \Delta P^h_t \rightarrow \Delta P^u_t$

$\uparrow$ $\uparrow$ $\uparrow$

$u_t$ $v_t$ $w_t$

DAG portrays recursive contemporaneous correlation
DAG implied system is:

\[ \Delta E_t = u_t \]
\[ \Delta P_t^h = \delta_h \Delta E_t + v_t \]
\[ \Delta P_t^u = \delta_{ue} \Delta E_t + \delta_{uh} \Delta P_t^h + w_t \]

Following Swanson & Granger, the DAG implies that the partial correlation \( \rho(\Delta E_t, \Delta P_t^u | \Delta P_t^h) = 0 \)

*estimate by regressing residuals of individual VEC equations on each other*

Use order of \( E, P^h, P^u \) in calculating information shares reported in Table 4

Table 4 info. shares

* \( E \) unaffected by stock price innovations

* \( E \) info share of about 0 for \( P^h \) and more than 5% for \( P^u \)

* \( P^h \) info share on \( P^h \) ranges from 99% for DT to 79% for SAP

* \( P^h \) info share on \( P^u \) ranges from 94% for DT to 76% for SAP

* \( P^u \) info share on \( P^h \) ranges from 20% for SAP to 1% for DT

* \( P^u \) info share on \( P^u \) ranges from 19% for SAP to 1% for DT

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DT appears to be more of a domestic firm while DCX and SAP are multinationals with more of a role for international price discovery

*U.S. revenue as share of total revenue supports this

DT, 1%       DCX and SAP about 50%

*Ratio of NYSE-traded shares owned by U.S. mutual funds to those owned by non-U.S. funds:

DT: 0.03     DCX: 0.7     SAP: 8.3

Why bigger role for NYSE in price discovery for SAP?

*bigger U.S. following?
**”new economy” stock?
*main rivals in U.S.?

Table 5 additional check for robustness of results over alternative orderings

*tight bounds so ordering of variables relatively unimportant
CONCLUSIONS

Where does price discovery occur for internationally-traded firms?

*largely in home market

*home-market info share larger for purely domestic firm than multinational

How do international stock prices adjust to an exchange rate shock?

*home market price appears to be independent of exchange rate

*foreign market (NYSE) price contains all of the adjustment
Table 1

Descriptive Statistics for Firms and Markets

Summary statistics are reported for three firms: DaimlerChrysler (DCX), Deutsche Telekom (DT), and SAP. Trading in the U.S. occurs on the NYSE and trading in Germany occurs on the XETRA system. The data are for the period of trading overlap each day: 14:30-16:00 (or 16:30 from September 20, 1999) over the period from August 1 to October 31, 1999. XETRA prices are quoted in euro and NYSE prices are quoted in dollars (the mean bid quote for the exchange rate over the sample period was 1.0607 dollars per euro). DCX and DT shares in the U.S. trade at a 1 to 1 ratio against German shares. SAP shares in the U.S. trade at a 12 to 1 ratio against the German shares, but the table adjusts the NYSE prices and volume by a factor of 12 to make the SAP numbers for each market comparable.

<table>
<thead>
<tr>
<th></th>
<th>Avg. bid price</th>
<th>Avg. ask price</th>
<th>Avg. daily no. of quotes</th>
<th>Avg. daily trading volume</th>
<th>Avg. daily turnover</th>
</tr>
</thead>
<tbody>
<tr>
<td>DCX</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>XETRA</td>
<td>69.72</td>
<td>69.79</td>
<td>731</td>
<td>794,523</td>
<td>55,478,987</td>
</tr>
<tr>
<td>NYSE</td>
<td>73.80</td>
<td>73.96</td>
<td>215</td>
<td>203,909</td>
<td>15,102,534</td>
</tr>
<tr>
<td>DT</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>XETRA</td>
<td>40.60</td>
<td>40.67</td>
<td>593</td>
<td>1,024,785</td>
<td>41,579,511</td>
</tr>
<tr>
<td>NYSE</td>
<td>42.97</td>
<td>43.14</td>
<td>151</td>
<td>572,902</td>
<td>28,491,202</td>
</tr>
<tr>
<td>SAP</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>XETRA</td>
<td>402.00</td>
<td>402.70</td>
<td>563</td>
<td>92,917</td>
<td>37,657,635</td>
</tr>
<tr>
<td>NYSE</td>
<td>429.24</td>
<td>430.92</td>
<td>162</td>
<td>30,749</td>
<td>13,388,669</td>
</tr>
</tbody>
</table>

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Vector error correction models are estimated for each firm. The form of equation is:
\[ \Delta P_t = \alpha + BZ_{t-1} + \delta_1 \Delta P_{t-1} + \delta_2 \Delta P_{t-2} + \ldots + \Delta P_{t-q+1} + \varepsilon_t \]

where \( \Delta P \) contains the change in the logs of the exchange rate, the home-market price, and the U.S. price; \( Z_{t-1} \) is the lagged log-levels of each variable in the cointegrating equation estimated by the Johansen method. The table reports the cointegrating vector that applies to \( Z \). \( \alpha, B, \text{ and } \delta \) are coefficients to be estimated and are not reported to conserve space. The bootstrap standard errors are in parentheses. At the bottom of each table is the number of observations for that firm (each day, the time of the first observation is defined by the first quote), the log likelihood associated with the estimated system, and summary statistics associated with the Johansen test for the order of cointegration, where \( h = \) number of cointegrating relations, \( LR = \) likelihood ratio statistic, crit. 5 %: critical values of LR statistics taken from Hamilton (1994), pp. 767-768. In each case, the results support 1 cointegrating vector.

Table 2a: DCX Estimation results

<table>
<thead>
<tr>
<th>Cointegrating Eq.</th>
<th>E</th>
<th>1.000000 (0.00000)</th>
</tr>
</thead>
<tbody>
<tr>
<td>p^b</td>
<td>1.01520 (0.01683)</td>
<td></td>
</tr>
<tr>
<td>p^w</td>
<td>-1.01512 (0.01615)</td>
<td></td>
</tr>
</tbody>
</table>

<p>| Number of obs. | 38704 |
| Log Likelihood | 812177.0 |
| Johansen’s trace statistic |</p>
<table>
<thead>
<tr>
<th>( h=0 )</th>
<th>H0</th>
<th>H1</th>
<th>LR</th>
<th>crit. 5%</th>
</tr>
</thead>
<tbody>
<tr>
<td>h=0 h=3</td>
<td>437.51</td>
<td>24.31</td>
<td></td>
<td></td>
</tr>
<tr>
<td>h=1 h=3</td>
<td>4.33</td>
<td>12.53</td>
<td></td>
<td></td>
</tr>
<tr>
<td>h=2 h=3</td>
<td>0.08</td>
<td>3.84</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Johansen’s max. Eigenvalue statistic

<table>
<thead>
<tr>
<th>( h=0 )</th>
<th>H0</th>
<th>H1</th>
<th>LR</th>
<th>crit. 5%</th>
</tr>
</thead>
<tbody>
<tr>
<td>h=0 h=1</td>
<td>433.18</td>
<td>17.89</td>
<td></td>
<td></td>
</tr>
<tr>
<td>h=1 h=2</td>
<td>4.25</td>
<td>11.44</td>
<td></td>
<td></td>
</tr>
<tr>
<td>h=2 h=3</td>
<td>0.08</td>
<td>3.84</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 2b: DT Estimation results

<table>
<thead>
<tr>
<th>Cointegrating Eq.</th>
<th>E</th>
<th>1.000000 (0.00000)</th>
</tr>
</thead>
<tbody>
<tr>
<td>p^b</td>
<td>1.01516 (0.01754)</td>
<td></td>
</tr>
<tr>
<td>p^w</td>
<td>-1.01507 (0.01725)</td>
<td></td>
</tr>
</tbody>
</table>

<p>| Number of obs. | 38300 |
| Log Likelihood | 772688.2 |
| Johansen’s trace statistic |</p>
<table>
<thead>
<tr>
<th>( h=0 )</th>
<th>H0</th>
<th>H1</th>
<th>LR</th>
<th>crit. 5%</th>
</tr>
</thead>
<tbody>
<tr>
<td>h=0 h=3</td>
<td>684.36</td>
<td>24.31</td>
<td></td>
<td></td>
</tr>
<tr>
<td>h=1 h=3</td>
<td>7.07</td>
<td>12.53</td>
<td></td>
<td></td>
</tr>
<tr>
<td>h=2 h=3</td>
<td>0.20</td>
<td>3.84</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Johansen’s max. Eigenvalue statistic

<table>
<thead>
<tr>
<th>( h=0 )</th>
<th>H0</th>
<th>H1</th>
<th>LR</th>
<th>crit. 5%</th>
</tr>
</thead>
<tbody>
<tr>
<td>h=0 h=1</td>
<td>677.29</td>
<td>17.89</td>
<td></td>
<td></td>
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<tr>
<td>h=1 h=2</td>
<td>6.86</td>
<td>11.44</td>
<td></td>
<td></td>
</tr>
<tr>
<td>h=2 h=3</td>
<td>0.20</td>
<td>3.84</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 2c: SAP Estimation results

<table>
<thead>
<tr>
<th>Cointegrating Eq.</th>
<th>E</th>
<th>1.000000 (0.00000)</th>
</tr>
</thead>
<tbody>
<tr>
<td>p^b</td>
<td>1.00538 (0.02204)</td>
<td></td>
</tr>
<tr>
<td>p^w</td>
<td>-1.00523 (0.02182)</td>
<td></td>
</tr>
</tbody>
</table>

<p>| Number of obs. | 38754 |
| Log Likelihood | 785231.2 |
| Johansen’s trace statistic |</p>
<table>
<thead>
<tr>
<th>( h=0 )</th>
<th>H0</th>
<th>H1</th>
<th>LR</th>
<th>crit. 5%</th>
</tr>
</thead>
<tbody>
<tr>
<td>h=0 h=3</td>
<td>435.32</td>
<td>24.31</td>
<td></td>
<td></td>
</tr>
<tr>
<td>h=1 h=3</td>
<td>2.12</td>
<td>12.53</td>
<td></td>
<td></td>
</tr>
<tr>
<td>h=2 h=3</td>
<td>0.01</td>
<td>3.84</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Johansen’s max. Eigenvalue statistic

<table>
<thead>
<tr>
<th>( h=0 )</th>
<th>H0</th>
<th>H1</th>
<th>LR</th>
<th>crit. 5%</th>
</tr>
</thead>
<tbody>
<tr>
<td>h=0 h=1</td>
<td>433.20</td>
<td>17.89</td>
<td></td>
<td></td>
</tr>
<tr>
<td>h=1 h=2</td>
<td>2.12</td>
<td>11.44</td>
<td></td>
<td></td>
</tr>
<tr>
<td>h=2 h=3</td>
<td>0.01</td>
<td>3.84</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Table 3

Vector Moving Average Coefficients

The matrices below are estimates of the $\Psi^{(1)}$ matrix associated with the vector moving average (VMA) models:

$$\begin{bmatrix}
\psi_{11} & \psi_{12} & \psi_{13} \\
\psi_{21} & \psi_{22} & \psi_{23} \\
\psi_{31} & \psi_{32} & \psi_{33}
\end{bmatrix}$$

The reported coefficients indicate that the exchange rate appears to be unaffected by innovations in the stock prices. The long-run impact of a shock to the home-market stock price appears to be similar for both XETRA and NYSE prices. Similarly, the long-run impact of a shock to the U.S. stock price appears to be the same for both XETRA and NYSE prices. The long-run impact of a shock to the home-market price is larger than the impact of a shock to the U.S. price in all cases. Shocks to the exchange rate appear to have a larger impact on the NYSE price than the XETRA price. Bootstrap standard errors are in parentheses.

**DCX**

$$\begin{bmatrix}
0.576 (0.010) & -0.005 (0.011) & 0.011 (0.012) \\
-0.132 (0.025) & 0.822 (0.031) & 0.250 (0.033) \\
0.435 (0.027) & 0.818 (0.032) & 0.261 (0.034)
\end{bmatrix}$$

**DT**

$$\begin{bmatrix}
0.594 (0.006) & -0.004 (0.007) & 0.004 (0.008) \\
-0.046 (0.026) & 0.879 (0.030) & 0.081 (0.031) \\
0.539 (0.027) & 0.875 (0.030) & 0.085 (0.031)
\end{bmatrix}$$

**SAP**

$$\begin{bmatrix}
0.596 (0.007) & -0.005 (0.008) & 0.001 (0.008) \\
-0.149 (0.021) & 0.689 (0.024) & 0.287 (0.026) \\
0.444 (0.023) & 0.685 (0.025) & 0.288 (0.026)
\end{bmatrix}$$
**Table 4**

Information Shares of the Exchange Rate, Home-Market Price, and U.S. Price in Price Discovery of Internationally-Traded Equities

The information shares are the proportion of the innovation variance in the value of asset $i$ that can be attributed to innovations in the price of asset $j$. The estimates are drawn from a VEC model involving the dollar/euro exchange rate, the home-market (XETRA) price, and the U.S. (NYSE) price. That particular order of the three variables is utilized in the triangularization of the covariance matrix. Elements of each row may not sum exactly to 1 due to rounding to 3 decimal places. Bootstrap standard errors are in parentheses.

<table>
<thead>
<tr>
<th></th>
<th>Exchange Rate Innovation</th>
<th>XETRA Innovation</th>
<th>NYSE Innovation</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>DCX</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Exchange Rate</td>
<td>0.999 (0.005)</td>
<td>0.000 (0.002)</td>
<td>0.001 (0.004)</td>
</tr>
<tr>
<td>XETRA Price</td>
<td>0.007 (0.003)</td>
<td>0.906 (0.029)</td>
<td>0.087 (0.027)</td>
</tr>
<tr>
<td>NYSE Price</td>
<td>0.073 (0.007)</td>
<td>0.838 (0.024)</td>
<td>0.089 (0.027)</td>
</tr>
<tr>
<td><strong>DT</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Exchange Rate</td>
<td>0.999 (0.004)</td>
<td>0.000 (0.002)</td>
<td>0.000 (0.002)</td>
</tr>
<tr>
<td>XETRA Price</td>
<td>0.000 (0.001)</td>
<td>0.991 (0.007)</td>
<td>0.009 (0.007)</td>
</tr>
<tr>
<td>NYSE Price</td>
<td>0.049 (0.005)</td>
<td>0.942 (0.008)</td>
<td>0.009 (0.007)</td>
</tr>
<tr>
<td><strong>SAP</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Exchange Rate</td>
<td>1.000 (0.004)</td>
<td>0.000 (0.002)</td>
<td>0.000 (0.002)</td>
</tr>
<tr>
<td>XETRA Price</td>
<td>0.006 (0.002)</td>
<td>0.798 (0.041)</td>
<td>0.196 (0.039)</td>
</tr>
<tr>
<td>NYSE Price</td>
<td>0.059 (0.006)</td>
<td>0.752 (0.036)</td>
<td>0.189 (0.039)</td>
</tr>
</tbody>
</table>
Table 5

Bounds for Information Shares

Permuting the order of the variables in the Cholesky decomposition of the covariance matrix allows the computation of the upper and lower bounds on information shares. The variable going first in the order has its share maximized and the variable listed last has its share minimized. The table gives the upper and lower bounds for each innovation pair. Only a single value is reported when the upper and lower bounds round to the same number at 3 decimal places.

<table>
<thead>
<tr>
<th></th>
<th>Exchange Rate Innovation</th>
<th>XETRA Innovation</th>
<th>NYSE Innovation</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>DCX</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Exchange Rate</td>
<td>0.998</td>
<td>0.000</td>
<td>0.001-0.003</td>
</tr>
<tr>
<td>XETRA Price</td>
<td>0.007</td>
<td>0.906-0.901</td>
<td>0.086-0.093</td>
</tr>
<tr>
<td>NYSE Price</td>
<td>0.072-0.081</td>
<td>0.833-0.838</td>
<td>0.089-0.097</td>
</tr>
<tr>
<td><strong>DT</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Exchange Rate</td>
<td>0.999</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>XETRA Price</td>
<td>0.000</td>
<td>0.988-0.991</td>
<td>0.009-0.012</td>
</tr>
<tr>
<td>NYSE Price</td>
<td>0.049-0.050</td>
<td>0.938-0.941</td>
<td>0.009-0.012</td>
</tr>
<tr>
<td><strong>SAP</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Exchange Rate</td>
<td>1.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>XETRA Price</td>
<td>0.006-0.007</td>
<td>0.794-0.797</td>
<td>0.196-0.199</td>
</tr>
<tr>
<td>NYSE Price</td>
<td>0.057-0.058</td>
<td>0.750-0.758</td>
<td>0.189-0.191</td>
</tr>
</tbody>
</table>
The data plotted in the figures shows the stock prices in Frankfurt trading (XETRA) and New York trading (NYSE) for 3 firms, DaimlerChrysler (DCX), Deutsche Telekom (DT), and SAP. In addition, the dollar/euro exchange rate is plotted. The sample period is August 1, 1999 to October 31, 1999.
Figure 2

Intra-daily Quoting Intensities

The figures show the average number of quotes per second for each 5-minute interval over the XETRA and NYSE trading day for the period August 1 – September 19, 1999 when XETRA closed at 16:00 GMT.

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BOOTSTRAP

As in Li & Maddala (1997) bootstrap from residuals rather than data
*data would distort dynamics of cointegrated series

1. Estimate VECM on original data
*store estimated coefficients & (Tx3) residual matrix

2. Simulate VECM representation
*use estimated parameters
*take first observations of original sample to initialize
*iterate forward, drawing (with replacement) from residual matrix to get new obs on each variable
*new obs is used as lagged value for next iteration for which a new residual vector is drawn........

3. Use new artificial data set created in 2. for new VECM estimation
*store new coefficient estimates, associated $\Psi(1)$ matrix, and info. shares

4. Repeat 2 & 3 1000 times
*compute std. error of each statistic

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