Grammig, Joachim G.; Peter, Franziska J.

Working Paper

International price discovery in the presence of market microstructure effects

CFR working paper, No. 08-10

Provided in cooperation with:
Universität zu Köln

CFR-Working Paper NO. 08-10

International Price Discovery in the Presence of Market Microstructure Effects

J. Grammig • F.J.Peter

centre for financial Research
Look deeper

International Price Discovery in the Presence of Market Microstructure Effects

Joachim Grammig
Franziska J. Peter [*]

December 12, 2008

Abstract

This paper addresses and resolves the problems caused by microstructure effects when measuring the relative importance of home and U.S. market in the price discovery process of internationally cross listed stocks. In order to avoid large bounds for information shares, previous studies applying the Cholesky decomposition within the Hasbrouck (1995) framework had to rely on high frequency data. However, this entails a potential bias of estimated information shares induced by microstructure effects. We propose a modified approach that relies on distributional assumptions and yields unique and unbiased information shares. Our results indicate that the role of the U.S. market in the price discovery process of Canadian interlisted stocks has been severely underestimated to date. Moreover, we find that rather than stock specific factors, market design determines information shares.

Keywords: international cross-listings, market microstructure effects, price discovery

JEL classification: F3, G15

---

[*]University of Tübingen, Department of Economics. Mohlstrasse 36, D-72074 Tübingen, Germany. Phone: +49 7071 29 76009. Fax: +49 7071 29 5546. Email addresses: joachim.grammig@uni-tuebingen.de and franziska-julia.peter@uni-tuebingen.de. We thank the participants of the Center for Financial Studies 2008 Conference on the Industrial Organisation of Securities Markets, the 2008 International Conference on Price, Liquidity, and Credit Risk (U Constance) and various seminars for helpful comments. Special thanks go to the Centre for Financial Research, Cologne, for financial support. We are grateful to Markku Lanne for providing us with his program code.

1 Introduction

According to Coffee (2002), increasing globalisation and improved technology will lead to a decay in the number of securities exchanges around the world. Small national exchanges will lose their share in trading to large international exchanges, which provide a more efficient trading environment. Carpentier et al. (2007) examine this development for the Canadian stock exchanges with respect to the U.S. markets. They report a rapidly growing share of U.S. markets in trades of Canadian interlisted stocks, up to the point where interlisted stocks are absorbed by the foreign market and delisted on the home market. These developments foreshadow small national stock exchanges to become markets for illiquid stocks that failed to attract investors on the large markets (Gaa et al., 2002). Thus, within the context of internationally cross-listed stocks, it is of paramount interest for national stock exchanges to remain the dominant market in regard to the price discovery process.[1] The competition among smaller national and the giant U.S. markets for the leadership in price discovery of interlisted stocks has grown immensely and has triggered a growing field of research.

In a recent study, Eun and Sabherwal (2003) examine US-listed Canadian stocks. They conclude that price discovery mainly takes place in the home market. This evidence is supported by Grammig et al. (2005, 2008), Hupperets and Menkveld (2002), and Phylaktis and Korczak (2007), who apply the Hasbrouck (1995) methodology to estimate the home and foreign market share in price discovery (information share) of interlisted stocks from various countries. They also find that the home market evolves as the dominant trading venue, while trading on the New York Stock Exchange (NYSE) mainly takes place to offset arbitrage opportunities.

In this paper we argue that this evidence might be misleading, since it is a) based on non-unique estimators and b) ignores microstructure effects present in high frequency financial data. We show that estimates resulting from the standard approach are either biased or rather imprecise and offer an alternative approach that resolves these drawbacks. This paper thus connects two strands of research, namely studies concerned with international price discovery and those dealing with market microstructure effects and their impact on financial volatility estimators.

As outlined by Hasbrouck (2002), Bandi and Russell (2008) and Aït-Sahalia et al. (2005), high frequency financial data contain a microstructure effects component which reflects characteristics of the trading mechanism. We reveal that if prices are sampled at high frequencies, and microstructure components differ in home and foreign market, information share estimates become severely biased. At lower sampling frequencies,

[1] For a comprehensive study concerned with international cross-listings in stock markets see Karolyi (2006).

however, at which microstructure effects are less pronounced, the applicability of the Hasbrouck (1995) methodology is limited as it delivers merely upper and lower bounds for information shares. The empirical analysis faces the following dilemma. On the one hand, in the case of low frequencies, the information share bounds diverge considerably due to the increasing contemporaneous correlation of the price series. The commonly reported midpoint of upper and lower bound then becomes rather unreliable as a proxy for the true information share. On the other hand, using high frequency data, the information share estimates are prone to a distortion by microstructure effects.

The methodological contribution of this paper is a modification of the Hasbrouck (1995) approach that yields unique information share estimates. The method is applicable to data sampled at lower frequencies which avoids distortion of the estimated information shares by microstructure effects. It is based on a recent contribution by Lanne and Lütkepohl (2005), and relies on distributional assumptions to identify structural shocks in a cointegrated vector autoregression. This idea is particularly appealing within the context of internationally cross-listed stocks, since stock returns exhibit a leptokurtic distribution and the application of a mixture distribution is quite appropriate to account for such non-normal price innovations.

We apply our method to Canadian stocks, which are traded on the Toronto Stock Exchange (TSX) and cross-listed on the NYSE. Our results imply bad and good news for the national exchanges facing the threat of the U.S. market. First, we show that the role of the NYSE within the price discovery process of Canadian interlisted stocks has to date been severely underestimated. In light of our findings, it seems that the processes described by Coffee (2002) have gained momentum and that the concern expressed by Carpentier et al. (2007) is quite justified. Second, compared to standard methods, we find a much smaller cross-sectional variation of information shares among our sample stocks. This suggests that contributions to price discovery are determined by market characteristics rather than by stock specific factors. Thus, by the design of their trading protocol, national stock exchanges themselves are able to influence the role they play within the price discovery process of interlisted stocks and use this to their advantage when facing the threat of the large international exchanges.

The remainder of the paper is organized as follows: Section 2 outlines the basic economic and statistical framework for our analysis as well as the main features and caveats of standard methods. Section 3 discusses the role of microstructure effects within the concept of measuring price discovery for internationally cross-listed stocks. We also report simulation evidence on the bias of information share estimates induced by microstructure effects. Section 4 explains the methodological details of our modified approach. Section 5 describes the data and sampling details. In Section 6 we present and discuss our empirical results. Section 7 concludes the paper.

2 Basic economic and statistical framework

2.1 International price discovery as an error correction process

There exist two prevalent methodologies in the current literature concerned with measuring contributions to international price discovery. A number of studies, including Eun and Sabherwal (2003) and Phylaktis and Korczak (2007), apply the methodology advocated by Harris et al. (2002b) and gauge a market's contribution to price discovery by its common factor component weight. The second approach put forth by Hasbrouck (1995) focuses on decomposing the variance of the efficient price into contributions attributable to home and foreign market. As pointed out by Baillie et al. (2002), both methodologies are closely related (see also De Jong, 2002; Harris et al., 2002a; Hasbrouck, 2002; Lehmann, 2002; Hasbrouck, 2007, chap. 10). In the following, we briefly review the economic and statistical framework which provides the foundation for our alternative methodology.

According to the law of one price, the quoted home market and exchange rate adjusted foreign market prices cannot diverge in the long run, since traders who seize arbitrage opportunities will force prices back together. In econometric terms the series of log home market prices (p_t^h) and log foreign market prices denominated in home market currency (p_t^f) are cointegrated with cointegrating vector $\beta = (1, -1)'$. This implies that one common stochastic trend associated with the notion of the efficient price exists. When we further assume that home and foreign market price dynamics can be described by a bivariate vector autoregression of order q, Granger's representation theorem applies, and the prices of interlisted stocks evolve according to a bivariate error correction process (ECM),

$$\Delta p_t = \alpha\beta' p_{t-1} + \Gamma_1 \Delta p_{t-1} + \ldots + \Gamma_{q-1}\Delta p_{t-q+1} + u_t, \tag{1}$$

where $p_t = (p_t^h, p_t^f)'$, Γ_1 to Γ_{q-1} are 2×2 parameter matrices. $u_t = (u_t^h, u_t^f)'$ is vector white noise with zero mean and covariance matrix Σ_u. The vector $\alpha = (\alpha^h, \alpha^f)'$ contains the coefficients associated with the speed of adjustment of each price series to deviations from the equilibrium. With cointegrating vector $\beta = (1, -1)'$, the long-run impacts of a one unit innovation in the home and the foreign price on the efficient price/common stochastic trend are given by

$$\begin{aligned} \xi^h &= \pi\alpha_\perp^h \quad \text{(long-run impact of an innovation in } u_t^h\text{)} \\ \xi^f &= \pi\alpha_\perp^f \quad \text{(long-run impact of an innovation in } u_t^f\text{)}, \end{aligned} \tag{2}$$

where $\pi = [\alpha'_\perp(I_2 - \sum_{i=1}^{q-1}\Gamma_i)\beta_\perp]^{-1}$ (Johansen, 1995). Here, $\alpha_\perp = (\alpha_\perp^h, \alpha_\perp^f)'$ and

$\beta_\perp = (1,1)'$ represent the orthogonal complements of α and β.[2] It can be shown that the adjustment coefficients are orthogonal to the Gonzalo and Granger (1995) common factor weights. The Gonzalo/Granger methodology thus provides the theoretical basis for Eun and Sabherwal's (2003) idea to draw on the adjustment coefficient ratios

$$Adj^h = \frac{\alpha^h}{\alpha^h + |\alpha^f|} \quad \text{and} \quad Adj^f = \frac{|\alpha^f|}{\alpha^h + |\alpha^f|} \tag{3}$$

as measures for home and foreign market contributions to the price discovery process.

2.2 Hasbrouck information shares

The exclusive focus on adjustment coefficients neglects two important aspects of the price process: the contemporaneous correlation between the innovations u_t^h and u_t^f and their variances. Hasbrouck's (1995) methodology avoids these drawbacks by identifying idiosyncratic price innovations in each market, and by decomposing the variance of the efficient price into home and foreign market contributions. Idiosyncratic innovations are contemporaneously and serially uncorrelated zero mean unit variance random variables, $\varepsilon_t = (\varepsilon_t^h, \varepsilon_t^f)' \sim (0, I_2)$. They relate to the "composite" innovations as $u_t = B\varepsilon_t$. Thus, $v_t = \xi' B \varepsilon_t$, where $\xi = (\xi^h, \xi^f)'$, gives the long-run impact of time t idiosyncratic innovations on the efficient price. Hasbrouck (1995) proposes to decompose the variance of efficient price innovations ($\mathrm{Var}(v_t) = \xi' B B' \xi$) into contributions of idiosyncratic innovations in each market. However, unless the variance covariance matrix Σ_u is diagonal, the matrix B is underidentified. This problem can be resolved by a Cholesky factorization of the variance covariance matrix $\Sigma_u = CC'$, where C denotes the lower triangular matrix derived from the Cholesky decomposition. This implies $B = C$, i.e. a hierarchic ordering of markets. Idiosyncratic innovations in the market ordered first contemporaneously affect both markets, while price innovations in the market ordered second do not contemporaneously affect the price in the market ordered first. With the home market ordered first, Hasbrouck information shares of home (IS^h) and foreign (IS^f) market can be computed as

$$IS^h = \frac{[\xi' C]_{[1]}^2}{\xi' C C' \xi} \quad \text{and} \quad IS^f = \frac{[\xi' C]_{[2]}^2}{\xi' C C' \xi} \ , \tag{4}$$

where $\xi' C_{[j]}$ denotes the jth element of the vector $\xi' C$. Due to the arbitrary ordering of markets, the information shares in (4) are not unique. The contribution of the

[2] The ratio of long-run impacts ξ^h/ξ^f represents an intuitive measure for the significance of a market concerning price discovery. Since π is a scalar, it follows from (2) that $\xi^h/\xi^f = \alpha_\perp^h/\alpha_\perp^f$. Hence, a simple way to compute the long-run impacts ratio is to use the information contained in the adjustment coefficients.

market ordered first is maximized and that of the market ordered second is minimized. Since there is no theoretical justification for such a hierarchy, the common solution is to permutate the ordering of the markets. This yields information share upper and lower bounds. The main drawback of the Hasbrouck methodology is that these bounds can diverge considerably, as the contemporaneous correlation between the composite innovations u_t^f and u_t^h tends to increase with decreasing sampling frequency. Figure 1 illustrates this phenomenon for one of our NYSE interlisted Canadian stocks (Abidibi Consolidated, ABY).

<Insert Figure 1 about here>

The graph shows that sampling prices at intervals longer than two minutes already leads to wide bounds of the foreign market information share. The midpoint therefore yields a very inaccurate measure for the true information share at lower sampling frequencies.

3 Price discovery and microstructure effects: concern, evidence, and implications

3.1 Sampling frequency and microstructure effects: the concern

In order to avoid divergence of information share bounds, the obvious strategy is to use data sampled at the highest possible frequency. In his seminal application Hasbrouck (1995) performed the econometric analysis based on price data sampled at one second intervals. However, a glance at recent papers dealing with the estimation of return volatility using high frequency data suggests that this is a problematic strategy. Andersen et al. (2001), Andersen et al. (2003) and Barndorff-Nielsen and Shephard (2002) popularized the idea to use price data sampled at high frequencies, e.g. five minutes, to estimate return volatility at a lower, e.g. daily, frequency. The basic idea is to divide the trading day d into M equi-distant time intervals, compute log price changes $r_{d,j}$ for each interval j, and compute the so-called realized variance estimator as $RV_d = \sum_{j=1}^{M} r_{d,j}^2$. If the underlying price process is a diffusion process with stochastic volatility, then RV_d converges in probability to the integrated volatility for day d.
Shortening the sampling intervals, i.e. increasing M, should improve the precision of the estimator. However, Aït-Sahalia et al. (2005) and Bandi and Russell (2008) point out that thriving for precision by increasing the sampling frequency is misleading. They show that in the case of too short a sampling interval, the realized variance estimator exhibits erratic behaviour. Figure 2 illustrates this effect, again for ABY. The graph shows that the realized variance estimate using NYSE returns is stable up to a sampling frequency of about two minutes and then sharply increases at shorter intervals. The

effect is different for the home market. Here, the realized variance estimate remains stable up to a sampling frequency of about one minute.

<Insert Figure 2 about here>

As a possible explanation for this phenomenon, Bandi and Russell (2008) and Aït-Sahalia et al. (2005) state that market microstructure effects interfere with the fundamental price process. These effects are negligible at longer sampling intervals, but dominate the realized variance estimate at high frequencies. Microstructure effects are transient price changes which are uninformative concerning the fundamental value of an asset. They arise from sources such as bid-ask bounces, temporary liquidity shocks, inventory effects, and minimum tick size.

As outlined above, computation of Hasbrouck information shares amounts to estimating and decomposing the variance of the efficient price. Our concern is that the strategy to move to a higher sampling frequency avoids large bounds, but at the same time might bias the estimated information shares. The question is therefore whether microstructure effects prevalent at high sampling frequencies affect the information share estimates in a similar way as they affect the realized variance estimate.

3.2 Simulation evidence

In order to address this issue we simulate the true price discovery process in home and foreign market using a parameterized version of the ECM in (1) and then distort the true prices p_t^h and p_t^f by adding independent microstructure effects. Observed log prices $\tilde{p}_t^h$ and $\tilde{p}_t^f$ are then given by $\tilde{p}_t^h = p_t^h + \eta_t^h$ and $\tilde{p}_t^f = p_t^f + \eta_t^f$. The microstructure components η_t^h and η_t^f are drawn from independent zero mean normal distributions with variances $\sigma^2_{\eta^h}$ and $\sigma^2_{\eta^f}$, respectively. The basic experimental design assumes symmetry of home and foreign market which implies identical Hasbrouck information shares $IS^h = IS^f = 0.5$. Parameter values are chosen to match typical numbers found in our sample. The innovations u_t^h and u_t^f are normally distributed with zero mean and identical standard deviation $\sigma_u = 0.0002$ and contemporaneously uncorrelated.[3] Along with the reference case, in which no microstructure effects are present, we consider seven scenarios in which we vary the variance of the microstructure effects, $\sigma^2_{\eta^h}$ and $\sigma^2_{\eta^f}$. In the first three scenarios, microstructure effects are prevalent only in the foreign market. In the other four scenarios, microstructure effects are present in both markets. In scenarios 5, 6 and 7, the foreign market microstructure variance exceeds that of the home market (a setup suggested by Figure 2).

[3] Setting $\sigma_u = 0.0002$ implies an annualized log return standard deviation of 20% when the sampling frequency is 10 seconds. With 265 trading days per year, 10 trading hours per day and sampling at 10 seconds we have $\sqrt{265 \times 10 \times 60 \times 6} \times 0.0002 \approx 0.2$.

<Insert Table 1 about here>

Table 1 reports the simulation results. The conclusive evidence is that microstructure effects can severely bias information share estimates. In detail, the information share attributed to the market in which microstructure effects are more prevalent is underestimated. Consider scenario 3, in which the home market is free of microstructure effects, but the foreign market microstructure component's standard deviation is two times that of the fundamental innovation's standard deviation. The estimated foreign market information share amounts to 20%, less than half of its true value. When microstructure effects are present in both markets, biased information shares result when the variances of the microstructure components differ between markets. In scenario 6, in which the foreign market microstructure variance is four times that of the home market, the downward bias of the foreign market information share is most pronounced. The estimated foreign market information share is less than one quarter of its true value. Besides, Table 1 shows that different microstructure effects in home and foreign markets also affect adjustment coefficient ratios (3) and long-run impact coefficients (2).

These findings are confirmed in two alternative experimental setups. The *asymmetric* design assumes a 30:70 distribution of home and foreign market information share. The *monopolistic* setup implies that 100% of price discovery takes place in the foreign market. The results for these alternative experimental designs are reported in the appendix Tables A-1 and A-2.

Estimating information shares of interlisted stocks using high frequency data therefore can lead to wrong conclusions if microstructure effects are more prevalent in one of the markets. Given the different designs of international stock markets, such a scenario seems to be the rule rather than the exception. Within the context of Canadian interlisted stocks, Figure 2 evinces that microstructure effects are more prominent at the NYSE than at the TSX. According to the results of our simulation study, this suggests that standard Hasbrouck information shares estimated at high frequencies underestimate the importance of the NYSE for the price discovery process. Moving to a lower sampling frequency, however, is not an option. Estimation at lower frequencies yields inaccurate results, as the bounds for the Hasbrouck information shares diverge considerably.[4] The next section proposes a solution to this dilemma.

[4] Without formally addressing the problems associated with microstructure effects, previous studies concerned with international price discovery have avoided modelling at very high sampling frequencies. Hupperets and Menkveld (2002), for instance, sample their data at five minutes intervals, Phylaktis and Korczak (2007) use a one minute frequency, Eun and Sabherwal (2003) use ten minutes intervals.

4 Modified Hasbrouck information shares

4.1 Unique information shares based on distributional assumptions

In the following, we advocate an alternative approach that yields unique information shares and consequently is applicable to data sampled at lower frequencies. The methodology is based on a recent contribution by Lanne and Lütkepohl (2005). They propose to identify structural shocks in a cointegrated system based on distributional assumptions. This is of major interest for the present problem since these assumptions are particularly plausible in our application. In detail, we propose to model the contemporaneously correlated ECM innovations u_t in (1) as a linear combination of uncorrelated innovations which follow a mixture normal distribution,

$$u_t = W w_t, \tag{5}$$

where W denotes a non-singular parameter matrix. Idiosyncratic, i.e. contemporaneously uncorrelated innovations, $w_t = (w_t^h, w_t^f)'$, are generated as a mixture of two Gaussian random vectors,

$$w_t = \begin{cases} e_{1t} \sim \mathscr{N}(0, I_2) & \text{with probability } \gamma \\ e_{2t} \sim \mathscr{N}(0, \Psi) & \text{with probability } 1-\gamma, \end{cases} \tag{6}$$

where $0 < \gamma < 1$ is referred to as the mixture probability, and Ψ is a diagonal matrix with positive elements ψ^h and ψ^f. The variance covariance matrix of w_t is a diagonal matrix given by

$$\Sigma_w = \begin{pmatrix} \mathrm{Var}(w_t^h) & 0 \\ 0 & \mathrm{Var}(w_t^f) \end{pmatrix} = \begin{pmatrix} \gamma + (1-\gamma)\psi^h & 0 \\ 0 & \gamma + (1-\gamma)\psi^f \end{pmatrix}. \tag{7}$$

If $\psi^h = 1$, the innovations in the home market price series would follow a normal distribution. With $\psi^h = \psi^f = 1$, innovations in both price series are normally distributed and the ECM in (1) with Gaussian innovations emerges as a special case. As a matter of fact, the use of mixture of normal distributions is particularly appealing since it captures the excess kurtosis found in financial return data (see e.g. Mittnik et al., 2004; Tsay, 2005, chap. 1).

The key advantage is that the mixture assumption offers the possibility to identify unique Hasbrouck-type information shares such that one can dispense with the Cholesky-based measures. The matrix B, which relates composite to idiosyncratic innovations via $u_t = B\varepsilon_t$, can be identified and estimated if the data support the mixture normal assumption. Lanne and Lütkepohl (2005) show that the elements of B are locally identified by the distributional assumptions concerning w_t if and only if all diagonal elements of Ψ are distinct, which in the present case requires that $\psi^h \neq \psi^f$.

When estimates of the mixture parameters W, γ, Ψ are available (we will address to estimation issues below), we can exploit the relation that $u_t = B\varepsilon_t = Ww_t$, such that

$$\Sigma_u = BB' = W\Sigma_w W'. \tag{8}$$

It follows that $B = W\Sigma_w^{0.5}$ and $\varepsilon_t = \Sigma_w^{-0.5} w_t$. Information shares in the spirit of Hasbrouck (1995) that result from the decomposition of the variance of the efficient price innovations $v_t = \xi' B\varepsilon_t$, can then be computed as

$$ISM^h = \frac{\left[\xi' W\Sigma_w^{0.5}\right]_{[1]}^2}{\xi' W\Sigma_w W'\xi} \quad \text{and} \quad ISM^f = \frac{\left[\xi' W\Sigma_w^{0.5}\right]_{[2]}^2}{\xi' W\Sigma_w W'\xi}, \tag{9}$$

with $\xi = (\xi^h, \xi^f)'$ defined as in (2). We refer to ISM^h and ISM^f as modified Hasbrouck information shares. The logic behind the decomposition can be seen by writing the variance of the efficient price innovations in detail as

$$\begin{aligned} \mathrm{Var}(v_t) &= \xi' BB'\xi = \xi' W\Sigma_w W'\xi \qquad (10)\\ = \quad &\left\{(\xi^h)^2 w_{11}^2 + 2\xi^h\xi^f w_{11}w_{21} + (\xi^f)^2 w_{21}^2\right\} \times \mathrm{Var}(w_t^h)\\ &+ \left\{\xi^f)^2 w_{22}^2 + 2\xi^h\xi^f w_{12}w_{22} + (\xi^h)^2 w_{12}^2\right\} \times \mathrm{Var}(w_t^f), \end{aligned}$$

where w_{ij} denotes the ith row, jth column element of W. Equation (10) illustrates that the variance of the efficient price innovation can be written as the weighted sum of idiosyncratic home and foreign innovation variances which are, as can be seen in (7), a function of the mixture parameters. The modified information shares in (9) are thus a function of all structural parameters.

Lanne and Lütkepohl (2005) point out that the matrix W is identified up to a multiplication by any of its columns by minus one. This does not change the modified information shares since the terms in (10) are robust to a change in the signs of the elements of a column in W. We provide an illustration of identification of information shares by the mixture assumption in Appendix A.

4.2 Parameter estimation

Estimation of a cointegrated system with mixture normal innovations is intricate, as it requires nonlinear optimization techniques. Maximum likelihood estimation can be performed as outlined by Lanne and Lütkepohl (2005). They propose to estimate the cointegrating vector in an initial step or fix it to its theoretical value ($\beta = (1, -1)'$ in our case). Since the joint density of the mixture normal variates w_t is given by

$$f(w_t) = \gamma(2\pi)^{-1}\exp\left\{-\frac{1}{2}w_t w_t'\right\} + (1-\gamma)2\pi\det(\Psi)^{-\frac{1}{2}}\exp\left\{-\frac{1}{2}w_t'\Psi^{-1}w_t\right\},$$

the joint density of log price changes at time t, conditioned on time $t-1$ information, can be written as

$$\begin{aligned} f_{t-1}(p_t) = {} & \gamma\det(W)^{-1} \\ & \times \exp\left\{-\frac{1}{2}(A(L)p_t)'(WW')^{-1}(A(L)p_t)\right\} \\ & + (1-\gamma)\det(\Psi)^{-\frac{1}{2}}\det(W)^{-1} \\ & \times \exp\left\{-\frac{1}{2}(A(L)p_t)'(W\Psi W')^{-1}A(L)p_t\right\}, \end{aligned}$$

where $A(L) = 1 - L - \alpha\beta' L - \Gamma_1\Delta L - \ldots - \Gamma_{q-1}\Delta L^{q-1}$. The conditional log likelihood

$$\mathscr{L}(\theta) = \sum_{t=1}^{T}\log f_{t-1}(p_t), \tag{11}$$

where θ collects the model parameters, has to be maximized by nonlinear optimization algorithms.

While the simultaneous estimation of ECM parameters (α, Γ_j- matrices) and mixture parameters (W, γ, Ψ) is feasible, maximization over the large parameter space, in combination with a lag length selection procedure, is computationally quite intensive. We therefore recommend a two-step estimation strategy. When the cointegrating vector is fixed to its theoretical value, $\beta = (1, -1)'$, equation by equation OLS of (1) delivers consistent first step estimates of the ECM parameters. The second estimation step entails maximization of the log-likelihood (11) in which the ECM parameters are replaced by their first step estimates. Nonlinear optimization is then performed for the mixture model parameters only. Standard errors of parameter estimates and modified information shares estimates resulting from this two-step procedure can be conveniently delivered by a parametric bootstrap along the lines of MacKinnon (2002). Details of the bootstrap procedure are provided in Appendix B.

5 Data and sampling

Our data include bid and ask quotes for 69 Canadian stocks. Initially we identify 83 Canadian stocks which were traded on the TSX and cross-listed on the NYSE between January 1st 2004 and 31st of March 2004, which is the period for which we have data available. 18 stocks have been excluded from the sample. In detail, we drop extremely infrequently quoted stocks. We thereby apply two criteria: we require our sample stocks to be quoted on each of the 62 trading days (considering the first two hours of trading) and the traded volume over the whole sampling period has to exceed 1 Mio. CAD on the TSX and NYSE, respectively. By the first criterion the stocks CNI, EXEA, BEI, ITN, LAF, MWI, RBA, TRA, and VTS are excluded and by the second we drop BR, CJR, CWG, and OPY (NYSE ticker symbols). Further we exclude BGM, since we were not able to identify and match the TSX midquote with the corresponding NYSE midquote. The number of stocks is comparable to the sample used by Eun and Sabherwal (2003) who consider 62 US cross-listed Canadian stocks (of which 41 were traded on NYSE and 21 on NASDAQ). Table A-3 in the appendix contains the stock tickers as well as the full company names. The NYSE data are taken from the Trade and Quote (TAQ) DVDs supplied by the New York Stock Exchange. Toronto quote data were obtained from the Equity Trades and Quotes data set provided by the TSX. CAN/US$ exchange rate Reuters quotes come from Olsen Associates. The foreign market price (p_t^f) is computed as the log midquote of NYSE bid and ask price which is converted into Canadian dollars using the midpoint of the Reuters quotes for the intra-daily exchange rate. The home market price (p_t^h) is the log midpoint of the TSX bid and ask quote. Although the continuous trading hours of the TSX and the NYSE overlap (9.30 am to 16.30 pm EST), we focus on data for the two hours of continuous trading (9.30 am to 11.30 am). Focusing on the first two trading hours retains more than 3000 observations per stock, enough to deliver precise results. Overnight log price changes are excluded from the analysis.

<Insert Table 2 about here>

Table 2 displays cross-sectional descriptives. Detailed stock-specific information can be found in Tables A-3 and A-4 in the appendix. It can be seen that the sample includes a range of stocks varying with respect to size and trading value. We choose a two minutes sampling frequency. As pointed out before, the sampling interval has to balance the potential bias by microstructure effects at high frequencies and, when Hasbrouck information shares are computed, the widening of upper and lower bounds. The two minutes frequency is suggested by volatility signature plots like the one in Figure 2 which indicate that microstructure effects are mitigated to a large extent at this sampling frequency. As a more formal selection criterion, we also compute stock specific optimal sampling frequencies along the lines of Bandi and Russell (2008). The cross-sectional distribution of the Bandi/Russell optimal sampling frequency reported in Table 2 indicates that a two minutes sampling interval is an appropriate choice.

6 Results and discussion

6.1 Specification test results

The computation of modified Hasbrouck information shares requires that log returns exhibit the leptokurtosis that justifies the mixture of normal assumption. In order to examine the distribution of log price changes we therefore apply the Jarque-Bera normality test to the two minutes return data. Table 2 reports the cross-sectional distribution of the p-value of the Jarque-Bera statistic. For all our sample stocks the null of normally distributed returns is rejected at any common level of significance. Table 2 also shows that the excess kurtosis of the return distributions supports the mixture normal assumption.

Parameter estimation follows the two-step procedure outlined in Section 4. The first step entails a standard cointegration analysis which involves testing the number of cointegrating relations and lag length selection for the equilibrium correction model (ECM) in Equation (1). We summarize the results in Table 3. Johansen's (1988) trace and max. eigenvalue statistics indicate the presence of one cointegrating relation, and hence one common stochastic trend. The normalized cointegrating vectors, estimated by reduced rank regressions (see Johansen, 1991), are close and not significantly different from $\beta = (1, -1)$ for all stocks. Hence, we fix the cointegrating vector to its theoretical value and estimate the ECM parameters by OLS. Results change only marginally when the analysis is based on estimated cointegrating vectors. The lag length in the ECM selected by the Schwarz information criterion (SIC) ranges from one to six.

<Insert Table 3 about here>

In the second step, we maximize the log likelihood function (11) conditioning on the first step estimates in order to obtain estimates for the mixture parameters γ, Ψ, and W. Table 4 displays the distribution of parameter estimates across the 69 sample stocks along with their standard errors averaged across stocks. Stock-specific results can be found in Appendix Table A-5. Estimates of the short run parameter matrices Γ_j are omitted for the sake of brevity.

<Insert Table 4 about here>

As discussed above, local identification of the mixture model parameters requires the diagonal elements of the matrix Ψ to be different. We therefore conduct a Wald test of the null hypothesis that $\psi^h = \psi^f$. Table 3 shows that the null is rejected for 67 of the 69 sample stocks at the 1% significance level. For two of the stocks, CLS and NT, the null cannot be rejected. These stocks will not be included in the subsequent cross-sectional analyses. The small parameter standard errors of the mixture parameters indicate estimation precision, which, combined with Wald and Jarque-Bera test results, support the identification of information shares by the mixture distribution assumption.

6.2 Discussion

First and second step estimates are combined to compute modified Hasbrouck information shares as outlined in Section 4.1. Their distribution across the sample stocks along with their average standard errors is reported in Table 5. Stock-specific results can be found in the Appendix Table A-6. The table also reports adjustment coefficient ratio estimates and standard errors. Adjustment coefficient ratios serve as a benchmark, since they have been used by Eun and Sabherwal (2003) to assess the importance of the US market for Canadian interlisted stocks. Recall from the discussion in Section 2.1 that a large foreign market adjustment coefficient ratio $Adj^f = \frac{|\alpha^f|}{\alpha^h+|\alpha^f|}$ and a small home market ratio $Adj^h = \frac{\alpha^h}{\alpha^h+|\alpha^f|}$ imply that the NYSE price corrects more strongly to deviations from the law of one price than the TSX price. Equivalently, this means that the common factor weight of the NYSE (TSX) price in the Gonzalo/Granger decomposition is relatively low (high). Large Adj^f and small Adj^h thus indicate a minor (major) role of the NYSE (TSX) in the price discovery of Canadian interlisted stocks.

<Insert Table 5 about here>

Whilst the sample average of the TSX adjustment coefficient ratio (Adj^h) amounts to 29%, that of the NYSE (Adj^f) is equal to 71%. The 42% difference in the contributions to price discovery indicates a clear leadership of the TSX. These findings update the results reported by Eun and Sabherwal (2003). Using 1997 data, they estimate an average TSX (US market) adjustment coefficient ratio of 38% (62%), i.e. the TSX contribution to price discovery exceeds that of the US markets by 24%. Although some parameters of the empirical analysis differ (10 min. vs. 2 min. sampling frequency, different set of stocks, NYSE/NASDAQ vs. NYSE only), this suggests that the TSX has extended its lead in terms of contributions to price discovery from 1997 to 2004. Is the concern that the importance of Canadian and other regional exchanges will deteriorate, and US exchange will take over the price discovery in the long run groundless? The results reported in Table 5 show that it is too early to jump to this conclusion. When contributions to price discovery are measured using the approach proposed in this paper, the picture changes: The modified Hasbrouck NYSE information share averaged across stocks amounts to 45%, that of the TSX is equal to 55%. Although the TSX still emerges as the leading market in terms of price discovery, its 10% winning margin appears small compared to the 42% lead reflected in the difference of adjustment coefficient ratios. The competitive edge of the TSX is much less pronounced.

<Insert Table 6 about here>

These divergent conclusions are attributable to the different methodologies. As outlined in Section 2.2, the focus on adjustment coefficient ratios ignores the variances of price innovations in the markets and their contemporaneous correlations.
Hasbrouck's (1995) methodology takes standard deviations and correlations of price innovations into account. However, the Cholesky decomposition imposes an informational hierarchy of markets that is hardly justifiable, and the permutation of the ordering is often a dissatisfying solution due to the wide information share bounds. This is the case in the present application. The average midpoint of standard Hasbrouck TSX information shares amounts to 61% and that of the NYSE is equal to 39%, indicating the leadership of the TSX in the price discovery process. However, the evidence is weakend by the wide upper and lower bounds, which on average differ by 65%.
Another interesting result lies in the variation of estimated information shares among the sample stocks. Tables 5 and 6 show that the cross-sectional standard deviation of the adjustment coefficient ratios amounts to 24% and that of the standard information share midpoints is equal to 13%. By contrast, the cross-sectional standard deviation of the market modified information share amounts to only 4 %. Percentiles, inter-quartile ranges, and the kernel density plots in Figure 3 tell the same story. The kernel estimates show the symmetric thin-tailed distribution of the modified information shares, which is much more concentrated than the distributions of standard information share midpoints and the adjustment coefficient ratios. The latter is especially widely dispersed.

<Insert Figure 3 about here>

This result is of paramount interest when considering the determinants of a market's contribution to the price discovery process. To date, cross-sectional analysis focused on stock-specific explanatory variables such as market capitalization, ownership structure, industry et cetera to explain the considerable cross stock variation of foreign market price discovery contributions. Yet, given the small cross-sectional variation of the modified information shares among the sample stocks, our results indicate that stock-specific factors actually play a minor role within the price discovery process.
This conclusion is confirmed by the cross section regression results reported in Table 7. The regression explains the cross-sectional variation of modified Hasbrouck NYSE information shares using the set of covariates proposed by Eun and Sabherwal (2003). The results show that only the regressors directly related to the trading process - ratio of NYSE and TSX effective spread, and NYSE share of the total number of trades -

are statistically significant. A higher share of medium sized trades at the NYSE is not associated with a higher NYSE information share.[5] On the other hand, stock specific variables - firm size, measured as the log of the TSX market capitalization, and the years listed at the NYSE - have no explanatory power. Moreover, the dummy variables indicating the industry of the stocks are (as in Eun and Sabherwal 2003) not jointly significant. Interestingly, the puzzling result of a significantly higher price discovery contribution of the NYSE for small Canadian stocks reported by Eun and Sabherwal (2003) is not present when using the modified Hasbrouck information shares.

<Insert Table 7 about here>

The conclusion that it is the design of a market itself which determines its information share means good and bad news for national and regional exchange operators sensing the threat of the US exchanges. On the one hand, they cannot claim that factors out of their control (like firm size or foreign ownership) determine the importance of the foreign market. On the other hand, the competition between exchanges to achieve leadership in terms of price discovery works through parameters that they themselves control, namely those which generate a trading environment that fosters the process through which prices incorporate new information.

7 Concluding remarks

This paper examines the price discovery process of Canadian interlisted stocks and proposes a modification of the Hasbrouck (1995) approach. The main drawback of the standard Hasbrouck information shares is their non-uniqueness: they are derived as midpoint of lower and upper bounds, which tend to become extremely wide at lower sampling frequencies. At high frequencies, however, estimated information shares can be biased by microstructure effects. We offer a solution to this dilemma. Based on distributional assumptions as an alternative method for identification, our approach yields unique Hasbrouck-type information shares. As a result, the methodology can be applied to data sampled at lower frequencies, at which the dominance of the market microstructure effects component in the price series is alleviated.

We apply our modified approach to Canadian stocks which interlist on the NYSE. Our results suggest that the contribution of the NYSE to the price discovery process of Canadian interlisted stocks is severely underestimated by standard methods. We reveal that the home market leadership found by previous studies is less pronounced and

[5] Medium sized trades are considered informative. An exchange with a higher share in medium sized trades is hypothesized to contribute more to price discovery due to the informational content in those trades. Eun and Sabherwal (2003) reported results that supported this argument. However they also argued that the finding is not robust across different definitions of medium sized trades.

actually price discovery is more evenly divided between TSX and NYSE. Moreover, we find that the variation of information shares across stocks is much smaller than indicated by standard methods. In contrast to recent studies, which focus on stock specific factors as the determinants of a market's contribution to international price discovery, we argue for market design as the major factor. In the light of the present development towards a small number of very large international exchanges, this result is of paramount interest for national stocks exchanges, since it implies that by improving their trading protocol, and providing a more efficient trading environment, stock exchanges may be able to maintain or even increase their share in the price discovery process of interlisted stocks.

Albeit modified information share estimation is computationally more intricate, since it involves nonlinear optimisation, its applicability is not limited to internationally cross-listed stocks. Figuerola-Ferrett and Gonzalo (2007) measure price discovery in commodity markets, Chakravarty et al. (2004) examine the relative contribution to price discovery of stock and options markets, and Blanco et al. (2005) use Hasbrouck information shares to document a lead for credit default swap (CDS) prices over credit spreads in the price discovery process. These analyses also suffer from the non-uniqueness of the standard information shares and are prone to microstructure effects. Our modified approach that identifies unique information shares and alleviates the bias by microstructure effects presents an appealing alternative.

References

Aït-Sahalia, Y., P. Mykland, and L. Zhang (2005): "How often to sample a continuous-time process in the presence of microstructure noise," *Review of Financial Studies*, 18, 352–416.

Andersen, T. G., T. Bollerslev, F. X. Diebold, and R. H. E. Ebens (2001): "The distribution of realized stock return volatility," *Journal of Financial Economics*, 61, 43–76.

Andersen, T. G., T. Bollerslev, F. X. Diebold, and P. Labys (2003): "Modeling and forecasting realized volatility," *Econometrica*, 71, 579–625.

Baillie, R. T., B. G. Geoffrey, Y. Tse, and T. Zabotina (2002): "Price discovery and common factor models," *Journal of Financial Markets*, 5, 309–321.

Bandi, F. and J. Russell (2008): "Microstructure noise, realized variance, and optimal sampling," *Review of Economic Studies*, 75, 339–369.

Barndorff-Nielsen, O. and N. Shephard (2002): "Estimating quadratic variation using realized variance," *Journal of Applied Econometrics*, 17, 457–477.

Blanco, R., S. Brennan, and I. W. Marsh (2005): "An empirical analysis of the dynamic relation between investment-grade bonds and credit default swaps," *Journal of Finance*, 60, 2255–2281.

Carpentier, C., J.-F. L'Her, and J.-M. Suret (2007): "Competition and survival of stock exchanges: lessons from Canada," CIRANO working paper.

Chakravarty, S., H. Gulen, and S. Mayhew (2004): "Informed trading in stock and options markets," *Journal of Finance*, 59, 1235–1258.

Chen, S. X. (1999): "Beta kernel estimators for density functions," *Computational Statistics & Data Analysis*, 31, 131–145.

Coffee, J. C. (2002): "Racing towards the top?: The impact of cross-listings and stock market competition on International Corporate Governance," *Columbia Law Review*, 102, 1757–1832.

Davidson, R. and J. G. MacKinnon (2000): *Econometric theory and methods*, Oxford: Oxford University Press.

De Jong, F. (2002): "Measures on contributions to price discovery: a comparison," *Journal of Financial Markets*, 5, 323–327.

Eun, C. S. and S. Sabherwal (2003): "Cross-border listings and price discovery : evidence from U.S.-listed Canadian stocks," *Journal of Finance*, 58, 549–575.

Figuerola-Ferrett, I. and J. Gonzalo (2007): "Modelling and measuring price discovery in commodity markets," Working Paper Universidad Carlos III.

Gaa, C., S. Lumkin, R. Ogrodnik, and P. Thurlow (2002): "The future prospects of national markets and trading centers," Bank of Canada Working Paper 2001-10.

Gonzalo, J. and C. W. J. Granger (1995): "Estimation of common long-memory components in co-integrated systems," *Journal of Business and Economic Statistics*, 13, 27–36.

Grammig, J., M. Melvin, and C. Schlag (2005): "Internationally cross-listed stock prices during overlapping trading hours: price discovery and exchange rate effects," *Journal of Empirical Finance*, 12, 139–164.

——— (2008): "The role of U.S. trading in pricing internationally cross-listed stocks," Tübingen University, Arizona State University and Frankfurt University.

Harris, F. H. d., T. H. McInish, and R. A. Wood (2002a): "Common factor components versus information shares: a reply," *Journal of Financial Markets*, 5, 341–348.

——— (2002b): "Security price adjustment across exchanges: an investigation of common factor components for Dow stocks," *Journal of Financial Markets*, 5, 277–308.

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

——— (2002): "Stalking the "efficient price" in market microstructure specifications: an overwiev," *Journal of Financial Markets*, 5, 329–339.

——— (2007): *Empirical market microstructure*, Oxford University Press.

Hupperets, E. C. and A. J. Menkveld (2002): "Intraday analysis of market integration: Dutch blue chips traded in Amsterdam and New York," *Journal of Financial Markets*, 5, 57–82.

Johansen, S. (1988): "Statistical analysis of cointegration vectors," *Journal of Economic Dynamics and Control*, 12, 231–254.

——— (1991): "Estimation and hypothesis testing of cointegration vectors in Gaussian vector autoregressive models," *Econometrica*, 59, 1551–1580.

——— (1995): *Likelihood-based inference in cointegrated vector autoregressive models*, Oxford: Oxford University Press.

Karolyi, G. A. (2006): "The world of cross-listings and cross-listings of the world: challenging conventional wisdom," *Review of Finance*, 10, 99–152.

Lanne, M. and H. Lütkepohl (2005): "Structural vector autoregressions with non-normal residuals," EUI Working Paper, Department of Economics, European University Institute.

Lehmann, B. N. (2002): "Some desiderata for the measurement of price discovery across markets," *Journal of Financial Markets*, 5, 259–276.

MacKinnon, J. (2002): "Bootstrap inference in econometrics," *Canadian Journal of Economics*, 29, 305–325.

Mittnik, S., M. Haas, and M. Paolella (2004): "Mixed normal conditional heteroskedasticity," *Journal of Financial Econometrics*, 2, 211–250.

Phylaktis, K. and P. Korczak (2007): "Specialist trading and the price discovery process of NYSE-listed non-US stocks," Working Paper Europa-University Viadrina Frankfurt.

Silverman, B. W. (1986): *Density Estimation for Statistics and Data Analysis*, "London": Chapman and Hall.

Toronto Stock Exchange (2003): *TSX Factbook*, Toronto: TSX Datalinx.

Tsay, R. S. (2005): *Analysis of Financial Time Series*, Hoboken, NJ: Wiley.

APPENDIX

A Illustrating identification by the mixture normal assumption

In order to illustrate the identification method of our modified approach consider the following numerical example. The left panel of Figure 4 depicts time series of contemporaneously correlated price innovations u_t^h and u_t^f.

<Insert Figure 4 about here>

The stochastic process which generated the data is a parameterized bivariate mixture model with $\gamma = 0.9$, $\psi^h = 1$, $\psi^f = 10$ and

$$W = \begin{pmatrix} 0.0001 & 0.00003 \\ 0.00003 & 0.0001 \end{pmatrix}.$$

Using (8), this implies $\mathrm{corr}(u_t^h, u_t^f) = 0.57$. Recall from Section 2.1 that the standardized idiosyncratic market innovations we are seeking to identify are serially and contemporaneously uncorrelated $\varepsilon_t \sim (0, I_2)$ random variables. They relate to the non-standardized idiosyncratic innovations w_t generated by (6) via $\varepsilon_t = \Sigma_w^{-0.5} w_t$. The time series of idiosyncratic innovations w_t^h and w_t^f, which generate the sequences of composite innovations ($u_t = W w_t$) are depicted in the right panel of Figure 4.

The estimation procedure has to solve the inverse problem to back out the unknown structural parameters from the observed sequence of composite innovations. What are the properties the data must exhibit to enable us to estimate the structural parameters and modified information shares? To answer this question, it is helpful to take a closer look at the time series depicted in Figure 4. The left panel shows that at certain points in time, most prominently at $t = 60$, the foreign market composite innovation u_t^f is deep in the tails of the empirical distribution. From our knowledge of the data generating process, and by looking at the right panel series of Figure 4, we can see that a large negative idiosyncratic foreign price innovation occurred at time $t = 60$. It resulted from a large negative draw from a normal distribution with variance $\psi^f = 10$. The small positive home market idiosyncratic innovation w_{60}^h resulted from a draw from a normal distribution with unit variance ($\psi^h = 1$). Due to the structure of the matrix W, the large negative price innovation in the foreign market spills over contemporaneously to the home market. As a consequence, the composite home market innovation u_{60}^h becomes negative.

The occurrence of outliers like the one at $t = 60$ enables us to identify and estimate the structural parameters W, ψ^h, ψ^f and γ. Put simply, what the maximization of the log likelihood (11) does is to match the empirical variances of the composite innovations and their correlations by choosing appropriate values for W. Occasional large absolute price shocks in one market, but not in the other, induce the maximum likelihood procedure to assign a non-zero value to the mixture probability γ and to choose state variances ψ^f and ψ^h which may considerably differ. The requirement on the data is thus that they contain, at certain points in time, price innovations in home and foreign market which are, despite their relatively strong correlation, of quite different sizes.

If the state variances ψ^h and ψ^f were identical, it would not be possible to identify the mixture model parameters and compute modified information shares. We would then not observe those identifying outliers. Some may occur by chance, which would imply that the mixture parameters would be very imprecisely estimated.

We recommend checking the standard errors of the mixture parameter estimates and testing the null that $\psi^f = \psi^h$ before modified Hasbrouck information shares are computed. Taking a look at the kurtosis of log price changes and testing for non-normality via a Jarque-Bera test are further checks that should be employed to assess whether the identification of modified information shares by distributional assumptions is supported by the data. This is ultimately an empirical question. If identification by distributional assumptions is supported, the method offers the opportunity to allocate unique home and foreign market contributions to price discovery within the framework proposed by Hasbrouck (1995). The dilemma outlined in Section 2 is resolved as there is no need to move to high frequencies in order to narrow the information share bounds.

B Parametric bootstrap procedure

We conduct a parametric bootstrap to compute standard errors and confidence intervals for parameter and information share estimates resulting from the two-step estimation procedure outlined in Section 4.2. The procedure works as follows. We first draw an iid sequence of random variables from a normal mixture distribution. This distribution is generated using the mixture parameters which are estimated in the second (maximum likelihood) step of the estimation procedure. Next, we simulate price series according to the ECM (1) using observations from the original price series as starting values, the cointegrating vector $\beta = (1, -1)'$, first step OLS estimates of the ECM parameters, and simulated mixture residuals. The number of lags in the ECM corresponds to the optimal lag length as chosen by the Schwarz criterion. The length of the simulated series equals the number of observations in the original data set plus 100. We discard the first 100 simulated data points in order to reduce the dependence on the starting values. The two-step estimation procedure described in Section 4.2 is then applied to the simulated data. We store the resulting parameter estimates and compute standard Hasbrouck information shares, adjustment coefficient ratios and modified Hasbrouck information shares. This procedure is repeated $B = 399$ times, as suggested by Davidson and MacKinnon (2000).[6] Standard errors for parameter and information share estimates are computed from the empirical distribution of the bootstrap estimates.

C Additional Tables

<Insert Table A-1 about here>

<Insert Table A-2 about here>

<Insert Table A-3 about here>

<Insert Table A-4 about here>

<Insert Table A-5 about here>

<Insert Table A-6 about here>

<Insert Table A-7 about here>

[6] Davidson and MacKinnon (2000) recommend choosing the number of bootstrap replications B such that $\alpha(B + 1)$ is an integer. Testing one-sided at 5% significance, $B = 399$ implies that the 20th largest bootstrap estimate is the critical value at $\alpha = 0.05$.

FIGURES AND TABLES

Figure 1: Information share estimates at different frequencies.

The graph shows the dependence of Hasbrouck information shares on the sampling frequency. It displays the upper and lower bound (solid lines) of the NYSE information share as well as the associated midpoint (dotted line) for the Canadian NYSE interlisted stock *Abitibi Consolidated Inc.* (ABY), estimated at different frequencies (details on the data can be found in Section 5). The estimates are calculated over the 62 days (January first 2004 to March 31st 2004) using the first two hours of trading. As depicted by the graph, the bounds diverge considerably as the sampling frequency decreases. At low sampling frequencies the average over the bounds converges to 0.5, i.e., to the point, where price discovery is divided evenly between the markets.

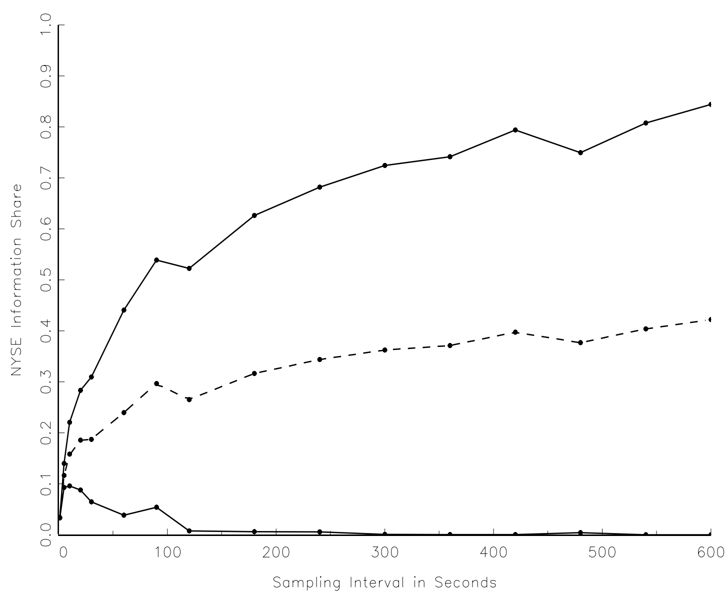

Figure 2: Volatility signature plot of TSX and NYSE log returns.

The graph shows the realized variance estimate for home and foreign market log returns of our sample stock (ABY) calculated over a range of sampling frequencies. The estimates are calculated for each day and averaged over the 62 days (January 1st 2004 to March 31st 2004) using the first two hours of trading. The graph depicts the increasing bias in the variance estimate at fine sampling frequencies: at frequencies higher than two minutes, the realized variance estimate rises sharply, indicating the increasing prevalence of microstructure effects in the price series.

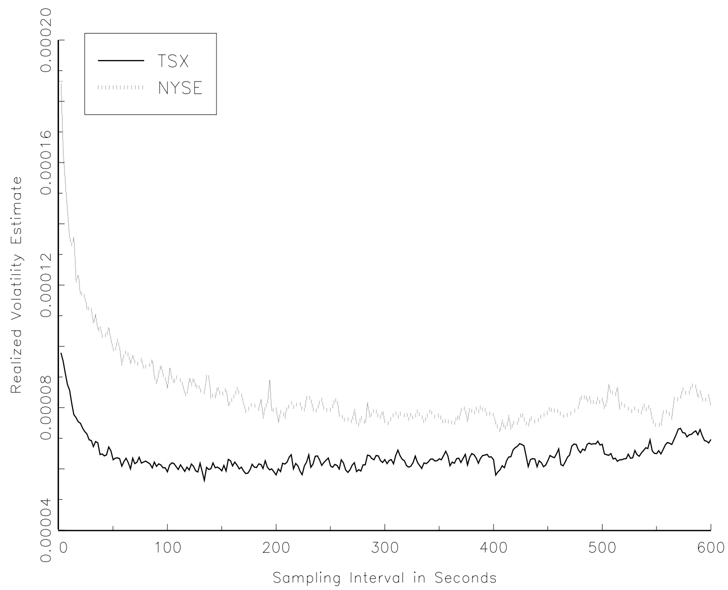

Figure 3: Kernel density estimates NYSE contribution to price discovery.

The graph illustrates the cross sectional distribution of the modified NYSE information share ISM^f (thick solid line), midpoint of Hasbrouck NYSE information share IS^f (thin solid line) and the TSX adjustment coefficient Adj^h (dashed line) by means of a kernel density estimation. To account for the bounded support of the data (the measures of contributions to price discovery are defined between zero and one) the beta kernel proposed by Chen (1999) is used. We use a bandwidth as suggested by Silverman (1986), adjusted for variable kernels.

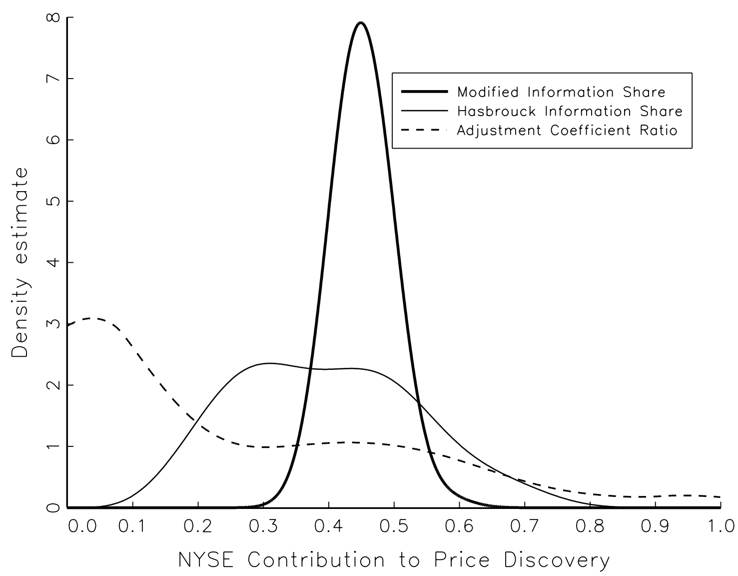

Figure 4: Composite and idiosyncratic mixture normal innovations.

The panels show time series that result from 100 iid draws from a bivariate mixture distribution where $\gamma = 0.9$, $\psi^h = 1$, $\psi^f = 10$ and $W = \begin{pmatrix} 0.0001 & 0.00003 \\ 0.00003 & 0.0001 \end{pmatrix}$. The right hand side panel depicts the contemporaneously uncorrelated innovations w_t^f (solid line) and w_t^h (dashed line). The left hand side panel shows the composite innovations u_t^f (solid line) and u_t^h (dashed line).

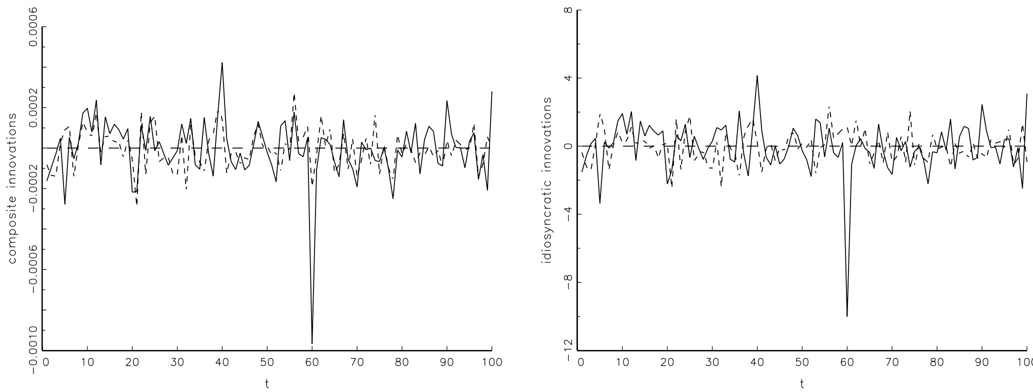

Table 1: Microstructure effects and information share estimates. Symmetric design.

We simulate home and foreign market log prices p_t^h and p_t^f from a bivariate error correction model

$$\begin{pmatrix}\Delta p_t^h\\ \Delta p_t^f\end{pmatrix} = \begin{pmatrix}\alpha^h\\ \alpha^f\end{pmatrix}(p_{t-1}^h - p_{t-1}^f) + \Gamma_1\begin{pmatrix}\Delta p_{t-1}^h\\ \Delta p_{t-1}^f\end{pmatrix} + \Gamma_2\begin{pmatrix}\Delta p_{t-2}^h\\ \Delta p_{t-2}^f\end{pmatrix} + \begin{pmatrix}u_t^h\\ u_t^f\end{pmatrix}.$$

Symmetry of home and foreign market is imposed by setting $\alpha_f = -\alpha_h = 0.2$, $\Gamma_1 = \begin{pmatrix}-0.05 & 0.1\\ 0.1 & -0.05\end{pmatrix}$ and $\Gamma_2 = \begin{pmatrix}-0.05 & 0.05\\ 0.05 & -0.05\end{pmatrix}$. The innovations u^h and u^f are contemporaneously and serially uncorrelated mean zero normally distributed random variables with standard deviation $\sigma_u = \sigma_u^f = \sigma_u^h = 0.0002$. According to Equation (2.1), the true long run impact of home and foreign market innovations is $\xi^h = \xi^f = 0.53$ and the true information share of the foreign market (IS^f) is 50 %. The simulated true prices are disturbed by additive independent microstructure effects, $\tilde{p}_t^h = p_t^h + \eta_t^h$ and $\tilde{p}_t^h = p_t^h + \eta_t^h$. The microstructure effects η_t^h and η_t^f are mean zero uncorrelated random variables with standard deviations σ_{η^h} and σ_{η^f}. The second row shows how the microstructure effects standard deviations σ_{η^h} and σ_{η^f} are varied as multiples of the fundamental innovation standard deviation σ_u. The simulation is replicated 500 times with $n = 100,000$. In each replication the model parameters are estimated based on the true and noised price series. Foreign market information shares (IS^f), long run price impacts ξ^h and ξ^f, and foreign market adjustment coefficient ratio $Adj^f = \frac{\alpha^f}{\alpha^f + |\alpha^h|}$ are computed as outlined in Equations (3) and (4). The table reports mean and standard deviation (in parentheses) of the estimates computed over the 500 Monte Carlo replications. IS^f denotes the average of the upper and lower bound of the foreign market information share which result from permuting the order of home and foreign market in the Cholesky decomposition.

scenario	base	1	2	3	4	5	6	7
$\sigma_{\eta^h}/\sigma_{\eta^f}$	0/0	$0/0.5\sigma_u$	$0/\sigma_u$	$0/2\sigma_u$	σ_u/σ_u	$\sigma_u/2\sigma_u$	$\sigma_u/4\sigma_u$	$2\sigma_u/4\sigma_u$
IS^f (%)	50.0	45.7	36.3	19.9	50.0	30.4	12.0	23.7
	(0.91)	(0.86)	(0.75)	(0.51)	(0.76)	(0.53)	(0.32)	(0.41)
Adj_f(%)	50.0	55.9	66.9	83.3	50.0	71.1	89.2	77.1
	(0.44)	(0.43)	(0.39)	(0.27)	(0.41)	(0.31)	(0.20)	(0.25)
ξ^h	0.53	0.53	0.57	0.66	0.34	0.45	0.55	0.42
	(0.005)	(0.005)	(0.004)	(0.004)	(0.003)	(0.002)	(0.002)	(0.002)
ξ^f	0.53	0.42	0.28	0.13	0.34	0.18	0.07	0.12
	(0.005)	(0.004)	(0.003)	(0.002)	(0.003)	(0.002)	(0.001)	(0.001)

Table 2: Summary statistics of sample stocks.

The table shows summary statistics on our sample stocks. The first line gives statistics on the number of observations used for information share estimation and inference (i.e., the first two hours of trading sampled at a two minute frequency). The spread, relative spread, trading value, and midpoint are calculated using the first two trading hours. Further the table shows the optimal trading frequency according to by Bandi and Russell's (2008) rule of thumb. The last four lines report summary statistics on the return distribution, including the kurtosis of two minute returns and the associated p-value of the Jarque-Bera normality test.

	Mean	Std.dev	5th Perc.	25th Perc.	Median	75th Perc.	95th Perc.
Observations	3661	65	3548	3614	3672	3708	3748
Spread (CAD)							
TSX	0.08	0.09	0.02	0.04	0.06	0.09	0.18
NYSE	0.07	0.08	0.03	0.04	0.06	0.09	0.14
Rel. spread (%)							
TSX	0.24	0.15	0.08	0.13	0.22	0.28	0.47
NYSE	0.23	0.14	0.09	0.13	0.17	0.28	0.51
Trading value (Mio. CAD)							
TSX	733.09	1157.86	36.52	157.52	367.95	863.83	2107.16
NYSE	332.19	903.84	5.36	30.75	85.81	243.95	1204.26
Midpoint (CAD)							
TSX	38.92	30.76	9.15	21.19	34.03	49.30	73.67
NYSE	38.92	30.76	9.15	21.21	34.04	49.29	73.65
Bandi/Russell sampling frequency (min)							
TSX	1.75	0.53	1.13	1.41	1.73	1.98	2.77
NYSE	2.39	1.35	1.24	1.68	2.19	2.69	4.08
Kurtosis returns							
TSX	29.32	55.36	3.30	7.55	13.97	28.28	94.76
NYSE	59.42	248.00	3.45	5.92	13.31	21.33	163.18
P-val. Jarque-Bera							
TSX	0.00	0.00	0.00	0.00	0.00	0.00	0.00
NYSE	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table 3: Specification test results.

The table shows summary statistics on specification test results. It includes Johansen's (1988) trace and maximum eigenvalue statistics to determine the number of cointegration relations. Using the trace statistic we test the null hypothesis of no cointegrating relation, with the maximum eigenvalue statistic we test the null of one cointegrating relation. The critical values for $\alpha = 0.01$ are 16.31 (trace) and 6.51 (max. eigenvalue) respectively. The table also reports the p-values of a Wald test of the null hypothesis $\psi^h \neq \psi^f$. The last column shows the number of stocks for which the null is rejected at $\alpha = 0.01$. The last row gives information on the number of lags included in the ECM (1) according to the Schwarz information criterion (SIC).

	Mean	Median	Min	Max	# stocks H_0 rejected ($\alpha = 1\%$)
Trace stat. H_0: no coint. rel.	1194.0	966.4	145.1	6756.8	69
Max. eigenv. stat. H_0: one coint. rel.	2.0	0.9	0.00	13.9	5
P-val. Wald test H_0: $\psi^f = \psi^h$	0.00	0.00	0.00	0.03	69
ECM lags (q) by SIC	1.7	1	1	6	-

Table 4: Cross-sectional distribution of parameter estimates.

The table shows the distribution of the parameters estimates shares across the 69 sample stocks. ψ^h and ψ^f denote the diagonal elements of matrix Ψ, γ gives the mixture probability. α^h and α^f are adjustment coefficients of home and foreign market return series and ξ^h and ξ^f denote the permanent impact of shocks on the home market and foreign market returns series, respectively. Avg.Std.Er. gives the standard error of the respective estimate averaged across the sample stocks. Standard errors are obtained by the parametric bootstrap procedure described in Appendix B.

	ψ^h	ψ^f	γ	α^h	α^f	ξ^h	ξ^f
5th Perc.	0.00	0.07	0.12	-0.45	0.05	0.26	-0.02
25th Perc.	0.01	0.16	0.27	-0.24	0.24	0.54	0.09
Median	0.03	0.23	0.34	-0.09	0.35	0.85	0.29
Mean	0.04	0.24	0.36	-0.16	0.35	0.79	0.35
Avg.Std.Er.	(0.003)	(0.015)	(0.012)	(0.026)	(0.028)	(0.034)	(0.032)
75th Perc.	0.06	0.31	0.47	-0.04	0.46	1.04	0.56
95th Perc.	0.14	0.44	0.57	0.01	0.68	1.21	0.84

Table 5: Cross-sectional distribution of modified Hasbrouck information shares and adjustment coefficient ratios.

The first two columns of the table show the distribution of the modified Hasbrouck information shares across sample stocks. The last two columns display the distribution of the adjustment coefficient ratios computed as $Adj^h = \frac{\alpha^h}{\alpha^h+|\alpha^f|}$ (TSX) and $Adj^f = \frac{|\alpha^f|}{\alpha^h+|\alpha^f|}$ (NYSE). If the adjustment coefficient ratio is high then its contribution to price discovery is small. Ratios and information shares are reported as percentages. Avg.Std.Er. gives the standard error of the respective estimate averaged across the sample stocks. Standard errors are obtained by the parametric bootstrap procedure described in Appendix B.

	Modified Hasbrouck Information Shares		Adjustment Coeff. Ratios	
	ISM^h (TSX)	ISM^f (NYSE)	Adj^f (NYSE)	Adj^h (TSX)
5th Perc.	50.0	40.5	31.2	2.2
25th Perc.	52.7	42.6	51.0	8.0
Median	55.1	44.9	77.5	22.5
Mean	54.9	45.1	71.1	28.9
Avg.Std.Er.	(0.8)	(0.8)	(5.1)	(5.1)
Std. Dev.	3.5	3.5	24.2	24.2
75th Perc.	57.4	47.3	92.0	49.3
95th Perc.	59.5	50.0	97.8	68.8

Table 6: Cross-sectional distribution of Hasbrouck information shares.

The table shows the distribution of the of the lower and upper bounds of standard Hasbrouck information shares as well as the associated midpoints across the sample stocks. Ratios and information shares are reported in percent. Avg.Std.Er. gives the standard error of the respective estimate averaged across the sample stocks. Standard errors are obtained by the parametric bootstrap procedure described in Appendix B.

	IS^h (TSX)			IS^f (NYSE)		
	Low. Bound	Upp. Bound	Midpoint	Low. Bound	Upp. Bound	Midpoint
5th Perc.	4.2	67.5	37.6	0.0	40.9	20.5
25th Perc.	11.4	89.8	50.9	0.5	56.2	28.4
Median	26.9	98.1	61.5	1.9	73.1	38.5
Mean	28.4	93.2	60.8	6.8	71.6	39.2
Avg.Std.Er.			(2.4)			(2.4)
Std. Dev.	19.5	9.9	13.4	9.9	19.5	13.4
75th Perc.	43.8	99.5	71.6	10.2	88.6	49.1
95th Perc.	59.1	100.0	79.5	32.5	95.8	62.4

Table 7: Regression results.

The table reports cross-sectional OLS estimates with standard errors in parentheses. The dependent variable is the logistic transformation of the modified NYSE information share, $\ln\left(\frac{ISM^f}{1-ISM^f}\right)$. The logistic transformation insures that the predicted regression values lie between 0 and 1. LogMktCap is the log market capitalization as reported on 31 Dec. 2003 in the TSX Factbook. USVol gives the share of NYSE traded shares in the number of total shares traded in both markets. SpreadRatio denotes the ratio of effective spreads on the NYSE and TSX. MediumTrades is the ratio of the proportion of shares traded in medium sized lots on the TSX and the NYSE, where medium size refers to trades of 2,501 to 10,000 shares. YearsListed denotes the number of years a company has been listed on the NYSE (as indicated by the NYSE webpage). Manufacturing, Finance/Realestate, Retail and Utility/Transport, and Mining are sector dummies. The benchmark sector is services. ***, **, and * indicate statistical significance at $\alpha = 0.01$, 0.05, and 0.10, respectively.

	(1)	(2)	(3)
Constant	-0.215***	-0.356***	-0.454***
	(0.039)	(0.132)	(0.145)
USVol	0.342***		0.312***
	(0.090)		(0.068)
SpreadRatio	-0.121***		-0.090**
	(0.032)		(0.041)
MediumTrades	0.012***		0.007
	(0.003)		(0.005)
LogMktCap		0.018	0.023
		(0.016)	(0.014)
YearsListed		0.001	0.001
		(0.001)	(0.001)
Manufacturing			- 0.007
			(0.045)
Finance/Realestate			0.067
			(0.046)
Retail			-0.038
			(0.078)
Utility/Transport			0.019
			(0.055)
Mining			0.080*
			(0.046)
Observations	67	67	67
Adjusted R-squared (%)	39.5	1.7	45.8

Table A-1: Microstructure effects and information share estimates. Asymmetric design.

We simulate home and foreign market log prices p_t^h and p_t^f from a bivariate error correction model

$$\begin{pmatrix}\Delta p_t^h \\ \Delta p_t^f\end{pmatrix} = \begin{pmatrix}\alpha^h \\ \alpha^f\end{pmatrix}(p_{t-1}^h - p_{t-1}^f) + \Gamma_1\begin{pmatrix}\Delta p_{t-1}^h \\ \Delta p_{t-1}^f\end{pmatrix} + \Gamma_2\begin{pmatrix}\Delta p_{t-2}^h \\ \Delta p_{t-2}^f\end{pmatrix} + \begin{pmatrix}u_t^h \\ u_t^f\end{pmatrix}.$$

A true information share of 70 % of foreign and 30% of home market is imposed by setting $\alpha_h = -0.3$ and $\alpha_f = 0.2$, $\Gamma_1 = \begin{pmatrix}-0.05 & 0.1 \\ 0.1 & -0.05\end{pmatrix}$ and $\Gamma_2 = \begin{pmatrix}-0.05 & 0.05 \\ 0.05 & -0.05.\end{pmatrix}$ The innovations u^h and u^f are contemporaneously and serially uncorrelated mean zero normally distributed random variables with standard deviation $\sigma_u = \sigma_u^f = \sigma_u^h = 0.0002$. According to Equation (2.1), the true long run impact of home and foreign market innovations is $\xi^h = \xi^f = 0.53$ and the true information share of the foreign market (IS^f) is 50 %. The simulated true prices are disturbed by additive independent microstructure effects, $\tilde{p}_t^h = p_t^h + \eta_t^h$ and $\tilde{p}_t^h = p_t^h + \eta_t^h$. The microstructure effects components η_t^h and η_t^f are mean zero uncorrelated random variables with standard deviations σ_{η^h} and σ_{η^f}. The second row shows how the microstructure effects standard deviations σ_{η^h} and σ_{η^f} are varied as multiples of the fundamental innovation standard deviation σ_u. The simulation is replicated 500 times with $n = 100,000$. In each replication the model parameters are estimated based on the true and noised price series. Foreign market information shares (IS^f), long run price impacts ξ^h and ξ^f, and foreign market adjustment coefficient ratio $Adj^f = \frac{\alpha^f}{\alpha^f + |\alpha^h|}$ are computed as outlined in Equations (3) and (4). The table reports mean and standard deviation (in parentheses) of the estimates computed over the 500 Monte Carlo replications. IS^f denotes the average of the upper and lower bound of the foreign market information share which result from permuting the order of home and foreign market in the Cholesky decomposition.

scenario	base	1	2	3	4	5	6	7
$\sigma_{\eta^h}/\sigma_{\eta^f}$	0/0	$0/0.5\sigma_u$	$0/\sigma_u$	$0/2\sigma_u$	σ_u/σ_u	$\sigma_u/2\sigma_u$	$\sigma_u/4\sigma_u$	$2\sigma_u/4\sigma_u$
IS^f (%)	69.2	63.7	51.2	28.3	63.4	38.9	15.3	26.9
	(0.76)	(0.76)	(0.73)	(0.54)	(0.71)	(0.55)	(0.36)	(0.43)
Adj^f (%)	40.0	46.1	58.8	79.1	42.4	66.6	87.6	75.5
	(0.41)	(0.40)	(0.38)	(0.27)	(0.39)	(0.31)	(0.20)	(0.25)
ξ^h	0.42	0.43	0.49	0.61	0.29	0.41	0.53	0.41
	(0.005)	(0.004)	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
ξ^f	0.63	0.51	0.34	0.16	0.39	0.21	0.08	0.13
	(0.005)	(0.004)	(0.003)	(0.002)	(0.003)	(0.002)	(0.001)	(0.001)

Table A-2: Microstructure effects and information share estimates. Monopolistic design.

We simulate home and foreign market log prices p_t^h and p_t^f from a bivariate error correction model

$$\begin{pmatrix} \Delta p_t^h \\ \Delta p_t^f \end{pmatrix} = \begin{pmatrix} \alpha^h \\ \alpha^f \end{pmatrix} (p_{t-1}^h - p_{t-1}^f) + \Gamma_1 \begin{pmatrix} \Delta p_{t-1}^h \\ \Delta p_{t-1}^f \end{pmatrix} + \Gamma_2 \begin{pmatrix} \Delta p_{t-2}^h \\ \Delta p_{t-2}^f \end{pmatrix} + \begin{pmatrix} u_t^h \\ u_t^f \end{pmatrix}.$$

A 100 % information share of the foreign market is imposed by setting $\alpha_h = -0.2$ and $\alpha_f = 0$, $\Gamma_1 = \begin{pmatrix} -0 & 0.1 \\ 0 & -0.05 \end{pmatrix}$ and $\Gamma_2 = \begin{pmatrix} 0 & 0.05 \\ 0 & -0.05. \end{pmatrix}$ The innovations u^h and u^f are contemporaneously and serially uncorrelated mean zero normally distributed random variables with standard deviation $\sigma_u = \sigma_u^f = \sigma_u^h = 0.0002$. According to Equation (2.1), the true long run impact of home and foreign market innovations is $\xi^h = \xi^f = 0.53$ and the true information share of the foreign market (IS^f) is 50 %. The simulated true prices are disturbed by additive independent microstructure effects, $\tilde{p}_t^h = p_t^h + \eta_t^h$ and $\tilde{p}_t^h = p_t^h + \eta_t^h$. The microstructure effects components η_t^h and η_t^f are mean zero uncorrelated random variables with standard deviations σ_{η^h} and σ_{η^f}. The second row shows how the microstructure effects standard deviations σ_{η^h} and σ_{η^f} are varied as multiples of the fundamental innovation standard deviation σ_u. The simulation is replicated 500 times with $n = 100,000$. In each replication the model parameters are estimated based on the true and noised price series. Foreign market information shares (IS^f), long run price impacts ξ^h and ξ^f, and foreign market adjustment coefficient ratio $Adj^f = \frac{\alpha^f}{\alpha^f + |\alpha^h|}$ are computed as outlined in Equations (3) and (4). The table reports mean and standard deviation (in parentheses) of the estimates computed over the 500 Monte Carlo replications. IS^f denotes the average of the upper and lower bound of the foreign market information share which result from permuting the order of home and foreign market in the Cholesky decomposition of the residual variance covariance matrix.

scenario	base	1	2	3	4	5	6	7
$\sigma_{\eta^h}/\sigma_{\eta^f}$	0/0	$0/0.5\sigma_u$	$0/\sigma_u$	$0/2\sigma_u$	σ_u/σ_u	$\sigma_u/2\sigma_u$	$\sigma_u/4\sigma_u$	$2\sigma_u/4\sigma_u$
IS^f (%)	100.0	99.7	96.5	74.6	97.7	78.4	38.5	45.4
	(0.01)	(0.11)	(0.37)	(0.76)	(0.31)	(0.69)	(0.66)	(0.62)
Adj^f(%)	0.7	3.6	19.4	57.2	10.5	43.7	78.4	66.5
	(0.49)	(0.93)	(0.88)	(0.51)	(0.68)	(0.52)	(0.27)	(0.31)
ξ^h	0.00	0.03	0.15	0.46	0.07	0.28	0.51	0.37
	(0.009)	(0.008)	(0.007)	(0.006)	(0.005)	(0.004)	(0.003)	(0.002)
ξ^f	1.05	0.87	0.63	0.34	0.62	0.36	0.14	0.19
	(0.009)	(0.008)	(0.006)	(0.004)	(0.005)	(0.003)	(0.002)	(0.002)

Table A-3: Sample stocks.
The table shows the stock ticker symbols of the 69 Canadian sample stocks together with the full company name and its industry.

Ticker	Company Name	Industry
ABX	Barrick Gold	Gold Mining
ABY	Abitibi Consolidated Inc.	Paper
AEM	Agnico Eagle Mines Ltd.	Gold Mining
AGU	Agrium Inc.	Chemicals (Speciality)
AL	Alcan Inc.	Metals and Mining
BCE	BCE Inc.	Foreign Telecom.
BCM	Canadian Imp. Bank of Commerce	Bank
BMO	Bank of Montreal	Bank
BNN	Brascan Corp.	Real Estate Holding
BNS	Bank of Nova Scotia	Bank
BPO	Brookfield Properties Corporation	Real Estate Holding
BVF	Biovail Corp.	Pharmaceuticals
CCJ	Cameco Corp.	Nonferrous Metals
CGT	CAE Inc.	Aerospace
CLS	Celestica Inc.	Electronics
CNQ	Canadian Natural Ressources	Petroleum (Producing)
COT	Cott Corp.	Soft Drinks
CP	Canadian Pacific Railway	Railroad
DTC	Domtar Corp.	Paper
ECA	EnCana Corp.	Energy
ENB	Enbridge Inc.	Gas Distribution
ERF	Enerplus Resource Fund	Exploration and Production
FDG	Fording Canadian Coal Trust	Mining (Other Mines)
FFH	Fairfax Financial Holdings Ltd.	Property and Casualty Insurance
FHR	Fairmont Hotels Resorts Inc.	Hotels
FS	Four Seasons Hotels Inc.	Hotels
GG	Goldcorp Inc.	Gold Mining
GIB	CGI Group Inc.	Computer Services
GIL	Gildan Activewear Inc.	Clothing and Accessories
GLG	Glamis Golds Ltd.	Gold Mining
HBG	Hub International Ltd.	Insurance
IDR	Intrawest Corp..	Hotels
IPS	IPSCO Inc.	Metals and Mining
IQW	Quebecor World	Publishing
ITP	ntertape Polymer Group Inc.	Containers and Packaging
KFS	Kingsway Financial Services Inc.	Insurance
KGC	Kinross Gold Corp.	Gold Mining
MDG	Meridian Gold Inc.	Gold Mining
MDZ	MDS Inc.	Medical Equipment
MFC	Manulife Financial Corp.	Insurance
MGA	Magna International Inc.	Auto Parts
MHM	Masonite International Corp.	Building Products
MIM	MI Developments Inc.	Gambling
N	Inco Ltd.	Metals and Mining

continued on next page

Table A-3: continued

Ticker	Company Name	Industry
NCX	Nova Chemicals Corp.	Commodity Chemicals
NRD	Noranda Inc.	Metals and Mining
NT	Nortel Networks	Foreign Telecom.
NXY	Nexen Inc.	Energy
PCZ	Petro-Canadian Com.	Integrated Oil and Gas
PDG	Placer Dome	Precious Metals
PDS	Precision Drilling Corp	Oil Equipment and Services
PGH	Pengrowth Energy	Exploration and Production
PKZ	PetroKazakhstan Inc.	Petroleum
POT	Potash Corp.	Chemical
PWI	Primewest Energy Trust	Energy
RCN	Radiant Communications	Telecommunications
RG	Rogers Publishing Limited	Publishing
RY	Royal Bank of Canada	Bank
RYG	Royal Group Technologies Ltd.	Building Products
SLF	Sun Life Financial Serv.	Insurance
SU	Suncor Engery	Petroleum
TAC	TransAlta Corp.	Conventional Electricity
TD	Toronto-Dominion	Bank
TEU	CP Ships Ltd.	Maritime
TLM	Talisman Energy	Energy
TOC	Thomson Corp.	Information Services
TRP	TransCanada Corp.	Energy
TU	Telus Corp.	Telecommunications
ZL	Zarlink Semiconductor Inc.	Semiconductors

Table A-4: Descriptives.

The first two columns show the average TSX and NYSE midquotes denoted in local currency. Column three gives the exchange rate adjusted NYSE midquote. Columns four and five contain the average relative TSX and NYSE spread and columns six and seven display the average spread denoted in CAD. The last two columns give the trading value of the stocks on the TSX and NYSE in million CAD. All statistics are calculated over our sample period (the first two trading hours from January 1st to 31st of March 2004). For full company names see Table A-3.

	Midquote			**Rel. Spread**		**Spread**		**Trading Value**	
	TSX	NYSE	NYSE conv.	TSX	NYSE	TSX	NYSE	TSX	NYSE
ABX	27.94	21.20	27.95	0.12	0.10	0.03	0.03	1,378.91	1,386.92
ABY	10.17	7.72	10.18	0.21	0.26	0.02	0.03	508.56	53.36
AEM	17.76	13.46	17.75	0.28	0.16	0.05	0.03	216.70	286.03
AGU	19.82	15.04	19.83	0.27	0.15	0.05	0.03	238.04	130.64
AL	59.69	45.26	59.68	0.09	0.07	0.05	0.04	2,058.46	2,323.31
BCE	28.94	21.96	28.95	0.08	0.10	0.02	0.03	1,792.65	179.02
BCM	67.47	51.16	67.45	0.09	0.12	0.06	0.08	2,439.12	61.44
BMO	55.34	41.97	55.34	0.09	0.13	0.05	0.07	1,754.94	54.63
BNN	45.95	34.83	45.91	0.20	0.23	0.09	0.10	433.75	33.39
BNS	68.32	51.81	68.30	0.07	0.13	0.05	0.09	1,730.60	17.61
BPO	39.38	29.85	39.36	0.22	0.15	0.09	0.06	59.50	51.92
BVF	26.97	20.47	26.99	0.20	0.15	0.05	0.04	456.16	691.41
CCJ	64.09	48.65	64.15	0.22	0.18	0.14	0.12	578.40	181.71
CGT	6.06	4.60	6.06	0.28	0.63	0.02	0.04	257.74	3.88
CLS	23.14	17.55	23.14	0.16	0.14	0.04	0.03	778.07	794.73
CNQ	69.94	53.04	69.93	0.14	0.15	0.10	0.11	878.40	136.69
COT	37.80	28.66	37.62	0.23	0.13	0.09	0.05	93.24	63.00
CP	33.59	25.49	33.61	0.17	0.16	0.06	0.05	533.67	64.89
DTC	15.59	11.83	15.60	0.26	0.27	0.04	0.04	380.26	16.01
ECA	54.92	41.65	54.92	0.09	0.09	0.05	0.05	1,956.17	465.06
ENB	52.70	39.98	52.71	0.15	0.21	0.08	0.11	460.52	10.71
ERF	38.83	29.46	38.84	0.27	0.23	0.10	0.09	191.99	218.33
FDG	49.55	37.56	49.53	0.39	0.34	0.19	0.17	246.70	208.64
FFH	216.9	164.56	216.94	0.35	0.29	0.76	0.63	123.97	134.43
FHR	34.03	25.82	34.04	0.22	0.12	0.08	0.04	80.63	169.86
FS	70.16	53.19	70.12	0.26	0.12	0.18	0.08	36.55	235.11
GG	18.38	13.95	18.38	0.19	0.14	0.04	0.03	389.38	577.94
GIB	8.58	6.51	8.58	0.36	0.52	0.03	0.04	13.43	6.53
GIL	41.77	31.68	41.77	0.44	0.35	0.18	0.14	36.51	11.42
GLG	21.43	16.25	21.43	0.28	0.17	0.06	0.04	266.04	303.72
HBG	22.71	17.23	22.71	0.81	0.30	0.18	0.07	2.97	44.67
IDR	23.6	17.91	23.61	0.40	0.27	0.09	0.06	33.68	37.31
IPS	23.09	17.51	23.08	0.59	0.59	0.14	0.14	94.31	4.57
IQW	25.78	19.56	25.78	0.28	0.30	0.07	0.08	190.81	8.95
ITP	14.42	10.95	14.43	0.69	0.44	0.10	0.06	27.80	11.53
KFS	14.64	11.10	14.64	0.26	0.38	0.04	0.05	109.06	18.01
KGC	9.44	7.17	9.45	0.22	0.22	0.02	0.02	552.81	317.89

continued on next page

Table A-4: continued

	Midquote			**Rel. Spread**		**Spread**		**Trading Value**	
	TSX	NYSE	NYSE conv.	TSX	NYSE	TSX	NYSE	TSX	NYSE
MDG	17.12	12.99	17.15	0.31	0.17	0.05	0.03	115.76	211.57
MDZ	21.02	15.93	21.00	0.34	0.51	0.07	0.11	157.52	1.55
MFC	46.59	35.31	46.55	0.09	0.07	0.04	0.03	1,764.05	576.41
MGA	105.27	79.85	105.27	0.13	0.08	0.14	0.09	448.25	471.28
MHM	35.36	26.81	35.35	0.41	0.39	0.14	0.14	174.50	9.51
MIM	36.60	27.75	36.59	0.42	0.28	0.15	0.10	75.02	87.03
N	48.18	36.56	47.98	0.13	0.09	0.06	0.04	1,608.12	1,787.86
NCX	34.88	26.46	34.88	0.20	0.14	0.07	0.05	189.60	52.26
NRD	21.19	16.07	21.19	0.19	0.26	0.04	0.06	718.36	43.47
NT	8.95	6.78	8.94	0.13	0.20	0.01	0.02	8,364.08	6,954.78
NXY	49.30	37.38	49.35	0.19	0.21	0.09	0.10	863.80	69.16
PCZ	60.89	46.22	60.94	0.11	0.14	0.06	0.09	1,622.88	89.30
PDG	22.32	16.94	22.33	0.15	0.11	0.03	0.03	1,163.05	930.26
PDS	62.37	47.29	62.35	0.14	0.09	0.09	0.06	367.95	235.54
PGH	18.74	14.23	18.76	0.25	0.27	0.05	0.05	194.08	249.79
PKZ	34.11	25.86	34.09	0.34	0.26	0.11	0.09	262.23	338.03
POT	109.07	82.75	109.09	0.18	0.10	0.20	0.11	158.14	243.95
PWI	25.76	19.56	25.79	0.27	0.25	0.07	0.07	169.84	168.48
RCN	34.06	25.83	34.30	0.47	0.44	0.16	0.15	42.22	11.07
RG	24.83	18.82	24.82	0.26	0.27	0.07	0.07	383.90	14.53
RY	62.91	47.70	62.89	0.07	0.10	0.05	0.07	2,993.09	85.81
RYG	13.77	10.44	13.76	0.46	0.46	0.06	0.06	105.47	15.11
SLF	35.07	26.59	35.05	0.14	0.15	0.05	0.05	921.92	67.78
SU	34.73	26.34	34.72	0.12	0.11	0.04	0.04	1,180.70	374.66
TAC	18.14	13.77	18.15	0.19	0.36	0.03	0.07	186.22	3.73
TD	44.98	34.11	44.97	0.08	0.13	0.04	0.06	2,139.64	48.18
TEU	24.34	18.47	24.35	0.22	0.22	0.05	0.05	297.70	82.46
TLM	76.01	57.64	76.00	0.13	0.11	0.10	0.08	726.57	189.37
TOC	43.08	32.69	43.10	0.13	0.14	0.06	0.06	451.59	40.50
TRP	27.84	21.12	27.95	0.10	0.14	0.03	0.04	863.83	114.10
TU	24.03	18.23	24.04	0.26	0.36	0.06	0.09	215.17	7.51
ZL	5.15	3.91	5.16	0.47	0.65	0.02	0.03	156.15	30.75

Table A-5: Detailed parameter estimates.

The table reports the parameter estimates for the 69 sample stocks. ψ^h and ψ^f denote the diagonal elements of matrix Ψ, γ denotes the mixture probability. α^h and α^f give the adjustment coefficients of the home and foreign market return series, ξ^h and ξ^f denote the permanent impact of shocks on the home market and foreign market returns series, respectively. The numbers in parentheses are standard errors obtained by the parametric bootstrap procedure described in Appendix B. For full company names see Table A-3.

	ψ^h	ψ^f	γ	ξ^h	ξ^f	α^h	α^f
ABX	0.15	0.45	0.43	0.67	0.29	-0.21	0.48
	(0.010)	(0.033)	(0.030)	(0.040)	(0.035)	(0.042)	(0.046)
ABY	0.02	0.30	0.47	0.93	0.16	-0.08	0.49
	(0.001)	(0.018)	(0.011)	(0.018)	(0.020)	(0.019)	(0.023)
AEM	0.08	0.36	0.48	0.57	0.58	-0.32	0.31
	(0.005)	(0.025)	(0.018)	(0.028)	(0.033)	(0.033)	(0.037)
AGU	0.03	0.27	0.40	0.51	0.53	-0.22	0.21
	(0.001)	(0.016)	(0.012)	(0.025)	(0.027)	(0.021)	(0.020)
AL	0.18	0.33	0.22	0.57	0.60	-0.39	0.37
	(0.013)	(0.026)	(0.023)	(0.032)	(0.036)	(0.047)	(0.049)
BCE	0.05	0.47	0.48	1.09	0.14	-0.05	0.38
	(0.003)	(0.034)	(0.015)	(0.038)	(0.033)	(0.021)	(0.024)
BCM	0.03	0.37	0.58	1.07	0.05	-0.03	0.67
	(0.002)	(0.023)	(0.014)	(0.029)	(0.030)	(0.036)	(0.038)
BMO	0.08	0.17	0.22	1.04	0.08	-0.04	0.55
	(0.005)	(0.011)	(0.012)	(0.019)	(0.020)	(0.026)	(0.027)
BNN	0.00	0.16	0.50	0.91	0.03	-0.01	0.42
	(0.000)	(0.008)	(0.010)	(0.026)	(0.026)	(0.023)	(0.025)
BNS	0.01	0.36	0.59	0.97	0.11	-0.08	0.71
	(0.001)	(0.023)	(0.010)	(0.022)	(0.024)	(0.030)	(0.031)
BPO	0.02	0.33	0.31	0.57	0.38	-0.14	0.20
	(0.001)	(0.020)	(0.009)	(0.031)	(0.027)	(0.018)	(0.022)
BVF	0.09	0.20	0.27	0.74	0.56	-0.30	0.40
	(0.005)	(0.013)	(0.014)	(0.028)	(0.031)	(0.040)	(0.040)
CCJ	0.03	0.19	0.35	1.05	0.69	-0.23	0.35
	(0.002)	(0.011)	(0.011)	(0.042)	(0.037)	(0.034)	(0.035)
CGT	0.00	0.30	0.58	1.09	0.08	-0.02	0.32
	(0.001)	(0.016)	(0.010)	(0.037)	(0.036)	(0.023)	(0.023)
CLS	0.11	0.08	0.12	0.91	0.44	-0.23	0.49
	(0.009)	(0.007)	(0.008)	(0.027)	(0.028)	(0.034)	(0.036)
CNQ	0.04	0.28	0.43	1.11	0.20	-0.12	0.66
	(0.002)	(0.018)	(0.013)	(0.046)	(0.041)	(0.046)	(0.047)
COT	0.04	0.28	0.27	0.31	0.69	-0.42	0.19
	(0.003)	(0.017)	(0.012)	(0.019)	(0.017)	(0.019)	(0.018)
CP	0.02	0.30	0.47	1.01	0.09	-0.05	0.53
	(0.001)	(0.017)	(0.011)	(0.022)	(0.025)	(0.024)	(0.025)
DTC	0.01	0.30	0.48	0.94	0.13	-0.05	0.32
	(0.001)	(0.018)	(0.010)	(0.029)	(0.027)	(0.019)	(0.020)
ECA	0.10	0.39	0.33	0.85	0.41	-0.18	0.37
	(0.006)	(0.026)	(0.018)	(0.064)	(0.042)	(0.043)	(0.044)
ENB	0.01	0.22	0.40	1.01	0.07	-0.06	0.88
	(0.000)	(0.011)	(0.009)	(0.019)	(0.017)	(0.019)	(0.025)
ERF	0.04	0.15	0.20	0.44	0.84	-0.39	0.20
	(0.003)	(0.010)	(0.009)	(0.046)	(0.037)	(0.033)	(0.038)

continued on next page

Table A-5: continued

	ψ^h	ψ^f	γ	ξ^h	ξ^f	α^h	α^f
FDG	0.02	0.09	0.34	0.54	0.62	-0.31	0.27
	(0.001)	(0.005)	(0.010)	(0.030)	(0.031)	(0.029)	(0.030)
FFH	0.02	0.12	0.29	0.47	0.51	-0.27	0.24
	(0.001)	(0.007)	(0.009)	(0.024)	(0.025)	(0.021)	(0.022)
FHR	0.04	0.26	0.30	0.43	0.59	-0.29	0.22
	(0.002)	(0.017)	(0.011)	(0.028)	(0.028)	(0.025)	(0.027)
FS	0.02	0.29	0.47	0.03	0.94	-0.70	0.03
	(0.001)	(0.018)	(0.012)	(0.031)	(0.028)	(0.036)	(0.032)
GG	0.13	0.49	0.39	0.53	0.56	-0.36	0.34
	(0.008)	(0.037)	(0.025)	(0.039)	(0.033)	(0.040)	(0.045)
GIB	0.00	0.30	0.50	0.96	0.06	-0.02	0.36
	(0.000)	(0.000)	(0.000)	(0.024)	(0.023)	(0.015)	(0.017)
GIL	0.01	0.20	0.32	0.78	0.27	-0.06	0.16
	(0.000)	(0.011)	(0.009)	(0.041)	(0.037)	(0.015)	(0.015)
GLG	0.06	0.39	0.45	0.48	0.71	-0.42	0.28
	(0.003)	(0.024)	(0.017)	(0.032)	(0.033)	(0.038)	(0.039)
HBG	0.01	0.05	0.21	0.22	0.84	-0.08	0.02
	(0.001)	(0.003)	(0.007)	(0.038)	(0.043)	(0.007)	(0.005)
IDR	0.03	0.12	0.21	0.32	0.67	-0.32	0.16
	(0.002)	(0.007)	(0.009)	(0.017)	(0.017)	(0.020)	(0.019)
IPS	0.00	0.15	0.34	0.79	0.15	-0.06	0.29
	(0.000)	(0.008)	(0.009)	(0.029)	(0.029)	(0.018)	(0.017)
IQW	0.01	0.23	0.39	1.10	0.12	-0.04	0.35
	(0.001)	(0.013)	(0.010)	(0.034)	(0.032)	(0.022)	(0.023)
ITP	0.01	0.12	0.33	0.63	0.34	-0.09	0.16
	(0.001)	(0.007)	(0.009)	(0.028)	(0.032)	(0.015)	(0.016)
KFS	0.00	0.23	0.51	1.04	0.09	-0.02	0.27
	(0.000)	(0.012)	(0.009)	(0.020)	(0.021)	(0.012)	(0.016)
KGC	0.15	0.35	0.31	0.63	0.51	-0.30	0.38
	(0.010)	(0.024)	(0.024)	(0.021)	(0.023)	(0.028)	(0.030)
MDG	0.08	0.32	0.30	0.41	0.62	-0.46	0.31
	(0.005)	(0.022)	(0.016)	(0.041)	(0.035)	(0.039)	(0.042)
MDZ	0.00	0.21	0.46	1.02	0.04	-0.01	0.32
	(0.000)	(0.011)	(0.009)	(0.033)	(0.031)	(0.021)	(0.022)
MFC	0.07	0.31	0.36	0.66	0.49	-0.09	0.13
	(0.004)	(0.019)	(0.016)	(0.062)	(0.049)	(0.018)	(0.020)
MGA	0.05	0.24	0.24	0.59	0.55	-0.23	0.25
	(0.003)	(0.015)	(0.011)	(0.035)	(0.034)	(0.030)	(0.029)
MHM	0.00	0.21	0.33	0.85	0.12	-0.04	0.28
	(0.000)	(0.012)	(0.008)	(0.025)	(0.027)	(0.017)	(0.018)
MIM	0.03	0.12	0.18	0.12	0.79	-0.48	0.07
	(0.002)	(0.007)	(0.007)	(0.025)	(0.023)	(0.023)	(0.021)
N	0.12	0.22	0.19	1.02	0.18	-0.13	0.77
	(0.008)	(0.016)	(0.013)	(0.031)	(0.028)	(0.041)	(0.042)
NCX	0.02	0.23	0.29	0.71	0.34	-0.16	0.33
	(0.001)	(0.014)	(0.010)	(0.021)	(0.025)	(0.023)	(0.022)
NRD	0.03	0.17	0.56	1.16	0.07	-0.03	0.46
	(0.002)	(0.010)	(0.013)	(0.026)	(0.026)	(0.022)	(0.021)
NT	0.10	0.12	0.12	0.55	0.64	-0.37	0.32
	(0.007)	(0.009)	(0.009)	(0.053)	(0.050)	(0.056)	(0.055)
NXY	0.02	0.13	0.46	1.21	-0.04	0.01	0.47
	(0.001)	(0.007)	(0.011)	(0.024)	(0.025)	(0.021)	(0.022)

continued on next page

Table A-5: continued

	ψ^h	ψ^f	γ	ξ^h	ξ^f	α^h	α^f
PCZ	0.05	0.20	0.26	1.21	0.03	-0.02	0.69
	(0.003)	(0.012)	(0.011)	(0.032)	(0.031)	(0.033)	(0.034)
PDG	0.16	0.31	0.26	0.76	0.22	-0.15	0.50
	(0.011)	(0.022)	(0.022)	(0.041)	(0.036)	(0.040)	(0.045)
PDS	0.05	0.27	0.39	0.81	0.42	-0.16	0.31
	(0.003)	(0.017)	(0.014)	(0.043)	(0.039)	(0.030)	(0.031)
PGH	0.02	0.04	0.10	1.20	0.68	-0.13	0.23
	(0.002)	(0.003)	(0.006)	(0.032)	(0.040)	(0.014)	(0.015)
PKZ	0.05	0.10	0.16	0.95	0.55	-0.24	0.41
	(0.003)	(0.007)	(0.009)	(0.043)	(0.041)	(0.036)	(0.039)
POT	0.08	0.23	0.26	0.47	0.72	-0.44	0.29
	(0.005)	(0.015)	(0.013)	(0.024)	(0.030)	(0.029)	(0.028)
PWI	0.03	0.07	0.12	0.76	0.38	-0.21	0.43
	(0.002)	(0.005)	(0.007)	(0.046)	(0.036)	(0.035)	(0.041)
RCN	0.01	0.13	0.27	0.54	0.54	-0.13	0.13
	(0.001)	(0.007)	(0.008)	(0.040)	(0.039)	(0.019)	(0.019)
RG	0.00	0.31	0.45	1.25	-0.04	0.02	0.51
	(0.000)	(0.017)	(0.008)	(0.044)	(0.039)	(0.028)	(0.029)
RY	0.02	0.38	0.60	1.08	-0.02	0.01	0.60
	(0.002)	(0.026)	(0.012)	(0.032)	(0.030)	(0.031)	(0.032)
RYG	0.00	0.20	0.44	0.91	0.12	-0.05	0.37
	(0.000)	(0.011)	(0.009)	(0.030)	(0.031)	(0.023)	(0.024)
SLF	0.06	0.35	0.40	1.01	-0.02	0.01	0.41
	(0.003)	(0.022)	(0.015)	(0.061)	(0.052)	(0.033)	(0.036)
SU	0.07	0.21	0.30	1.08	0.17	-0.07	0.45
	(0.004)	(0.013)	(0.013)	(0.025)	(0.029)	(0.028)	(0.026)
TAC	0.00	0.31	0.55	0.91	0.08	-0.03	0.37
	(0.000)	(0.016)	(0.009)	(0.027)	(0.025)	(0.017)	(0.018)
TD	0.04	0.47	0.50	1.10	0.01	0.00	0.45
	(0.003)	(0.033)	(0.014)	(0.039)	(0.035)	(0.027)	(0.026)
TEU	0.03	0.19	0.32	0.82	0.21	-0.09	0.34
	(0.002)	(0.011)	(0.010)	(0.107)	(0.079)	(0.027)	(0.028)
TLM	0.02	0.44	0.50	1.01	0.29	-0.13	0.45
	(0.002)	(0.029)	(0.013)	(0.049)	(0.041)	(0.042)	(0.043)
TOC	0.01	0.35	0.47	1.45	-0.08	0.03	0.53
	(0.001)	(0.020)	(0.010)	(0.041)	(0.039)	(0.031)	(0.032)
TRP	0.05	0.02	0.03	1.24	0.03	-0.01	0.48
	(0.007)	(0.003)	(0.003)	(0.022)	(0.017)	(0.016)	(0.023)
TU	0.00	0.10	0.50	1.18	-0.11	0.05	0.58
	(0.000)	(0.005)	(0.009)	(0.022)	(0.020)	(0.018)	(0.023)
ZL	0.05	0.16	0.28	0.93	0.19	-0.08	0.38
	(0.003)	(0.010)	(0.011)	(0.020)	(0.022)	(0.019)	(0.020)

Table A-6: Modified Hasbrouck information shares and adjustment coefficient ratios. The first two columns of the table report the estimated modified Hasbrouck information shares. The last two columns report the estimated adjustment coefficient ratios computed as $Adj^h = \frac{\alpha^h}{\alpha^h + |\alpha^f|}$ (TSX) and $Adj^f = \frac{|\alpha^f|}{\alpha^h + |\alpha^f|}$ (NYSE). If the adjustment coefficient ratio is high then its contribution to price discovery is small. Ratios and information shares are multiplied by 100 to obtain percentages. The numbers in parentheses are standard errors of the respective estimates obtained by the parametric bootstrap procedure described in Appendix B. For full company names see Table A-3.

	Modified Hasbrouck Information Shares		Adjustment Coeff. Ratios	
	ISM^h (TSX)	ISM^f (NYSE)	Adj^f (NYSE)	Adj^h (TSX)
ABX	49.8	50.2	69.5	30.5
	(0.34)	(0.34)	(7.24)	(7.24)
ABY	55.8	44.2	85.6	14.4
	(0.82)	(0.82)	(3.73)	(3.73)
AEM	49.5	50.5	49.6	50.4
	(0.35)	(0.35)	(5.77)	(5.77)
AGU	54.9	45.1	49.3	50.7
	(0.57)	(0.57)	(5.11)	(5.11)
AL	50.0	50.0	48.7	51.3
	(0.28)	(0.28)	(6.41)	(6.41)
BCE	58.8	41.2	88.3	11.7
	(1.01)	(1.01)	(4.47)	(4.47)
BCM	53.3	46.7	95.7	4.3
	(0.40)	(0.40)	(3.81)	(3.81)
BMO	56.6	43.4	93.2	6.8
	(0.78)	(0.78)	(3.51)	(3.51)
BNN	59.6	40.4	97.3	2.7
	(1.30)	(1.30)	(2.91)	(2.91)
BNS	53.6	46.4	90.0	10.0
	(0.54)	(0.54)	(3.28)	(3.28)
BPO	50.0	50.0	59.7	40.3
	(0.74)	(0.74)	(5.82)	(5.82)
BVF	51.9	48.1	57.1	42.9
	(0.33)	(0.33)	(5.23)	(5.23)
CCJ	54.1	45.9	60.4	39.6
	(0.47)	(0.47)	(6.08)	(6.08)
CGT	57.1	42.9	93.5	6.5
	(0.81)	(0.81)	(5.29)	(5.29)
CLS	54.6	45.4	67.6	32.4
	(3.69)	(3.69)	(4.60)	(4.60)
CNQ	52.1	47.9	84.8	15.2
	(0.36)	(0.36)	(6.20)	(6.20)
COT	54.9	45.1	30.7	69.3
	(0.60)	(0.60)	(3.45)	(3.45)
CP	55.5	44.5	91.8	8.2
	(0.65)	(0.65)	(4.46)	(4.46)
DTC	58.8	41.2	87.5	(12.496)
	(1.10)	(1.10)	(5.20)	(5.20)
ECA	53.7	46.3	67.4	32.6
	(0.37)	(0.37)	(8.28)	(8.28)

continued on next page

Table A-6: continued

	ISM^h (TSX)	ISM^f (NYSE)	Adj^f (NYSE)	Adj^h (TSX)
ENB	57.6	42.4	93.6	6.4
	(1.54)	(1.54)	(3.24)	(3.24)
ERF	50.4	49.6	34.1	65.9
	(0.53)	(0.53)	(7.52)	(7.52)
FDG	51.6	48.4	46.2	53.8
	(0.41)	(0.41)	(5.66)	(5.66)
FFH	53.8	46.2	47.9	52.1
	(0.61)	(0.61)	(4.99)	(4.99)
FHR	52.4	47.6	42.3	57.7
	(0.49)	(0.49)	(5.51)	(5.51)
FS	55.3	44.7	3.5	96.5
	(0.26)	(0.26)	(5.58)	(5.58)
GG	50.0	50.0	48.5	51.5
	(0.36)	(0.36)	(6.51)	(6.51)
GIB	58.4	41.6	94.6	5.4
	(0.91)	(0.91)	(2.41)	(2.41)
GIL	62.9	37.1	74.3	25.7
	(1.67)	(1.67)	(7.21)	(7.21)
GLG	51.0	49.0	40.3	59.7
	(0.33)	(0.33)	(6.01)	(6.01)
HBG	59.3	40.7	20.6	79.4
	(1.70)	(1.70)	(7.22)	(7.22)
IDR	56.7	43.3	32.4	67.6
	(0.74)	(0.74)	(3.41)	(3.41)
IPS	58.1	41.9	83.8	16.2
	(0.83)	(0.83)	(5.69)	(5.69)
IQW	58.2	41.8	90.2	9.8
	(0.96)	(0.96)	(5.01)	(5.01)
ITP	54.2	45.8	65.0	35.0
	(0.96)	(0.96)	(6.34)	(6.34)
KFS	58.6	41.4	92.2	7.8
	(1.35)	(1.35)	(3.90)	(3.90)
KGC	53.0	47.0	55.5	44.5
	(0.64)	(0.64)	(4.26)	(4.26)
MDG	50.2	49.8	39.8	60.2
	(0.39)	(0.39)	(6.86)	(6.86)
MDZ	58.6	41.4	96.3	3.7
	(0.89)	(0.89)	(5.13)	(5.13)
MFC	54.1	45.9	57.6	42.4
	(0.92)	(0.92)	(10.05)	(10.05)
MGA	53.8	46.2	51.8	48.2
	(0.46)	(0.46)	(6.29)	(6.29)
MHM	57.7	42.3	87.6	12.4
	(0.80)	(0.80)	(5.44)	(5.44)
MIM	55.8	44.2	12.9	87.1
	(0.61)	(0.61)	(5.15)	(5.15)
N	50.8	49.2	85.1	14.9
	(0.39)	(0.39)	(5.39)	(5.39)
NCX	57.2	42.8	67.5	32.5
	(0.80)	(0.80)	(4.85)	(4.85)

continued on next page

Table A-6: continued

	ISM^h (TSX)	ISM^f (NYSE)	Adj^f (NYSE)	Adj^h (TSX)
NRD	59.5	40.5	94.1	5.9
	(0.97)	(0.97)	(2.83)	(2.83)
NT	11.2	88.8	46.3	53.7
	(19.52)	(19.52)	(8.31)	(8.31)
NXY	58.3	41.7	97.1	2.9
	(0.85)	(0.85)	(2.47)	(2.47)
PCZ	55.1	44.9	97.2	2.8
	(0.48)	(0.48)	(2.70)	(2.70)
PDG	51.2	48.8	77.4	22.6
	(0.53)	(0.53)	(6.90)	(6.90)
PDS	53.1	46.9	65.7	34.3
	(0.54)	(0.54)	(7.15)	(7.15)
PGH	42.0	58.0	63.8	36.2
	(3.02)	(3.02)	(4.01)	(4.01)
PKZ	52.7	47.3	63.4	36.6
	(0.44)	(0.44)	(5.92)	(5.92)
POT	52.7	47.3	39.6	60.4
	(0.48)	(0.48)	(5.19)	(5.19)
PWI	52.3	47.7	66.8	33.2
	(0.95)	(0.95)	(6.50)	(6.50)
RCN	55.5	44.5	50.2	49.8
	(0.69)	(0.69)	(7.55)	(7.55)
RG	54.8	45.2	96.9	3.1
	(0.59)	(0.59)	(4.10)	(4.10)
RY	56.0	44.0	98.4	1.6
	(0.67)	(0.67)	(3.28)	(3.28)
RYG	57.1	42.9	88.5	11.5
	(0.63)	(0.63)	(5.51)	(5.51)
SLF	55.6	44.4	98.5	1.5
	(0.86)	(0.86)	(4.53)	(4.53)
SU	57.5	42.5	86.2	13.8
	(0.52)	(0.52)	(4.73)	(4.73)
TAC	58.5	41.5	91.5	8.5
	(1.10)	(1.10)	(5.01)	(5.01)
TD	57.0	43.0	99.4	0.6
	(0.83)	(0.83)	(3.35)	(3.35)
TEU	54.6	45.4	80.0	20.0
	(1.82)	(1.82)	(3.19)	(3.19)
TLM	52.7	47.3	77.5	22.5
	(0.38)	(0.38)	(7.50)	(7.50)
TOC	55.9	44.1	95.0	5.0
	(0.68)	(0.68)	(4.06)	(4.06)
TRP	55.7	44.3	98.0	2.0
	(6.12)	(6.12)	(2.85)	(2.85)
TU	57.1	42.9	91.4	8.6
	(1.11)	(1.11)	(2.53)	(2.53)
ZL	61.1	38.9	82.7	17.3
	(0.93)	(0.93)	(3.89)	(3.89)

Table A-7: Hasbrouck information shares.
The table reports lower and upper bounds of standard Hasbrouck information shares as well as the associated midpoints. Ratios and information shares are multiplied by 100 to obtain percentages. The numbers in parentheses give the standard error of the midpoint estimate obtained by the parametric bootstrap procedure described in Appendix B.

	IS^h (TSX)			IS^f (NYSE)		
	Low. Bound	Upp. Bound	Midpoint	Low. Bound	Upp. Bound	Midpoint
ABX	11.5	97.3	54.4	2.7	88.5	45.6
			(1.87)			(1.87)
ABY	43.7	98.3	71.0	1.7	56.3	29.0
			(2.12)			(2.12)
AEM	6.3	91.8	49.0	8.2	93.7	51.0
			(1.69)			(1.69)
AGU	13.1	86.4	49.8	13.6	86.9	50.2
			(2.69)			(2.69)
AL	4.2	94.9	49.6	5.1	95.8	50.4
			(1.19)			(1.19)
BCE	45.7	99.0	72.4	1.0	54.3	27.6
			(2.70)			(2.70)
BCM	26.9	99.9	63.4	0.1	73.1	36.6
			(1.52)			(1.52)
BMO	42.2	99.7	71.0	0.3	57.8	29.0
			(1.65)			(1.65)
BNN	59.8	99.9	79.9	0.1	40.2	20.1
			(2.43)			(2.43)
BNS	32.3	99.5	65.9	0.5	67.7	34.1
			(1.62)			(1.62)
BPO	18.1	88.1	53.1	11.9	81.9	46.9
			(3.56)			(3.56)
BVF	8.3	95.0	51.6	5.0	91.7	48.4
			(1.37)			(1.37)
CCJ	15.1	93.7	54.4	6.3	84.9	45.6
			(2.44)			(2.44)
CGT	43.9	99.8	71.8	0.2	56.1	28.2
			(2.78)			(2.78)
CLS	15.3	96.4	55.8	3.6	84.7	44.2
			(1.50)			(1.50)
CNQ	18.2	99.4	58.8	0.6	81.8	41.2
			(1.74)			(1.74)
COT	6.5	68.5	37.5	31.5	93.5	62.5
			(2.37)			(2.37)
CP	41.6	99.6	70.6	0.4	58.4	29.4
			(2.14)			(2.14)
DTC	52.5	98.8	75.6	1.2	47.5	24.4
			(3.07)			(3.07)
ECA	13.6	96.9	55.3	3.1	86.4	44.7
			(2.45)			(2.45)
ENB	57.3	99.5	78.4	0.5	42.7	21.6
			(2.48)			(2.48)
ERF	3.8	82.0	42.9	18.0	96.2	57.1
			(2.80)			(2.80)

continued on next page

Table A-7: continued

	IS^h (TSX)			IS^f (NYSE)		
	Low. Bound	Upp. Bound	Midpoint	Low. Bound	Upp. Bound	Midpoint
FDG	7.1	89.4	48.3 (1.99)	10.6	92.9	51.7 (1.99)
FFH	10.5	86.5	48.5 (2.38)	13.5	89.5	51.5 (2.38)
FHR	7.6	84.5	46.1 (2.47)	15.5	92.4	53.9 (2.47)
FS	0.1	64.3	32.2 (1.36)	35.7	99.9	67.8 (1.36)
GG	6.1	91.7	48.9 (1.86)	8.3	93.9	51.1 (1.86)
GIB	56.6	99.8	78.2 (2.07)	0.2	43.4	21.8 (2.07)
GIL	34.6	95.6	65.1 (4.15)	4.4	65.4	34.9 (4.15)
GLG	4.2	89.6	46.9 (1.67)	10.4	95.8	53.1 (1.67)
HBG	6.4	53.6	30.0 (6.96)	46.4	93.6	70.0 (6.96)
IDR	8.5	67.1	37.8 (2.64)	32.9	91.5	62.2 (2.64)
IPS	39.7	98.6	69.1 (2.75)	1.4	60.3	30.9 (2.75)
IQW	47.8	99.4	73.6 (2.78)	0.6	52.2	26.4 (2.78)
ITP	23.3	91.6	57.5 (3.68)	8.4	76.7	42.5 (3.68)
KFS	63.1	99.3	81.2 (2.68)	0.7	36.9	18.8 (2.68)
KGC	14.3	89.7	52.0 (2.08)	10.3	85.7	48.0 (2.08)
MDG	4.4	88.1	46.2 (2.12)	11.9	95.6	53.8 (2.12)
MDZ	51.0	99.9	75.4 (2.69)	0.1	49.0	24.6 (2.69)
MFC	17.1	90.0	53.5 (5.21)	10.0	82.9	46.5 (5.21)
MGA	11.4	90.8	51.1 (2.59)	9.2	88.6	48.9 (2.59)
MHM	42.9	99.1	71.0 (2.72)	0.9	57.1	29.0 (2.72)
MIM	0.9	64.9	32.9 (2.54)	35.1	99.1	67.1 (2.54)
N	15.6	99.5	57.6 (1.19)	0.5	84.4	42.4 (1.19)
NCX	29.6	93.5	61.5 (2.67)	6.5	70.4	38.5 (2.67)
NRD	54.0	99.8	76.9 (1.92)	0.2	46.0	23.1 (1.92)

continued on next page

Table A-7: continued

	IS^h (TSX)			IS^f (NYSE)		
	Low. Bound	Upp. Bound	Midpoint	Low. Bound	Upp. Bound	Midpoint
NT	4.8	94.1	49.5	5.9	95.2	50.5
			(1.67)			(1.67)
NXY	56.9	99.9	78.4	0.1	43.1	21.6
			(1.87)			(1.87)
PCZ	31.8	100.0	65.9	0.0	68.2	34.1
			(1.51)			(1.51)
PDG	15.5	98.4	56.9	1.6	84.5	43.1
			(1.89)			(1.89)
PDS	17.8	94.8	56.3	5.2	82.2	43.7
			(2.95)			(2.95)
PGH	37.6	86.2	61.9	13.8	62.4	38.1
			(3.43)			(3.43)
PKZ	13.4	95.3	54.3	4.7	86.6	45.7
			(2.02)			(2.02)
POT	6.4	84.6	45.5	15.4	93.6	54.5
			(2.14)			(2.14)
PWI	19.4	93.3	56.3	6.7	80.6	43.7
			(3.29)			(3.29)
RCN	14.7	86.9	50.8	13.1	85.3	49.2
			(3.84)			(3.84)
RG	38.2	100.0	69.1	0.0	61.8	30.9
			(2.23)			(2.23)
RY	44.6	100.0	72.3	0.0	55.4	27.7
			(1.90)			(1.90)
RYG	35.1	99.4	67.3	0.6	64.9	32.7
			(2.23)			(2.23)
SLF	39.2	100.0	69.6	0.0	60.8	30.4
			(2.87)			(2.87)
SU	32.9	99.3	66.1	0.7	67.1	33.9
			(1.77)			(1.77)
TAC	55.8	99.4	77.6	0.6	44.2	22.4
			(2.96)			(2.96)
TD	45.2	100.0	72.6	0.0	54.8	27.4
			(2.33)			(2.33)
TEU	27.8	98.1	62.9	1.9	72.2	37.1
			(1.52)			(1.52)
TLM	17.3	98.5	57.9	1.5	82.7	42.1
			(2.17)			(2.17)
TOC	42.8	99.9	71.3	0.1	57.2	28.7
			(1.80)			(1.80)
TRP	71.6	99.9	85.7	0.1	28.4	14.3
			(2.84)			(2.84)
TU	69.1	99.0	84.0	1.0	30.9	16.0
			(1.51)			(1.51)
ZL	45.4	98.1	71.8	1.9	54.6	28.2
			(2.16)			(2.16)

cfr/working paper series

centre for financial research
Look deeper

cFR working papers are available for download from **www.cfr-cologne.de**.

Hardcopies can be ordered from: centre for financial research (CFR), Albertus Magnus Platz, 50923 Koeln, Germany.

2008

No.	Author(s)	Title
08-10	J. Grammig, F.J. Peter	International Price Discovery in the Presence of Market Microstructure Effects
08-09	C. M. Kuhnen, A. Niessen	Is Executive Compensation Shaped by Public Attitudes?
08-08	A. Pütz, S. Ruenzi	Overconfidence among Professional Investors: Evidence from Mutual Fund Managers
08-07	P. Osthoff	What matters to SRI investors?
08-06	A. Betzer, E. Theissen	Sooner Or Later: Delays in Trade Reporting by Corporate Insiders
08-05	P. Linge, E. Theissen	Determinanten der Aktionärspräsenz auf Hauptversammlungen deutscher Aktiengesellschaften
08-04	N. Hautsch, D. Hess, C. Müller	Price Adjustment to News with Uncertain Precision
08-03	D. Hess, H. Huang, A. Niessen	How Do Commodity Futures Respond to Macroeconomic News?
08-02	R. Chakrabarti, W. Megginson, P. Yadav	Corporate Governance in India
08-01	C. Andres, E. Theissen	Setting a Fox to Keep the Geese - Does the Comply-or-Explain Principle Work?

2007

No.	Author(s)	Title
07-16	M. Bär, A. Niessen, S. Ruenzi	The Impact of Work Group Diversity on Performance: Large Sample Evidence from the Mutual Fund Industry
07-15	A. Niessen, S. Ruenzi	Political Connectedness and Firm Performance: Evidence From Germany
07-14	O. Korn	Hedging Price Risk when Payment Dates are Uncertain
07-13	A. Kempf, P. Osthoff	SRI Funds: Nomen est Omen
07-12	J. Grammig, E. Theissen, O. Wuensche	Time and Price Impact of a Trade: A Structural Approach
07-11	V. Agarwal, J. R. Kale	On the Relative Performance of Multi-Strategy and Funds of Hedge Funds
07-10	M. Kasch-Haroutounian, E. Theissen	Competition Between Exchanges: Euronext versus Xetra

No.	Author(s)	Title
07-09	V. Agarwal, N. D. Daniel, N. Y. Naik	Why is Santa so kind to hedge funds? The December return puzzle!
07-08	N. C. Brown, K. D. Wei, R. Wermers	Analyst Recommendations, Mutual Fund Herding, and Overreaction in Stock Prices
07-07	A. Betzer, E. Theissen	Insider Trading and Corporate Governance: The Case of Germany
07-06	V. Agarwal, L. Wang	Transaction Costs and Value Premium
07-05	J. Grammig, A. Schrimpf	Asset Pricing with a Reference Level of Consumption: New Evidence from the Cross-Section of Stock Returns
07-04	V. Agarwal, N.M. Boyson, N.Y. Naik	Hedge Funds for retail investors? An examination of hedged mutual funds
07-03	D. Hess, A. Niessen	The Early News Catches the Attention: On the Relative Price Impact of Similar Economic Indicators
07-02	A. Kempf, S. Ruenzi, T. Thiele	Employment Risk, Compensation Incentives and Managerial Risk Taking - Evidence from the Mutual Fund Industry -
07-01	M. Hagemeister, A. Kempf	CAPM und erwartete Renditen: Eine Untersuchung auf Basis der Erwartung von Marktteilnehmern

2006

No.	Author(s)	Title
06-13	S. Čeljo-Hörhager, A. Niessen	How do Self-fulfilling Prophecies affect Financial Ratings? - An experimental study -
06-12	R. Wermers, Y. Wu, J. Zechner	Portfolio Performance, Discount Dynamics, and the Turnover of Closed-End Fund Managers
06-11	U. v. Lilienfeld-Toal, S. Ruenzi	Why Managers Hold Shares of Their Firm: An Empirical Analysis
06-10	A. Kempf, P. Osthoff	The Effect of Socially Responsible Investing on Portfolio Performance
06-09	R. Wermers, T. Yao, J. Zhao	The Investment Value of Mutual Fund Portfolio Disclosure
06-08	M. Hoffmann, B. Kempa	The Poole Analysis in the New Open Economy Macroeconomic Framework
06-07	K. Drachter, A. Kempf, M. Wagner	Decision Processes in German Mutual Fund Companies: Evidence from a Telephone Survey
06-06	J.P. Krahnen, F.A. Schmid, E. Theissen	Investment Performance and Market Share: A Study of the German Mutual Fund Industry
06-05	S. Ber, S. Ruenzi	On the Usability of Synthetic Measures of Mutual Fund Net-Flows
06-04	A. Kempf, D. Mayston	Liquidity Commonality Beyond Best Prices
06-03	O. Korn, C. Koziol	Bond Portfolio Optimization: A Risk-Return Approach
06-02	O. Scaillet, L. Barras, R. Wermers	False Discoveries in Mutual Fund Performance: Measuring Luck in Estimated Alphas
06-01	A. Niessen, S. Ruenzi	Sex Matters: Gender Differences in a Professional Setting

2005

No.	Author(s)	Title
05-16	E. Theissen	An Analysis of Private Investors´ Stock Market Return Forecasts

No.	Author(s)	Title
05-15	T. Foucault, S. Moinas, E. Theissen	Does Anonymity Matter in Electronic Limit Order Markets
05-14	R. Kosowski, A. Timmermann, R. Wermers, H. White	Can Mutual Fund „Stars“ Really Pick Stocks? New Evidence from a Bootstrap Analysis
05-13	D. Avramov, R. Wermers	Investing in Mutual Funds when Returns are Predictable
05-12	K. Griese, A. Kempf	Liquiditätsdynamik am deutschen Aktienmarkt
05-11	S. Ber, A. Kempf, S. Ruenzi	Determinanten der Mittelzuflüsse bei deutschen Aktienfonds
05-10	M. Bär, A. Kempf, S. Ruenzi	Is a Team Different From the Sum of Its Parts? Evidence from Mutual Fund Managers
05-09	M. Hoffmann	Saving, Investment and the Net Foreign Asset Position
05-08	S. Ruenzi	Mutual Fund Growth in Standard and Specialist Market Segments
05-07	A. Kempf, S. Ruenzi	Status Quo Bias and the Number of Alternatives - An Empirical Illustration from the Mutual Fund Industry –
05-06	J. Grammig, E. Theissen	Is Best Really Better? Internalization in Xetra Best
05-05	H. Beltran, J. Grammig, A.J. Menkveld	Understanding the Limit Order Book: Conditioning on Trade Informativeness
05-04	M. Hoffmann	Compensating Wages under different Exchange rate Regimes
05-03	M. Hoffmann	Fixed versus Flexible Exchange Rates: Evidence from Developing Countries
05-02	A. Kempf, C. Memmel	On the Estimation of the Global Minimum Variance Portfolio
05-01	S. Frey, J. Grammig	Liquidity supply and adverse selection in a pure limit order book market

2004

No.	Author(s)	Title
04-10	N. Hautsch, D. Hess	Bayesian Learning in Financial Markets – Testing for the Relevance of Information Precision in Price Discovery
04-09	A. Kempf, K. Kreuzberg	Portfolio Disclosure, Portfolio Selection and Mutual Fund Performance Evaluation
04-08	N.F. Carline, S.C. Linn, P.K. Yadav	Can the Stock Market Systematically make Use of Firm- and Deal-Specific Factors when Initially Capitalizing the Real Gains from Mergers and Acquisitions
04-07	J.J. Merrick, Jr., N.Y. Naik, P.K. Yadav	Strategic Trading Behavior and Price Distortion in a Manipulated Market: Anatomy of a Squeeze
04-06	N.Y. Naik, P.K. Yadav	Trading Costs of Public Investors with Obligatory and Voluntary Market-Making: Evidence from Market Reforms
04-05	A. Kempf, S. Ruenzi	Family Matters: Rankings Within Fund Families and Fund Inflows
04-04	V. Agarwal, N.D. Daniel, N.Y. Naik	Role of Managerial Incentives and Discretion in Hedge Fund Performance
04-03	V. Agarwal, W.H. Fung, J.C. Loon, N.Y. Naik	Liquidity Provision in the Convertible Bond Market: Analysis of Convertible Arbitrage Hedge Funds

No.	Author(s)	Title
04-02	A. Kempf, S. Ruenzi	Tournaments in Mutual Fund Families
04-01	I. Chowdhury, M. Hoffmann, A. Schabert	Inflation Dynamics and the Cost Channel of Monetary Transmission

centre for financial research
cfr/university of cologne
Albertus-Magnus-Platz
D-50923 cologne
fon +49(0)221-470-6995
fax +49(0)221-470-3992
kempf@cfr-cologne.de
www.cfr-cologne.de