

Splitting Orders in Overlapping Markets: A Study of Cross-Listed Stocks

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Abstract

Securities are increasingly traded through multiple venues. Chowdhry and Nanda (1991) show that sophisticated investors benefit by splitting orders across markets at the cost of local investors who only trade through one venue. If trading hours do not perfectly overlap, we can test for order-splitting by studying trading in the overlap vis-à-vis the non-overlap. We consider trading in NYSE-listed British and Dutch stocks an ideal experiment and tailor the model to this setting. We then extend it by allowing sophisticated investors to time their trades as in Admati and Pfleiderer (1988). We document increased volatility, increased volume, and unchanged market depth for the overlap, consistent with our predictions. Order-splitting is further evidenced through positive correlation in order imbalance across markets, controlling for arbitrage trades, synchronous information arrival, and microstructure effects.

JEL-code: G15, G10, G18

Key words: cross-listing, trading, fragmentation, high-frequency

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In the last decades, firms have increasingly cross-listed their shares at foreign exchanges (see Pagano, Roëll, and Zechner (2002)). This trend has been particularly strong for the U.S., where, at the New York Stock Exchange (NYSE) for example, the number of non-U.S. listings quadrupled over the last decade to 467 firms at the end of 2002. They generated approximately 10% of total volume that year.¹ The NASDAQ lists even more non-U.S. firms. Further international evidence is, for example, the large number of non-domestic stocks that are traded on European exchanges, up to 50% for the exchanges in Amsterdam, Brussels, Frankfurt, and Switzerland (see Pagano et al. (2001)). This trend has prompted many academic studies. Most of them focus on the benefits of cross-listings, such as reduced cost of capital and enhanced liquidity of a firm's stock.²

Relatively unexplored is trading in the fragmented market after the cross-listing. Most classic paradigms in microstructure focus on centralized markets, which is justified by the common belief that markets tend to consolidate. The increase in fragmented trading, however, triggered theorists to prove that a fragmented market can exist as an equilibrium (see, e.g., Pagano (1989), Chowdhry and Nanda (1991), Biais (1993), Bernhardt and Hughson (1997), Biais, Martimort, and Rochet (2000), de Frutos and Manzano (2002), Yin (2004)). The model developed in Chowdhry and Nanda (1991) appears to be most suitable for cross-listed securities, as it assumes all markets have an idiosyncratic pool of traders, who only trade locally for exogenous reasons. Sophisticated investors benefit by splitting orders across markets. In equilibrium, wealth is transferred from local to sophisticated investors, since local investors are shown to be better off in a single, centralized market. Moreover, Foucault and Gehrig (2002) prove that this equilibrium might emerge endogenously, since issuers benefit from the increased informational efficiency of a fragmented market. This enables them to make better investment decisions (see, e.g., Holmstrom and Tirole (1993) and Subrahmanyam and Titman (1999)).

Our objective is to test whether (sophisticated) investors split orders in real world

¹See the on-line NYSE factbook (www.nysedata.com).

²See, e.g., Alexander, Eun, and Janakiraman (1987, 1988), Foerster and Karolyi (1999), Karolyi (1998), Domowitz, Glen, and Madhavan (1998), and Miller (1999).

markets and how this affects the trading process. We study a natural experiment of overlapping markets, so that the non-overlap serves as a benchmark period. This is an ideal laboratory, since, if order-splitting really benefits sophisticated investors and if they can time their trades, they might want to concentrate their orders in the overlap. These notions are formalized and tested and we see three areas where the paper contributes to the literature.

First, we tailor the Chowdhry and Nanda (1991) model to overlapping markets and extend it by allowing sophisticated traders to time their trades as in Admati and Pfleiderer (1988). We show that concentrated trading in the overlap is a Nash equilibrium. Moreover, it is the Nash equilibrium with lowest cost for sophisticated traders and, under fairly mild conditions, the only Nash equilibrium. And, we find analytic expressions for volume, which are absent in Chowdhry and Nanda (1991). In a stepwise approach from fully segmented markets to markets with maximum choice for traders, referred to as the full-fledged model, we develop intraday patterns in volatility, volume, and market depth. Although the existing literature offers an excellent intuition for these patterns, it lacks a model to formalize it (see, e.g., Werner and Kleidon (1996), Hupperets and Menkveld (2002)).

Second, in addition to studying intraday patterns, we develop a direct test for order-splitting through a high-frequency analysis of order imbalance in the overlap. The model distinguishes two types of traders who split orders: (i) informed traders who maximize profit and exploit their private signal on the true value of the security by trading in each market and (ii) large liquidity traders who have to trade an exogenous number of shares and minimize cost by splitting the order optimally across markets. Either way, these traders trade in the same direction and their activity should show through positive correlation in order imbalance, defined as buy volume minus sell volume in a five-minute time interval. In hunting for such a footprint in the data, we have to control for three effects. First, we control for potential arbitrage trading as it causes negative correlation in order imbalance. Second, we control for the positive correlation that is due to arrival of new (private) information in both markets. Third, we control for “microstructure” dynamics in order imbalance due to,

for example, program trading or inventory management by liquidity suppliers.

Third, we explore the natural experiment of British and Dutch securities that are cross-listed at the NYSE. The main attractions of this experiment are (i) a non-overlapping period that serves as a benchmark period and (ii) significant trading in both markets, which creates optimal conditions for the order-splitting predicted by the model. It, therefore, compares particularly well with another natural candidate: fragmented trading on the NYSE and the U.S. regional exchanges. For this pure U.S. experiment, the non-overlap is either small or non-existent and trading at the regional exchanges is significantly less liquid.³ For our set of securities, the NYSE generates up to a third of total volume in the overlap on comparable, if not better, spreads. In 2002, trading in British and Dutch stocks generated roughly 50% of “European” volume in New York, which, in turn, represents 50% of non-U.S. volume at the NYSE.⁴ Werner and Kleidon (1996) are the first to document intraday trading patterns for cross-listed British shares. At the time of their study, the London market was a pure dealer market, whereas today it is based on a consolidated limit order book that is easily accessible through electronic channels. This makes order-splitting easier and the bid-ask spread proxy for liquidity more reliable, as spreads are firm rather than indicative as in a dealer market. Nevertheless, the trading patterns we find are largely consistent with the ones reported in Werner and Kleidon (1996).

The empirical results support the model predictions for the stocks that generate most volume at the NYSE. We do not see the predicted pattern across *all* cross-listed stocks, which is not surprising, because the benefit of order-splitting is reduced for stocks with low (idiosyncratic) volume in New York. The empirical pattern for the high NYSE-volume stocks is increased volume, volatility, and unchanged or slightly lower depth in the overlap vis-à-vis the non-overlap. The magnitude of volume increases is such that we reject all models, except

³Hasbrouck (1995, p.1188) reports for the thirty Dow stocks that the regional exchanges trade an average 2,080 shares each five minutes up to 9,299 shares for Merck. For the cross-listed stocks, we find that the NYSE trades an average 19,586 shares each five minutes up to 132,679 shares for Vodafone.

⁴See the on-line NYSE factbook. Incidentally, two of the Dutch stocks, Royal Dutch and Unilever, were members of the S&P500 at the time of our experiment. They are the only European stocks to ever have reached that status (see press release Standard & Poor’s, “Standard & Poor’s Announces Changes to the S&P Indices”, 7/9/02, www.spglobal.com).

the full-fledged model. This implies that the increases are primarily due to large liquidity traders, who concentrate their trading in the overlap and split their orders across markets. This demonstrates the importance of the model extension, as the standard Chowdhry and Nanda (1991) model is rejected by the data. For these stocks, we zoom in on the overlap and find that the direction of trades is positively correlated across markets, consistent with order-splitting. We control for positive correlation due to new information by exploiting the British tax regime. In the test, we also find evidence of arbitrage activity, although at a small scale. This is consistent with earlier studies on cross-listed stocks (see, e.g., Jorion and Schwartz (1986), Kato, Linn, and Schallheim (1991), Ben-Zion, Hauser, and Lieberman (1996), and Gagnon and Karolyi (2004)).⁵

Our findings add to the regulatory debate on fragmented markets. The chairman of the Securities and Exchange Commission (SEC) has spoken of the harmful effects of fragmentation.⁶ The heads of Goldman Sachs, Merrill Lynch, and Morgan Stanley testified on the need for a centralized limit order book to consolidate order flow and assure price-time priority.⁷ The early academic literature agrees as centralized markets are considered to be cost-effective due to economies-of-scale and beneficial for price discovery as a result of maximum interaction of order flow (see, e.g., Hamilton (1979)). And, it is fair to *all* investors. Our evidence supports the notion that order-splitting investors benefit at the cost of local investors in a fragmented market setting. Recent literature, however, mentions two main drawbacks. First, centralization ignores the heterogeneity of investors, whose trading needs might require different market structures (see, e.g., Harris (1993), Blume (2000), Harris (2003)). U.S. investors, in our setting, might prefer to trade foreign stocks at the NYSE for a number of reasons, e.g., trades are dollar-denominated, U.S. clearing and settlement, same broker as for U.S. securities. Second, multiple trading venues create competition, which fosters innovation and reduces trading costs (see, e.g., Amihud and Mendelson (1995), Stoll (2001)). This argument features particularly strong in Steil (2002), who calls on U.S. and

⁵Incidentally, order-splitting could explain why Ellul (2002) finds that home market prices for continental European stocks cross-listed in London adjust to large London trades *ahead* of their execution.

⁶Speech Levitt at Columbia Law School, 9/23/99, and Northwestern Law School, 4/16/00.

⁷See Wall Street Journal article, “Sweeping Changes in Market Structure Sought,” 2/29/00.

European regulators to agree on transatlantic exchange access.

Furthermore, our evidence suggests that theory should consider order-splitting as a real possibility. It is, therefore, at odds with models that currently do not, e.g., Pagano (1989), Biais (1993), de Frutos and Manzano (2002), and Yin (2004).

Our paper relates to a contemporaneous paper on the subject—Baruch, Karolyi, and Lemmon (2004). The objectives are different, as Baruch et al. focus on explaining the U.S. share of total trading volume. In our model, this share is determined by the (exogenous) trading activity of local liquidity traders. They find that volume migrates to the exchange where the stock returns have highest correlation with other assets traded at the exchange.

Finally, order-splitting by informed traders could explain why some information cannot be uniquely assigned to markets in the widely used “information share” methodology developed in Hasbrouck (1995).⁸ The information share of a market measures the contribution of price innovations in that market to the innovation in the (common) efficient price. As Hasbrouck (2002, p.333) notes, if “innovations in the markets are correlated,” some information cannot be assigned uniquely to any of the markets and he, therefore, suggests to calculate lower- and upperbounds. These correlated innovations are consistent with order-splitting by informed traders.

Section 1 develops the model and compares volume, volatility, and market depth for the overlap with the non-overlap for different scenarios. Section 2 uses these results to generate testable hypotheses and introduces the natural experiment of NYSE-listed British and Dutch stocks. Section 3 presents the empirical results. First, it estimates the patterns in volume, volatility, and market depth. Second, it designs and implements a high-frequency analysis of order imbalance to trace down order-splitting during the overlap. Section 4 summarizes the main conclusions.

⁸For applications, see e.g. Huang (2002), Hasbrouck (2003), Chakravarty, Gulen, and Mayhew (2004).

1 The Model: One Security, Overlapping Markets

In this section, we study what intraday trading patterns—trading during the overlap as compared to the non-overlap—arise endogenously when a security trades in (partially) overlapping markets. We first tailor the one-period model of Chowdhry and Nanda (1991) to our setting. We derive an analytical result for trading volume. To make the model more realistic, we add an additional round to the game, so that liquidity suppliers can condition on the foreign transaction price when issuing their new quote. We then derive an analytical expression for volatility. We expand the model to a multi-period-overlapping-markets setting to generate model-implied trading patterns. We analyze a number of scenarios from a benchmark scenario of fully segmented markets to a full-fledged scenario with maximum choice for sophisticated traders. The step-by-step build-up in scenarios allows us to identify patterns that can arise endogenously, and, more importantly, it illuminates the mechanisms that generate these patterns.

1.1 The Basic One-Period Model

We start with a brief review of the one-period-two-markets model developed in Chowdhry and Nanda (1991). Each market consists of a liquidity supplier, an informed trader, a small, and a large liquidity trader. All agents are assumed to be risk-neutral. The informed trader trades on a private signal on the true value of the security, whereas the liquidity traders trade for exogenous reasons, e.g. hedging or shocks to their wealth. The large liquidity trader has access to both markets, whereas the small liquidity trader only trades in her “home market.” These traders could, for example, represent institutional and retail investors, respectively.⁹ The informed trader only trades in her home market, an assumption that will be relaxed at a later stage. We further assume that liquidity suppliers trade on their own account and absorb potential order imbalances. The one-period game consists of three rounds:

⁹The small liquidity trader represents investors whose trading demand is too small to make the benefit of access to a second market weigh up against the (fixed) cost of such access.

1. Liquidity suppliers announce price schedules;
2. Traders observe these schedules and submit their orders—informed traders maximizing expected profit, liquidity traders minimizing expected cost; and
3. Liquidity suppliers observe and absorb the aggregate order imbalance according to their announced price schedules.

At the start of each period, let

- $v \equiv$ the innovation in the value of the security at the end of the period;
- $u_i \equiv$ liquidity demand (signed volume) of the small liquidity trader in market i ;
- $d^k \equiv$ liquidity demand (signed volume) of the large liquidity trader in market k .

For the remainder of the paper we use superscripts k to indicate the market in which the agent originates and subscripts i to indicate her activity in market i . We drop the superscript for order imbalance of the small liquidity trader, since, by assumption, she only trades in her home market. The two markets are labeled A and B. We assume that v, u_A, u_B, d^A , and d^B are identically, independently, and normally distributed:

$$(v, u_i, d^A, d^B)' \sim N(\underline{0}, \text{diag}(\sigma_v^2, \sigma_{u,i}^2, \sigma_{d,A}^2, \sigma_{d,A}^2)),$$

where “diag” transforms a vector into a diagonal matrix with the vector as its diagonal. The endogenous variables are:

- $x_i \equiv$ signed volume in market i by the informed trader of market i ;
- $d_i^k \equiv$ signed volume in market i by the large liquidity trader of market k .

Let

$P \equiv$ unconditional value of the security before trading begins;

$P_i \equiv$ price charged by the liquidity supplier in market i .

The liquidity supplier in market i only observes the *aggregate* signed volume in her market. That is, she does not see the individual contribution of each trader group. Her pricing function, therefore, can only depend on the aggregate signed volume, which we define as the order imbalance:

$$\omega_i \equiv x_i + u_i + d_i^A + d_i^B.$$

The strategy for finding market equilibrium involves three basic steps. First, we hypothesize linear pricing rules for liquidity suppliers:

$$P_i - P = \lambda_i \omega_i, \tag{1}$$

where λ_i^{-1} is a measure of depth in market i . Second, we solve the optimization problems for the informed and liquidity traders. Third, we use the optimized signed volume of all traders to find the order imbalance and calculate the liquidity suppliers' profit. Fourth, we set her profit to zero, as we assume liquidity supply to be perfectly competitive or regulated.¹⁰ We find:

$$\lambda_i = \frac{1}{2} \frac{1}{\sigma_{u,i} \sqrt{1 + \Phi}} \sigma_v; \quad d_i^k = \frac{\lambda_{j \neq i}}{\lambda_i + \lambda_{j \neq i}} d^k; \quad x_i = \frac{1}{2\lambda_i} v; \quad \text{with} \quad \Phi \equiv \frac{\sigma_{d,A}^2 + \sigma_{d,B}^2}{(\sigma_{u,A} + \sigma_{u,B})^2}; \tag{2}$$

where the indices i, j , and k are either A or B. With a few small adjustments that are discussed in appendix A, the proof of this result is in Chowdhry and Nanda (1991). In equilibrium, the large liquidity traders split their orders across markets, since $\lambda_B(\lambda_A + \lambda_B)^{-1}$ and $\lambda_A(\lambda_A + \lambda_B)^{-1}$ are strictly positive numbers, as both markets have a small liquidity

¹⁰In an electronic limit order book market we assume liquidity supply through limit orders to be competitive; in a specialist market we assume monitoring by the exchange in order to ensure specialists do not earn monopolist rents.

trader. They appear to send more to the market with most small liquidity trading, since the share of the order sent to market i increases in the level of small liquidity trading in that market ($\sigma_{u,i}$). The signed volume of informed traders in both markets is proportional to the innovation in the value of the security. These proportions are increasing in market depth (λ_i^{-1}), which confirms the intuition that informed traders trade more in deeper markets as it is easier to hide information.

In the remainder of this section, we use the equilibrium results to determine three more variables of interest: trading volume, volatility, and correlation in order imbalance across markets.

The expected trading volume in market i is derived in appendix A as:

$$Volume_i = \frac{\sigma_{u,i}}{\sqrt{2\pi}} \left\{ 1 + \Theta + (3 + \sqrt{2})\sqrt{1 + \Phi} \right\}, \text{ with } \Theta \equiv \frac{\sigma_{d,A} + \sigma_{d,B}}{\sigma_{u,A} + \sigma_{u,B}}. \quad (3)$$

Note that this is a non-trivial result, as it is not simply the expected value of the order imbalance size. The reason is that the latter only measures the size of the transaction between “the market” and the liquidity supplier and it, therefore, does not include transactions among the traders.

Contrary to Chowdhry and Nanda (1991), volatility is calculated *after* we allow the liquidity suppliers to update their quotes based on the transaction price in the foreign market. The original model implicitly assumes that liquidity suppliers do not observe the foreign price after trading. In modern markets, transaction prices are communicated in real time and we, therefore, add a fourth round to the game, to allow liquidity suppliers to update their estimate of the true value conditional on the transaction prices in both markets. Since their information sets are equal, both liquidity suppliers quote the same new price, say P^* . In appendix A, we find that volatility based on this new price equals:

$$Volatility = var(P^* - P) = var(E[v|\Delta P_A, \Delta P_B]) = \frac{2\Phi + 2}{4\Phi + 3} \sigma_v^2. \quad (4)$$

Interestingly, volatility is decreasing in the “ratio” of large liquidity trading to total liquidity trading. Intuitively, order-splitting by large liquidity traders makes prices move in lockstep. Hence, to a lesser extent can liquidity suppliers benefit from two “independent” signals on the true value of the security.

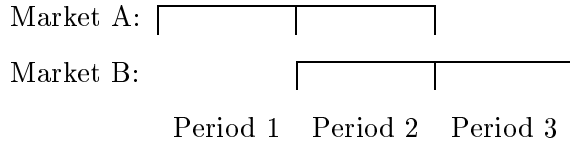
The correlation in order imbalance is calculated in appendix A to be:

$$\rho(\omega_A, \omega_B) = \frac{2\Phi + 1}{2\Phi + 2}. \quad (5)$$

The correlation increases in large liquidity demand due to increased order-splitting.

1.2 The Multi-Period Model

For two overlapping markets, the trading day can be split in three periods. In the first period, market A is the only market open; in the second period both markets are open; and in the third period market B is the only market open. The associated time line is:



Both markets consist of a liquidity supplier, an informed trader, a small, and a large liquidity trader. In period 2 the results of equation (2) hold, whereas in periods 1 and 3, the basic one-period model simplifies to a one-market model for which the results are summarized in appendix A.

The results we developed thus far enable us to study how the availability of a second market affects trading in the home market. To this end, we set parameters to be equal across periods and study how a second market affects trading in the home market in terms of volume, volatility, and market depth. We start with the analysis of a benchmark scenario (0), in which both markets are fully segmented. We then depart in two directions by either allowing large liquidity traders access to the other market or by allowing the informed

traders access to the other market (1a and 1b). The next scenario (2) allows both types of traders to access the other market. Finally, in a full-fledged scenario (3), we also allow large liquidity traders to time their trade in the spirit of Admati and Pfleiderer (1988). In other words, they can choose whether to trade in the first, second, or third period. The model extensions needed for scenarios 1b through 3 are developed in appendix A, as well as the proofs of the propositions. The trading pattern implications of all scenarios are summarized in Panel A of table 1; the corresponding formulas are included in appendix A. Panel B presents a numerical example.

Scenario 0: Fully Segmented Markets

In the benchmark scenario, no agent has access to the foreign market. The implied trading pattern, however, is non-trivial, as volatility during the overlap is higher than outside the overlap. The reason is that liquidity suppliers, in the fourth round of the game, observe the transaction price in the foreign market and use this to update their quote.

Proposition 0. *If markets are fully segmented in that no trader has access to the other market, we find that for the overlap as compared to the non-overlap: (i) volume is equal, (ii) volatility is higher and, (iii) market depth is equal. Finally, order imbalance is positively correlated during the overlap.*

The positive correlation in order imbalance is due to the informed traders in both markets, who trade on the same signal.

Scenario 1a: Allow Large Liquidity Traders to Access Other Market

In scenario 1a, we allow large liquidity traders to access the foreign market. The implied patterns change and are summarized in the following proposition.

Proposition 1a. *If large liquidity traders are the only ones with access to the other market, we find that for the overlap as compared to the non-overlap: (i) for at least one of the two*

markets, volume is lower, (ii) volatility is higher in both markets, and, (iii) for at least one of the two markets, market depth is lower. Finally, order imbalance is positively correlated during the overlap.

The result of lower depth and less volume during the overlap seems counterintuitive, but is essentially due to less (signed) volume by large liquidity traders. They, effectively, trade among themselves when trading in both markets. These cross-trades reduce the aggregate *signed* volume from large liquidity traders in at least one market comparing the overlap with the non-overlap. As a result, the liquidity supplier in this market reduces depth—increases λ_i —to protect herself against this reduction in liquidity trading.

Compared to the benchmark scenario, the volatility increase is lower and the order imbalance correlation is higher. As discussed, order-splitting by large liquidity traders reduces the information liquidity suppliers can retrieve from price changes in both markets, which results in a lower volatility increase. And, order-splitting causes higher order imbalance correlation across markets.

Scenario 1b: Allow Informed Traders to Access Other Market

The results change if we, instead of large liquidity traders, allow informed traders to access the other market.

Proposition 1b. *If informed traders are the only ones with access to the other market, we find that for the overlap as compared to the non-overlap: (i) volume is higher, (ii) volatility is higher, and, (iii) market depth is higher in both markets. Finally, order imbalance is positively correlated during the overlap.*

In equilibrium, informed traders trade more aggressively during the overlap as compared to the non-overlap. In their optimization, informed traders decide for every marginal order whether or not the additional expected profit on this order is higher than the expected loss on their “outstanding” orders due to price concession. During the overlap they compete,

which means that, effectively, they share the losses on the “outstanding” informed orders when submitting an additional order, whereas they privately enjoy the expected profit of the additional order. This makes them trade more aggressively during the overlap. This is why volume and volatility are higher during the overlap as compared to the non-overlap. In fact, the volatility increase is higher than in the scenarios 0 and 1a. This squares well with intuition, since liquidity suppliers in the current scenario get a better signal on the true security value due to more aggressive informed trading. To study the effect on market depth, we note that liquidity suppliers set the price change such that, in expectation, it is equal to the true value of the security. This goes for the overlap as well as for the non-overlap and it is for this reason that they use a lower factor λ_i for order imbalance during the overlap, since the informed traders’ order is larger and total liquidity demand does not change. In other words, market depth (λ_i^{-1}) is higher during the overlap.

The correlation in order imbalance is higher than in the benchmark scenario 0, due to more aggressive informed trading.

Scenario 2: Allow Informed and Large Liquidity Traders to Access Other Market (1a+1b)

In scenario 2, we combine scenarios 1a and 1b and thus allow both the informed and the large liquidity traders to access the foreign market.

Proposition 2. *If both large liquidity traders and informed traders have access to the other market, we find that volatility is higher for the overlap as compared to the non-overlap. Volume and market depth can be higher, unchanged, or lower during the overlap depending on parameter values. Finally, order imbalance is positively correlated during the overlap.*

The results for volume and depth are ambiguous, since opening up the foreign market for large liquidity traders or for informed traders has opposite effects. The relative strength of each effect depends on how important large liquidity trading is compared to small liquidity trading and on the volatility of the true value, respectively. The volatility increase is higher

than in scenarios 0 and 1a, due to more aggressive informed trading, but smaller than in scenario 1b, since order-splitting by large liquidity traders hampers liquidity suppliers in retrieving the true value of the security.

Correlation in order imbalance across markets is higher than in any previous scenario due to the contribution of both order-splitting by large liquidity traders and aggressive trading by informed traders.

Scenario 3: Allow Informed and Large Liquidity Traders to Access Other Market and Allow Large Liquidity Traders to Time their Trade (2+)

In scenario 3, we extend the previous scenario by allowing large liquidity traders to time their trade in the spirit of Admati and Pfleiderer (1988). Both can decide to trade in period 1, 2, or 3.

Proposition 3. *If both large liquidity traders and informed traders have access to the other market and large liquidity traders are allowed to time their trades, we find that large liquidity trading in the overlap is always a Nash equilibrium and, under certain conditions, it is the only Nash equilibrium. Compared to other potential Nash equilibria—concentrated trading in period 1 or 3—this equilibrium is shown to result in lowest trading costs for both large liquidity traders. For this equilibrium, we find that for the overlap as compared to the non-overlap: (i) volume is higher, (ii) volatility is higher, and, (iii) market depth is higher in both markets. Finally, order imbalance is positively correlated during the overlap.*

The Nash equilibrium of concentrated large liquidity trading in the overlap appears to be the dominant equilibrium. The intuition is that this is the only period in which large liquidity traders can benefit from each other and from small liquidity traders in *both* markets. In the two other candidate Nash equilibria—concentrated trading in period 1 or 3—the large liquidity traders benefit only from one small liquidity trader. Under parameter conditions that are specified in appendix A, which can be read as small liquidity trading being large enough, large liquidity traders have an incentive to deviate from these alternative Nash

equilibria, since the benefit of additional small liquidity trading during the overlap dominates the benefit of trading with the other large liquidity trader outside the overlap. Even if these alternative Nash equilibria are viable, the Nash equilibrium of concentrated large liquidity trading during the overlap is dominant, because it leads to lowest expected trading costs for *both* large liquidity traders.

In the most likely Nash equilibrium of concentrated trading in the overlap, we find higher volume, volatility, and market depth during the overlap. Comparing these results with those of scenario 2, we find that the volatility increase is lower, which, again, can be traced back to the intuition that order-splitting hampers liquidity suppliers in inferring the “true” value of the security.

2 Hypotheses and Natural Experiment

We test the predicted multi-market trading by either the informed or the large liquidity traders in a natural experiment of NYSE-listed British and Dutch securities. Henceforth, for ease of exposition, we refer to both types of trading as order-splitting. The test involves two stages. First, we use the non-overlap as a benchmark period and test whether the model-implied trading patterns are consistent with the empirical patterns. Second, we test directly for order-splitting through a high-frequency analysis of order imbalance during the overlap.

2.1 Hypotheses

The model’s prediction for volatility is consistent across all scenarios.

H1. *Volatility is higher during the overlap as compared to the non-overlap.*

But, volume and market depth patterns allow us to discriminate scenarios.

H2(0). *If markets are fully segmented—no trader has access to the other market—volume and market depth remain unchanged during the overlap as compared to the non-overlap;*

H2(alt). *Volume and depth are lower in at least one of the markets (scenario 1a) or volume and depth are higher in both markets (scenarios 1b and 3) or a combination of both (scenario 2).*¹¹

And, zooming in on the overlap, the model’s prediction for order imbalance is consistent across all scenarios.

H3. *Order imbalance is positively correlated across markets.*

But, in order to test whether this is due to order-splitting or just a result of the same (private) information arriving at both markets, we use the following result.

H4. *Order imbalance correlation across markets is higher at times of order-splitting (scenarios 1-3) as compared to the benchmark scenario of segmented markets (scenario 0).*

It turns out that the British tax regime allows us to identify conditions under which order-splitting is not optimal. We will come back to this issue, when we design the test.

2.2 Natural Experiment: NYSE-Listed British and Dutch Stocks

For order-splitting to occur in real-world markets, an ideal experiment should consist of markets that satisfy (i) synchronicity, (ii) liquid trading in the same security, (iii) simultaneous accessibility by at least one trader, (iv) security fungibility, and (v) an equal level of transparency. The last condition is imposed to prevent traders from routing orders to the least transparent market (see, e.g., Gemmill (1996) and Bloomfield and O’Hara (2000)). In addition, to detect the effects of order-splitting, we need a significant non-overlap as a benchmark period.

The natural experiment we propose is U.S. and European trading in NYSE-listed European stocks. We analyze 1997-1998 trading in Dutch stocks and 2002-2003 trading in

¹¹Volume and market depth remaining unchanged in scenario 2 is a highly unlikely outcome. If parameters are sampled from a continuous distribution, this would be a zero probability event.

British stocks. These stocks both represent roughly a quarter of “European” volume at the NYSE in recent years. We select 25 British stocks and controls that match these stocks in terms of volume.¹² For the Dutch market, we select four stocks, as, stronger than the British market, U.S. volume is skewed towards a very limited number of shares. A complete list of all stocks and their volume in both markets has been added as Appendix C.¹³

London						
Amsterdam						
New York						
	↑	↑	↑	↑	↑	↑
EST	3:00	3:30	9:30	10:30	11:30	16:00
	London	Amsterdam	New York	Amsterdam	London	New York
	Open	Open	Open	Close	Close	Close

The experiment meets the five conditions. (i) Synchronicity: the above time table for London, Amsterdam, and New York trading shows that there is a one- or two-hour trading overlap.¹⁴ (ii) Liquidity: on both sides of the Atlantic trading is highly liquid, in particular during the overlap. Volume in New York is at least US\$ 10 million a month for all stocks and, relative to the home market, the U.S. market share ranges from 1% to 30%. (iii) Accessibility: investors can trade in all markets simultaneously, as all markets are equipped with electronic order routing systems open to foreign investors. As a matter of fact, the author has seen traders access both markets from a split screen on the trading floor of a major bank on Wall Street. (iv) Fungibility: the Depositary Receipt (e.g. ADR) that is traded on the NYSE can be converted to the ordinary share (or vice versa) at a

¹²The volume matching is not straightforward for the British market, as the stocks that generate most volume are almost all cross-listed. For these, it is, therefore, hard to find control stocks with the same volume. We follow Werner and Kleidon (1996) and choose to assign control stocks top-down, starting with the highest volume stock available and not using the same stock more than once.

¹³Some of the shares also trade on other (European) exchanges, but volume in these venues is typically negligible vis-à-vis NYSE and home market volume. We note that the firms Unilever and Royal Dutch/Shell have securities trading in Amsterdam and London, but, although entitled to the same dividend, these are *not* the same securities and are, therefore, not fungible. For a thorough discussion of these so-called “twin shares,” we refer to Froot and Dabora (1999).

¹⁴In the spring, Europe changes to daylight-savings time one week ahead of the U.S. This week has been removed from the sample.

cost of approximately 15 basis points at a depository bank.¹⁵ For the British market, a conversion tax of 150 basis points applies, which makes order-splitting optimal only when price differences are “large enough.” We will make this precise when designing our test on order-splitting. (v) Transparency: the level of transparency in all markets is high since trades and best quotes are disseminated in real time.¹⁶ The time table also shows that there is a significant non-overlap to serve as a benchmark period.

All three markets, essentially, feature an electronic limit order book. Amsterdam can be considered a pure limit order book market, as specialist intervention is negligible.¹⁷ London runs a similar system, but allows for off-market trading among dealers. New York allows for the specialist or floor brokers to improve on the liquidity in the order book.

For both samples, we exploit one year of tick data. The British sample runs from November 1, 2002, through October 31, 2003; the Dutch sample from July 1, 1997, through June 30, 1998. The dataset contains all trades and quotes in the cross-listed shares on both sides of the Atlantic and it contains all quotes in the exchange rate.¹⁸

Table 2 provides summary statistics for both samples. We aggregate the British stocks in quintiles based on U.S. trading volume to conserve space. We retain, however, individual results for stocks in the first quintile, as we expect strongest results for these stocks. Panel A presents average volume, volatility, quoted and effective spread for the overlapping period; Panel B presents these statistics for the full trading day. The results lead to some interesting observations. First, U.S. volume is non-trivial as the NYSE trades, on average, more than 1,000 shares every five minutes. Relative to the home market, the U.S. market share ranges from 1% to 10% for British stocks and from 30% to 50% for Dutch stocks. Second, volatility differences across markets are small. This is not surprising for the

¹⁵This service is provided by, e.g. the Bank of New York, Citibank, and JPMorgan. Although the transaction is not done in real-time, the arbitrageur does not run a risk on an “open position,” as he does not have to settle the trades in both markets immediately, but in a matter of days.

¹⁶The LSE allows for off-market trades that need not be reported instantaneously. Most volume, however, comes through the electronic order book SETS and is reported in real-time.

¹⁷At the time of the experiment, a specialist (“hoekman”) was assigned to each stock, but for the most liquid stocks, he participated in very few trades, as was confirmed by a Euronext official.

¹⁸The data sources are: NYSE, Euronext-Amsterdam, the London Stock Exchange, and Olsen&Associates.

overlapping period, as arbitrage ensures that prices move in lockstep. For the non-overlap, it shows that continued NYSE trading, after the European markets close, appears to move prices significantly.¹⁹ Third, quoted spreads at the NYSE are lower than the London spreads for the top quintile of British stocks, but higher for the other stocks. This comparison, however, is unfair to the NYSE, as the specialist often provides price improvement over the quoted spread. If we compare both markets in terms of effective spread, we find that the NYSE is competitive, which is promising in view of the order-splitting hypotheses considered in this paper.

3 Results

The results are presented in two subsections. First, we study intraday patterns to test hypotheses 1 and 2. Second, we test for order-splitting by zooming in on the overlap and studying five-minute order imbalance correlations.

3.1 Intraday Trading Patterns

We study intraday patterns in volatility, volume, and liquidity by documenting the change in the home market when the NYSE opens and the change at the NYSE when the home market closes. We use half-hour intervals before and after the event. For the British sample, we do the same for the volume-matched single-listed stocks in order to isolate the effect of the cross-listing. We calculate standard errors after correcting for differences in daily values.²⁰

¹⁹In a contemporary paper, Menkveld, Koopman, and Lucas (2003), we study to what extent this volatility is noise or information.

²⁰We scale all values by daily averages, as we are interested in *intraday* effects and, therefore, want to dispose of interday variation.

H1: Higher Volatility during the Overlap?

For the stocks that generate most volume in New York, we find evidence consistent with the model’s prediction of increased volatility during the overlap. Table 3 presents volatility changes in the home market (left-hand side) and volatility changes on the NYSE (right-hand side). For the top quintile of British stocks, volatility in London increases by 93.4% when the NYSE opens. The changes for the lower quintiles are smaller and range from 49.1% to 58.7%. Part of the increase is arguably due to the fact that the NYSE open is a (common) information event. This is reflected in the significant volatility increases for the control stocks. We find that only for the top quintile British stocks, volatility is significantly higher than its control group, 43.9% higher on average.²¹ In New York, we find that volatility for this quintile decreases a significant 23.9% more than it does for the control stocks when the London market closes. The top graphs in figure 1 illustrate the increased volatility during the overlap for this top quintile. For the U.S. market, the control stocks are not appropriate benchmarks for the start of the interval, as they cannot lean on a European market for reference prices. We do see a drop in volatility when London closes for the cross-listed shares, which we do not see for the control stocks. For the Dutch stocks, we also find volatility increases on the NYSE open, 70.7% on average, and volatility decreases on the Amsterdam close, 30.2% on average.

H2: No Change in Volume and Depth?

Consistent with the volatility results, we find that volume during the overlap is significantly higher for the stocks that generate most U.S. volume. Table 4 shows that, for the top quintile British stocks, volume increases by 81.9% on the NYSE open, which is a significant 42.7% higher than the increase for the control stocks. And, NYSE volume decreases for these stocks by an average 105.9% on the London close, a significant 87.7% more than the

²¹The other British quintiles do not show disproportionate volatility increases in London on the NYSE open. This seems to be at odds with the model as it predicts increased volatility even in a segmented market setting. The model, however, assumes the existence of an informed trader in the NYSE market, which might be too strong an assumption for these thinly traded stocks.

decrease for control stocks. The bottom graphs in figure 1 illustrate these findings. For the other quintiles, the volume increases are not significantly different from the control stocks. For the Dutch stocks, we find an average volume increase in Amsterdam of 67.9% on the NYSE open and an average volume decrease in New York of 29.0% on the Amsterdam close.

Market depth as measured by effective spread remains largely unchanged in the home market on the NYSE open, but increases in New York on the home market close. Table 5 shows that for the top quintile British stocks, we find that spreads are 0.4% higher on the NYSE open, a significant 4.6% less than the increase for control stocks. The effect is small economically and not uniform across all stocks in this quintile. The increase in New York on the London close is 7.2%, which is a significant 14.4% higher than the 7.2% decrease for the control stocks. We find similar results for the other quintiles and for the Dutch stocks.

The pattern of largely unchanged depth in London for the overlap and slightly higher depth in New York appears to be consistent across three measures of liquidity. Figure 2 plots the top quintile intraday pattern for quoted spread, effective spread, and an “empirical” Kyle- λ . The last measure is based on OLS regressions of five-minute midquote returns on order imbalance and proxies market impact. The patterns for quoted and effective spread are very similar, which shows that the “displayed” liquidity correlates high with the “consumed” liquidity. The second measure of “consumed” liquidity, the Kyle- λ , seems to increase in London on the New York open and the increase is significantly higher vis-à-vis the control stocks. This seems to be a temporary increase as it drops back to control stock levels further into the overlap.²²

²²The results of an increase in Kyle- λ and unchanged effective spreads can be reconciled when the direction of market orders in the first half-hour of NYSE trading is positively correlated with the change in quotes due to public information (i.e. not triggered by an incoming market order). That is, effective spreads measure the impact from trade to trade, whereas the “empirical” Kyle- λ is an aggregate measure, which relates order imbalance to the *sum* of all quote changes, thus including quote changes that are not triggered by order flow.

Discussion of the Results

In summary, we find increased volatility, volume, and largely unchanged or (slightly) higher depth in the overlapping period for the top quintile of British stocks and the Dutch experiment seems to reconfirm this result. For the other British quintiles we do not find significant differences comparing the results for cross-listed stocks to their controls.

For the top quintile British stocks and the Dutch stocks, qualitatively, scenarios 1b, 2, and 3 are consistent with the observed patterns, but scenario 3 is the most likely candidate. In appendix A we show that volume increases in scenarios 1a and 2 are bounded to a maximum of 21.82%, whereas they are unbounded in the third scenario. We document a 42.7% higher volume in London and a 87.7% higher volume in New York. Such levels are, therefore, only consistent with scenario 3. This implies that the result is partially due to large liquidity traders who concentrate their orders in the overlap and split them across markets at the cost of small liquidity traders. Interestingly, the absence of significant increases for the other British quintiles is consistent with one of the conditions of scenario 3, i.e. “small liquidity trading” should be large enough to create the incentive for large liquidity traders to allocate their orders to the overlap. As liquidity in the U.S. market is relatively low for these quintiles, such incentive might be absent for these stocks. The unchanged market depth, however, seems to be at odds with the model’s predicted higher depth. The model can be calibrated to yield unchanged market depth by increasing the (exogenous) arrival rate of information (σ_v) for the overlapping hour. This change does not affect the volume pattern, but leads to stronger increases in volatility for the overlap. The observed patterns are, therefore, consistent with the third scenario.

In the next section, we zoom in on the overlap to conduct a direct test on the order-splitting that is predicted by the third scenario.

3.2 High Frequency Analysis of Order Imbalance

To detect order-splitting (for hypotheses 3 and 4), we study correlation in order imbalance across markets for five minute intervals. A clean test accounts for potential arbitrage trades, British transaction tax, and potential “microstructure” dynamics in order flow.

We control for negative correlation in order imbalance due to arbitrage by conditioning on the availability of arbitrage opportunities. An arbitrage trade in both experiments is not free of cost, as the NYSE Depositary Receipt (DR) is exchanged for the ordinary share (or vice versa) at a cost of approximately 15 basis points. As arbitrage trades cause negative correlation in order imbalance—a buy in one market coincides with a sell in the other—this could dampen or even annihilate the positive correlation due to order-splitting. We condition on the availability of arbitrage opportunities at the start of an interval to control for potential arbitrage trades. That is, if the ask in one market is 15 basis points higher than the bid in the other market, we consider the interval a potentially arbitrage “contaminated” interval. In evaluating arbitrage opportunities, we also consider the exchange rate transaction, that is, we take the bid or ask side in the the FX market, as appropriate. Finally, we have to consider the British transaction tax, and the precise definition of an arbitrage opportunity is, therefore, postponed to the next paragraphs.

The tax imposed on transactions in London, Stamp Duty Reserve Tax (SDRT), allows us to discriminate order-splitting from same direction trades due to new information arriving at both markets. Contrary to Amsterdam and New York, buyers in London are taxed 50 basis points. And, to prevent order flow from migrating to the U.S., conversions to U.S. Depositary Receipts are taxed 150 basis points. For reverse transactions, a tax of 50 pence applies. We use the SDRT to sort intervals into three categories: arbitrage, order-splitting, and control intervals. Arbitrage in the British tax regime, essentially, sets the lower bound price of Depositary Receipts equal to the London price and the upper bound price equal to 150 basis points above the London price. In the implementation, we use exact conditions for arbitrage that also account for the 15 basis points conversion fee and the exchange rate transaction. These conditions are included as appendix B. To find

the optimal conditions for order-splitting in this regime, we differentiate between DR buyers and sellers and ordinary share buyers and sellers. These conditions amount to order-splitting opportunities when “prices are at or close to the arbitrage bounds.” We label the intervals where these conditions are met, within a 10 basis point margin, as “order-splitting” intervals. For the exact conditions we refer to appendix B. We note that these conditions assign some intervals to the order-splitting category as well as the arbitrage category and we decide to label these intervals as arbitrage intervals to preserve clean order-splitting intervals. The unlabelled intervals serve as controls that potentially exhibit positive correlation in order imbalance due to new information.

As Amsterdam transactions are not taxed, price differentials are considerably smaller and the order-splitting conditions are practically always met. We decide to label all no-arbitrage intervals as order-splitting intervals for this experiment. Figure 3 illustrates the impact of the SDRT by plotting midquote differentials across markets for both experiments. The SDRT causes differentials for British securities to have a bimodal distribution, whereas we find a unimodal distribution for the Dutch securities.

Finally, we control for “microstructure” dynamics in order flow by studying order imbalance as well as order imbalance innovations. The latter are defined as the difference between the observed order imbalance for time interval t and the predicted order imbalance for the interval based on information available at the start of the interval. Inspired by Hasbrouck (1991), we estimate a vector-autoregressive (VAR) model for foreign as well as domestic order imbalance and include lagged returns as explanatory variables. Consistent with Hasbrouck’s results, we find positive coefficients for lagged imbalance and negative coefficients for lagged returns.²³ We then use these results to calculate order imbalance innovations.

For the test, we construct the order imbalances as the sum of signed trade sizes, where we use the standard Lee and Ready (1991) algorithm to sign each trade.

²³The results are available from the author upon request.

H3: Positive Correlation in Order Imbalance?

We find strong empirical support for positive correlation in order imbalance, with the exception of some “arbitrage” intervals that show negative correlation. Panel A of table 6 reports five-minute order imbalance correlations for the three types of intervals we distinguish; panel B reports these results for order imbalance *innovations*. We find highest correlations for the top quintile British stocks and the Dutch stocks. For the order-splitting intervals, order imbalance correlations range from 0.15 to 0.40. For the intervals that are neither order-splitting, nor arbitrage, we also find significant positive correlation, consistent with trading in both markets that is triggered by the arrival of the same new (private) information. We find similar results for the other British quintiles, with the exception that positive correlation is now insignificant for order-splitting intervals. For the arbitrage intervals, we find positive and negative correlations, but none of them is significant. Panel B shows that these results are robust, as correlations appear to be unaffected by controlling for microstructure effects. Incidentally, arbitrage opportunities are almost non-existent for the top quintile of British stocks and occur with low frequency (less than 15%) for the other stocks.

H4: Higher Correlation at times of Order-Splitting?

For the top quintile British stocks and for the Dutch stocks, we find significantly higher correlations for intervals with order-splitting opportunities. We find that the average correlation for the top quintile British stocks is 0.23, which is a significant 0.08 higher than the 0.15 correlation for control stocks. Furthermore, we find that this correlation is higher for each of the five member stocks, which is a $2^{-5} = 0.03$ probability event for five draws from a standard binomial distribution. If we take the 0.15 as a benchmark for the Dutch stocks, we find that correlations are a significant 0.11 higher, again consistent across all stocks.²⁴ Panel B reveals that these results are robust to controlling for microstructure effects. Consistent

²⁴Interestingly, for the Dutch stocks we find a similar level of correlation for the arbitrage intervals. Further inspection shows that these arbitrage opportunities typically occur at times of strong buying or selling in both markets and disappear within the interval. We consider this a by-product of multi-market trading rather than real “arbitrage opportunities.”

with the intraday patterns, we do not find evidence of increased correlation for the other British quintiles.

4 Conclusion

In this paper, we study order-splitting based on a natural experiment of NYSE-listed British and Dutch stocks. Theoretically, we expect two types of traders—informed traders and large liquidity traders—to split orders, which is at the cost of local traders. We study this behavior in a two-stage approach.

First, we study trading patterns and use the non-overlap as a benchmark period. We develop a model for trading in partially overlapping markets, by extending the Chowdhry and Nanda (1991) model to allow for large liquidity traders to time their trades in the spirit of Admati and Pfleiderer (1988). We use the model to understand trading in the overlap and to predict the trading patterns that might arise endogenously. That is, we predict volume, volatility, and market depth for the overlap and for the non-overlap. Several scenarios are explored from a benchmark scenario of fully segmented markets—no participant has access to the other market—to a full-fledged model—informed traders and large liquidity traders have access to the other market and large liquidity traders are allowed to time their trades. For the British and Dutch stocks that generate most U.S. volume, we find increased volume, volatility, and unchanged market depth in the overlap. This pattern is inconsistent with most of the scenarios, including the standard Chowdhry and Nanda (1991) model. It is only consistent with the full-fledged model, if we increase the (exogenous) arrival rate of information for the overlap vis-à-vis the non-overlap. In this scenario, informed investors split their orders across markets as well as large liquidity traders who allocate their orders to the overlap. For the stocks that generate less U.S. volume, we do not find significant differences comparing the overlap to the non-overlap, which is consistent with the model’s prediction that large liquidity traders only allocate to the overlap if local trading (by small liquidity traders) is sufficiently high.

Second, we design a direct test on order-splitting through a high-frequency analysis of order imbalance during the overlap. We find that home market and NYSE order imbalance are significantly positively correlated, which is consistent with order-splitting. Our main concern is that this positive correlation is also consistent with the benchmark scenario of segmented markets, as this is due to informed traders in both markets, who trade on the same new (private) information. We benefit from British tax law that allows us discriminate intervals with order-splitting opportunities from intervals without such opportunities. For the stocks that we expect to exhibit order-splitting based on the intraday pattern analysis (i.e. those with most U.S. volume), we find that correlation is significantly higher for the intervals with order-splitting opportunities. For the remaining stocks, this difference is not significant. In the analysis, we control for arbitrage trading by conditioning on the intervals without arbitrage opportunities.

Appendix A: Proofs of Propositions

Summary results: We start with a summary table that contains equilibrium values for volume, volatility, market depth, and order imbalance correlation for all scenarios. It presents equilibrium values for the overlap and the non-overlap. We only report the non-overlap values for market A, because the model is symmetric in A and B. The results for scenario 3 are based on the most likely Nash equilibrium of concentrated trading during the overlap.

scenario	volume	volatility	λ (Depth ⁻¹)	ρ (order imbalance)
<i>Panel A: The Non-Overlap</i>				
0,1a,1b,2	$\frac{1}{\sqrt{2\pi}}(\sigma_{u,A} + \sigma_{d,A} + \alpha\sqrt{\sigma_{u,A}^2 + \sigma_{d,A}^2})$	$\frac{1}{2}\sigma_v^2$	$\frac{1}{2\sqrt{\sigma_{u,A}^2 + \sigma_{d,A}^2}}\sigma_v$	
3	$\frac{1}{\sqrt{2\pi}}(4 + \sqrt{2})\sigma_{u,A}$	$\frac{1}{2}\sigma_v^2$	$\frac{1}{2\sigma_{u,A}}\sigma_v$	
<i>Panel B: The Overlap</i>				
0	$\frac{1}{\sqrt{2\pi}}\left\{\sigma_{u,A} + \sigma_{d,A} + \alpha\sqrt{\sigma_{u,A}^2 + \sigma_{d,A}^2}\right\}$	$\frac{2}{3}\sigma_v^2$	$\frac{1}{2}\frac{1}{\sqrt{\sigma_{u,A}^2 + \sigma_{d,A}^2}}\sigma_v$	$\frac{1}{2}$
1a	$\frac{\sigma_{u,A}}{\sqrt{2\pi}}\left\{1 + \Theta + \alpha\sqrt{1 + \Phi}\right\}$	$\frac{2}{3 + \left(\frac{\Phi}{\Phi+1}\right)}\sigma_v^2$	$\frac{1}{2}\frac{1}{\sigma_{u,A}\sqrt{1 + \Phi}}\sigma_v$	$\frac{1}{2}\left\{1 + \left(\frac{\Phi}{\Phi+1}\right)\right\}$
1b	$\frac{1}{\sqrt{2\pi}}\left\{\sigma_{u,A} + \sigma_{d,A} + \beta\sqrt{\sigma_{u,A}^2 + \sigma_{d,A}^2}\right\}$	$\frac{4}{5}\sigma_v^2$	$\sqrt{\frac{8}{9}}\frac{1}{2}\frac{1}{\sqrt{\sigma_{u,A}^2 + \sigma_{d,A}^2}}\sigma_v$	$\frac{9}{17}$
2	$\frac{\sigma_{u,A}}{\sqrt{2\pi}}\left\{1 + \Theta + \beta\sqrt{1 + \Phi}\right\}$	$\frac{4}{5 + \left(\frac{\Phi}{\Phi+1}\right)}\sigma_v^2$	$\sqrt{\frac{8}{9}}\frac{1}{2}\frac{1}{\sigma_{u,A}\sqrt{1 + \Phi}}\sigma_v$	$\frac{9}{17}\left\{1 + \left(\frac{\Phi}{\Phi+1}\right)\right\}$
3	$\frac{\sigma_{u,A}}{\sqrt{2\pi}}\left\{1 + \sqrt{2}\Theta + \beta\sqrt{1 + 2\Phi}\right\}$	$\frac{4}{5 + \left(\frac{2\Phi}{2\Phi+1}\right)}\sigma_v^2$	$\sqrt{\frac{8}{9}}\frac{1}{2}\frac{1}{\sigma_{u,A}\sqrt{1 + 2\Phi}}\sigma_v$	$\frac{9}{17}\left\{1 + \left(\frac{2\Phi}{2\Phi+1}\right)\right\}$
$\alpha \equiv 3 + \sqrt{2}, \quad \beta \equiv \sqrt{2} + (1 + \sqrt{2})\sqrt{3}, \quad \Theta \equiv \frac{\sigma_{d,A} + \sigma_{d,B}}{\sigma_{u,A} + \sigma_{u,B}}, \quad \Phi \equiv \frac{\sigma_{d,A}^2 + \sigma_{d,B}^2}{(\sigma_{u,A} + \sigma_{u,B})^2}$				

Proof of equilibrium results for the basic one-period model: The differences between our one-period model and the standard model in Chowdhry and Nanda (1991) are minor and we therefore rely on the original proof and only discuss how the differences affect the results and the proof. First, contrary to one informed trader with access to both markets in Chowdhry and Nanda (1991), our model features an informed trader in both markets without access to the other market. This does not affect the results, since the informed trader's maximization problem in market i ,

$$\max_{x_A} E[x_A(v - \lambda_A \cdot \omega_A)], \quad (6)$$

is the same whether it is our “domestic” informed trader or the “Chowdhry and Nanda (1991)” informed trader. Second, Chowdhry and Nanda (1991) only have one large liquidity trader with access to both markets, whereas we generalize this model to two large liquidity traders, one in each market. Both these traders face the minimization problem:

$$\min_{\{d_A^A, d_B^A\}} \sum_{i=A,B} E[d_i^A \cdot \lambda_i \cdot \omega_i] \text{ such that } d_A^A + d_B^A = d^A. \quad (7)$$

Solving first order conditions for this equation leads to

$$d_j^{i*} = k_j d^i \text{ for } i,j \in \{A,B\} \text{ with } k_j = \frac{\lambda_{i \neq j}}{\lambda_{i \neq j} + \lambda_j} \text{ and thus } (d_j^{A*} + d_j^{B*}) = k_j (d^A + d^B), \quad (8)$$

which, essentially, is one of the intermediary equations in the Chowdhry and Nanda (1991) model, when we interpret $(d^A + d^B)$ as the signed volume demand by the large liquidity trader in their model. The results of equation (2), therefore, naturally follow from Chowdhry and Nanda (1991) by replacing the variance of the large liquidity trader's signed volume in the original model (σ_d^2) by the sum of variances of the large liquidity traders in our model ($\sigma_{d,A}^2 + \sigma_{d,B}^2$).

Proof for expected volume in the basic one-period model: The variance of order imbalance (ω_i) is not an appropriate measure of trading volume, since it does *not* capture trades that are crossed between

traders. In general, suppose we have n traders with market orders $s_1, s_2, \dots, s_k$, which are independently and identically distributed with mean 0. Let $s_i^+ = \max(s_i, 0)$ and $s_i^- = \max(-s_i, 0)$. The total volume of trade is $\max(S^+, S^-)$, where $S^+ = s_1^+ + \dots + s_n^+$ and $S^- = s_1^- + \dots + s_n^-$. The expected volume is

$$E(\max(S^+, S^-)) = \frac{1}{2} \sum_{i=1}^n E|s_i| + \frac{1}{2} E \sum_{i=1}^n |s_i| = \frac{1}{\sqrt{2\pi}} \left(\sum_{i=1}^n \sigma_i + \sqrt{\sum_{i=1}^n \sigma_i^2} \right), \quad (9)$$

where σ_i is the standard deviation of s_i (see Admati and Pfleiderer (1988)). For our model we, therefore, find

$$Volume_i = \frac{1}{\sqrt{2\pi}} ((\sigma_{u,A} + k_i \sigma_{d,A} + k_i \sigma_{d,B} + c_i \sigma_v + \sigma_{\omega_i}) + \sqrt{\sigma_{u,A}^2 + k_i^2 \sigma_{d,A}^2 + k_i^2 \sigma_{d,B}^2 + c_i^2 \sigma_v^2 + \sigma_{\omega_i}^2}); \quad (10)$$

with $c_i \equiv \frac{1}{2\lambda_i}$; $k_i \equiv \frac{\lambda_{j \neq i}}{\lambda_{j \neq i} + \lambda_i}$; and $\sigma_{\omega_i} = \sqrt{\sigma_{u,A}^2 + k_i^2 \sigma_{d,A}^2 + k_i^2 \sigma_{d,B}^2 + c_i \sigma_v^2}$. If we insert all constants we find the result presented in equation (3).

Proof for volatility in the basic one-period model: The technical proof is in Chowdhry and Nanda (1991, p. 504): proof of proposition 2. Whereas the focus of their proof is the informativeness of prices, it, essentially, is a proof of the variance of the expected value of the security conditional on the price changes witnessed in both markets, which is our measure of volatility.

Proof for order flow correlation in the basic one-period model: The proof is in Chowdhry and Nanda (1991, p. 503): proof of proposition 1.

Equilibrium results for one-market model: The equilibrium results for the one-market setting are relatively straightforward:

$$\lambda_i = \frac{1}{2} \frac{\sigma_v}{\sqrt{\sigma_{u,i}^2 + \sigma_{d,i}^2}}; \quad d_i^i = d^i; \quad x_i = \frac{1}{2\lambda_i} v; \quad (11)$$

$$Volume_i = \frac{1}{\sqrt{2\pi}} (\sigma_{u,i} + \sigma_{d,i} + (3 + \sqrt{2}) \sqrt{\sigma_{u,i}^2 + \sigma_{d,i}^2}); \quad Volatility = \frac{1}{2} \sigma_v^2; \quad i \in \{A, B\}.$$

Proof of Proposition 0: Trading during the overlap equals trading during the non-overlap, as no trader has access to the other market. Therefore volume and depth do not change. The liquidity supplier, however, in the final stage of the game observes the transaction price in the foreign market and uses it to update her estimate of the value of the security (v). Since, in this final stage, both liquidity suppliers have the same information set, their conditional estimate of v is the same and they therefore issue the same new quote. The volatility of this quote is:

$$Volatility = var(P^* - P) = var(E[v|\{\Delta P_A, \Delta P_B\}]) = \frac{2}{3} \sigma_v^2. \quad (12)$$

Since this scenario is a special case of the basic one-period model, we use the volatility equation for this model, equation (4), and set the demand of small liquidity traders so that it includes the demand of the “domestic” large liquidity trader. Large liquidity traders’ demand is then set to zero. The same approach is used to calculate correlation in net volume for which we find:

$$\rho(\omega_A, \omega_B) = \frac{1}{2}. \quad (13)$$

Proof of Proposition 1a: In this scenario, only large liquidity traders have access to the other market, so we use the results of the multi-period model developed in the main text. For order imbalance correlation and volatility, the claims in proposition 1a follow from inspection of equations (4), (5) and (11). The claims on market depth and volume require explicit proofs.

We claim market depth is lower in at least one market. Suppose not, then we know market depth during the overlap in both markets is at least as good as outside the overlap and for market A we find:

$$\lambda_{A,2} \leq \lambda_{A,1} \Leftrightarrow \frac{1}{2\sigma_{u,A}\sqrt{1+\Phi}}\sigma_v \leq \frac{1}{2\sqrt{\sigma_{u,A}^2 + \sigma_{d,A}^2}}\sigma_v \Leftrightarrow \sigma_{u,A}^2(\sigma_{d,A}^2 + \sigma_{d,B}^2) \geq \sigma_{d,A}^2(\sigma_{u,A}^2 + \sigma_{u,B}^2). \quad (14)$$

We get a similar result for market B. Adding these two inequalities we get

$$\sigma_{u,A}^2 + \sigma_{u,B}^2 \geq (\sigma_{u,A} + \sigma_{u,B})^2, \quad (15)$$

which contradicts both markets having a small liquidity trader ($\sigma_{u,A} > 0$, $\sigma_{u,B} > 0$). Hence market depth during the overlap is lower in at least one market.

We claim volume is lower in at least one market. Suppose not. This implies that total volume during the overlap is not lower than the sum of volumes in both markets outside the overlap and, thus,

$$\begin{aligned} \frac{(\sigma_{u,A} + \sigma_{u,B})}{\sqrt{2\pi}}(1 + \Theta + (3 + \sqrt{2})\sqrt{1 + \Phi}) &\geq \frac{1}{\sqrt{2\pi}}(\sigma_{u,A} + \sigma_{u,B} + \sigma_{d,A} + \sigma_{d,B} + (3 + \sqrt{2})(\sqrt{\sigma_{u,A}^2 + \sigma_{d,A}^2} + \sqrt{\sigma_{u,B}^2 + \sigma_{d,B}^2})) \Leftrightarrow \\ &\sqrt{(\sigma_{u,A} + \sigma_{u,B})^2 + \sigma_{d,A}^2 + \sigma_{d,B}^2} \geq \sqrt{\sigma_{u,A}^2 + \sigma_{d,A}^2} + \sqrt{\sigma_{u,B}^2 + \sigma_{d,B}^2}. \end{aligned} \quad (16)$$

This implies $\exists(\bar{x}_1, \bar{x}_2, \bar{y}_1, \bar{y}_2) \in \mathbb{R}_+^4$ for which $(f - g)(x_1, x_2, y_1, y_2) > 0$ with $f(x_1, x_2, y_1, y_2) = \sqrt{x_1^2 + y_1^2} + \sqrt{x_2^2 + y_2^2}$ and $g(x_1, x_2, y_1, y_2) = \sqrt{(x_1 + x_2)^2 + y_1^2 + y_2^2}$. We proceed by studying the zeros of $(f - g)$ fixing (x_2, y_1, y_2) at $(c, \sqrt{a}, \sqrt{b})$:

$$(f - g)(x, c, \sqrt{a}, \sqrt{b}) = 0 \Leftrightarrow \sqrt{(x^2 + a)(c^2 + b)} = cx \Rightarrow x^2 < 0, \quad (17)$$

hence $(f - g)$ does not have zeros in $\mathbb{R}_+^4$. Since it is a continuous function and $\frac{\partial}{\partial x_1}(f - g)(0, c, \sqrt{a}, \sqrt{b}) = \frac{-c}{\sqrt{c^2 + a + b}} < 0$, we know $(f - g)(x_1, x_2, x_3, x_4) < 0$ for $x \in (0, \infty)$. Since this holds for all $(c, \sqrt{a}, \sqrt{b}) \in \mathbb{R}_+^3$ the claim that $\exists(x_1, x_2, x_3, x_4) \in \mathbb{R}_+^4$ for which $(f - g)(x_1, x_2, x_3, x_4) \geq 0$ is not true. Hence, market volume is lower in at least one of the markets.

Proof of Proposition 1b and 2: In propositions 1b and 2, the informed traders in each market have access to the other market. As 1b is a special case of 2, we focus on 2. We extend the basic one-period model by re-evaluating equation (6), i.e. the optimization problem of the informed trader. The new optimization equation is:

$$\max_{x_i^A} E[x_i^A(v - \lambda_i(x_i^A + x_i^B + u_A + d_i^A + d_i^B))]. \quad (18)$$

Solving this problem for informed trader A yields:

$$x_i^{A*} = \frac{1}{2\lambda_i}v - \frac{1}{2}x_i^B. \quad (19)$$

As informed trader B faces a similar optimization problem in market i , we can calculate order imbalance in market i due to informed traders to be:

$$x_i^* \equiv x_i^{A*} + x_i^{B*} = \frac{4}{3}\left(\frac{1}{2\lambda_i}v\right). \quad (20)$$

We then solve each large liquidity trader's optimization problem presented in equation (7) and find

$$d_i^{j*} = \frac{\lambda_{j \neq i}}{\lambda_i + \lambda_{j \neq i}}d^j; \quad (21)$$

for the signed volume in market i originating from large liquidity traders:

$$d_i^* \equiv d_i^{A*} + d_i^{B*} = \frac{\lambda_{j \neq i}}{\lambda_i + \lambda_{j \neq i}}(d^A + d^B). \quad (22)$$

We use equations (20) and (22) to find the order imbalance in each market and solve the model by setting the liquidity supplier's profit equal to zero. For liquidity supplier A, we find:

$$\Delta P_A = E[v|\omega_A] = \lambda_A \cdot \omega_A \text{ with } \lambda_A = \frac{\text{cov}(\omega_A, v)}{\text{var}(\omega_A)}; \quad (23)$$

we solve it and find:

$$\frac{4}{3} \frac{1}{2\lambda_i} \sigma_b^2 = \lambda_i \left(\frac{16}{9} \frac{1}{4\lambda_i^2} \sigma_b^2 + \sigma_i^2 + \frac{\lambda_{j \neq i}^2}{(\lambda_i + \lambda_{j \neq i})^2} \sigma_d^2 \right) \Leftrightarrow \lambda_i = \sqrt{\frac{8}{9}} \frac{1}{2\sigma_{u,i} \sqrt{1+\Phi}} \sigma_v \text{ for } i,j \in \{A,B\}. \quad (24)$$

With this result, we calculate volume, volatility, and order imbalance correlation. For volume we apply equation (9) and get:

$$Volume_i = \frac{1}{\sqrt{2\pi}} ((\sigma_{u,A} + k_i \sigma_{d,A} + k_i \sigma_{d,B} + \frac{4}{3} c_i \sigma_v + \sigma_{\omega_i}) + \sqrt{\sigma_{u,A}^2 + k_i^2 \sigma_{d,A}^2 + k_i^2 \sigma_{d,B}^2 + \frac{16}{9} c_i^2 \sigma_v^2 + \sigma_{\omega_i}^2}); \quad (25)$$

with $c_i \equiv \frac{1}{2\lambda_i}$, $k_i \equiv \frac{\lambda_{j \neq i}}{\lambda_{j \neq i} + \lambda_i}$, and, $\sigma_{\omega_i} = \sqrt{\sigma_{u,A}^2 + k_i^2 \sigma_{d,A}^2 + k_i^2 \sigma_{d,B}^2 + \frac{16}{9} c_i^2 \sigma_v^2}$. If we insert the equilibrium value of market depth, we get:

$$Volume_i = \frac{\sigma_{u,i}}{\sqrt{2\pi}} \left\{ 1 + \Theta + (\sqrt{2} + (1 + \sqrt{2})\sqrt{3})\sqrt{1+\Phi} \right\}. \quad (26)$$

To calculate volatility, we follow the methodology of proposition 2 in Chowdhry and Nanda (1991), with the following (intermediate) results:

$$\text{var}(\Delta P) = \left(\frac{3+3\Phi}{5+6\Phi} \right)^2 (\text{var}(\Delta P_A) + \text{var}(\Delta P_B) + 2\text{cov}(\Delta P_A, \Delta P_B)) = \frac{4+4\Phi}{5+6\Phi} \sigma_v^2. \quad (27)$$

To calculate order imbalance correlation, we follow the methodology of proposition 1 in Chowdhry and Nanda (1991), with the following (intermediate) results:

$$c_i^2 \sigma_v^2 + \sigma_i^2 + k_i^2 \sigma_d^2 = \frac{17}{9} c_i^2 \sigma_v^2; \quad \rho(\omega_A, \omega_B) = \frac{9}{17} \left(1 + \frac{\Phi}{1+\Phi} \right). \quad (28)$$

With these results we prove proposition 1b, which states that if informed traders are the only ones with access to the other market, volume, volatility, and market depth are higher during the overlap as compared the non-overlap and that there is a positive correlation in order imbalance across markets. For the non-overlap, nothing changes and the results are summarized in equation (11). For the overlap we can use the results of equations (24), (26), (27), and (28), in which, for each market, we add the demand of the large liquidity traders to that of the small liquidity traders, as large liquidity traders cannot access the foreign market. In this case, the parameters Φ and Θ are equal to zero, the formulas simplify and the desired results follow by inspection.

We then use equations (24), (26), (27), and (28) to prove proposition 2, which claims that volatility is higher during the overlap, order imbalance correlation is positive, and no predictions can be made for volume and market depth. To prove the last two claims, we argue that scenario 2 is a combination of scenarios 1a and 1b, since both informed traders and large liquidity traders have access to the other market. For volume and market depth, these two scenarios lead to opposite predictions and we can get arbitrarily close to both predictions in scenario 2 by setting the demand of large liquidity traders to a small or large enough number. For example, the values $(\sigma_{u,A}, \sigma_{u,B}, \sigma_{d,A}, \sigma_{d,B}) = (0.9, 0.9, 0.1, 0.1)$ and $(\sigma_{u,A}, \sigma_{u,B}, \sigma_{d,A}, \sigma_{d,B}) = (0.1, 0.1, 0.9, 0.9)$ yield the desired results. The volatility during the overlap is higher, since for the overlap we know $\frac{2}{3} < \text{var}(\Delta P) \leq \frac{4}{5}$ and volatility is, therefore, higher than the non-overlap volatility. The correlation in order imbalance is positive, as it evident from equation (28).

Proof of Proposition 3: In scenario 3, large liquidity traders are allowed to time their trade. To prove the claims of proposition 3 we have to find all Nash equilibria. Large liquidity traders choose

the period they want to trade based on the cost of trading. Using equations (7) and (21) we find for large liquidity trader A:

$$\begin{aligned}\text{Cost Overlap} &= E \left[\lambda_{A,2} \left(\frac{\lambda_{B,2}}{\lambda_{A,2} + \lambda_{B,2}} d^A \right)^2 + \lambda_{B,2} \left(\frac{\lambda_{A,2}}{\lambda_{A,2} + \lambda_{B,2}} d^A \right)^2 \right] = \frac{\lambda_{A,2} \lambda_{B,2}}{\lambda_{A,2} + \lambda_{B,2}} 2\sigma_{d,A}^2; \\ \text{Cost Non-Overlap} &= E \left[\lambda_m (d^A)^2 \right] = \lambda_m 2\sigma_{d,A}^2, \text{ m} \in \{\lambda_{A,1}, \lambda_{B,3}\},\end{aligned}\quad (29)$$

where the subscripts indicate the market and the period, respectively. Note that total large liquidity demand is set to $2\sigma_{d,A}^2$, which ensures consistency across scenarios. We find similar expressions for trader B. The options of this game are, therefore:

Trader A \ Trader B	Period 1	Period 2	Period 3
Period 1	I	II	III
Period 2	IV	V	
Period 3	VI		

We restrict attention to options I through VI, as the problem is symmetric. We start with options II, III, and V and show that in these cases it is optimal for the trader trading outside the overlap to switch to the overlap. In option II it is optimal for trader A to switch from period 1 to period 2, since using equations (11), (24), and (29), we find:

$$\Delta \text{Cost} = \left(\frac{\lambda_{A,2} \lambda_{B,2}}{\lambda_{A,2} + \lambda_{B,2}} - \lambda_{A,1} \right) \sigma_{d,A}^2 = \frac{1}{2} \left(\sqrt{\frac{8}{9} \frac{1}{(\sigma_{u,A} + \sigma_{u,B})^2 + \sigma_{d,A}^2 + \sigma_{d,B}^2}} - \frac{1}{\sqrt{\sigma_{u,A}^2 + \sigma_{d,A}^2}} \right) < 0. \quad (30)$$

For the same reason, trader B will move from period 3 to the overlap in option V. Options II and V, therefore, cannot be Nash equilibria. In option III, it is optimal for trader A to move to the overlap, since:

$$\Delta \text{Cost} = \left(\frac{\lambda_{A,2} \lambda_{B,2}}{\lambda_{A,2} + \lambda_{B,2}} - \lambda_{A,1} \right) \sigma_{d,A}^2 = \frac{1}{2} \left(\sqrt{\frac{8}{9} \frac{1}{(\sigma_{u,A} + \sigma_{u,B})^2 + \sigma_{d,A}^2 + \sigma_{d,B}^2}} - \frac{1}{\sqrt{\sigma_{u,A}^2 + \sigma_{d,A}^2}} \right) < 0. \quad (31)$$

The same goes for trader B. Options I, IV, and VI remain as potential Nash equilibria. For option I, the change in cost for trader A when moving from period 1 to period 2 equals:

$$\Delta \text{Cost} = \left(\frac{\lambda_{A,2} \lambda_{B,2}}{\lambda_{A,2} + \lambda_{B,2}} - \lambda_{A,1} \right) \sigma_{d,A}^2 = \frac{1}{2} \left(\sqrt{\frac{8}{9} \frac{1}{(\sigma_{u,A} + \sigma_{u,B})^2 + \sigma_{d,A}^2 + \sigma_{d,B}^2}} - \frac{1}{\sqrt{\sigma_{u,A}^2 + \sigma_{d,A}^2 + \sigma_{d,B}^2}} \right). \quad (32)$$

This expression is negative, if

$$\begin{aligned}\text{either } \sigma_{d,A}^2 &> 8\sigma_{d,B}^2 + 8 * 9\sigma_{u,B}^2 (*) \text{ or,} \\ \text{if not } (*) \text{ then } \sigma_{u,A} &> -9\sigma_{u,B} + \sqrt{8 * 9\sigma_{u,B}^2 - \sigma_{d,A}^2 + 8\sigma_{d,B}^2}.\end{aligned}\quad (33)$$

If we change $\sigma_{d,A}^2$ and $\sigma_{d,B}^2$, we get the expression for trader B. If for either trader A or trader B, it is cost-efficient to move to the second period, we know from evaluating options II and V that the other trader moves as well and we end up with concentrated trading in the overlap. It is evident from options II and V that no trader will move to the non-overlap and concentrated trading during the overlap is therefore a Nash equilibrium. If these conditions are not satisfied for traders A and B, either concentrated trading in period 1 or in period 3 is a Nash equilibrium, as neither trader is willing to move to period 2 from concentrated trading in either period 1 or period 3—options I and VI. We also conclude that they are not willing to move to the other non-overlap, since they would reduce cost even more by moving to the overlapping period—see cost analysis option III. Since it is sub-optimal for them to move to period 2, we conclude that it is therefore sub-optimal for them to move to the other non-overlapping period.

Although concentrated trading by large liquidity traders in periods 1 and 3 are potential Nash equilibria, the cost of trading for both liquidity traders are higher in these two alternative Nash equilibria, as, e.g., the cost difference for trader A between trading in period 1 and 2 is,

$$\text{Cost}_1 - \text{Cost}_2 = (\lambda_{A,1} - \frac{\lambda_{A,2}\lambda_{B,2}}{\lambda_{A,2} + \lambda_{B,2}})\sigma_{d,A}^2 = \frac{1}{2}(\frac{1}{\sqrt{\sigma_{u,A}^2 + \sigma_{d,A}^2 + \sigma_{d,B}^2}} - \sqrt{\frac{8}{9}} \frac{1}{\sqrt{(\sigma_{u,A} + \sigma_{u,B})^2 + \sigma_{d,A}^2 + \sigma_{d,B}^2}})\sigma_{d,A}^2 > 0 \quad (34)$$

Similar expressions hold for trader B and comparing period 3 with period 2.

As concentrated trading in period 2 is the Nash equilibrium with lowest trading cost, we further analyze this equilibrium to show that, as claimed in proposition 3, volume, volatility, and market depth are higher during the overlap. In this equilibrium, the volume difference comparing period 1 to period 2 is:

$$\text{Volume}_{A,2} - \text{Volume}_{A,1} = \frac{\sigma_{u,A}}{\sqrt{2\pi}}(4 + \sqrt{2}) - (1 + \sqrt{2}\Theta + (\sqrt{2} + (1 + \sqrt{2})\sqrt{3})\sqrt{1 + 2\Phi}) > 0, \quad (35)$$

since Θ and Φ are greater or equal to zero. The volatility difference is:

$$\text{Volatility}_{A,2} - \text{Volatility}_{A,1} = (\frac{8\Phi + 4}{12\Phi + 5} - \frac{1}{2}) > 0, \quad (36)$$

since Φ is greater or equal to zero. The difference in market depth is:

$$\lambda_{A,2} - \lambda_{A,1} = \frac{1}{2} \frac{\sigma_v}{\sigma_{u,A}} (\sqrt{\frac{8}{9}} \frac{1}{\sqrt{1 + 2\Phi}} - 1) < 0, \quad (37)$$

since Φ is greater or equal to zero. This shows that markets are deeper during the overlap.

The correlation in order imbalance equals:

$$\rho(\omega_A, \omega_B) = \frac{9}{17}(1 + \frac{2\Phi}{2\Phi + 1}) > 0. \quad (38)$$

Comparing period 3 with period 2 yields the same results.

Appendix B: Arbitrage and Order-Splitting Conditions

Arbitrage opportunities exist, when

$$DR_{bid} > (1 + CF + 0.015) \cdot ORD_{ask} \cdot FX_{ask} \quad (\text{Buy London, Sell New York}); \quad (39)$$

$$ORD_{bid} > (1 + CF) \cdot ADR_{ask} \cdot FX_{bid}^{-1} + 50p \quad (\text{Buy New York, Sell London}); \quad (40)$$

where DR is depositary receipt, ORD is ordinary share, CF is the conversion fee for changing DRs to ORDs or vice versa, and FX is the exchange rate, expressed as British Pounds to the U.S. Dollar. Opportunities for order-splitting exist, when

$$DR_{bid} = (1 - CF) \cdot ORD_{bid} \cdot FX_{bid} \quad (\text{DR sellers split}); \quad (41)$$

$$ORD_{bid} = (1 - CF) \cdot DR_{bid} \cdot FX_{ask}^{-1} - 0.015 \cdot ORD_{bid} \quad (\text{ORD sellers split}); \quad (42)$$

$$DR_{ask} = ORD_{ask} \cdot FX_{ask} \cdot (1 + CF) + 0.015 \cdot ORD_{ask} \cdot FX_{ask} \quad (\text{DR buyers split}); \quad (43)$$

$$1.005 \cdot ORD_{ask} = DR_{ask} \cdot FX_{bid}^{-1} \cdot (1 + CF) + 50p \quad (\text{ORD buyers split}); \quad (44)$$

where in equations (42) and (43) the one-off tax of 150 basis points applies and in equation (44) the regular SDRT of 50 basis points applies as the ORD buyer has to pay, and, if buying in the U.S., the conversion fee of 50 pence applies.

Appendix C: NYSE-listed British and Dutch Stocks and Control Stocks

This table presents (i) NYSE-listed British stocks and their U.S. and U.K. control stocks and (ii) NYSE-listed Dutch stocks. Security codes are presented for all stocks as well as average 2003 monthly trading volume for the British stocks and 1997-1998 volume for the Dutch stocks. We follow the methodology proposed by Werner and Kleidon (1996) in assigning control stocks to the cross-listed stocks.

	UK(NL) Symbol	US Symbol	UK(NL) Volume in mln £(€)	US Vol- ume in mln \$	UK Control Stock	UK Symbol	UK Volume in mln £	US Control Stock	US Symbol	US Vol- ume in mln \$
<i>British stocks</i>										
BP plc	BP	BP.	7,433	2,447	Marks & Spencer	MKS	1,585	Lennar Corp.	LEN	1,783
Vodafone	VOD	VOD	9,105	1,136	Tesco	TSCO	1,733	Abercrombie & Fitch	ANF	1,080
HSBC Holdings	HBC	HSBA	5,553	1,136	BAE Systems	BA.	1,071	Caremark Rx	CMX	1,060
AstraZeneca	AZN	AZN	3,795	1,059	Standard Chartered	STAN	1,052	Cox Comm. Inc.	COX	1,029
GlaxoSmithKline	GSK	GSK	6,016	731	Centrica	CNA	1,091	Amdocs Ltd.	DOX	722
Diageo	DEO	DGE	1,784	285	Safeway	SFW	871	NovaStar Financ. Inc.	NFI	284
Shell Transport & Trading	SC	SHEL	3,146	249	WPP Group	WPP	942	Covance Inc.	CVD	247
Rio Tinto	RTP	RIO	1,999	141	Kingfisher	KGF	894	Sierra Health Services	SIE	141
Unilever	UL	ULVR	1,487	130	Scottish & Southern	SSE	740	Longs Drug Stores Corp.	LDG	130
Cadbury Schweppes	CSG	CBRY	1,082	81	Man Group	EMG	685	Extended Stay America	ESA	81
Barclays Bank	BCS	BARC	3,328	65	BAA plc	BAA	968	Comstock Res. Inc.	CRK	65
Scottish Power	SPI	SPW	1,241	60	Rolls Royce	RR.	719	Oxford Industries	OXM	60
Lloyds TSB Group	LYG	LLOY	3,499	55	Aviva plc	AV.	981	Remington Iol & Gas	REM	55
BT Group	BTY	BT.A	3,637	43	Compass Group	CPG	1,011	Tetra Techn.	TTI	42
Smith & Newpew	SNN	SN.	611	39	Sabmiller	SAB	611	Checkpoint Systems	CKP	39
Imperial Chemical Industr.	ICI	ICI	336	28	EMI Group	EMI	331	Haventys furniture Comp	HVT	28
British Airways	BAB	BAY	678	27	Rentokil Initial	RTO	654	Skechers USA	SKX	27
Gallaher Group	GLH	GLH	524	26	Rexam	REX	518	Sovran Self Storage	SSS	26
Amersham	AHM	AHM	1,177	21	Next	NXT	728	Florida East Coast Ind.	FLA	21
Amvescap	AVZ	AVZ	1,134	20	Gus	GUS	731	Applied Industrial Techn.	AIT	20
National Grid Transco	NGG	NGT	2,014	20	Boots Group	BOOT	922	Russ Bernie & Co. Inc.	RUS	19
Cable and Wireless	CWP	CW.	1,007	18	Reckitt Benckiser	RB.	681	McMoran Exploration	MMR	18
Reed Elsevier	RUK	REL	1,584	18	Xstrata	XTA	763	Tennessee Valley Auth.	TVC	18
Pearson	PSO	PSON	1,122	13	Smiths Group	SMIN	692	Adv. Market Services	MKT	13
BSkyB	BSY	BSY	1,672	11	Sainsbury	SBRY	865	Department 56 Inc.	DFS	11
BOC Group	BOX	BOC	955	11	Hays	HAS	658	Buckeye techn. Inc.	BKI	11
Imperial Tobacco Group	ITY	IMT	961	10	Dixons Group	DXNS	659	Criimi MAE Incorp CMM	CMM	10
<i>Dutch stocks</i>										
KLM Royal Dutch Airlines	KLM	KLM	189	52						
Philips Electronics	PHIA	PHG	1,623	458						
Royal Dutch	RDA	RD	2,065	987						
Unilever	UNIA	UN	1,034	332						

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Table 1: Pattern Predictions: Values Overlap vs. Non-Overlap

This table contains trading pattern predictions for a security trading in two partially overlapping markets. Based on a model that builds on Chowdhry and Nanda (1991) and Admati and Pfleiderer (1988), we determine values for volume, volatility, and market depth during the overlap and compare them to non-overlap values and we calculate the correlation in order imbalance during the overlap. We study different scenarios. In the benchmark scenario both markets are fully segmented; no trader has access to the other market. We label this scenario 0 and depart from it in different directions by allowing different types of traders access to the other market and by allowing large liquidity traders to time their trade. This leads to scenarios 1a, 1b, 2, and 3.

		Scenarios						
		0	1a	1b	2	3		
		Fully Segmented Markets	Allow Large Liquidity Traders to Access Other Market	Allow Informed Traders to Access Other Market	Allow Large Liquidity and Informed Traders to Access Other Market	Allow Large Liquidity and Informed Traders to Access Other Market	Liquidity and Informed Traders to Access Other Market	Time their Trade
<i>Panel A: Predicted Value Overlap as compared to Non-Overlap</i>								
Volume	Unchanged		Lower in at least one market	Higher ($< 21.82\%$)	Unpredictable		Higher ^b	
Volatility	Higher		Higher	Higher	Higher		Higher	
Depth ^a (λ^{-1})	Unchanged		Lower in at least one market	Higher	Unpredictable		Higher ^b	
Correlation Order Imbalance	Positive		Positive	Positive	Positive		Positive	
<i>Panel B: Numerical Example^c</i>								
Volume	0%		-10%	20%	7%		91%	
Volatility	33%		20%	60%	50%		45%	
Depth ^a (λ^{-1})	0%		-13%	6%	-8%		52%	
Correlation Order Imbalance	0.50		0.67	0.53	0.71		0.79	

^a: Note that higher values of λ indicate lower market depth.

^b: These values have been calculated for the Nash equilibrium of both large liquidity traders trading during the overlap. This is the equilibrium with lowest trading costs for both large liquidity traders.

^c: Values for the overlap as compared to non-overlap for the special case when (i) all liquidity traders are of equal size and (ii) the standard deviation of liquidity demand equals the standard deviation of the change in the security's true value (v).

Table 2: Trade Statistics: Overlap and Full Day

This table presents trade statistics for home market and NYSE trading of all British and Dutch stocks. Both samples consist of a full year of trade and quote data for both markets and intraday quotes on the exchange rate. The British sample runs from November 2002 through October 2003; the Dutch sample from July 1997 through June 1998. The averages have been calculated for five-minute intervals.

	5-minute (#Shares)	Volume	5-minute Re- turn Volatility (bp)		Quoted Spread (bp)		Effective Spread (bp)	
	Home	NYSE	Home	NYSE	Home	NYSE	Home	NYSE
Panel A: Overlap								
1 st Quintile UK Stocks	916,364	60,583	18.4	20.0	12.1	9.2	12.3	6.8
British Petroleum plc	663,253	97,980	17.0	25.4	9.2	6.4	8.9	4.5
Vodafone	3,224,708	132,679	20.7	20.3	22.3	13.5	21.2	8.7
HSBC Holdings	447,381	32,683	12.4	12.0	8.5	6.9	11.6	5.3
AstraZeneca	71,793	21,824	19.2	19.1	9.4	9.6	10.0	7.9
GlaxoSmithKline	174,687	17,750	21.6	20.7	10.9	9.8	9.9	7.8
2 nd Quintile UK Stocks	169,455	6,161	16.7	17.2	11.6	15.1	10.3	13.6
3 rd Quintile UK Stocks	243,680	2,650	24.4	23.8	14.8	24.7	14.4	20.7
4 th Quintile UK Stocks	98,870	1,848	29.3	30.3	24.6	37.0	27.6	33.8
5 th Quintile UK Stocks	155,991	2,088	25.2	29.3	19.4	47.2	22.3	38.0
All Dutch Stocks	120,897	50,339	36.3	35.7	25.5	48.6	23.3	32.0
KLM	32,897	10,535	44.1	41.0	36.2	82.9	32.5	57.7
Philips	123,180	37,511	42.2	39.4	25	44.2	27.6	32.7
Royal Dutch	232,409	119,635	29.9	35.8	21.2	47.2	16.9	16.5
Unilever	95,103	33,675	28.8	26.6	19.6	19.9	16.3	21.1
Panel B: Full Day								
1 st Quintile UK Stocks	593,824	37,769	16.3	14.7	12.6	8.8	11.3	6.2
British Petroleum plc	403,646	59,914	15.1	16.3	9.8	6.4	8.5	4.3
Vodafone	2,120,701	82,516	18.1	16.3	22.4	13.1	20.3	8.2
HSBC Holdings	291,289	22,000	10.8	9.6	8.5	6.2	8.0	4.5
AstraZeneca	44,360	13,163	17.6	15.2	10.6	9.0	9.8	7.2
GlaxoSmithKline	109,126	11,254	18.6	15.1	11.9	9.1	10.1	6.7
2 nd Quintile UK Stocks	109,866	3,601	15.7	15.8	13.1	17.7	11.9	14.6
3 rd Quintile UK Stocks	166,612	1,714	22.8	20.8	17.6	27.8	15.7	21.1
4 th Quintile UK Stocks	64,298	1,133	29.6	29.0	31.1	44.5	26.5	35.3
5 th Quintile UK Stocks	103,496	1,241	26.3	29.8	22.3	61.3	22.7	43.2
All Dutch Stocks	73,247	30,363	27.3	26.7	25.2	41.8	18.9	18.5
KLM	19,706	5,929	30.5	26.2	36.5	66.4	28	31.7
Philips	77,149	23,609	33.4	27.3	25.5	37.7	18.3	14.5
Royal Dutch	138,665	71,871	24.5	30.2	20.4	43.8	14.7	14.5
Unilever	57,467	20,044	20.9	23.1	18.4	19.2	14.4	13.2

Table 3: Overlap vs. Non-Overlap: Volatility

This table compares volatility during the overlap to volatility outside the overlap for both the home market and the NYSE. We calculate how volatility in the home market changes when the NYSE opens and we do the same for the NYSE when the home market closes. We use half-hour intervals before and after the event. For the British sample, we repeat this procedure for volume-matched single-listed stocks to control for the regular intraday pattern. Standard errors are calculated after removing interday variation through scaling.

	%age Change Home Market on New York Open						%age Change New York on Home Market Close					
	Cross-Listed		Control		Difference		Cross-Listed		Control		Difference	
	Stocks		Stocks		Cross-Listed		Stocks		Stocks		Cross-Listed	
	Change	σ	Change	σ	Change	σ	Change	σ	Change	σ	Change	σ
1 st Quintile UK Stocks	93.4	4.5	49.5	4.4	43.9	6.3	-65.2	5.6	-41.3	4.8	-23.9	7.4
British Petroleum plc	101.7	10.0	56.7	9.4	45.1	13.7	-83.0	12.1	-31.3	9.5	-51.8	15.4
Vodafone	118.0	12.2	47.2	10.2	70.8	15.9	-24.8	10.0	-43.9	9.5	19.1	13.8
HSBC Holdings	105.9	9.8	48.5	11.0	57.4	14.8	-56.0	12.1	-33.3	12.4	-22.6	17.3
AstraZeneca	78.4	9.4	61.7	9.1	16.7	13.1	-37.0	11.7	-44.8	9.9	7.7	15.4
GlaxoSmithKline	56.2	8.7	38.1	9.2	18.1	12.7	-125.4	15.9	-51.3	11.3	-74.1	19.5
2 nd Quintile UK Stocks	55.7	4.4	52.8	4.5	3.0	6.3	-29.6	5.7	-47.9	5.4	18.3	7.8
3 rd Quintile UK Stocks	58.7	4.5	54.9	5.0	3.9	6.7	-111.3	10.0	-60.2	6.9	-51.0	12.2
4 th Quintile UK Stocks	49.1	5.1	43.1	4.6	6.0	6.9	-72.5	9.5	-38.7	5.7	-33.8	11.1
5 th Quintile UK Stocks	56.4	4.7	36.9	4.9	19.6	6.8	-66.1	10.7	-33.2	6.2	-32.9	12.4
All Dutch Stocks	70.7	10.4					-30.2	4.3				
KLM	37.5	28.9					-45.7	10.2				
Philips	51.6	13.8					-29.9	8.7				
Royal Dutch	155.4	20.5					-14.3	7.9				
Unilever	91.2	16.3					-23.4	7.8				

Table 4: Overlap vs. Non-Overlap: Volume

This table compares volume during the overlap to volume outside the overlap for both the home market and the NYSE. We calculate how volume in the home market changes when the NYSE opens and we do the same for the NYSE when the home market closes. We use half-hour intervals before and after the event. For the British sample, we repeat this procedure for volume-matched single-listed stocks to control for the regular intraday pattern. Standard errors are calculated after removing interday variation through scaling.

	%age Change Home Market on New York Open						%age Change New York on Home Market Close					
	Cross-Listed		Control		Difference		Cross-Listed		Control		Difference	
	Stocks		Stocks		Cross-Listed		Stocks		Stocks		Cross-Listed	
	Change	σ	Change	σ	Change	σ	Change	σ	Change	σ	Change	σ
1 st Quintile UK Stocks	81.9	2.6	39.2	2.8	42.7	3.8	-105.9	3.9	-18.3	2.4	-87.7	4.6
British Petroleum plc	102.0	5.4	49.2	6.7	52.8	8.6	-94.2	7.1	-17.3	4.7	-76.9	8.6
Vodafone	83.8	6.1	32.2	5.3	51.6	8.1	-98.0	10.5	-17.0	6.0	-80.9	12.0
HSBC Holdings	74.4	5.6	29.1	6.9	45.2	8.9	-78.8	7.7	-11.8	5.9	-67.0	9.7
AstraZeneca	74.2	6.1	49.0	6.1	25.2	8.6	-141.5	9.5	-15.6	4.4	-125.8	10.5
GlaxoSmithKline	72.9	5.8	35.8	5.8	37.1	8.2	-115.8	7.9	-29.7	6.1	-86.1	10.0
2 nd Quintile UK Stocks	54.5	2.7	57.8	3.4	-3.3	4.4	-144.9	5.7	-16.1	2.9	-128.7	6.4
3 rd Quintile UK Stocks	47.1	2.8	47.3	2.9	-0.2	4.0	-194.5	12.6	-32.5	4.1	-162.0	13.2
4 th Quintile UK Stocks	45.6	3.7	46.2	3.5	-0.6	5.1	-215.9	12.9	-15.7	4.0	-200.2	13.6
5 th Quintile UK Stocks	46.2	3.3	54.8	4.2	-8.7	5.3	-216.9	12.9	-20.2	4.7	-196.6	13.7
All Dutch Stocks	67.9	3.6					-29.0	2.8				
KLM	76.9	9.7					-45.5	7.6				
Philips	51.0	6.2					-35.4	5.5				
Royal Dutch	80.0	5.9					-23.8	4.0				
Unilever	67.9	3.6					-32.5	4.9				

Table 5: Overlap vs. Non-Overlap: Effective Spread

This table compares the effective spread during the overlap to the effective spread outside the overlap for both the home market and the NYSE. We calculate how the effective spread in the home market changes when the NYSE opens and we do the same for the NYSE when the home market closes. We use half-hour intervals before and after the event. For the British sample, we repeat this procedure for volume-matched single-listed stocks to control for the regular intraday pattern. Standard errors are calculated after removing interday variation through scaling.

	%age Change Home Market on New York Open						%age Change New York on Home Market Close					
	Cross-Listed		Control		Difference		Cross-Listed		Control		Difference	
	Stocks		Stocks		Cross-Listed		Stocks		Stocks		Cross-Listed	
					and Control						and Control	
	Change	σ	Change	σ	Change	σ	Change	σ	Change	σ	Change	σ
1 st Quintile UK Stocks	0.4	1.1	5.0	1.3	-4.6	1.7	7.2	1.8	-7.2	1.7	14.4	2.4
British Petroleum plc	0.6	2.7	3.2	3.0	-2.6	4.0	2.4	3.5	-4.5	3.5	6.9	5.0
Vodafone	1.5	1.3	-0.6	2.0	2.1	2.4	12.2	3.6	-9.5	3.7	21.6	5.2
HSBC Holdings	1.8	2.2	4.8	2.9	-3.0	3.7	2.8	4.0	-2.6	3.8	5.4	5.5
AstraZeneca	1.7	3.3	17.7	3.7	-16.0	5.0	14.1	4.2	-8.7	3.7	22.7	5.6
GlaxoSmithKline	-2.4	2.5	1.8	2.6	-4.2	3.6	4.6	4.2	-10.1	3.7	14.7	5.5
2 nd Quintile UK Stocks	-1.1	1.3	2.5	1.6	-3.6	2.0	25.5	1.9	-3.1	1.8	28.7	2.6
3 rd Quintile UK Stocks	6.9	1.5	3.6	1.5	3.3	2.2	13.0	1.9	-8.9	2.1	21.9	2.9
4 th Quintile UK Stocks	-2.3	1.6	4.4	1.6	-6.7	2.3	16.8	2.2	-9.7	2.0	26.5	2.9
5 th Quintile UK Stocks	4.4	1.5	-4.1	1.8	8.5	2.3	19.9	2.1	-4.4	2.1	24.3	3.0
All Dutch Stocks	3.5	1.3					0.4	1.5				
KLM	3.9	2.9					-3.2	3.3				
Philips	-0.7	2.3					-1.1	3.0				
Royal Dutch	7.9	2.2					0.5	2.3				
Unilever	3.5	2.7					11.4	3.3				

Table 6: Correlation Order Imbalance across Markets

This table presents correlations of order imbalance across markets based on five-minute intervals. Panel A reports these correlations for three types of intervals: (i) order-splitting intervals, where the market snapshot at the start of the interval shows an opportunity for order-splitting; (ii) arbitrage intervals, where the same snapshot shows an arbitrage opportunity; and (iii) the remaining intervals. Panel B reports the correlations for order imbalance *innovations*, which are defined as the difference between the observed order imbalance and its predicted value. These predictions are based on a vector-autoregressive model for order imbalance in both markets with lagged returns as explanatory variables.

	Order-Splitting			Arbitrage			Other		
	Opportunity			Opportunity					
	Corr	σ_ρ	#Obsv	Corr	σ_ρ	#Obsv	Corr	σ_ρ	#Obsv
<i>Panel A: Correlation Order Imbalance across Markets</i>									
1 st Quintile UK Stocks	0.23	0.03	2,849	0.02	0.27	14	0.15	0.02	20,672
British Petroleum plc	0.23	0.04	575	1.00	0.71	2	0.21	0.02	4,130
Vodafone	0.17	0.07	178	-0.30	0.35	8	0.14	0.01	4,521
HSBC Holdings	0.15	0.02	1,793	-0.58	0.50	4	0.13	0.02	2,910
AstraZeneca	0.29	0.08	144	0.00	0.00	0	0.12	0.01	4,563
GlaxoSmithKline	0.30	0.08	159	0.00	0.00	0	0.17	0.01	4,548
2 nd Quintile UK Stocks	0.06	0.05	1,465	0.09	0.24	32	0.09	0.02	22,036
3 rd Quintile UK Stocks	0.10	0.03	1,327	-0.28	0.15	54	0.08	0.01	22,150
4 th Quintile UK Stocks	0.07	0.03	4,650	-0.17	0.17	225	0.06	0.01	18,647
5 th Quintile UK Stocks	0.06	0.02	2,191	0.03	0.01	1,243	0.04	0.01	20,089
All Dutch Stocks	0.26	0.05	6,689	0.24	0.05	730			
KLM	0.19	0.03	1,566	0.21	0.06	255			
Philips	0.19	0.02	1,704	0.20	0.08	144			
Royal Dutch	0.40	0.02	1,712	0.37	0.08	152			
Unilever	0.24	0.02	1,707	0.16	0.07	179			
<i>Panel B: Correlation Order Imbalance Innovation, i.e. Controlling for “Microstructure” Dynamics</i>									
1 st Quintile UK Stocks	0.25	0.05	2,839	0.43	0.22	14	0.15	0.02	20,183
British Petroleum plc	0.24	0.04	572	1.00	0.71	2	0.21	0.02	3,990
Vodafone	0.42	0.07	178	0.20	0.35	8	0.13	0.01	4,514
HSBC Holdings	0.16	0.02	1,786	0.93	0.50	4	0.11	0.02	2,828
AstraZeneca	0.19	0.08	144	0.00	0.00	0	0.13	0.02	4,390
GlaxoSmithKline	0.24	0.08	159	0.00	0.00	0	0.18	0.01	4,461
2 nd Quintile UK Stocks	0.08	0.03	1,463	-0.29	0.20	32	0.09	0.02	21,571
3 rd Quintile UK Stocks	-0.08	0.07	1,326	-0.15	0.18	54	0.08	0.01	21,551
4 th Quintile UK Stocks	0.08	0.02	4,575	-0.13	0.18	225	0.05	0.01	18,318
5 th Quintile UK Stocks	0.04	0.01	2,187	0.05	0.02	1,241	0.04	0.01	19,472
All Dutch Stocks	0.25	0.05	6,620	0.23	0.05	776			
KLM	0.19	0.03	1,563	0.12	0.06	249			
Philips	0.16	0.02	1,682	0.33	0.08	159			
Royal Dutch	0.40	0.02	1,688	0.31	0.08	171			
Unilever	0.24	0.02	1,687	0.15	0.07	197			

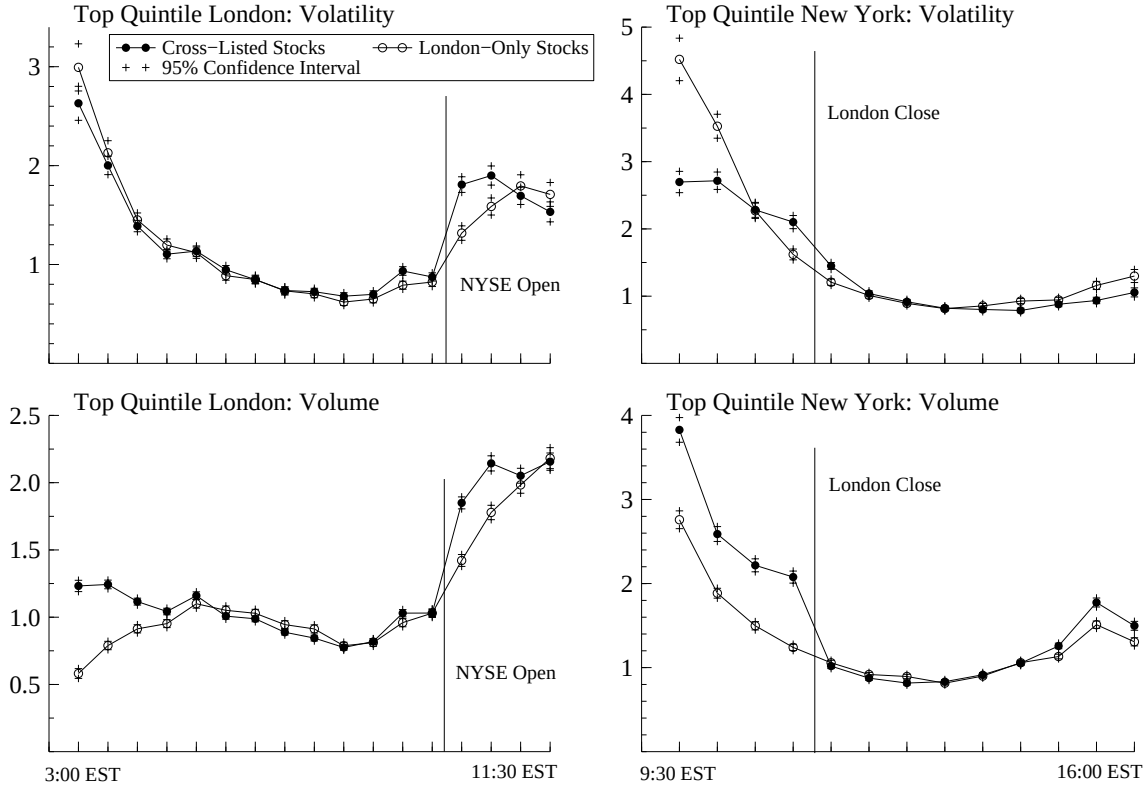


Figure 1: **Intraday Patterns Volatility and Volume for Top Quintile British stocks.** This figure depicts the intraday patterns in volatility (top two graphs) and volume (bottom two graphs) for the five British stocks that generate most volume at the NYSE. The line with the filled dots represents the pattern as estimated for these stocks and the one with open dots represents the pattern for volume-matched single-listed control stocks. On the left hand side are the graphs for the home market and on the right hand side are the graphs for the NYSE. 95% confidence intervals have been calculated after removing interday variation through scaling.

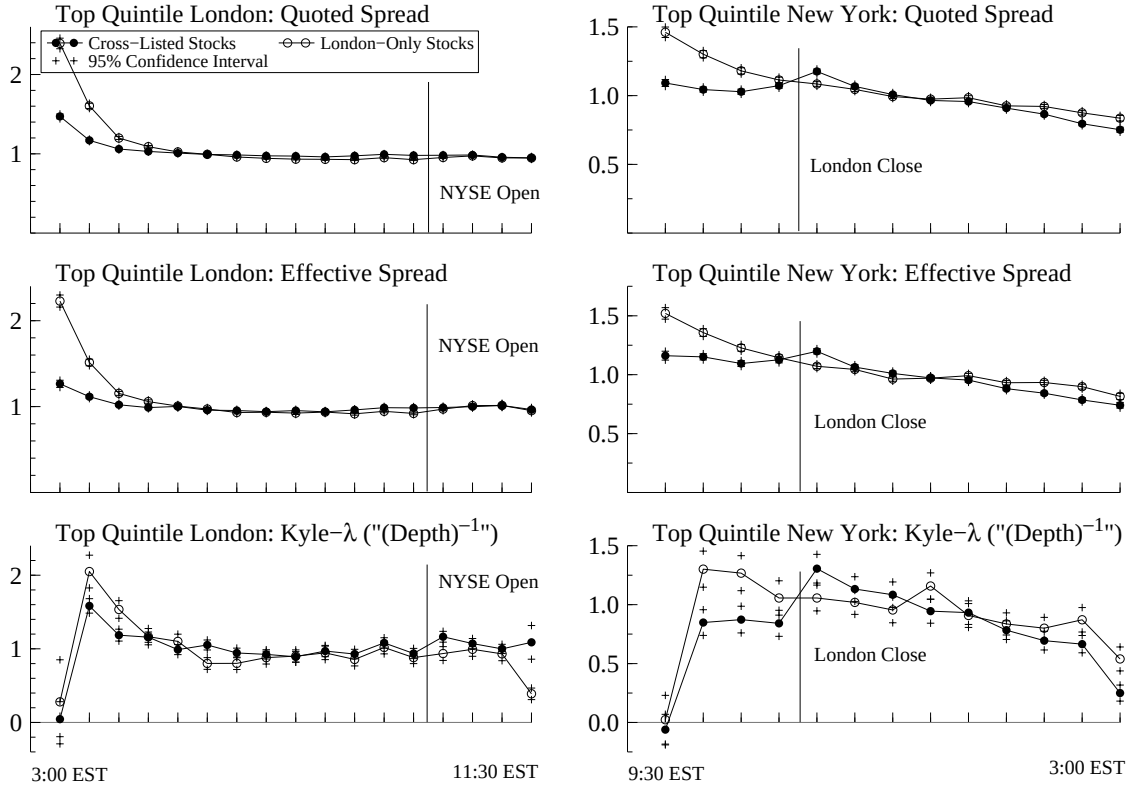


Figure 2: **Intraday Patterns Liquidity for Top Quintile British stocks.** This figure depicts the intraday patterns in quoted spread (top two graphs), effective spread (middle two graphs), and Kyle- λ (bottom two graphs) for the five British stocks that generate most volume at the NYSE. The line with the filled dots represents the pattern as estimated for these stocks and the line with open dots represents the pattern for volume-matched single-listed control stocks. On the left hand side are the graphs for the home market and on the right hand side are the graphs for the NYSE. 95% confidence intervals have been calculated after removing interday variation through scaling.

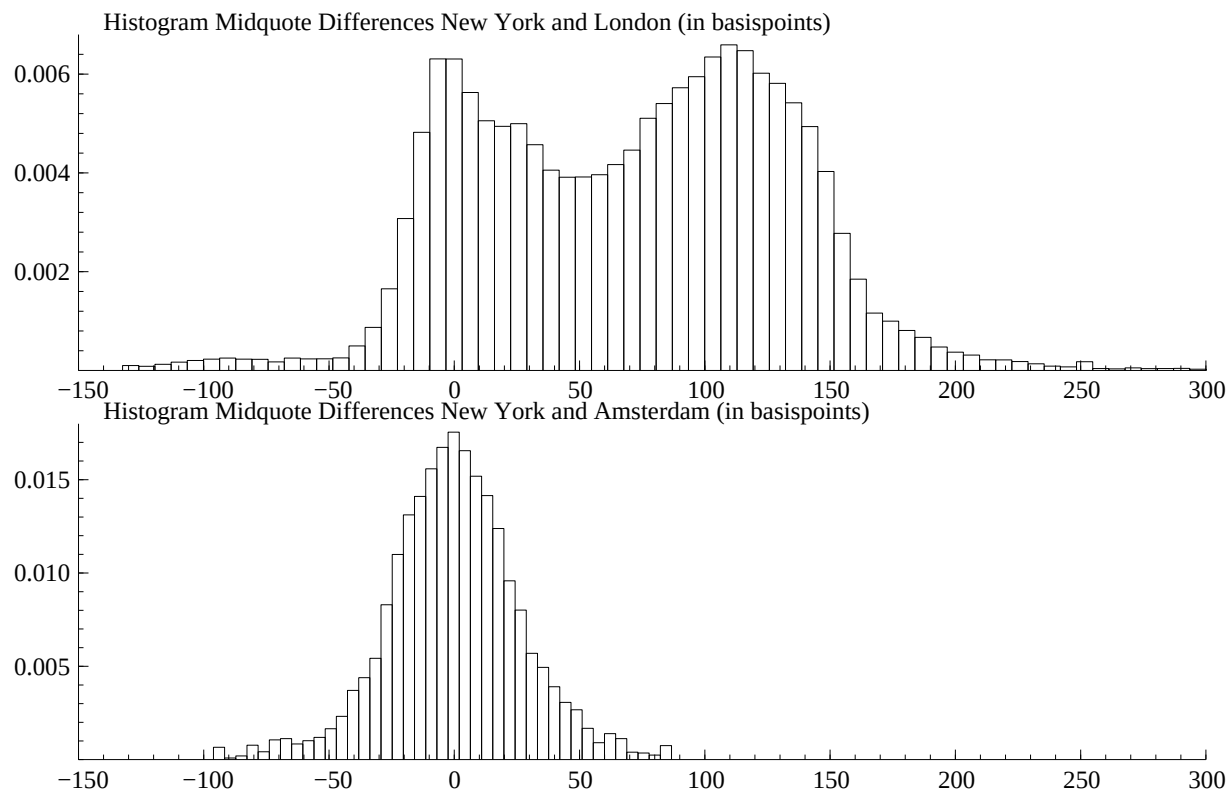


Figure 3: **Histogram Log Midquote Differentials Across the Home Market and the NYSE.** The top graph contains a histogram for the relative difference between the New York midquote in British pounds and the British midquote during the overlapping period. The bottom graph contains this histogram for Dutch stocks. Both graphs are based five-minute snapshots for all stocks in the sample.