Related Securities, Allocation of Attention and Price Discovery: Evidence from NYSE-Listed Non-U.S. Stocks

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Abstract: In this paper we explore how the composition of a market maker's portfolio and allocation of attention across securities in the portfolio affect pricing. We analyze whether more attention devoted to similar securities enables a market maker to extract information relevant to a stock from order flow to related securities and consequently whether it leads to improved price discovery of the stock. We base on the recent literature on allocation of attention in share trading (Corwin and Coughenour, 2008; Boulatov et al., 2009) and define the prominence of a security as the proportion of its dollar volume in the total volume of the specialist portfolio it belongs to. Our empirical tests are focused on New York Stock Exchange specialists and the U.S. share in price discovery of 64 British and French companies cross-listed on the NYSE. We define related securities as stocks from the same country, the same region or other foreign stocks. We find strong evidence that an increase in the prominence of related stocks in the specialist portfolio leads to a higher U.S. share in price discovery of our sample stocks. We interpret our findings as evidence that concentrating market makers in similar stocks reduces information asymmetries and improves the information environment. To support our argument, we show that an increase in the prominence of other foreign stocks in the specialist portfolio significantly reduces the adverse selection component of the bid-ask spread.

JEL Classification: G14, G15

Keywords: NYSE specialists, cross-listing, related stocks, price discovery

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Related Securities, Allocation of Attention and Price Discovery: Evidence from NYSE-Listed Non-U.S. Stocks

Abstract: In this paper we explore how the composition of a market maker's portfolio and allocation of attention across securities in the portfolio affect pricing. We analyze whether more attention devoted to similar securities enables a market maker to extract information relevant to a stock from order flow to related securities and consequently whether it leads to improved price discovery of the stock. We base on the recent literature on allocation of attention in share trading (Corwin and Coughenour, 2008; Boulatov et al., 2009) and define the prominence of a security as the proportion of its dollar volume in the total volume of the specialist portfolio it belongs to. Our empirical tests are focused on New York Stock Exchange specialists and the U.S. share in price discovery of 64 British and French companies cross-listed on the NYSE. We define related securities as stocks from the same country, the same region or other foreign stocks. We find strong evidence that an increase in the prominence of related stocks in the specialist portfolio leads to a higher U.S. share in price discovery of our sample stocks. We interpret our findings as evidence that concentrating market makers in similar stocks reduces information asymmetries and improves the information environment. To support our argument, we show that an increase in the prominence of other foreign stocks in the specialist portfolio significantly reduces the adverse selection component of the bid-ask spread.

1. Introduction

In this paper we explore how the composition of a market maker's portfolio and allocation of attention across securities in the portfolio affect pricing. We analyze whether more attention devoted to similar securities improves the information environment and helps to incorporate new information in prices of a stock. Towards this end we look at New York Stock Exchange specialists and price discovery of non-U.S. stocks in their portfolios, which is an ideal setting to perform our tests. First, market making in non-U.S. stocks is associated with inherent information asymmetries (Bacidore and Sofianos, 2002) and we expect any benefits from the enhanced information environment to be particularly evident for foreign stocks. And second, by focusing on NYSE specialists we can observe individuals handling well-defined small sets of securities across which they must divide their attention (Corwin and Coughenour, 2008). On the basis of the trading activity within a specialist portfolio we can determine the relative prominence of every constituent of the portfolio. Our empirical tests are focused on the question of whether the prominence of other stocks from the same country, the same region or other foreign stocks in a specialist portfolio affects price discovery of a non-U.S. stock occurring on the NYSE relative to the stock's home market. Our study complements the literature on the link between allocation of attention in securities trading and market quality (Corwin and Coughenour, 2008; Boulatov et al., 2009), but is also related to the substantial body of literature on price discovery in cross-listings and on the role of dedicated market makers (e.g., Venkataraman and Waisburd, 2007).

According to anecdotal evidence, specialist firms aim to cluster related firms with individual specialists to exploit information advantages and match firm characteristics with specialists' talents (see, Anand et al., 2008). The premise is supported by theoretical models. Strobl (2001) models the trade-off between a higher information precision when trading stocks with correlated payoffs and lower competition between dealers when the stocks are clustered. He shows that both specialists and investors can benefit when related stocks are concentrated within specialists. In a similar vein, Baruch et al. (2007) develop a model to show that, when trading a set of related stocks, market makers can infer information from the observed order flow of the related stocks, and the order flow of one firm can be relevant for pricing of other firms. They argue that the clustering of closely related stocks can have a direct impact on the reduction of market making costs. Empirical studies of stock allocations confirm the tendency to cluster related stocks. Looking at the specialist firm level, Corwin (2004) finds that new stocks are allocated to firms that trade similar stocks, for example stocks in the same industry or other foreign stocks. At the individual specialist level, Anand et al. (2008) uncover that stocks reassignments between specialists within a specialist firm tend to increase industrial concentration of specialist portfolios.

In this paper we employ the U.S. share in price discovery of non-U.S. stocks cross-listed on the NYSE as our measure of the quality of the information environment of NYSE specialists and the competitiveness of NYSE pricing of cross-listed stocks. Earlier studies of price discovery in international cross-listings based on both daily and intraday data find that, on average, the home market is dominant in the pricing process.[1] However, the studies uncover a substantial variation in the foreign market's contribution to price discovery across companies. For example, Eun and Sabherwal (2003) find that the U.S. share in price discovery of Canadian firms ranges from 0.2 percent to 98.2 percent. This guarantees that the U.S. share in price discovery can be used as a meaningful measure in our tests. Building on the theoretical arguments on informational benefits of concentrated market making we aim to explore whether the share in price discovery increases when related stocks have a greater importance in a specialist portfolio. We measure the relatedness at three levels: the group of stocks from the same country, the group of stocks from the same region and the group of all non-U.S. stocks. We expect that stocks within these three groups have some degree of similarity and hence payoff correlation. The similarities can come from shared macroeconomic fundamentals including currency movements, common institutional factors, regulations or cultural and geographical proximity.

To measure the concentration and stocks' prominence in a portfolio we base on the recent literature on allocation of attention in share trading (Corwin and Coughenour, 2008; Boulatov et al., 2009). The underlying concept comes from the psychology literature on limited attention and constraints in the ability to process information (e.g., Kahneman, 1973). In the context of NYSE specialists, Corwin and Coughenour (2008) and Boulatov et al. (2009) argue that specialists allocate their attention across securities in their portfolios taking into account portfolio profits and risks, and most attention goes to most active stocks. The studies provide strong evidence that the market quality for individual stocks is driven by the attention allocated to them. We use the concept of attention to measure the prominence of stocks from the same country, the same region or foreign stocks in general in a NYSE specialist's portfolio. Following the theoretical arguments in Strobl (2001) and Baruch et al. (2007), we expect informational advantages to arise when a specialist allocates more attention to similar stocks and hence is able to extract information relevant to a stock from order flow to related securities. Consequently, we expect that the U.S. share in price discovery is increasing with the prominence of similar firms. Our argument is also in line with one of the policy recommendations in Bacidore and Sofianos (2002) who suggest that the information environment can be enhanced by higher concentration of foreign stocks in particular specialists. Moreover, we expect that the U.S. share in price discovery is increasing in the stock's own prominence in the portfolio, consistent with the notion that prices of stocks that receive more attention are more informative.

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[1] See, e.g. Lieberman et al. (1999), Kim et al. (2000), and Wang et al. (2002) for evidence on daily data; and Hupperets and Menkveld (2002), Eun and Sabherwal (2003), Grammig et al. (2005a, 2005b), Pascual et al.

Our sample consists of 64 NYSE-listed British and French companies and the sample period spans January to June 2003. As of the end of 2002, the United Kingdom had the largest number of NYSE cross-listings and the largest NYSE trading value among European countries, and France followed as the second and the fourth most important one, respectively. The estimated U.S. share in price discovery in our sample ranges from 0.0 percent to 70.2 percent based on the approach proposed by Hasbrouck (1995), and from 0.0 percent to 86.4 percent based on the method proposed by Gonzalo and Granger (1995). We argue that the significant differences in NYSE pricing of our sample of cross-listed stocks are driven by differences in the information environment across NYSE specialists who make a market in our sample stocks. Based on the meaningful cross-sectional variation of our price discovery measure we run a set of cross-sectional tests to show how the U.S. share in price discovery differs with the prominence of other related stocks in the specialist portfolio. We find strong evidence that the U.S. share in price discovery increases when a specialist pays more attention to other related stocks and there is a larger informational advantage from allocating attention across a broader set of international securities rather than focusing on country-specific groups of firms. We interpret the finding as evidence that a specialist who pays more attention to other related stocks has an informational advantage as he can extract information from order flow to a set of firms with correlated pay-offs. We support our argument by showing that the adverse selection component of the bid-ask spread is reduced with the increased prominence of other foreign stocks in the portfolio. Our main findings and conclusions are robust to the exclusion of stocks reassigned between specialists in our sample period, the alternative definition of prominence, and to the alternative price discovery estimation methods.

We contribute to the literature in three ways. First, our findings complement and extend the literature on the link between allocation of attention in securities trading and

(2006), Kaul and Mehrotra (2007), and Menkveld et al. (2007) for intraday studies.

market quality (Corwin and Coughenour, 2008; Boulatov et al., 2009). We show that not only the stock that receives more attention trades more efficiently but it is also important how much of the attention is allocated to related stocks in the portfolio. Second, we add to the literature on the value of dedicated market makers (e.g., Venkataraman and Waisburd, 2007). We analyze a trading design with dedicated specialists who are responsible for maintaining markets for a set of stocks and we show the empirical evidence to confirm theoretical predictions of the benefits of concentrating specialists in similar securities (Strobl, 2001; Baruch et al., 2007), and also to complement earlier empirical evidence on concentration (Corwin, 2004; Anand et al., 2008). And third, we add to the literature on price discovery in cross-listings by providing evidence on the intra-day price discovery process of NYSE-listed U.K and French stocks which are a significant group of foreign issuers on the NYSE.

The remainder of the paper is organized as follows. The role of NYSE specialists and differences in market making in U.S. and non-U.S. stocks are outlined in Section 2. Section 3 describes data sources and the sample of U.K. and French stocks under investigation. In Section 4, we present the methodology of our analysis. First, we discuss two approaches used to calculate relative contribution to the price discovery process based on Hasbrouck (1995) and Gonzalo and Granger (1995). Then, we outline the methodology of our cross-sectional analysis and construction of our prominence measures and control variables. Section 5 presents the main empirical results and discusses various robustness checks. Section 6 summarizes and concludes the paper.

2. The Role of NYSE Specialist and Market Making in Non-U.S. Stocks

Every security traded on the NYSE has a single designated specialist.[2] The specialists are responsible for maintaining a fair and orderly market in assigned securities. They facilitate price discovery and maintain liquidity by posting firm and continuous bid and ask quotes, committing own capital to supply short-term liquidity in the absence of public bids and offers, and reducing stock price volatility by trading against the market trend. At times of significant information releases or extreme order imbalances, the specialist may halt trading to allow investors to react to new information. In line with the previous literature on NYSE specialists, we identify a specialist by a unique panel location on the NYSE floor. At the beginning of 2003, specialists were located in 359 panels. Individual specialists are employed by specialist firms, and in 2003 there were seven specialist firms. When a new security is listed on the NYSE, the Exchange's Allocation Committee shortlists applications from specialist firms interested in handling the security and then the listing firm chooses a specialist firm from this pool (see, Corwin (2004) for details). Specialists firms assign securities across their own individual specialists. Stocks are hardly ever relocated between specialist firms but reassignments of securities between specialists within a firm are relatively common (Anand et al., 2008; Corwin and Coughenour, 2008).

There are inherent differences between making a market in non-U.S. stocks traded on the NYSE and their U.S. domestic counterparts. They result from different institutional details and differences in the flow of information related to the security. The foreign firms' securities may not be fully fungible across home and U.S. markets, they may be subject to different national regulations, accounting and reporting standards, and their trading may be influenced by time zone differences between home country and the U.S., all of which can lead to

[2] The market model based on specialists described here was in place until October 2008, covering our sample period. Under the new rules, NYSE specialists became Designated Market Makers (DDM). DDMs have no 'advanced look' at incoming orders and hence compete as market participants but have new rights in the way they trade.

differences in pricing in markets where the firm lists (Gagnon and Karolyi, 2004). Moreover, foreign stocks are usually actively traded in their home markets and U.S. traders may have limited access to information on trading there. Domowitz et al. (1998) show that the level of information linkages between markets has a direct impact on the market quality. If the markets are not fully integrated and access to information is indeed limited, greater adverse selection increases trading costs when informed arbitrage traders exploit price differences at the expense of less informed liquidity providers.

Empirical evidence of the importance of information asymmetry and adverse selection in trading behavior and liquidity provision by NYSE specialist in non-U.S. stocks is provided by Bacidore and Sofianos (2002). Using proprietary data, they find that specialist closing inventories for non-U.S. stocks are closer to zero than for U.S. stocks, and specialist participation and stabilization rates for non-U.S. developed market stocks are higher than those of U.S. stocks, while for non-U.S. emerging market securities they are significantly smaller. Non-U.S. stocks are also found to have larger spreads, less quoted depth and greater volatility. The authors conclude that higher trading costs reflect additional compensation demanded by the NYSE specialists to compensate for higher adverse selection risks borne in trading foreign stocks. Higher adverse selection inherent in trading non-U.S. stocks is confirmed by Bacidore et al. (2005) in a study of the sources of liquidity for non-U.S. NYSE-listed stocks. They find that foreign stocks have less displayed liquidity and a similar level of non-displayed liquidity than comparable U.S. stocks. In a related study, Moulton and Wei (2009) document narrower spreads and more competitive liquidity provision for NYSE-listed European stocks when their home markets are open. The authors interpret these findings as evidence of the impact of the availability of substitutes and the improved information environment of specialist trading during the trading overlap.

Bacidore and Sofianos (2002) provide a few policy recommendations which they believe could lead to a reduction in information asymmetries associated with market making in foreign stocks and hence could reduce trading costs and increase NYSE competitiveness. One of the suggestions is a stock allocation policy that encourages concentration of non-U.S. stocks in particular specialists.[3] Bacidore and Sofianos (2002) argue that ‘a specialist ‘‘specializing’’ in Mexican stocks, for example, will have strong incentives to develop ties with the home market including, possibly, an association with local broker-dealers’ (p. 157). Corwin (2004) confirms that newly listed non-U.S. stocks indeed tend to be allocated to specialist firms that already trade other foreign stocks. The benefits of the concentration go beyond the institutional links with international stock markets though. They are also related to the theoretical arguments on informational advantages of clustering similar stocks with correlated payoffs in market makers’ books (Strobl, 2001; Baruch et al., 2007). As shown by Baruch et al. (2007), when market makers trade ‘closely related’ stocks, they can infer information not only from an asset’s own order flow, but also from order flows of the other related assets. The authors build a theoretical model and provide empirical evidence which shows that the volume in the U.S. is higher for cross-listed stocks that are correlated with other stocks traded in the U.S. market, and that is explained by the lower costs of trading in these cross-listed stocks.

3. Data and Sample

The data were taken from various sources. NYSE trades and quotes were downloaded from the Trade and Quote (TAQ) database. The London Stock Exchange and the Euronext Paris provided tick data at one minute interval on domestic trading of British and French stocks, respectively. Intra-day exchange rates were obtained from Olsen. Data on the ratio of

[3] Other policy recommendations include extension of NYSE trading hours, developing and strengthening linkages between the NYSE and foreign stock markets and efforts to improve insider trading regulations across

ADR and ordinary shares come from The Bank of New York web page (www.adrbny.com), and allocation of stocks across specialists is from the NYSE. The sample period spans six months from January 2003 through June 2003 and covers 122 trading days in both U.K. and French subsamples, after exclusion of public holidays in either home or U.S. market. All three stock markets (U.S., U.K. and France) followed similar patterns during this period. There was a downward drift with a local minimum of market indices about mid-March, followed by upward trend towards the end of the sample period. There seems to be no single event or day that may be particularly noteworthy over those six months.

The sample includes British and French companies listed on the domestic exchange and cross-listed on the New York Stock Exchange throughout the whole six-month sample period. We exclude two companies that changed ADR ratios (British Energy and P&O Princess Cruises) since this action could have a significant impact on liquidity (see, Muscarella and Vetsuypens, 1996). Any shocks to liquidity and microstructure environment for our sample stocks could lead to a break in comparability of the relevant characteristics of the home and U.S. markets throughout the period. We also exclude ADRs representing preferred stocks, as their pricing mechanism may be substantially different from common ADRs and ordinary shares. We depart from many prior studies by not making any exclusions on the basis of trading intensity and liquidity. We investigate the price discovery process and its determinants in the breadth of the sample, not confining it to the most liquid, and hence conceivably largest companies.[4] Altogether, our sample includes 64 companies, 43 from the U.K. and 21 from France. Table 1 presents basic characteristics of the sample stocks.

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the globe.

[4] Additionally, for France Telecom, we exclude the period between March 25, 2003 and April 14, 2003 which was the difference between the date of distribution of warrants to holders of ordinary shares and the date of distribution of cash proceeds from the sale of warrants to holders of ADRs. In that period, the price difference between ADRs and ordinary shares depended on the price of warrants. Similarly, for Lafarge we exclude the period after June 19, 2003 that was the date of distribution of rights in the local markets only. Proceeds from the sale of these local rights were distributed to the ADR holders at a later date outside our sample period.

The market capitalization of individual firms varies from USD 196 million for France's Compagnie Generale de Geophysique to USD 146,975 million for BP. While there is no clear difference in the average size of U.K. and French sample companies and their home liquidity, U.K. stocks tend to have higher liquidity in the U.S. market, as measured by trading volume and spreads, than their French counterparts. Still, in both U.K. and French subsamples liquidity in the home market is overwhelmingly larger than in the U.S. in terms of the dollar trading volume and the number of trades. The sample mean (median) dollar trading volume in the U.S. market as a percent of the total dollar trading volume in both the home and the U.S. market during the overlapping trading hours is 4.4% (2.0%). For only two stocks, BP and France's STMicroelectronics, the NYSE captures more than 20% of total trading volume.[5] The lower liquidity in the U.S. is also reflected in larger effective spreads which are, on average, over twice larger in the U.S. than in the home market. However, it is worth noting the frequent quote revisions in the U.S. market. There are fewer revisions in the U.S. than in the home market but the gap is considerably smaller than the gap in the trading activity.

The London Stock Exchange and the Euronext Paris are automated, electronic limit order markets, and the New York Stock Exchange operates as a hybrid system, with both a limit book and specialists acting as market makers (see, for example, Parlour and Seppi (2003) and Hendershott and Moulton (2009) for details). There is a two-hour overlap in trading in the three exchanges. It starts at 14:30 GMT (9:30 EST) when the U.S. market opens and lasts until 16:30 GMT (11:30 EST) when both London and Paris exchanges close. The exact overlap between Paris and London excludes the possibility of the results being influenced by different trading designs. Figure 1 depicts trading times in the markets covered by the study. Specifically, since we focus on continuous trading only, our price series from

[5] Our estimates are similar to Moulton and Wei's (2009) who find in their sample of 40 U.K. stocks cross-listed on the NYSE in the whole 2003 that, on average, 4.4% of global trading occurred on the NYSE, with a range of less than 1% to 27%. The findings are consistent with findings by Halling et al. (2008), who document the

the Euronext Paris end at 16:25 GMT, when continuous trading finishes followed by the closing auction. The closing auction in London starts after 16:30 GMT. Because daylight saving time started in Europe one week earlier than in the U.S., there was a one-hour overlap (15:30-16:30 GMT) from March 30, 2003 to April 6, 2003.

Following the approach commonly used in previous intra-day price discovery studies, we form our price series on the basis of equally-spaced midpoints of the best bid and ask quotes. Using transaction prices instead may suffer from the problem of autocorrelation and, moreover, quotes can be updated even if there is no trading. Supporting evidence for that is reported in Table 1, where differences in the frequency of quoting between the home and the U.S. market are visibly smaller than discrepancies in the trading volume and the number of transactions. We set our interval to one minute[6], and each point in our price series represents the average of the last best bid and ask prices within the 1-minute interval. If no change of the best quotes is reported within the interval, the observation represents the last available quotes. The first 1-minute interval each day containing quotes in both markets is the initial observation for that day in our series.[7] The choice of the sampling interval is done arbitrarily with a tradeoff in mind between too many stale quotes if the interval is too narrow and dissolution of one-way causality into contemporaneous correlations when too much activity is observed within an interval at lower frequencies.

4. Methodology

4.1 Measures of Information Shares

widespread presence of flow-back towards the home market and a decline in foreign trading to extremely low levels.

[6] As a robustness check we perform the analysis on the 2, 3 and 10-minute intervals. See Section 5 for the discussion of the results.

[7] The median NYSE opening delay across 7785 firm-day observations in our sample is 4 minutes. In 25 cases it is longer than 15 minutes, and in 3 cases it is longer than 30 minutes.

In calculating the information share of the U.S. and home markets in the price discovery process, we use both the Hasbrouck (1995) information share technique and the Gonzalo and Granger (1995) common component method. These models are the two most prevalent common factor models. They are directly related and the results of both models are primarily derived from the vector error correction model (VECM). They provide similar results if the VECM residuals are uncorrelated. In the case where there is contemporaneous correlation we use Cholesky factorization, which is, however, variable order dependent. Following Hasbrouck's (1995) suggestion we use different orders and average the upper and lower information share bounds. In our paper, we use both of the above models as complementary methods.[8] We present below both estimation approaches based on Baillie et al. (2002).

We expect the price of an instrument cross-listed in a foreign market, adjusted for the exchange rate, not to deviate from the price in the home market. The law of one price, which prevents any arbitrage opportunities in international cross-listings, implies a cointegrating relationship between the log home price, p_{1t}, and log U.S. price, p_{2t}, converted to the same currency with a cointegrating vector $\beta = (\beta_1, \beta_2)' = (1, -1)'$. In our analysis, we denominate all price series in U.S. dollars and convert local U.K. and French prices using intra-day exchange rates.[9] Both models start from the estimation of the following VECM:

(1) $$\Delta P_t = \alpha\beta' P_{t-1} + \sum_{j=1}^{k} A_j \Delta P_{t-j} + e_t ,$$

where $\alpha = (\alpha_1, \alpha_2)'$ is the error correction vector, $P_t = (p_{1t}, p_{2t})'$ is a vector of log prices and e_t is a zero-mean vector of serially uncorrelated innovations with covariance matrix Ω,

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[8] Previous studies have used one of the two methods, e.g. Eun and Sabherwal (2003) and Kaul and Mehrotra (2007) use the Gonzalo-Granger method, while Grammig et al. (2005a, 2005b) use the Hasbrouck method.
[9] The main results remain unchanged when we convert the price series to local currencies, i.e. to pounds for U.K. stocks and to euros for French stocks.

(2) $$\Omega = \begin{pmatrix} \sigma_1^2 & \rho\sigma_1\sigma_2 \\ \rho\sigma_1\sigma_2 & \sigma_2^2 \end{pmatrix}.$$

The VECM has two components: the first one, $\alpha\beta' P_{t-1}$, represents the long-run or equilibrium dynamics between the two price series, and the second one, $\sum_{j=1}^{k} A_j \Delta P_{t-j}$, shows the short-term dynamics caused by market imperfections.

Hasbrouck (1995) transforms equation (1) into a vector moving average (VMA) in an integrated form

(3) $$P_t = \psi(1)\sum_{s=1}^{t} e_s + \psi^*(L)e_t,$$

where $\psi(L)$ and $\psi^*(L)$ are matrix polynomials in the lag operator, L. Denoting $\psi = (\psi_1, \psi_2)$ as the common row vector in $\psi(1)$, equation (3) becomes

(4) $$P_t = \iota\psi(\sum_{s=1}^{t} e_s) + \psi^*(L)e_t,$$

where $\iota = (1,\ 1)'$ is a column vector of ones.

The increment ψe_t in equation (4) is considered by Hasbrouck (1995) as the component of the price change that is permanently impounded into the price and could be due to new information. He defines this component as the common efficient price – common factor. If price innovations are significantly correlated across prices, Hasbrouck (1995) uses Cholesky factorization $\Omega = MM'$ to eliminate the contemporaneous correlation, where:

(5) $$M = \begin{bmatrix} m_{11} & 0 \\ m_{12} & m_{22} \end{bmatrix}.$$

If we further denote $\alpha\perp = (\gamma_1, \gamma_2)'$, which is also the Γ in Gonzalo and Granger's (1995) model, then the information shares of the two prices are:

(6) $$S_1 = \frac{(\gamma_1 m_{11} + \gamma_2 m_{12})^2}{(\gamma_1 m_{11} + \gamma_2 m_{12})^2 + (\gamma_2 m_{22})^2}, \text{ and}$$

(7) $$S_2 = \frac{(\gamma_2 m_{22})^2}{(\gamma_1 m_{11} + \gamma_2 m_{12})^2 + (\gamma_2 m_{22})^2}.$$

In order to get the information share of each market, the order of the prices is changed and the calculation process is repeated. The average of the two results is suggested by Hasbrouck to be the final information share.

Gonzalo and Granger (1995) define the common factor to be a combination of the variables P_t, such that $h_t = \Gamma P_t$, where Γ is the common factor coefficient vector. The information shares of the two markets according to this model are as follows:

(8) $$S_1 = \frac{\gamma_1}{\gamma_1 + \gamma_2}, \text{ and}$$

(9) $$S_2 = \frac{\gamma_2}{\gamma_1 + \gamma_2}.$$

Thus, the Gonzalo and Granger's (1995) approach is concerned with only the error correction process, which involves only permanent as opposed to transitory shocks that result in a disequilibrium. It ignores the correlation among the two prices and measures each price's contribution to the common factor on the basis of its error term. The price which adjusts the least to the other price movements has the leading role in the price discovery process. In contrast, Hasbrouck (1995) defines price discovery in terms of the variance of the innovations to the common factor assuming that price volatility reflects the flow of information. Information share in this model is each price's relative contribution to the variance.[10]

We conduct the usual procedures of unit root and cointegration tests before estimating the information share of each market. Because overnight price discovery may follow different dynamics, overnight returns and lags that reach the previous day are excluded from the

[10] According to Baillie et al. (2002) the two models complement each other and provide different views of the price discovery process between markets. On the other hand, de Jong (2002) concludes that Hasbrouck's measure is a more proper measure of the amount of information generated by each market. Harris et al. (2002) have different view and employ Granger and Gonzalo (1995) to estimate and test common factor components attributable to each market.

estimation. Consequently, for each stock we exclude first k observations of the dependent variables each day. The lag length k is determined by the Schwarz Information Criterion (SIC).

4.2. Cross-Sectional Analysis of the U.S. Contribution to Price Discovery

The size of our sample, 64 stocks in total, enables us to run cross-sectional regressions to examine factors which affect the size of the U.S. market contribution to price discovery. Our dependent variable is the logistic transformation of the U.S. market contribution to price discovery.[11] The logistic transformation ensures that the predicted values lie between zero and one, which by definition are the bounds of the contribution.

We start with a set of the following regressions to analyze the association between the U.S. share in price discovery and stocks' prominence in specialist portfolios:

(10) $\textit{U.S. share in price discovery}_i = \beta_0 + \beta_1 \textit{ Own prominence}_i + \varepsilon_i\,;$

(11) $\textit{U.S. share in price discovery}_i = \beta_0 + \beta_1 \textit{ Prominence of related stocks}_i + \varepsilon_i\,;$

(12) $\textit{U.S. share in price discovery}_i = \beta_0 + \beta_1 \textit{ Own prominence}_i +$

$$+ \beta_2 \textit{ Prominence of related stocks less own}_i + \varepsilon_i\,.$$

Related stocks refer to stocks from the same country, European stocks or non-U.S. stocks interchangeably. To calculate the prominence variables we base on approaches in Corwin and Coughenour (2008) and Boulatov et al. (2009). First, we collect all daily NYSE specialist directory files for our sample period. The files list the specialist firm assigned to each security, as well as the trading location of the security on the NYSE floor as described by different posts and panels. There are 18 posts and various alphabetically labeled panels on each post, and the individual specialist responsible for each stock is identified by a unique post and panel. On the basis of the files we identify the post and panel location of our 64

[11] If S is the information share, then our dependent variable is $\ln(S/(1-S))$.

sample stocks and for every day in our sample period we identify all other stocks traded together with the sample stocks in the same location. We call all stocks traded in the same location a specialist portfolio. Following Corwin and Coughenour (2008), in our analysis we include only common stocks and ADRs (CRSP share codes equal to 10, 11, 12, 30 or 31).

Using TAQ trading data, for every security for every day in our sample we calculate the dollar volume in the trading overlap between New York and London and New York and Paris. We define a stock's prominence as the proportion of its dollar volume in the total volume of the specialist portfolio it belongs to.[12] In regressions (10) and (11) we look at the stock's own prominence, the prominence of all stocks from the same country (i.e., all U.K. or all French stocks, respectively) in the portfolio, the prominence of all European stocks in the portfolio and the prominence of all non-U.S. stocks in the portfolio. To disentangle the effect of a stock's own prominence and the effect of the prominence of other related stocks in the specialist portfolio, in regression (12) we also look at the prominence of related stocks that excludes the stock's own prominence. All prominence variables are calculated for each sample firm for each day and then averaged over the sample period. The daily calculation allows for daily changes in the composition of a specialist portfolio due to stock reassignments between specialists, new stock listings or delistings.

We further proceed with a set of regressions that control for factors found to affect the foreign market's share in price discovery of cross-listed stocks:

$$\text{(13)} \quad \textit{U.S. share in price discovery}_i = \beta_0 + \beta_1 \textit{ Own prominence}_i + \\ + \beta_2 \textit{ Prominence of related stocks less own}_i + \\ + \beta_3 \textit{ U.S. / Total dollar volume}_i + \beta_4 \textit{ U.S. / Home effective spread}_i + \\ + \beta_5 \textit{ Ln (Market capitalization}_i\textit{)} + \beta_6 \textit{ U.K. dummy}_i + \varepsilon_i .$$

[12] As a robustness test we recalculate the prominence on the basis of the number of trades rather than the dollar volume. The results are unchanged.

Eun and Sabherwal (2003) and Grammig et al. (2005b) show that the share in the price discovery process is directly related to the share in total trading volume and inversely related to the ratio of bid-ask spreads.[13] A higher share in total trading is likely to increase efficiency of the market and may indicate informativeness of the underlying demand (Stickel and Verrecchia, 1994). As suggested by Foerster and Karolyi (1998), it may also reflect higher competition for order flow by the foreign market, which might make the local market more responsive to the foreign market prices. For each stock, we calculate the dollar trading volume in the U.S. as a percentage of the total home and U.S. dollar volume within the trading overlap for each day in the sample period, and then the daily observations are averaged over the sample period. The bid-ask spread represents a major proportion of the trading costs, and we expect the U.S. market contribution to the price discovery process to increase when its spreads relative to domestic spreads decline. The lower the spread on the U.S. exchange, the greater the competition from the U.S. market makers and the greater the response of the local markets. On the NYSE trades often occur inside the bid-ask quotes reflecting price improvements coming from specialists or floor brokers (see, Chordia et al., 2001), therefore we look at effective spreads to capture competitiveness between markets.[14] Effective spread is calculated as twice the absolute value of the difference between the trade price and the midpoint of the prevailing bid and ask quotes at the time of the trade, divided by the quote midpoint. It is averaged across all trades for a given firm within the trading overlap each day, and then the daily observations are averaged over the sample period.

We also control for the firm size measured as the logarithm of the average daily market capitalization (in millions of U.S. dollars) over the sample period.[15] Larger firms have high transparency and tend to be of greater interest to foreign investors as found by studies of

[13] Harris et al. (2003) make also a connection between liquidity, information and home bias in international investment. Domestic investors may be better informed and better able to monitor local firms than foreign firms.
[14] The exchanges in London and Paris are electronic order markets and transactions occur at the quoted bid or ask prices. In this respect effective spread is equal to the quoted spread.

cross-border stock holdings (see e.g., Kang and Stulz, 1997). We further control for the company's country of origin by including a dummy variable equal to one for British companies and to zero for French ones. This is a proxy for familiarity and for sharing the same language and cultural background, which are documented to influence stock holding and trading decisions (see, e.g., Grinblatt and Keloharju, 2001, and Chan et al., 2005). We can expect a relatively higher U.S. share in price discovery for U.K. stocks than for French stocks. Definitions of all explanatory variables used in the regressions are summarized in the Appendix.

5. Empirical Results

5.1. Vector Error Correction Results and the U.S. Share in Price Discovery

We perform ADF unit root tests on the levels of two log price series for each sample firm using three different test specifications, i.e. without constant, with a constant and with a constant and time trend. The test in the first specification does not reject the null hypothesis of a unit root at the 5% significance level for any of the firms. We obtain rejections at the 5% level for at least one of the two price series for 6 stocks in the test with a constant, and for 4 stocks in the test with a constant and trend. For differenced series we can reject the null of a unit root at the 1% significance level for all stocks. In the next step we test for cointegration between prices in the home and U.S. market using the Johansen's (1991) trace statistic. For all sample stocks, we can reject the null hypothesis of no cointegration.

The lag structure of the VECM is determined by the SIC criterion. We started with 15 lags, and then keeping the number of observations constant, we re-estimated the model at each shorter lag. The lag length that minimizes the criterion varies from one for Compagnie Generale de Geophysique to 13 for The BOC Group, with the sample mean and median of 7

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[15] Market capitalization data are taken from Datastream.

lags. Cross-sectional descriptive statistics of the estimated cointegrating vectors are presented in Panel A of Table 2. We normalize our estimates on the home market by setting β_1 equal to one. As expected, prices in the home and U.S. market move closely together, and the average estimates of the elements of the cointegrating vector are close to the β vector of the form $\beta = (1, -1)'$ as indicated by the theory of the law of one price. We find median β_2 is equal to –1.0029. Divergence from the theoretical value of minus one in the case of individual stocks is conceivably caused by transaction costs bounds implying that small divergences cannot be arbitraged away.

Panel B of Table 2 presents cross-sectional descriptive statistics of the estimates of the error correction vectors α from the Vector Error Correction Models given by equation (1). The error correction vectors provide information on the adjustment of each price series to the deviation from the equilibrium in the previous period, $\beta' P_{t-1}$. Either or both home share and ADR prices must respond to the deviation to prevent riskless arbitrage opportunities. For instance, if the price in the U.S. market is lower than the price in the home market (adjusted for the exchange rate), the U.S. price will increase and the home market price will decrease in the following period to restore the equilibrium.[16] Thus, the expected signs of α^H and α^{US} will be negative and positive, respectively, and their absolute values show the magnitude of the response. We find that the median adjustment coefficient for the home market prices, α_1, is -0.0076 compared to the median correction in the U.S. market, α_2, of 0.0363. Looking at the significance of individual estimates (not reported in the table), α_1 has a negative sign and is significant at the 5% level for 30 out of 64 stocks. In contrast, adjustment in the U.S. market, α_2, is positive and significant at the 5% level for 63 out of 64 stocks. The results provide first evidence that new information tends to be incorporated into stock prices in the home market, while the U.S. market follows and is responsive to what is happening on the home exchange.

We subsequently calculate the U.S. share in the price discovery process using both the Hasbrouck (1995) information share approach as given by equation (7) and the Gonzalo and Granger (1995) common component method as given by (9).[17] Descriptive cross-sectional statistics of the shares in the whole sample, as well as in the U.K. and French subsamples are presented in Panels C and D of Table 3. Looking first at Panel C which reports the results of the Gonzalo-Granger approach, we find that the mean contribution of the U.S. market in our whole sample is 20.3% with the median of 14.3%. While there is no difference in the mean contribution between U.K and French stocks, U.K. stocks have a higher median U.S. contribution. The results for the Hasbrouck method are presented in Panel D. The mean (median) U.S. information share is 15.5% (9.0%) and there is a very small difference between the UK and the French stocks. As noted earlier the Cholesky factorization of the innovation variance-covariance matrix produces results which are variable order dependent. We adopt Hasbrouck's (1995) suggestion and report the average of both extreme bounds. In our case the mean (median) lower bound for the U.S. share in price discovery is 6.4% (2.8%) when the home price comes first in the ordering and the mean (median) upper bound is 24.6% (16.2%) when the U.S. price comes first.[18] It is worth noting that the correlation between the price discovery measures calculated according to the Gonzalo-Granger method and the Hasbrouck method is 0.96.

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[16] It is also possible that the home price increases and the U.S. price increases more, or the home price decreases but the U.S. price decreases less.

[17] For five stocks both α_1 and α_2 are positive. In those cases the home market seems not to be affected by the divergence from equilibrium. In the following minute, the home market moves further away and the U.S. market makes up for the divergence adjusting more in absolute values. The Gonzalo-Granger method yields a negative U.S. share in price discovery then. In those cases we arbitrarily assign a 0.01% U.S. share in the price discovery to make it tractable in further steps involving logistic transformation of the variable.

[18] The distance between the lower and upper bound is driven by the correlation of VECM residuals. The average correlation coefficient in our estimations is 0.27.

Thus, similarly to earlier studies, we find a dominant role of the home market in price discovery. Our average estimates are below the U.S. share in the pricing process of cross-listed Canadian companies found by Eun and Sabherwal (2003). Their mean and median are 38.1% and 36.2%, respectively. The difference could be due to the higher economic integration between Canada and U.S. and to the larger proportion of trading on U.S. exchanges in total trading of cross-listed Canadian stocks. However, Kaul and Mehrotra (2007), who also examined Canadian stocks, report a difference between U.S. price discovery share for cross-listed stocks in NYSE and NASDAQ. They find that the mean (median) is 13% (6%) for NYSE stocks and 47% (41%) for NASDAQ stocks. Looking at other European cross-listed stocks, our results show a larger role of the U.S. market than the results of Grammig et al. (2005a) for German blue chips, and are of a similar magnitude to Hupperets and Menkveld (2002) findings for Dutch companies.

From our perspective, the most important finding is the meaningful cross-sectional variability of the price discovery measure, in line with previous studies on different samples. We find that the estimated U.S. share in the pricing process varies from virtually zero to as high as 70.2% according to the Hasbrouck method and even 86.4% according to the Gonzalo-Granger method. Stocks with the highest U.S. share in price discovery following the Gonzalo-Granger (Hasbrouck) approach are Bunzl 86.4% (67.0%), Total 81.4% (70.2%), BP 57.9% (48.2%), HSBC Holdings 55.9% (41.5%) and AstraZeneca 55.8% (49.1%). On the other hand, the U.S. market contributes less than 2% to price discovery of Technip, Compagnie Generale de Geophysique, Scor, Veolia Environment, Publicis Groupe, Corus Group, Enodis and Premier Farnell. We interpret the dispersion of the U.S. share in price discovery in our sample as evidence of differences in the information environment of NYSE specialists who are market makers our sample stocks. In the subsequent sections we explore how the U.S.

share in price discovery varies with the prominence of related stocks in the specialist portfolio which, we argue, has an impact on the informational advantage of specialists.

As a robustness check we re-estimate the shares in price discovery lowering the frequency to 2, 3 and 10 minutes. With lower frequencies we may reduce the number of stale quotes, but an important caveat is in order. With lower sampling frequencies cross-correlation between price changes in the home and U.S. market increases leading to larger estimation errors in the markets' share in price discovery. Contemporaneous price movements in larger windows blur the picture and make it difficult to assign the role in price discovery to individual markets. In the Hasbrouck approach, the cross-correlation results in a wider gap between the lower and upper bound of the information share, ultimately pushing the midpoint between the two towards the 50% mark. Indeed, the mean (median) Hasbrouck's U.S. share in price discovery increases monotonically from 15.5% (9.0%) for a 1-minute interval to 36.4% (38.4%) for a 10-minute interval. The estimates according to the Gonzalo-Granger method are more stable, and their sample mean (median) changes from 20.3% (14.3%) for a 1-minute interval to 29.0% (25.5%) for a 10-minute interval.

5.2. Prominence of Stocks in Specialist Portfolios

This section analyzes the prominence measures of the sample stocks – our main explanatory variables of interest. As defined in detail in Section 4.2, a stock's prominence is proxied by the proportion of its dollar volume in the total volume of the specialist portfolio it belongs to. We look at the prominence of our sample stocks and at the prominence of a set other similar stocks assigned to the same NYSE specialist. We define similar stocks at three levels: as stocks from the same country, the same region (in our case Europe) or other foreign stocks. The descriptive statistics of the measures for all sample stocks and for the U.K. and French subsamples are presented in Table 3.

The average prominence of our sample stocks in their respective post and panel locations is 11.3%. Each stock is, on average, located with sibling stocks from the same country that generate 10.2% prominence, bringing the total prominence of all stocks from the same country to 21.5%. The average stock is also assigned to a specialist who allocates 40.7% of his attention to other European stocks and as high as 61.7% of his attention to other non-U.S. stocks. Our findings extend the evidence in Corwin (2004) who finds that foreign firms tend to be clustered in NYSE specialist firms. We further find that specialist firms tend to concentrate foreign stocks in individual specialists, and more than a quarter of our sample firms are assigned to panels that trade non-U.S. stocks only. It is worth noting though that specialist firms appear to concentrate individual specialists in international stocks from multiple countries as opposed to concentrating them in securities from one country or one region. If the latter was the case, we would find no or little difference between the prominence of country's, European and non-U.S. stocks as a specialist with, for example, U.K. stocks would trade few other European or non-U.S. stocks. Furthermore, we find substantial cross-sectional variation of all prominence variables, which squares with the cross-sectional variation in the price discovery measure reported earlier. The meaningful differences in the variables across our sample stocks lend further support to the design of our empirical tests.

Looking at the statistics across the U.K. and French subsamples, we find that U.K. stocks tend to be assigned to specialist portfolios with a larger average prominence of other stocks from the same country (11.7% versus 7.2% for French firms) but with a lower prominence of other European or other non-U.S. stocks (38.1% versus 45.8%, and 58.8% versus 67.7%, respectively). Despite the higher NYSE dollar trading volume for U.K than for French stocks as reported in Table 1, there is no gap between the average measure of own prominence between U.K. and French firms. It is consistent with Boulatov et al. (2009) who show that there is no evidence that specialist firms follow a simple rule whereby stocks with the highest trading activity are assigned to be the most prominent stocks in their respective locations. Similarly to Boulatov et al. (2009) we interpret our finding as evidence that the prominence is not driven solely by trading activity but is determined by the way specialist firms assign stocks to individual specialists. It further validates the empirical design of our tests and strengthens our argument on the importance of the specialist portfolio composition and allocation of attention across stocks in the portfolio that go beyond the absolute trading activity of the sample stocks.

Table 4 presents correlation coefficients between the prominence variables and other explanatory variables we use in the subsequent cross-sectional regressions. The measure of own prominence is highly correlated with the U.S. share in total trading volume (correlation coefficient of 0.82) which is not surprising considering that both variables are derived from the stock's trading activity. *Own prominence* is also strongly negatively correlated with another measure of relative liquidity, the ratio of effective spreads (coefficient of -0.47), and positively correlated with the size of the firm proxied by the natural logarithm of market capitalization (coefficient of 0.67). By construction, *Own prominence* is positively correlated with the prominence of the country's, European and non-U.S. stocks, with the strength of the correlation diminishing towards the higher level of aggregation. The three control variables, *U.S. / Total dollar volume*, *U.S. / Home effective spread* and *Ln (Market capitalization)*, are correlated between one another with the absolute values of the correlation coefficients of just under 0.50. However, there is no significant correlation between them and the prominence of the group of related stocks that exclude the stock's own prominence. To minimize the potential impact of multicollinearity on our results, the correlations between the explanatory variables are taken into account in the choice of regression specifications in the following section.

5.3. Multivariate Cross-Sectional Analysis

In this section we present results of a set of cross-sectional regressions to show how the U.S. share in price discovery differs with the prominence of related stocks in the specialist portfolio. The dependent variable in the regressions is the logistic transformation of the U.S. share in price discovery. The results are presented separately for the shares in price discovery calculated following the Gonzalo and Granger (1995) and Hasbrouck (1995) methods.

We start with regressions that analyze the link between price discovery and prominence without controlling for other factors, as shown in Table 5 (the Gonzalo-Granger method) and Table 6 (the Hasbrouck method). The specifications minimize the potential problem of multicollinearity, considering the high correlations between *Own prominence* and the control variables presented in Table 4. Overall, we find strong evidence that the U.S. share in price discovery increases with the stock's own prominence in the NYSE specialist portfolio, with highly significant positive coefficients across all regression specifications and both price discovery estimation methods. The result confirms the findings in Corwin and Coughenour (2008) and Boulatov et al. (2009) who document improved market quality for stocks that receive more attention. Specifications (ii), (iv) and (vi) presented in the tables look at the prominence of groups of related stocks: stocks from the same country, European stocks and non-U.S. stocks, respectively. By construction those variables capture the stock's own prominence but also measure the prominence of other related stocks traded by the same specialist. We find that the estimated coefficients are also consistently positive and highly significant.

However, our main interest focuses on the incremental impact of the prominence of other related firms over the stock's own prominence and the results for such tests are presented in columns (iii), (v) and (vii) of the tables. We find that a greater prominence of other similar stocks assigned to the same specialist portfolio increases the U.S. share in price discovery of our sample stocks. The coefficients are positive and statistically significant in all but one specification (*Prominence of country's stocks less own* with the share in price discovery calculated using the Hasbrouck method presented in column (iii) of Table 6), and the addition of the variable reflecting the prominence of other related stocks improves the explanatory power of regressions measured by adjusted R-square. To illustrate the economic significance of the prominence of similar stocks[19], with *Own prominence* set to its sample median, increasing the prominence of other stocks from the same country from the 25th to the 75th percentile of its distribution increases the U.S. share in price discovery of the stock by 2.6 percentage points. The same increase in the prominence of other European stocks increases the U.S. share in price discovery by 3.7 percentage points, while an increase in the prominence of other non-U.S. stocks moves the U.S. market's contribution up by as much as 8.3 percentage points. To put this in a perspective, the median U.S. share in price discovery calculated according to the Gonzalo-Granger method is 14.3%. We interpret the finding as evidence that a specialist who pays more attention to other similar stocks has an informational advantage. He can extract information from order flow to a set of firms with correlated pay-offs and hence is able to provide more efficient and informative pricing.

In further regressions we extend the specifications that focus on the effect of the prominence of other similar stocks and add control variables identified in earlier research to influence the price discovery in international cross-listings, as discussed in Section 4.2. As mentioned above, the three control variables, *U.S. / Total dollar volume*, *U.S. / Home effective spread* and *Ln (Market capitalization)*, are correlated between one another and therefore we include them one by one, but for the completeness of the picture we also include them simultaneously. We acknowledge the problem of correlation between *Own prominence* and the control variables and also between the control variables themselves, but we want to make

[19] Note that direct interpretation of the estimated coefficients is difficult because of the logistic transformation of the U.S. share in price discovery used as our dependent variable. The illustration is based on the results presented

sure that the strongly significant link between our prominence measures and the U.S. share in price discovery reported in Tables 5 and 6 is not driven by the fact that our prominence variables capture the effect of the excluded control variables. The results of the extended regressions are presented in Table 7 (the Gonzalo-Granger method) and Table 8 (the Hasbrouck method).

The findings on the prominence of other similar stocks reported in Tables 5 and 6 remain to a large extent unchanged after the inclusion of control variables. The only difference is the lack of significance of the *Prominence of European stocks less own* in some specifications with the U.S. share in price discovery calculated following the Gonzalo-Granger method (columns (vi), (vii) and (viii) of Table 7). Also, as in the earlier regressions, the *Prominence of country's stocks less own* remains insignificant in tests with Hasbrouck's definition of shares in price discovery. In all other specifications the prominence of related stocks is found to have a strong positive impact on the U.S. share in price discovery confirming informational advantages of concentrated market making. Considering the mixed results for the prominence of sibling stocks from the same country or the prominence of other European stocks, which as we find depend on the definition of the shares in price discovery, the most consistent results are found for the prominence of other non-U.S. stocks. We show that a NYSE specialist is able to improve price discovery of a non-U.S. stock if he pays more attention to other foreign stocks. It shows the benefits of concentrating specialists in international stocks from multiple countries as reported in Section 5.2. It appears that there is a larger informational advantage from allocating attention across a broader set of international securities rather than focusing on country-specific groups of firms. The finding is also in line with evidence in Corwin (2004) who shows that new foreign stocks tend to be allocated to

in Table 5.

specialist firms that already trade other foreign securities. Our findings document the benefits of clustering non-U.S. stocks at the individual specialist level.

The positive effect of the stock's own prominence remains highly significant when the control variables are added individually but loses its significance when they are all added at the same time (specifications (iv), (viii) and (xii)). It is worth noting that *Own prominence* has a much stronger effect than the relative trading volume which is found to be the key driver of the U.S. share in price discovery in earlier studies (Eun and Sabherwal, 2003; Grammig et al., 2005b). When the two variables are included jointly in the regressions, *U.S. / Total dollar volume* is never significant. Looking at other control variables, we find strong evidence that lower bid-ask spreads in the U.S. relative to the home market increase the U.S. contribution to price discovery calculated following the Hasbrouck method (reported in Table 8), consistent with earlier research (Eun and Sabherwal, 2003; Grammig et al., 2005b). We also find some evidence that the U.S. share increases for larger firms. After controlling for other factors, there is no difference in the U.S. share in price discovery between the U.K. and French stocks as the *U.K. dummy* is by and large insignificant.

We are aware of the potential endogenous relations in our tests. For example, one may argue that there is a reversed causality between the U.S. share in price discovery and the (relative) liquidity of a stock (see, e.g. Grammig et al., 2005b, and Baruch et al., 2007). However, it is not clear how this affects our main conclusions. If indeed the higher U.S. share in price discovery increases the stock's own liquidity and hence its own prominence, it would in turn lead to a reduction in the prominence of other related stocks (the negative correlation between the two is reported in Table 4). So in fact, our findings on the positive relation between the U.S. share in price discovery and the prominence of other related stocks may be underestimated and the true relation is even stronger. Furthermore, the relation between stock characteristics and specialist portfolios can be endogenous (Corwin and Coughenour, 2008).

The endogeneity problems could be solved in a two-stage procedure with appropriate instruments for all endogenous variables. However, we are unable to find suitable variables that could serve as valid instruments which hinders the application and relevance of the procedure.

5.4. Prominence of Related Stocks and Adverse Selection

To find some direct evidence on whether paying more attention to similar stocks improves the information environment of market makers, we analyze how the adverse selection component of the bid-ask spread of a stock varies across different levels of the prominence of related stocks in the same specialist portfolio. Following Huang and Stoll (1996) and Bacidore and Sofianos (2002), for each sample stock we calculate the adverse selection component as the difference between the effective and realized spreads. The effective spread is calculated as twice the absolute value of the difference between the trade price and the quote midpoint at the time of the trade, divided by the quote midpoint. The realized spread is calculated as twice the difference between the trade price and the quote midpoint prevailing 5 minutes after the trade[20], multiplied by –1 if the trade is seller-initiated, and divided by the quote midpoint at the time of the trade. A trade is considered seller-initiated if the trade price is below the quoted midpoint. The equally weighted mean of the adverse selection component across all trades for each stock in the trading overlap each day is calculated first, and then the daily means are averaged over the sample period. The adverse selection component is then regressed on a constant, *Prominence of related stocks less own*, where *related stocks*, as before, refer to stocks from the same country, European stocks or non-U.S. stocks interchangeably, and *Ln (Market capitalization)* to control for unobservable firm information characteristics correlated with size, such as transparency and visibility.

[20] The analysis based on realised spreads calculated with a 30-minute lag yields qualitatively and quantitatively similar results.

The (untabulated) results[21] confirm our earlier findings. The estimated coefficients of the prominence of other similar stocks are all negative, but only the coefficient of *Prominence of non-U.S. stocks less own* is statistically significant (-0.0048, with p-value of 0.080). We find that, on average, an increase in the prominence of other foreign stocks from the 25th to the 75th percentile of its distribution is associated with a reduction in the adverse selection component of the bid-ask spread by 25 basis points. It lends further support to our hypothesis that concentrating market makers in similar stocks increases the U.S. contribution to price discovery due to reduced information asymmetries.

5.5. Robustness of Cross-Sectional Results to Stock Reassignments

As mentioned in Section 2, stocks are hardly ever relocated between specialist firms[22] but reassignments of securities between individual specialists within a firm are relatively common (Anand et al., 2008; Corwin and Coughenour, 2008). During our sample period, reassignments within a specialists firm affected 13 sample stocks on four different days.[23] As mentioned earlier, we construct our prominence variables to take into account the daily changes in the composition of specialist portfolios. However, Battalio et al. (2006) and Anand et al. (2008) document that trading behavior and liquidity change when securities change the location at which they trade on the NYSE floor. To check whether our main findings on the prominence of similar stocks are robust to stock reassignments between specialist portfolios, we re-estimate all cross-sectional regressions excluding the 13 relocated stocks. The (untabulated) results remain to a very large extent qualitatively and quantitatively unchanged. The only differences in the main variables of interest are the marginally insignificant coefficients of the *Prominence of non-U.S. stocks less own* in two specifications with the

[21] The results in this and subsequent sections are not tabulated to preserve space. They are all available from the authors upon request.
[22] We do not find any such reallocation of any of the sample stock in the sample period.
[23] Among those 13 stocks, two stocks were reassigned twice.

Hasbrouck share in price discovery (equivalent to specification (vii) of Table 6 and specification (xii) of Table 8). In a regression equivalent to the specification (vi) of Table 7, the *Prominence of European stocks less own* becomes marginally significant.

5.6. Robustness of Cross-Sectional Results to Alternative Price Discovery Estimation

We start with (untabulated) robustness checks of our main cross-sectional tests changing the sampling intervals at which the VECM models and consequently shares in price discovery are estimated. The results with the U.S. share in price discovery estimated at 2-minute intervals change little compared to the results at 1-minute intervals reported in Tables 5 to 8. When the interval is lowered to 3 minutes or to 10 minutes, we find improvement in the coefficients of the *Prominence of European stocks less own* that become significant in Gonzalo-Granger specifications equivalent to specifications (vi), (vii) and (viii) of Table 7. However, with the interval set to 10 minutes, the prominence of other European or non-U.S. stocks loses its significance in selected specifications with the Hasbrouck share in price discovery.

We also re-estimate the information shares excluding the first and the last 15 minutes of the trading overlap of each trading day, with the interval set to one minute as in the main tests. Werner and Kleidon (1996) found in their study of U.S.-listed U.K. stocks that the trading volume and price volatility follow a U-shaped pattern throughout the day, with the higher levels around the beginning and closing of the market. On the other hand, Moulton and Wei (2009) using a more recent sample of U.S.-listed British stocks find that during the overlapping trading hours spreads trade at an intermediate line rather than following separate U-shaped curves on the London Stock Exchange and NYSE. They ascribe this development to greater market integration in recent years. Nevertheless, one may argue that the estimation of shares in price discovery can be distorted in the period immediately after the U.S. market opening and before the European market closing. We find little qualitative difference in our general cross-sectional results when the first and the last 15 minutes of the overlap are excluded. Generally, the results for the *Prominence of European stocks less own* become consistently significant across both Gonzalo-Granger and Hasbrouck definitions of shares in price discovery. The coefficients of the *Prominence of non-U.S. stocks less own* remain significant in the Gonzalo-Granger specifications but lose their significance in regressions with the Hasbrouck measure of price discovery.

Taken together, we confirm the importance of the prominence of other related stocks. We are not able to conclusively determine though which level of relatedness is most important as across our tests we find some significant evidence in favor of every of them.

6. Conclusions

In this paper we shed more light on informational benefits of concentrated market making. We base on theoretical arguments in Strobl (2001) and Baruch et al. (2007) to analyze whether more attention devoted to similar securities enables a market maker to extract information relevant to a stock from order flow to related securities and consequently whether it leads to improved price discovery of the stock. Our empirical tests are focused on New York Stock Exchange specialists and price discovery of non-U.S. stocks in their portfolios. We analyze 64 British and French companies cross-listed on the NYSE over the six-month period from January 2003 through June 2003. Applying both the Hasbrouck and Gonzalo-Granger methods to calculate the U.S. shares in price discovery we find a substantial variation of the U.S. share across our sample which we attribute to the differences in the information environment of NYSE specialists who make a market in our sample stocks. In a set of cross-sectional regressions we analyze how the U.S. share in price discovery differs with the prominence of related stocks in a specialist portfolio. We define related stocks as stocks from the same country (U.K. or France in our case), the same region (Europe) or all non-U.S. stocks in the specialist portfolio.

We find statistically and economically significant evidence that an increase in the prominence of related stocks in the specialist portfolio leads to a higher U.S. share in price discovery of our sample stocks. Considering that market making in foreign stocks is associated with inherent information asymmetries and adverse selection as documented by Bacidore and Sofianos (2002), we interpret our findings as evidence that concentrating market makers in similar stocks reduces information asymmetries and improves the information environment. We find that there is a larger informational advantage from allocating attention across a broader set of international securities rather than focusing on country-specific groups of firms. To support our argument on informational benefits of clustered market making, we show that an increase in the prominence of other foreign stocks in the specialist portfolio significantly reduces the adverse selection component of the bid-ask spread. Our findings complement the literature on the link between allocation on attention in securities trading and market quality (Corwin and Coughenour, 2008; Boulatov et al., 2009), but are also related to the substantial body of literature on price discovery in cross-listings and on the role of dedicated market makers (e.g., Venkataraman and Waisburd, 2007).

Our findings are based on NYSE data for cross-listed stocks but they can be generalized to any market design in which a dealer allocates attention across a set of securities. We show that the dealer's information environment can be improved if he allocates more attention to related securities. The application goes beyond dedicated market making though and may be also relevant to other trading designs with human involvement, such as trading desks in financial institutions.

References

Anand A, Chakravarty S, Chuwonganant C. Cleaning house: Stock reassignments on the NYSE. Journal of Financial Markets 2008 (forthcoming).

Bacidore JM, Battalio R, Galpin N, Jennings R. Sources of liquidity for NYSE-listed non-U.S. Stocks. Journal of Banking and Finance 2005;29; 3075-3098.

Bacidore JM, Sofianos G. Liquidity provision and specialist trading in NYSE-listed non-U.S. stocks. Journal of Financial Economics 2002;63; 133-158.

Baillie RT, Booth GG, Tse Y, Zabotina T. Price discovery and common factor models Journal of Financial Markets, 2002;5; 309-321.

Battalio R, Ellul A, Jennings R. Reputation effects in trading on the New York stock exchange. Journal of Finance 2007;62; 1243-1271.

Baruch S, Karolyi GA, Lemmon ML. Multi-market trading and liquidity: Theory and evidence. Journal of Finance 2007; 62; 2169-2200.

Boulatov A, Hatch BC, Johnson SA, Lei AYC. Dealer attention, the speed of quote adjustments to information and net dealer revenue. Journal of Banking and Finance 2009;33; 1531-1542.

Chan K, Covrig V, Ng L. What determines the domestic bias and foreign bias? Evidence from mutual fund equity allocations worldwide. Journal of Finance 2005;60; 1495-1534.

Chordia T, Roll R, Subrahmanyam A. Market liquidity and trading activity. Journal of Finance 2001;56; 501-530.

Corwin SA. Specialist performance and new listings allocations on the NYSE: An empirical analysis. Journal of Financial Markets 2004;7; 27-51.

Corwin SA, Coughenour JF. Limited attention and the allocation of effort in securities trading. Journal of Finance 2008;63; 3031-3067.

de Jong F. Measures of contributions to price discovery: A comparison. Journal of Financial Markets 2002;5; 323-327.

Domowitz I, Glen J, Madhavan A. International cross-listing and order flow migration: evidence from an emerging market. Journal of Finance 1998;53; 2001-2027.

Eun CS, Sabherwal S. Cross-border listings and price discovery: Evidence from U.S.-listed Canadian stocks. Journal of Finance 2003;58; 549-575.

Foerster SR, Karolyi GA. Multimarket trading and liquidity: A transaction data analysis of Canada-U.S. interlistings. Journal of International Financial Markets, Institutions and Money 1998;8; 393-412.

Gagnon L, Karolyi GA. Multi-market trading and arbitrage. Ohio State University Working Paper 2004.

Gonzalo J, Granger CWJ. Estimation of common long-memory components in cointegrating systems. Journal of Business and Economics Statistics; 1995;13; 27-36.

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

Grammig J, Melvin M, Schlag C. The role of U.S. trading in pricing internationally cross-listed stocks. University of Tuebingen Working Paper 2005b.

Grinblatt M, Keloharju M. How distance, language, and culture influence stockholdings and trades. Journal of Finance 2001;56; 1053-1073.

Halling M, Pagano M, Randl O, Zechner J. Where is the market? Evidence from cross-listings in the United States. Review of Financial Studies 2008;21; 725-761.

Harris FH deB, McInish TH, Wood RA. Security price adjustment across exchanges: An investigation of common factor components for Dow Stocks. Journal of Financial Markets 2002;5; 277-308.

Harris FH deB, McInish TH, Wood RA. DCX trading in New York and Frankfurt: corporate governance affects trading costs across international dual-listings. Wake Forest University Working Paper 2003.

Hasbrouck J. One security, many markets: determining the contributions to price discovery. Journal of Finance 1995;50; 1175-1199.

Hendershott T, Moulton PC. Speed and stock market quality. University of California, Berkeley Working Paper 2009.

Huang RD, Stoll HR. Dealer versus auction markets: A paired comparison of execution costs on NASDAQ and the NYSE. Journal of Financial Economics 1996;41; 313-357.

Hupperets ECJ, Menkveld AJ. Intraday analysis of market integration: Dutch blue chips traded in Amsterdam and New York. Journal of Financial Markets; 2002;5; 57-82.

Johansen S. Estimation and hypothesis testing of cointegration vectors in Gaussian vector autoregressive models. Econometrica 1991;59; 1551-1580.

Kahneman D. Attention and effort. Prentice Hall: Englewood Cliffs, NJ; 1973.

Kang J-K, Stulz RM. Why is there a home bias? An analysis of foreign portfolio equity ownership in Japan. Journal of Financial Economics 1997;46; 3-28.

Kaul A, Mehrotra V. The role of trades in price discovery convergence: A study of dual-listed Canadian stocks. Journal of Empirical Finance 2007;14; 196-219.

Kim M, Szakmary AC, Mathur I. Price transmission dynamics between ADRs and their underlying foreign securities. Journal of Banking and Finance 2000;24; 1359-1382.

Lieberman O, Ben-Zion U, Hauser S. A characterisation of the price behaviour of international dual stocks: An error correction approach. Journal of International Money and Finance 1999;18; 289-304.

Menkveld AJ, Koopman SJ, Lucas A. Modeling around-the-clock price discovery for cross-listed stocks using state space methods. Journal of Business and Economic Statistics 2007;25; 213-225.

Moulton PC, Wei L. A tale of two time zones: The impact of substitutes on cross- listed stock liquidity. Journal of Financial Markets 2009 (forthcoming).

Muscarella CJ, Vetsuypens MR. Stock splits: signalling or liquidity? The case of ADR 'solo-splits'. Journal of Financial Economics 1996;42; 3-26.

Parlour CA, Seppi DJ. Liquidity-based competition for order flow. Review of Financial Studies 2003;16; 301-343.

Pascual R, Pascual-Fuster B, Climent F. Cross-listing, price discovery and the informativeness of the trading process. Journal of Financial Markets 2006;9; 144-161.

Stickel SE, Verrecchia RE. Evidence that trading volume sustains stock price changes. Financial Analysts Journal 1994;50; 57-67.

Strobl G. On the optimal allocation of new security listings to specialists. Working Paper, University of Pennsylvania 2001.

Venkataraman K, Waisburd AC. The value of designated market maker. Journal of Financial and Quantitative Analysis 2007;42; 735-758.

Werner IM, Kleidon AW. U.K. and U.S. trading of British cross-listed stocks: An intraday analysis of market integration. Review of Financial Studies 1996; 9; 619-664.

Wang SS, Rui OM, Firth M. Return and volatility behavior of dually-traded stocks: The case of Hong Kong. Journal of International Money and Finance 2002;21; 265-293.

Appendix. Definitions of Explanatory Variables Used in Cross-Sectional Regressions

Variable	Definition
Own prominence	The sample stock's prominence in a NYSE specialist portfolio. A specialist portfolio is defined as all common stocks and ADRs traded in the same post and panel location on the NYSE floor. The prominence is calculated as the proportion of the stock's dollar volume in the total dollar volume of the specialist portfolio it belongs to. First, for every day dollar volume of all stocks in the portfolio in the trading overlap between the U.S. and home market is calculated. Then, the daily prominence of the stock is computed and the daily prominence is then averaged over the sample period.
Prominence of country's stocks	Prominence of all stocks from the sample stock's country in a NYSE specialist portfolio the sample stock belongs to. A specialist portfolio is defined as all common stocks and ADRs traded in the same post and panel location on the NYSE floor. The prominence is calculated as the proportion of the stocks' dollar volume in the total dollar volume of the specialist portfolio. First, for every day dollar volume of all stocks in the portfolio in the trading overlap between the U.S. and home market is calculated. Then, the daily prominence of the group of stocks is computed and the daily prominence is then averaged over the sample period.
Prominence of country's stocks less own	Calculated as *Prominence of country's stocks* minus *Own prominence*
Prominence of European stocks	Prominence of all European stocks in a NYSE specialist portfolio the sample stock belongs to. A specialist portfolio is defined as all common stocks and ADRs traded in the same post and panel location on the NYSE floor. The prominence is calculated as the proportion of European stocks' dollar volume in the total dollar volume of the specialist portfolio. First, for every day dollar volume of all stocks in the portfolio in the trading overlap between the U.S. and home market is calculated. Then, the daily prominence of the group of stocks is computed and the daily prominence is then averaged over the sample period.
Prominence of European stocks less own	Calculated as *Prominence of European stocks* minus *Own prominence*
Prominence of non-U.S. stocks	Prominence of all non-U.S. stocks in a NYSE specialist portfolio the sample stock belongs to. A specialist portfolio is defined as all common stocks and ADRs traded in the same post and panel location on the NYSE floor. The prominence is calculated as the proportion of non-U.S. stocks' dollar volume in the total dollar volume of the specialist portfolio. First, for every day dollar volume of all stocks in the portfolio in the trading overlap between the U.S. and home market is calculated. Then, the daily prominence of the group of stocks is computed and the daily prominence is then averaged over the sample period.
Prominence of non-U.S. stocks less own	Calculated as *Prominence of non-U.S. stocks* minus *Own prominence*
U.S. / Total dollar volume	The ratio of the dollar volume in the U.S. and the total (U.S. and home market) dollar volume. First, a stock's dollar volume is summed for both exchanges within the trading overlap every day and daily ratios are calculated. Then, the daily ratios are averaged over the sample period.
U.S. / Home effective spread	The ratio of U.S. and home effective spreads. Effective spread is calculated as twice the absolute value of the difference between the trade price and the midpoint of the prevailing bid and ask quotes at the time of the trade, divided by the quote midpoint. First, it is averaged across all trades on an exchange for a given firm within the trading overlap each day. Then, daily ratios are calculated and the daily ratios are averaged over the sample period.
Ln (Market capitalization)	The natural logarithm of the average daily capitalization (in USD millions) over the sample period.
U.K. dummy	A dummy variable equal to one for U.K. stocks and zero for French stocks.

Table 1. Capitalization of Sample Companies and Main Liquidity and Trading Characteristics within Overlapping Trading Hours

The table presents descriptive statistics for a sample that includes 43 U.K. and 21 French stocks cross-listed on the New York Stock Exchange from January 1, 2003 through June 30, 2003. *Market capitalization* is measured as the average daily market capitalization over the sample period. *Dollar volume*, *Number of Trades* and *Number of quote revisions* are first summed for each individual firm for each day within the trading overlap between the home and U.S. market, and then for each firm the daily observations are averaged over the sample period. *Number of quote revisions* is based on the number of changes in the best bid and/or best ask price. *Effective spread* is calculated as twice the absolute value of the difference between the trade price and the midpoint of the prevailing bid and ask quotes at the time of the trade, divided by the quote midpoint. It is averaged across all trades for a given firm within the trading overlap each day, and then the daily observations are averaged over the sample period. *U.S. / Total dollar volume* and *U.S. / Home effective spread* are based on the appropriate ratios calculated for each firm for each day, and then for each firm averaged over the sample period.

		Mean	std deviation	25th percentile	median	75th percentile
Panel A. All stocks						
Market capitalization ($m)		21,349.71	32,713.63	2,919.25	7,863.98	22,543.13
Dollar volume ($k)	Home	40,811.86	57,989.98	8,764.08	21,068.25	45,820.59
	U.S.	3,504.58	8,698.81	73.62	291.40	1,368.27
U.S. / Total dollar volume		0.0436	0.0527	0.0101	0.0204	0.0577
Effective spread (%)	Home	0.6747	1.9399	0.1461	0.1934	0.3707
	U.S.	0.6221	0.9058	0.1965	0.3458	0.6444
U.S. / Home effective spread		2.2946	1.5544	1.3108	2.1124	2.8075
Number of trades	Home	772.79	623.53	330.84	541.43	1,124.21
	U.S.	83.35	123.46	12.23	28.42	90.57
Number of quote revisions	Home	430.66	296.68	228.52	387.59	552.52
	U.S.	251.02	131.22	137.73	234.97	328.00
Panel B. U.K. stocks						
Market capitalization ($m)		23,470.69	36,780.28	2,933.38	6,936.03	25,333.32
Dollar volume ($k)	Home	45,338.11	65,748.12	10,615.22	19,824.13	46,422.51
	U.S.	4,045.78	10,135.08	82.67	335.04	1,291.67
U.S. / Total dollar volume		0.0447	0.0535	0.0124	0.0190	0.0627
Effective spread (%)	Home	0.8928	2.3408	0.1722	0.2428	0.4198
	U.S.	0.5523	0.8040	0.1866	0.3072	0.6050
U.S. / Home effective spread		1.8794	0.9592	1.1378	1.7344	2.3891
Number of trades	Home	604.89	426.97	322.60	433.14	813.03
	U.S.	86.31	131.77	15.30	29.92	87.23
Number of quote revisions	Home	364.05	209.37	227.62	359.83	456.96
	U.S.	248.43	126.06	157.37	228.48	307.88

(continued)

Table 1. – *continued*

		mean	std deviation	25th percentile	median	75th percentile
Panel C. French stocks						
Market capitalization ($m)		17,006.76	22,377.22	2,347.27	8,524.88	18,142.05
Dollar volume ($k)	Home	31,543.82	37,158.99	4,539.06	25,431.25	44,466.09
	U.S.	2,396.42	4,552.76	62.95	111.72	2,346.57
U.S. / Total dollar volume		0.0414	0.0524	0.0100	0.0219	0.0425
Effective spread (%)	Home	0.2283	0.1886	0.1105	0.1817	0.2381
	U.S.	0.7648	1.0933	0.2006	0.4923	0.7681
U.S. / Home effective spread		3.1449	2.1329	1.6010	2.7610	3.9029
Number of trades	Home	1,116.59	810.63	419.17	942.04	1,733.30
	U.S.	77.29	107.21	7.66	20.02	142.10
Number of quote revisions	Home	567.05	395.13	229.43	488.66	810.97
	U.S.	256.31	144.32	129.43	286.62	330.88

Table 2. Vector Error Correction Model Coefficients and the U.S. Share in Price Discovery

Panels A and B of the table present cross-sectional descriptive statistics of coefficients of Vector Error Correction Model given by equation (1). Panels C and D present descriptive statistics of the U.S. share in price discovery calculated using the Gonzalo and Granger (1995) method as given by equation (9) and the Hasbrouck (1995) method as given by equation (7), respectively. The sample includes 43 U.K. and 21 French stocks cross-listed on the NYSE from January 1, 2003 through June 30, 2003.

	mean	std deviation	25^{th} percentile	median	75^{th} percentile
Panel A. Cointegrating vector normalized on the home price					
β_1	1.0000	0.0000	1.0000	1.0000	1.0000
β_2	-1.0087	0.0338	-1.0097	-1.0029	-0.9975
Panel B. Adjustment coefficients					
α_1	-0.0116	0.0180	-0.0128	-0.0076	-0.0039
α_2	0.0526	0.0493	0.0204	0.0363	0.0717
Panel C. U.S. share in price discovery – Gonzalo-Granger method					
Full sample	0.2031	0.1908	0.0744	0.1427	0.2665
U.K. stocks	0.2031	0.1815	0.0960	0.1590	0.2540
French stocks	0.2031	0.2133	0.0540	0.1169	0.3163
Panel D. U.S. share in price discovery – Hasbrouck method					
Full sample	0.1550	0.1580	0.0521	0.0897	0.1913
U.K. stocks	0.1493	0.1442	0.0647	0.0898	0.1576
French stocks	0.1667	0.1865	0.0251	0.0855	0.2954

Table 3. Prominence of Sample Stocks and Stocks Related to Them in Specialist Portfolios

The table presents descriptive statistics for prominence measures used in cross-sectional regressions. The definitions of the variables are presented in the Appendix. The sample includes 43 U.K. and 21 French stocks cross-listed on the New York Stock Exchange from January 1, 2003 through June 30, 2003.

	mean	std deviation	25th percentile	median	75th percentile
Panel A. All stocks					
Own prominence	0.1132	0.1973	0.0060	0.0206	0.1119
Prominence of country's stocks	0.2153	0.2108	0.0211	0.1693	0.3083
Prominence of country's stocks less own	0.1021	0.1413	0.0002	0.0387	0.1500
Prominence of European stocks	0.5198	0.3284	0.2834	0.5026	0.7617
Prominence of European stocks less own	0.4066	0.3150	0.1241	0.3956	0.5782
Prominence of non-U.S. stocks	0.7305	0.3186	0.5608	0.8869	1.0000
Prominence of non-U.S. stocks less own	0.6173	0.3300	0.4059	0.7030	0.9242
Panel B. U.K. stocks					
Own prominence	0.1110	0.1968	0.0079	0.0282	0.1019
Prominence of country's stocks	0.2278	0.2115	0.0624	0.1772	0.4217
Prominence of country's stocks less own	0.1167	0.1483	0.0050	0.0566	0.1640
Prominence of European stocks	0.4924	0.2961	0.2893	0.4893	0.6699
Prominence of European stocks less own	0.3813	0.2690	0.1305	0.3943	0.5265
Prominence of non-U.S. stocks	0.6993	0.3398	0.5126	0.8098	0.9901
Prominence of non-U.S. stocks less own	0.5882	0.3470	0.2889	0.6912	0.9056
Panel B. French. stocks					
Own prominence	0.1176	0.2030	0.0038	0.0156	0.1743
Prominence of country's stocks	0.1898	0.2121	0.0175	0.0411	0.2964
Prominence of country's stocks less own	0.0722	0.1237	0.0000	0.0002	0.0466
Prominence of European stocks	0.5759	0.3880	0.1678	0.5679	0.9921
Prominence of European stocks less own	0.4583	0.3955	0.1124	0.4409	0.9029
Prominence of non-U.S. stocks	0.7943	0.2663	0.6059	0.9608	1.0000
Prominence of non-U.S. stocks less own	0.6767	0.2909	0.4494	0.7149	0.9711

Table 4. Correlation Matrix

The table presents Pearson correlation coefficients between variables used in cross-sectional regressions. See the Appendix for definitions of the variables. The sample includes 43 U.K. and 21 French stocks cross-listed on the New York Stock Exchange from January 1, 2003 through June 30, 2003. ***, ** and * denote significance of the correlation coefficient at the 0.01, 0.05 and 0.10 level, respectively.

	Own prominence	Prominence of country's stocks	Prominence of country's stocks less own	Prominence of European stocks	Prominence of European stocks less own	Prominence of non-U.S. stocks	Prominence of non-U.S. stocks less own	U.S. / Total dollar volume	U.S. / Home effective spread	Ln (Market capitalization)
Own prominence	1.0000	0.7622***	-0.2590**	0.3666***	-0.2441*	0.2507**	-0.3557***	0.8185***	-0.4695***	0.6689***
Prominence of country's stocks		1.0000	0.4278***	0.5347***	0.0800	0.3780***	-0.0906	0.6310***	-0.3976***	0.4904***
Prominence of country's stocks less own			1.0000	0.2859**	0.4602***	0.2139*	0.3614***	-0.2015	0.0622	-0.2022
Prominence of European stocks				1.0000	0.8128***	0.6999***	0.4566***	0.3250***	-0.2564**	0.4288***
Prominence of European stocks less own					1.0000	0.5726***	0.6987***	-0.1737	0.0268	0.0282
Prominence of non-U.S. stocks						1.0000	0.8156***	0.2003	-0.2641**	0.3491***
Prominence of non-U.S. stocks less own							1.0000	-0.2959**	0.0256	-0.0628
U.S. / Total dollar volume								1.0000	-0.4821***	0.4854***
U.S. / Home effective spread									1.0000	-0.4985***
Ln (Market capitalization)										1.0000

Table 5. Stocks' Prominence and the U.S. Share in Price Discovery - Gonzalo-Granger Method

The dependent variable is the logistic transformation of the U.S. share in price discovery calculated on the basis of the Gonzalo-Granger method given by equation (9). The explanatory variables are defined in the Appendix. The sample includes 43 U.K. and 21 French stocks cross-listed on the NYSE from January 1, 2003 through June 30, 2003. p-values of the t-test of the estimated coefficients are reported in parentheses. The t-test is based on heteroskedasticity consistent standard errors.

	Exp sign	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)
Constant		-2.852	-3.385	-3.283	-3.574	-3.568	-4.712	-4.711
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Own prominence	+	5.363		6.013		5.983		6.979
		(0.000)		(0.000)		(0.000)		(0.000)
Prominence of country's stocks	+		5.294					
			(0.000)					
Prominence of country's stocks less own	+			3.503				
				(0.034)				
Prominence of European stocks	+				2.556			
					(0.005)			
Prominence of European stocks less own	+					1.589		
						(0.068)		
Prominence of non-U.S. stocks	+						3.378	
							(0.003)	
Prominence of non-U.S. stocks less own	+							2.716
								(0.013)
Adjusted R-sq.		0.172	0.193	0.197	0.102	0.199	0.178	0.278
Number of observations		64	64	64	64	64	64	64

Table 6. Stocks' Prominence and the U.S. Share in Price Discovery - Hasbrouck Method

The dependent variable is the logistic transformation of the U.S. share in price discovery calculated on the basis of the Hasbrouck method given by equation (7). The explanatory variables are defined in the Appendix. The sample includes 43 U.K. and 21 French stocks cross-listed on the NYSE from January 1, 2003 through June 30, 2003. p-values of the t-test of the estimated coefficients are reported in parentheses. The t-test is based on heteroskedasticity consistent standard errors.

	Exp sign	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)
Constant		-2.820	-3.176	-3.057	-3.564	-3.559	-3.641	-3.640
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Own prominence	+	4.507		4.863		5.146		5.219
		(0.000)		(0.000)		(0.000)		(0.000)
Prominence of country's stocks	+		4.020					
			(0.000)					
Prominence of country's stocks less own	+			1.922				
				(0.159)				
Prominence of European stocks	+				2.412			
					(0.004)			
Prominence of European stocks less own	+					1.640		
						(0.046)		
Prominence of non-U.S. stocks	+						1.822	
							(0.008)	
Prominence of non-U.S. stocks less own	+							1.198
								(0.061)
Adjusted R-sq.		0.228	0.206	0.237	0.178	0.295	0.088	0.259
Number of observations		64	64	64	64	64	64	64

Table 7. Determinants of the U.S. Share in Price Discovery - Gonzalo-Granger Method

The dependent variable is the logistic transformation of the U.S. share in price discovery calculated on the basis of the Gonzalo-Granger method given by equation (9). The explanatory variables are defined in the Appendix. The sample includes 43 U.K. and 21 French stocks cross-listed on the NYSE from January 1, 2003 through June 30, 2003. p-values of the t-test of the estimated coefficients are reported in parentheses. The t-test is based on heteroskedasticity consistent standard errors.

	Exp sign	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)	(x)	(xi)	(xii)
Constant		-3.536	-2.019	-8.793	-7.421	-4.073	-2.669	-8.126	-6.817	-5.381	-4.284	-8.624	-7.896
		(0.000)	(0.009)	(0.000)	(0.036)	(0.000)	(0.016)	(0.001)	(0.056)	(0.000)	(0.010)	(0.000)	(0.023)
Own prominence	+	5.572	4.436	2.715	1.319	5.820	4.636	3.082	1.841	6.675	6.041	4.564	3.295
		(0.009)	(0.001)	(0.040)	(0.382)	(0.008)	(0.002)	(0.033)	(0.299)	(0.003)	(0.002)	(0.005)	(0.088)
Prominence of country’s stocks less own	+	3.310	3.301	3.614	3.572								
		(0.050)	(0.040)	(0.036)	(0.038)								
Prominence of European stocks less own	+					1.706	1.459	1.155	1.020				
						(0.061)	(0.120)	(0.116)	(0.188)				
Prominence of non-U.S. stocks less own	+									2.884	2.625	2.445	2.307
										(0.010)	(0.034)	(0.011)	(0.027)
U.S. / Total dollar volume	+	1.911			3.378	1.061			2.456	1.979			3.350
		(0.800)			(0.545)	(0.890)			(0.683)	(0.793)			(0.595)
U.S. / Home effective spread	-		-0.415		-0.257		-0.352		-0.243		-0.243		-0.146
			(0.078)		(0.397)		(0.158)		(0.424)		(0.364)		(0.636)
Ln (Market capitalization)	+			0.639	0.578			0.528	0.479			0.438	0.418
				(0.019)	(0.085)			(0.058)	(0.156)			(0.075)	(0.151)
U.K. dummy	+	0.356	-0.170	0.201	-0.131	0.639	0.170	0.476	0.152	0.765	0.437	0.631	0.418
		(0.562)	(0.739)	(0.745)	(0.792)	(0.290)	(0.714)	(0.460)	(0.752)	(0.186)	(0.363)	(0.309)	(0.394)
Adjusted R-sq.		0.176	0.221	0.268	0.264	0.188	0.220	0.246	0.237	0.278	0.292	0.317	0.302
Number of observations		64	64	64	64	64	64	64	64	64	64	64	64

Table 8. Determinants of the U.S. Share in Price Discovery – Hasbrouck Method

The dependent variable is the logistic transformation of the U.S. share in price discovery calculated on the basis of the Hasbrouck method given by equation (7). The explanatory variables are defined in the Appendix. The sample includes 43 U.K. and 21 French stocks cross-listed on the NYSE from January 1, 2003 through June 30, 2003. p-values of the t-test of the estimated coefficients are reported in parentheses. The t-test is based on heteroskedasticity consistent standard errors.

	Exp sign	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)	(x)	(xi)	(xii)
Constant		-3.577	-1.279	-6.892	-3.836	-4.320	-2.070	-6.462	-3.541	-4.474	-1.913	-6.794	-3.857
		(0.000)	(0.017)	(0.001)	(0.012)	(0.000)	(0.022)	(0.001)	(0.010)	(0.000)	(0.016)	(0.001)	(0.011)
Own prominence	+	3.612	2.507	2.714	0.738	4.243	3.011	3.641	1.793	4.156	2.893	3.500	1.180
		(0.010)	(0.000)	(0.005)	(0.465)	(0.008)	(0.000)	(0.001)	(0.204)	(0.007)	(0.000)	(0.000)	(0.323)
Prominence of country's stocks less own	+	1.542	1.534	1.745	1.657								
		(0.208)	(0.135)	(0.135)	(0.107)								
Prominence of European stocks less own	+					1.790	1.417	1.515	1.262				
						(0.043)	(0.068)	(0.046)	(0.096)				
Prominence of non-U.S. stocks less own	+									1.394	0.794	1.072	0.633
										(0.029)	(0.052)	(0.037)	(0.099)
U.S. / Total dollar volume	+	5.509			3.157	4.548			2.081	5.540			3.133
		(0.197)			(0.349)	(0.356)			(0.604)	(0.243)			(0.387)
U.S. / Home effective spread	-		-0.617		-0.537		-0.555		-0.512		-0.565		-0.508
			(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
Ln (Market capitalization)	+			0.411	0.268			0.286	0.165			0.322	0.220
				(0.039)	(0.037)			(0.081)	(0.122)			(0.063)	(0.070)
U.K. dummy	+	0.685	-0.084	0.606	-0.064	0.899	0.175	0.831	0.169	0.881	0.123	0.802	0.115
		(0.207)	(0.855)	(0.197)	(0.886)	(0.117)	(0.739)	(0.112)	(0.745)	(0.124)	(0.016)	(0.115)	(0.818)
Adjusted R-sq.		0.256	0.434	0.318	0.442	0.338	0.478	0.363	0.470	0.301	0.438	0.332	0.437
Number of observations		64	64	64	64	64	64	64	64	64	64	64	64

Figure 1. Opening Hours of Stock Exchanges under Consideration