Splitting orders in overlapping markets: A study of cross-listed stocks

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Abstract

Fragmented trading is widespread. Chowdhry and Nanda [Chowdhry, B., Nanda, V., 1991. Multimarket trading and market liquidity. Rev. Finan. Stud. 4, 483–511] show that some traders benefit by splitting orders across markets at the cost of small liquidity traders who, for exogenous reasons, only trade locally. We extend their model to analyze British and Dutch stocks with ADRs, which trade on both sides of the Atlantic for one or two hours each day. We predict that, in the presence of sufficient small liquidity trading, traders concentrate their trades in the overlapping period and split orders across markets. We document considerable empirical support. In the cross-section, we find order-splitting only for ADRs with most NYSE small liquidity trading. The evidence is (i) increased volatility, increased volume, and (weakly) higher liquidity supply in the overlap and (ii) positive correlation in order imbalance across markets. We further find that the common component in order imbalance has long-term price impact, which supports the notion that these order-splitters are informed traders.

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1. Introduction

In the last decades, firms have increasingly cross-listed their shares at foreign exchanges (see Pagano et al., 2002). This trend has been particularly strong for the US, where, at the New York Stock Exchange (NYSE) for example, the number of non-US listings quadrupled over the last decade to 467 firms at the end of 2002. They generated approximately 10% of total volume
that year. The NASDAQ lists even more non-US 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 markets 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 (see Karolyi, 2006 for survey).

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 et al., 2000; de Frutos and Manzano, 2002; Yin, 2005). 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 “small liquidity traders,” who only trade locally for exogenous reasons. Large liquidity traders and informed traders benefit by splitting orders across markets. In equilibrium, wealth is transferred from the small liquidity traders to the order-splitters, since the local traders are shown to be better off in a single, centralized market. Moreover, Foucault and Gehrig (2006) prove that this equilibrium might emerge endogenously, since issuers benefit from the increased informational efficiency of a fragmented market.

Our objective is to study order-splitting across markets empirically. We emphasize “across markets,” as it is different from order-splitting across time (in a single market), since, in that case, liquidity traders suffer from repeated interaction with informed traders (see Admati and Pfleiderer, 1988).2 We study an overlapping market where traders might endogenously prefer to trade in the overlap and benefit from two pools of small liquidity traders. This preference should show through increased trading activity in the overlap vis-à-vis the nonoverlap. These notions are formalized and tested using British and Dutch ADRs. We see three areas where the paper contributes to the literature.

First, we extend the Chowdhry and Nanda (1991) model to partially overlapping markets and allow “large liquidity traders” to time their trades. We show that concentrated trading in the overlap is the Nash equilibrium with lowest trading cost for “large liquidity traders.” If small liquidity trading is large enough, we show that it is the unique equilibrium. We develop the intraday patterns it predicts for volatility, volume, and liquidity supply. Although existing literature offers an excellent intuition for these patterns, it lacks a model to formalize them (see, e.g., Werner and Kleidon, 1996; Hupperets and Menkveld, 2002).

Second, in addition to studying intraday patterns, we detect 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 a 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 across markets, defined as buy volume minus sell volume in a five-minute time interval. We further analyze whether this common

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1 See the on-line NYSE factbook (http://www.nysedata.com).
2 We develop this issue further in the context of the Chowdhry and Nanda (1991) model in Section 2.2 (Lemma 1).
component in order imbalance has a long-term price impact (due to informed traders) through an analysis of its information share in the Hasbrouck (1991, 1995) framework.

Third, we document empirical support through the study of British and Dutch stocks that are cross-listed at the NYSE. The stocks trade simultaneously in the home market and on the NYSE during one or two hours each day. The main attractions of this application are (i) a nonoverlap to study the intraday pattern and (ii) considerable trading in both markets, consistent with the order-splitting predicted by the model. It therefore compares particularly well with another natural candidate: fragmented trading on the NYSE and the US regional exchanges. For this pure US experiment, the nonoverlap is either small or nonexistent and trading at the regional exchanges is considerably less liquid.3 In our data set, 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 half of “European” volume in New York, which, in turn, represents half of non-US 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, however, the London market was a pure dealer market, whereas today it also features a 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 Werner and Kleidon (1996).

The empirical results support the model predictions for the stocks that show highest NYSE activity. This is consistent with the model’s prediction that the Nash equilibrium of concentrated trading in the overlap is only the unique equilibrium if idiosyncratic “small liquidity trading” is sufficiently large. For the stocks with highest NYSE small liquidity trading, we find increased volume, volatility, and (weakly) higher liquidity supply for the overlap as compared to the nonoverlap. For these stocks, we document that five-minute order imbalance is positively correlated across markets, consistent with order-splitting. We further find that the common component in order imbalance for these stocks is informative as it has an average 10% “Hasbrouck” information share. Finally, we show that the order-splitting evidence is robust, as we exploit the British tax regime to control for the alternative explanation that local traders in each market simultaneously receive the same private signal and trade on it locally. In the test, we also find evidence of arbitrage activity, albeit on a small scale. This is consistent with earlier studies on cross-listed stocks (see, e.g., Jorion and Schwartz, 1986; Kato et al., 1991). Incidentally, order-splitting could also explain why Ellul (2006) finds that home market prices for continental European stocks cross-listed in London adjust to large London trades ahead of their execution.

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.5 The heads of Goldman Sachs, Merrill Lynch, and Morgan Stanley testified on the need for

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3 Hasbrouck (1995, p. 1188) reports for the thirty Dow stocks that the regional exchanges trade an average 2080 shares each five minutes up to 9299 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.

4 See 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, http://www.spglobal.com).

a centralized limit order book to consolidate order flow and assure price-time priority. 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). Recent literature, however, mentions three counterarguments. First, centralization ignores the heterogeneity of investors, whose trading needs might require different market structures (see, e.g., Harris, 1993, 2003; Blume, 2000). US investors, in our setting, might prefer to trade foreign stocks at the NYSE for a number of reasons, e.g., trades are dollar-denominated, US clearing and settlement, same broker as for US securities. Second, Gehrig et al. (1995) argue that regional markets might coexist with a dominant (national) market as a listing venue for (small) local stocks which benefit from an informational advantage of local traders. In their conclusion they admit, though, that technology might let the dominant market compete locally as it reduces the cost of access (e.g. through trading screens). Third, 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 US and European regulators to agree on transatlantic exchange access.

Our paper relates to two contemporaneous papers on the subject—Baruch et al. (2004) and Halling et al. (2005). The objectives are different, as these papers focus exclusively on explaining the foreign market share of total trading volume. In our model, this share is determined by the (exogenous) trading activity of local small liquidity traders. Baruch et al. find that volume migrates to the exchange where the stock returns have highest correlation with other assets traded at the exchange. Halling et al. document that the foreign market share is highest for smaller, more export and high-tech oriented companies.

Section 2 develops the model and predicts intraday patterns in volume, volatility, and liquidity supply. Section 3 argues that NYSE-traded British and Dutch stocks are an ideal laboratory to study order-splitting, introduces the data set, and presents sample statistics. Section 4 presents the empirical results. Section 5 draws conclusions.

2. The model: one security, overlapping markets

In this section, we study what intraday trading pattern—trading during the overlap as compared to the nonoverlap—arises endogenously when a security trades in two (partially) overlapping markets. We start from the one-period model of Chowdhry and Nanda (1991) and extend it in three ways. First, we assume a symmetric structure for both markets. That is, they both have a small liquidity trader, a large liquidity trader, and an informed trader. In the standard model, there is only one large liquidity trader and one informed trader, who have access to both markets. We need the extension to compare to a nonoverlap in which all types of agents could also trade. Second, to tailor the model to our setting, we add an additional round to the game so that liquidity suppliers can condition on the “foreign” transaction price when issuing their new quote. Third, we derive an expression for trading volume. In the remainder of the section, we first present the model for the overlap and then analyze what patterns arise when we add a nonoverlap and allow the strategic traders, i.e. the large liquidity traders and informed traders, to optimize as in Chowdhry and Nanda (1991).

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2.1. The basic one-period-two-markets model

We follow the Chowdhry and Nanda (1991) setting for the basic one-period-two-markets model, but let each market consist of a liquidity supplier, an informed trader, a small and a large liquidity trader. All agents are assumed 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.” We emphasize that the small liquidity trader is not necessarily irrational. Investor heterogeneity might make investors prefer a market for exogenous reasons (see, e.g., Stoll, 2001).\footnote{US retail investors, for example, might prefer the NYSE, as they can use their US broker to buy and sell foreign securities.} Alternatively, regulation could force some traders to trade in the local market.\footnote{For example, the European Union 1993 Investment Services Directive (ISD) allows member countries (until 2007) to impose a so-called “concentration rule” (Art 14(3)) which forces retail orders to execute on a “regulated market,” which, effectively, is the national market.} We further assume that liquidity suppliers trade on their own account and absorb potential order imbalances. The one-period game consists of four rounds:

(1) The liquidity supplier in each market announces her price schedule;
(2) Traders observe these schedules and submit their orders—informed traders maximize expected profit, liquidity traders minimize expected cost;
(3) Liquidity suppliers observe and absorb the aggregate order imbalance according to their announced price schedules;
(4) Liquidity suppliers observe transaction prices in both markets and condition on them to set the new midquote.

At the start of each period, let

\[ v \equiv \text{the innovation in the value of the security at the end of the period;} \]
\[ u_i \equiv \text{liq. demand (signed volume) of the small liq. trader in market } i; \]
\[ d^k \equiv \text{liq. demand (signed volume) of the large liq. trader in market } k. \]

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 \( v, u_A, u_B, d^A, \text{ and } d^B \) are identically, independently, and normally distributed:

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

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

\[ x_i \equiv \text{signed volume in market } i \text{ by the informed trader of market } i; \]
\[ d^k_i \equiv \text{signed volume in market } i \text{ by the large liquidity trader of market } k. \]
Let

\[ P \equiv \text{unconditional value of the security before trading begins}; \]
\[ P_i \equiv \text{price charged by the liquidity supplier in market } i. \]

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 follows Chowdhry and Nanda (1991) and involves three basic steps. First, we hypothesize linear pricing rules for liquidity suppliers:

\[ P_i - P = \lambda_i \omega_i \]  

where the price impact coefficient \( \lambda_i \) is a measure of liquidity supply 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. We then set her profit to zero, as we assume liquidity supply to be perfectly competitive or regulated.9

### 2.2. The multi-period–two-markets model

We define the multi-period model as, essentially, repeated one-period models, where the draws of the vector \((v, u_i, d_i^A, d_i^B)\) are independent across periods.10 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:

<table>
<thead>
<tr>
<th>Market A:</th>
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<tr>
<td>Period 1</td>
<td>Period 2</td>
<td>Period 3</td>
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<tr>
<td>Market B:</td>
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</table>

To study what pattern arises endogenously, we allow the large liquidity traders in both markets to time their trade (i.e. choose either period 1, 2, or 3) in the spirit of Admati and Pfleiderer (1988) and to potentially split across markets for the amount they decide to trade in period 2. The following proposition characterizes potential Nash equilibria.

**Lemma 1.** Any equilibrium can only be a Nash equilibrium if the large liquidity trader concentrates her total liquidity demand in a single period.

The proof for this result is in Appendix A. The intuition for this result is that the cost of trading (indirectly) with the informed trader in multiple periods instead of one period dominates the

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9 In a 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.

10 We, therefore, assume that informed investors can only trade on their signal in the period that they get it, not in later periods.
benefit of repeated trading with the small liquidity trader. This result is consistent with Admati and Pfleiderer (1988).

**Proposition 1.** The equilibrium where the two large liquidity traders concentrate their trading demand in period 2 to trade in both markets is a Nash equilibrium and it is the one with lowest cost for large liquidity traders. It is the unique Nash equilibrium in case small liquidity trading is large enough in market A and B. That is, in case the following condition holds for \( i = A \) and \( i = B \):

\[
\sigma_{u,i} + 2\sigma_{u,i} \sigma_{u,j \neq i} + \frac{1}{9} (2\sigma_{d,j}^2 + 2\sigma_{d,j \neq i}^2 + \sigma_{u,j \neq i}^2) > \min(2\sigma_{d,i}^2, 2\sigma_{d,j \neq i}^2)
\]  

(2)

where \( \min() \) takes the minimum of all arguments and \( j \neq i \) indicates the other market.

The proof for this proposition is in Appendix A. The concentrated trading in the overlap minimizes trading cost for large liquidity traders, since they benefit from each other’s presence, from the presence of small liquidity traders in both markets, and from the fact that these small liquidity traders, by construction, cannot trade among themselves (see Chowdhry and Nanda, 1991). Finally, they benefit from competition between the two informed traders who, in the overlap, have access to each other’s market. As a result, they trade more aggressively as they privately enjoy the additional revenue of increasing their order by one share, but share the cost of revealing more of their signal to the liquidity supplier. This reduces their aggregate expected profit, which, ultimately, is paid for by the liquidity traders (as liquidity suppliers earn zero profit by assumption).

The concentrated trading in the overlap is the only equilibrium if small liquidity trading is large enough. Intuitively, if condition (2) is true for \( i = B \) then concentrated large liquidity trading in period 1 collapses as a Nash equilibrium. That is, for either large liquidity trader A or B, it is optimal to move to period 2. The left-hand side of the equation consists of three terms that capture (i) the benefit of the ability to trade with the other small liquidity trader in the overlap (first term), (ii) the additional effect due to the inability of the two small liquidity traders in each market to trade among themselves (second term), and (iii) the increased liquidity due to competition by the informed traders in both markets (third term). The right-hand side represents the minimum loss that either large liquidity trader A or B incurs when she moves out of period 1 as she is no longer able to trade with the other large liquidity trader. In that case, this liquidity trader moves (and the other one follows) so that large liquidity trading in period 1 collapses. A similar argument holds for concentrated trading in period 3, which collapses when the condition is true for \( i = A \).

**Proposition 2.** The Nash equilibrium where the two large liquidity traders trade in both markets in the second period yields the following intraday trading pattern. We find that for the overlap relative to the nonoverlap: (i) volume is higher, (ii) volatility is higher, (iii) price impact is lower (i.e., liquidity supply is higher). Furthermore, order imbalance is positively correlated during the overlap.

The proof is included in Appendix A. The higher volume is not surprising as the two large liquidity traders concentrate their trading demand in the overlap. Interestingly, the higher volatility arises endogenously as the innovation \( v \) has equal variance across all periods. It is the result of two effects. First, the transaction price in the second market gives the liquidity supplier an additional signal on the true value, which she uses in round 4 of the game to set a new midquote.
Second, the informed traders originating in both markets compete in period 2, which makes them trade more aggressively and, therefore, reveal more of their signal to the liquidity suppliers. Liquidity supply is higher in the overlap as suppliers charge a lower price impact for two reasons. First, the additional liquidity trading due to the large liquidity traders makes the market more liquid. Second, more aggressive trading by the informed traders in the overlap due to competition also improves liquidity in the overlap, as their expected profit is lower and, in equilibrium, liquidity suppliers (who earn zero profit by assumption) can charge less adverse selection cost.

Finally, the order imbalance is positively correlated across markets for two reasons. First, the large liquidity traders split their order across markets. Second, the informed traders trade on the same signal in both markets.

3. Experiment: NYSE-listed British and Dutch stocks

In our model, we expect increased activity by both informed traders and large liquidity traders in an overlapping period in case two markets exhibit “sufficient” small liquidity trading. In this case, the overlap is characterized by increased volume, volatility, and liquidity supply. Furthermore, we expect positive correlation in order imbalance across markets as large liquidity traders and informed traders split orders across markets in the overlap.

In hunting for the hypothesized equilibrium in real-world markets, we propose the following interpretations. The small liquidity traders are investors who, for exogenous reasons, trade only in the local market, e.g., retail investors (see Section 2.1 for a discussion). The large liquidity traders and informed investors of the model represent the two types of trading motives that institutional investors might have. In the model, both types of investors are order-splitters and, from now on, we interpret the order-splitting to come from these institutional investors. In the empirical tests, we will show that the component in order flow that is correlated across markets is indeed informative on efficient price innovations (see Section 4.3).

We consider NYSE-listed British and Dutch stocks an ideal experiment to study the hypothesized equilibrium for five reasons.

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<td>New York</td>
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</table>

First, the above time table shows that both markets exhibit an overlapping trading period, which enables us to study the hypothesized intraday trading pattern. Trading in British stocks overlaps two hours with New York. Trading in Dutch stocks overlaps one hour.11

Second, we consider a one year trading sample for stocks that generate at least USD 10 million per month at the NYSE. For November 2002 through October 2003, we find that 25 British stocks meet this condition. We also study four Dutch stocks in the period July 1997 through June 1998. For these samples, the model predicts that concentrated trading in the overlap and order-splitting

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11 In the spring, Europe changes to daylight-savings time one week ahead of the US. This week has been removed from the sample.
is more likely if there is more small liquidity trading in New York. It is for this reason that we group the British stocks into quintiles based on NYSE small liquidity trading. The proxy we use is the frequency of NYSE trades conditional on London showing strictly better quotes. In other words, we consider a buy (market) order in New York when London features a strictly lower ask quote as originating from a small liquidity trader. Appendix B presents the ranking of all stocks and testifies to the significant cross-sectional variation in small liquidity trading as the top Q1 stock (BP) has an average 53.4 “small liquidity” trades per hour, which compares to 2.1 trades for the bottom Q5 stock (Amersham).

For the British stocks, we add volume-matched local control stocks to identify the intraday trading pattern due to the cross-listing. Admittedly, it is hard to find appropriate control stocks for the London market, as the most actively traded stocks are all cross-listed. We follow Werner and Kleidon (1996) and choose a relatively unrestrictive filter and only match on volume and not on industry, for example. We start with the highest volume stock and assign it the best volume-matched non-NYSE stock. We repeat the procedure for the other stocks, ranked by volume, and make sure that each control stock is used only once. Appendix C lists all control stocks and their volume. In the US market, we find good matches for the US volume of British stocks, whereas for the British market the match is relatively poor. We will discuss how the poor match affects our results when we present these in Section 4.1.

Third, the markets in Amsterdam, London, and New York are all accessible in real time as they provide instant electronic access. This is an important condition for order-splitting as slow execution would allow liquidity suppliers to adjust their quotes to what they observe in rival markets. 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.

All three markets feature a limit order book. Amsterdam can be considered a pure limit order book market, as specialist intervention is negligible. London runs a similar system, but allows for off-market trading through dealers. New York is a hybrid market, where the specialist and/or floor brokers can improve on the book's liquidity supply.

Fourth, the shares traded at both sides of the Atlantic are fully fungible. The Depositary Receipt (e.g., ADR) that is traded on the NYSE can be converted in the ordinary share (or vice versa) at a cost of approximately 15 basis points at a depositary bank. For the British market, a conversion tax of 150 basis points applies, which makes order-splitting optimal only when price differentials are “large enough.” We will make this precise when designing our test on order-splitting in Section 4.4.

Fifth, the markets have a similar level of pre- and post-trade transparency. This condition is important as it prevents traders from routing orders to the least transparent market (see, e.g., Gemmill, 1996 and Bloomfield and O’Hara, 2000). All markets have high levels of transparency as trades and (best) quotes are transmitted in real time.

12 Proposition 1 emphasizes sufficient small liquidity trading on both markets, but in our sample we only consider sufficient NYSE small liquidity trading as this condition is most likely to be violated.
13 In Section 4.4, we fill in the details on when London shows strictly better quotes for NYSE traders.
14 At the time of the experiment, a specialist (“hoekman”) is assigned to each stock but she trades little in the blue chip stocks we consider.
15 All our stocks need to reconcile their financial statements with US GAAP as they are listed on a US exchange (for the ADR program, for example, this requires level II status).
16 Depositary Banks (e.g., the Bank of New York, Citibank, and JPMorgan) provide this service.
17 The LSE allows for off-market trades through dealers, which do require instant reporting.
3.1. Data and summary statistics

We exploit one year of tick data for the NYSE-listed British and Dutch securities. The British sample runs from November 1, 2002, through October 31, 2003 and the Dutch sample from July 1, 1997, through June 30, 1998. The data set 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 1 presents summary statistics for both samples. Panel A presents average volume, volatility, quoted and effective spread for the full trading day. Panel B presents these statistics for the overlapping period. The results lead to some interesting observations. First, NYSE volume is non-trivial as the NYSE trades every five minutes, GBP 11,882 for an average British Q5 stock up to GBP 398,865 for an average Q1 stock. The average Dutch stock trades EUR 1,034,771 every five minutes. For the overlap, these numbers almost double. Relative to the home market, the NYSE market share ranges from 3% to 19% for the quartiles of British stocks and is 29% for the Dutch stocks. Second, volatility differences across markets are small. This is not surprising for the overlapping period, as arbitrage ensures that prices move in lockstep. For the nonoverlap, it shows that continued NYSE trading, after the European markets close, appears to move prices non-trivial as the NYSE trades, every five minutes, GBP 11,882 for an average British Q5 stock.

The results lead to some interesting observations. First, NYSE volume is roughly equal. 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

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<th>Home (1)</th>
<th>NYSE (2)</th>
<th>Home (1)</th>
<th>NYSE (2)</th>
<th>Home (1)</th>
<th>NYSE (2)</th>
<th>Home (1)</th>
<th>NYSE (2)</th>
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<tbody>
<tr>
<td>5-Minute volume (GBP/EUR)a</td>
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<td></td>
<td>15.8</td>
<td>14.1</td>
<td>0.89</td>
<td></td>
<td>12.4</td>
<td>8.7</td>
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<tr>
<td>5-Minute return volatility (basis points)</td>
<td></td>
<td></td>
<td>24.2</td>
<td>21.9</td>
<td>0.90</td>
<td></td>
<td>19.3</td>
<td>28.0</td>
</tr>
<tr>
<td>Quoted spread (basis points)</td>
<td></td>
<td></td>
<td>26.3</td>
<td>24.6</td>
<td>0.92</td>
<td></td>
<td>24.3</td>
<td>33.0</td>
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<tr>
<td>Effective spread (basis points)</td>
<td></td>
<td></td>
<td>24.1</td>
<td>25.1</td>
<td>1.04</td>
<td></td>
<td>21.6</td>
<td>39.1</td>
</tr>
<tr>
<td>Overlap</td>
<td></td>
<td></td>
<td>21.5</td>
<td>26.8</td>
<td>1.24</td>
<td></td>
<td>18.9</td>
<td>51.3</td>
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<tr>
<td>NL</td>
<td>2,496,258</td>
<td>1,034,771</td>
<td>27.3</td>
<td>26.7</td>
<td>0.98</td>
<td></td>
<td>25.2</td>
<td>41.8</td>
</tr>
</tbody>
</table>

Notes. This table presents summary 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 are calculated based on five-minute intervals.

a UK Volume in GBP and Dutch Volume in EUR.

---

18 The data sources are: NYSE, Euronext-Amsterdam, the London Stock Exchange, and Olsen&Associates.
spread, we find that the NYSE is competitive, which is promising in view of the order-splitting considered in this paper.

4. Results

The results are presented in four subsections. First, we study the intraday trading pattern to verify whether the predicted pattern of Proposition 2 exists in our data. Second, we verify whether order imbalance correlation across markets is positive as predicted in the presence of order-splitters. Furthermore, we test in the cross-section of British stocks whether it is stronger for the stocks that exhibit more small liquidity trading in New York, as Proposition 1 predicts that it will only occur if small liquidity trading is “large enough.” Third, we test whether this supposedly positively correlated component in order imbalance is informative for the efficient price by extending the Hasbrouck (1995) framework. Finally, we develop a more refined test to verify that it is really order-splitting and not (only) positive correlation due to local traders in both markets who trade on the same private signal.

4.1. Intraday trading pattern

We study the intraday patterns in volatility, volume, and liquidity by calculating 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. We do the same for the (single-listed) control stocks and, therefore, control for intraday patterns, in particular those associated with the opening and closing of markets. For the Dutch stocks, we do not have control stocks. In the statistical analysis, we control for interday variation by scaling the intraday observations by their daily average.

Volatility. 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. The top panel in Table 2 presents volatility changes in the home market (left-hand side) and volatility changes at the NYSE (right-hand side). For the top quintile of British stocks, volatility in London increases by 92.5% when the NYSE opens, which is a significant 42.3% more than its control group. And, volatility drops in New York by 73.9% when London closes, which is a significant 29.5% more than the control group. This pattern is depicted in the top two graphs of Fig. 1. For the other quintiles, we do not see the same pattern of increased volatility in the overlap relative to both the British and the NYSE nonoverlap with the exception of Q5. For most quartiles, the jump in London on the NYSE open is not significant. For Q5, however, the jump is significant relative to control stocks, but the jump (64.2%) is an order of magnitude smaller than for Q1 stocks. For the Dutch stocks, we find a volatility jump on the NYSE open, 70.7%, and a volatility drop on the Amsterdam close, 30.2%. Menkveld et al. (2007) decompose volatility around the NYSE open for these stocks and find that it is firm-specific volatility that jumps rather than common-factor volatility. We interpret this as evidence of increased “informed trading” during the overlap.

Volume. Consistent with the volatility results, we find that volume during the overlap is significantly higher for the stocks that generate most NYSE volume. Panel B in Table 2 shows that, for the top quintile British stocks, volume increases by 79.2% on the NYSE open, which is a significant 34.7% higher than the increase for the control stocks. And, NYSE volume drops for these stocks by an average 96.0% on the London close, which is a significant 77.3% more than the decrease for the control stocks. The middle graphs in Fig. 1 illustrate these findings. For the other quintiles, the volume increase in London on the NYSE open is not significantly different
Table 2
Intraday trading patterns: overlap vs. nonoverlap

<table>
<thead>
<tr>
<th></th>
<th>%-age Change Home Market on New York Open</th>
<th>%-age Change New York on Home Market Close</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1) Cross-listed stocks</td>
<td>(2) Control stocks</td>
</tr>
<tr>
<td><strong>Panel A: Volatility</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>UK Q1</td>
<td>92.5</td>
<td>50.2</td>
</tr>
<tr>
<td>UK Q2</td>
<td>51.5</td>
<td>58.4</td>
</tr>
<tr>
<td>UK Q3</td>
<td>54.7</td>
<td>45.1</td>
</tr>
<tr>
<td>UK Q4</td>
<td>50.0</td>
<td>52.6</td>
</tr>
<tr>
<td>UK Q5</td>
<td>64.2</td>
<td>28.9</td>
</tr>
<tr>
<td>NL</td>
<td>70.7</td>
<td></td>
</tr>
<tr>
<td><strong>Panel B: Volume</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>UK Q1</td>
<td>79.2</td>
<td>44.5</td>
</tr>
<tr>
<td>UK Q2</td>
<td>53.0</td>
<td>52.4</td>
</tr>
<tr>
<td>UK Q3</td>
<td>43.0</td>
<td>49.0</td>
</tr>
<tr>
<td>UK Q4</td>
<td>47.8</td>
<td>45.2</td>
</tr>
<tr>
<td>UK Q5</td>
<td>51.9</td>
<td>54.1</td>
</tr>
<tr>
<td>NL</td>
<td>67.9</td>
<td></td>
</tr>
<tr>
<td><strong>Panel C: Effective Spread</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>UK Q1</td>
<td>1.1</td>
<td>0.1</td>
</tr>
<tr>
<td>UK Q2</td>
<td>−0.4</td>
<td>7.9</td>
</tr>
<tr>
<td>UK Q3</td>
<td>2.3</td>
<td>4.4</td>
</tr>
<tr>
<td>UK Q4</td>
<td>3.1</td>
<td>3.9</td>
</tr>
<tr>
<td>UK Q5</td>
<td>2.6</td>
<td>−4.8</td>
</tr>
<tr>
<td>NL</td>
<td>3.5</td>
<td></td>
</tr>
</tbody>
</table>

* Significant at the 99% significance level.

Notes. This table compares volatility, volume, and effective spread for the overlap and the nonoverlap. We calculate changes in the home market 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. We calculate the difference between the cross-listed stocks and their controls and test whether it is statistically significant. Standard errors are calculated after removing interday variation by scaling all observations.

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 drop in New York of 29.0% on the Amsterdam close.

**Liquidity.** The effective spread remains largely unchanged in the home market on the NYSE open, but increases in New York on the home market close. Panel C of Table 2 shows that, for the top quintile British stocks, we find that spreads are 1.1% higher on the NYSE open, which is not significantly more than the 0.1% increase for the control stocks. The increase in New York on the London close is 6.8%, which is a significant 12.6% higher than the 5.8% decrease for the control stocks. The bottom graphs in Fig. 1 illustrate these findings. We find similar results for the other quintiles and for the Dutch stocks.

In summary, it seems that the top quintile of British stocks and the Dutch stocks show the intraday trading pattern predicted by the equilibrium of *Proposition 2*. We lack Dutch control stocks, but if we take the British Q1 control stocks as benchmark, we find the same intraday trading pattern due to the cross-listing: increased volatility, increased volume, and slightly better...
This figure depicts the intraday patterns in volatility (top graphs), volume (middle graphs), and effective spread (bottom graphs) for the five British stocks that exhibit most NYSE small liquidity trader activity. 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 day-by-day scaling.

Fig. 1. Intraday patterns volatility, volume, and effective spread for top quintile British stocks.

liquidity. For the other British quintiles, we do find the predicted pattern for New York trading, but not for London trading. We consider this result across the London quintiles robust in spite of the necessarily poor match with London control stocks (see Section 3). That is, the British top quintile increases in volume and volatility on the NYSE open are an order of magnitude larger than the increases in any of the London control stocks.

For all quintiles except Q1, it seems that small liquidity trading in New York is not sufficient for order-splitting to occur. In other words, the conditions for the unique equilibrium of Proposition 2 as laid out in Proposition 1 might not hold for these stocks. We exploit the cross-section of British stocks to study this issue further in the next section.

4.2. Order imbalance correlation across markets

For the overlap, Table 3 reports the correlation in five-minute order imbalance across markets. We define the order imbalance as the sum of signed trade sizes, where we use the standard Lee and Ready (1991) algorithm to sign each trade. We exclude the first and last fifteen minutes of trading in the overlap as they might be contaminated by idiosyncratic effects of trading during the open or close of a market. Ellul et al. (2005) analyze trading at (and just before) the close in the
Table 3
Order imbalance correlation and NYSE trade activity

**Panel A: 5-Min Order Imbalance Correlations**

<table>
<thead>
<tr>
<th></th>
<th>Corr</th>
<th>σρ</th>
<th>#Obsv</th>
</tr>
</thead>
<tbody>
<tr>
<td>UK Q1</td>
<td>0.16</td>
<td>0.01</td>
<td>24,035</td>
</tr>
<tr>
<td>UK Q2</td>
<td>0.08</td>
<td>0.01</td>
<td>24,035</td>
</tr>
<tr>
<td>UK Q3</td>
<td>0.08</td>
<td>0.01</td>
<td>24,035</td>
</tr>
<tr>
<td>UK Q4</td>
<td>0.06</td>
<td>0.01</td>
<td>24,035</td>
</tr>
<tr>
<td>UK Q5</td>
<td>0.04</td>
<td>0.01</td>
<td>24,035</td>
</tr>
<tr>
<td>NL</td>
<td>0.26</td>
<td>0.01</td>
<td>7419</td>
</tr>
</tbody>
</table>

**Panel B: Cross-Sectional Regressions 5-Min Order Imbalance Correlations**

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Panel B1: Frequency of Small Liquidity Trades as Explanatory Variable</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Frequency NYSE small liquidity trades</td>
<td>0.043**</td>
<td></td>
<td>0.027**</td>
<td></td>
</tr>
<tr>
<td>(9.24)</td>
<td></td>
<td>(3.97)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rel. freq. NYSE liquidity small trades</td>
<td>0.666**</td>
<td>0.420**</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(2.92)</td>
<td></td>
<td>(3.82)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total number of trades (NYSE + London)</td>
<td>0.001**</td>
<td>0.002**</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(3.15)</td>
<td></td>
<td>(8.88)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Volatility Londonb</td>
<td>0.097</td>
<td>0.045</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(1.10)</td>
<td></td>
<td>(0.51)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>R²</td>
<td>0.79</td>
<td>0.27</td>
<td>0.86</td>
<td>0.86</td>
</tr>
<tr>
<td>#Obsv</td>
<td>25</td>
<td>25</td>
<td>25</td>
<td>25</td>
</tr>
</tbody>
</table>

**Panel B2: Volume as Explanatory Variable**

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Volume NYSE</td>
<td>0.154**</td>
<td></td>
<td>0.081*</td>
<td></td>
</tr>
<tr>
<td>(6.70)</td>
<td></td>
<td>(1.75)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Relative volume NYSEa</td>
<td>0.564**</td>
<td>0.360**</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(6.96)</td>
<td></td>
<td>(3.26)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total volume (NYSE + London)</td>
<td>0.019*</td>
<td>0.019**</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(1.89)</td>
<td></td>
<td>(2.96)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Volatility Londonb</td>
<td>0.056</td>
<td>0.128</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(0.44)</td>
<td></td>
<td>(1.13)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>R²</td>
<td>0.66</td>
<td>0.68</td>
<td>0.71</td>
<td>0.78</td>
</tr>
<tr>
<td>#Obsv</td>
<td>25</td>
<td>25</td>
<td>25</td>
<td>25</td>
</tr>
</tbody>
</table>

**Notes.** Panel A documents that correlations in 5-min order imbalance across markets are positive. For the British stocks, Panel B performs cross-sectional regressions of these correlations on NYSE small liquidity trading. We hypothesize that (part of) the positive correlation is due to traders who concentrate their order flow in the overlap and split orders (see Proposition 2). From Proposition 1 we know that this is the unique Nash equilibrium only if there is sufficient NYSE “small liquidity trader” activity. We therefore expect the positive correlation to increase in NYSE small liquidity trader activity. We proxy for this activity by the frequency of NYSE trades after conditioning on times where NYSE traders would be strictly better off trading in London (see Appendix B). We use both the absolute and the relative frequency, where the latter is defined relative to overall small liquidity trading (i.e. we add the frequency of a similar proxy for London). We add overall volume and volatility as controls to account for, e.g., the level of information flow. Panel B1 reports these results and Panel B2 is a robustness check, where, instead of NYSE small liquidity trader activity, we use NYSE volume. In the analysis, we control for idiosyncratic open and close effects by excluding the first and last 15 minutes of the overlap. We report t-statistics in brackets.

a Divided by the aggregate amount across markets.
b Based on 5-min London midquote returns.
* Significant at the 90% significance level.
** Idem, 95%.
London market and show that traders leave the electronic market (i.e. the closing call auction), where they bear the risk of unexecuted trades, and, instead, go to the London dealer market.\textsuperscript{19} Panel A shows that these correlations are significantly positive for all British quintiles and for the Dutch stocks. The correlations are highest for the top quintile of British stocks, 0.16, and for the Dutch stocks, 0.26. For the other British quintiles they are significantly lower (0.08 or less).

In Panel B, we exploit the cross section of 25 British stocks to relate the order imbalance correlation—a proxy for order-splitting—to New York trade activity. The Nash equilibrium of Proposition 2, where both large liquidity traders and informed traders split orders, is most likely to occur when there is sufficient (idiosyncratic) small liquidity trading in New York (see Proposition 1). We therefore expect the positive correlation in the cross-section of British stocks to increase with our proxy of New York small liquidity trading (see Section 3). In Panel B1, we regress the correlation on either the frequency of NYSE small liquidity trades or the relative frequency of NYSE small liquidity trades. For the latter measure, we use the same proxy for the frequency of home market small liquidity trades. We also add overall volume and volatility as controls to account for, e.g., the level of information flow. The results show robust evidence that the correlation in order imbalance significantly increases with New York small liquidity trading, which confirms our prediction. The first regression shows that the frequency of small liquidity trading alone explains 79\% of the cross-sectional variation in order imbalance correlation. Panel B2 repeats the analysis where we use NYSE volume instead of our proxy of the frequency of small liquidity trades. In the standard Chowdhy and Nanda (1991) model, a market’s volume share is proportional to its small liquidity trading share (see also volume result in Appendix A). We find that the results are similar to those based on small liquidity trading. Interestingly, NYSE volume share only explains 66\% of the cross-sectional variation, which testifies to the quality of the small liquidity trading measure.

4.3. Informativeness of (correlated) order imbalance

In this section, we analyze whether order imbalance and, in particular, the component that correlates across markets, is important for price discovery in the overlap. In the model, the order-splitting agents represent an informational (“informed investor”) and a noninformational (“large liquidity trader”) motive for trade. In real-world markets, a trade might feature both trading motives at the same time (see also discussion at the start of Section 3). It is therefore hard to identify the trading motive in the data. We can, however, identify the extent to which trades of order-splitters are informationally-motivated by two observations. First, we can identify the order-splitting component of order imbalance through the common component across markets. Second, we can identify its information content through the long-term price impact of this common component. We can therefore trace how informative the common factor in order imbalance is for price discovery, which we interpret as the information share of trades from order-splitters.

Methodology. We use the Hasbrouck (1991) specification to identify the information content of order imbalance and extend this specification in the context of Hasbrouck (1995) to define “information shares” in a multimarket context. Following Hasbrouck (1991), we specify a vector autoregressive (VAR) model for five-minute midquote change and order imbalance and include

\textsuperscript{19} Our study suggests to extend their analysis to include a third possibility for cross-listed stocks, i.e. execute the trade at the NYSE.
contemporaneous order imbalance to explain midquote changes:

\[ \Delta p_t = \delta + \beta (\eta' p_{t-1}) + A_1 \Delta p_{t-1} + \cdots + B_0 x_t + \cdots + v_{1t}, \]

\[ x_t = \theta + \phi (\eta' p_{t-1}) + C_1 \Delta p_{t-1} + \cdots + D_1 x_{t-1} + \cdots + v_{2t}, \]

where \( \eta \equiv (-1 \ 1)' \)

\[ (3) \]

where capitalized symbols indicate \((2 \times 2)\) matrices and regular symbols indicate \((2 \times 1)\) vectors, in which the first element pertains to the home market and the second element to the NYSE, \( p_t \) is the midquote at timepoint \( t \), \( x_t \) is the order imbalance over the interval \( t - 1 \) to \( t \), and \( v_{1t} \) and \( v_{2t} \) are zero-mean disturbances that are independently and identically distributed and uncorrelated. Consistent with Hasbrouck (1995) and Harris et al. (1995), we add an error-correction term \( \eta' p_{t-1} \) (lagged price differential) to the midquote change equation as arbitrage ensures that price series are cointegrated across markets. The vector \( \beta \) captures how midquotes in both markets respond to (large) price differentials and the Hasbrouck “information shares” critically depend on them. We also add this error correction term in the order imbalance equation as large price differentials will trigger arbitrage trades.

We introduce the following notation:

\[ \Delta y_t \equiv (\Delta p_t \ x_t), \quad \zeta \equiv E^{-1} (\delta \ \theta), \quad v_t \equiv E^{-1} \left( \begin{array}{c} v_{1t} \\ v_{2t} \end{array} \right), \quad \alpha \equiv E^{-1} \left( \begin{array}{c} \beta \\ \phi \end{array} \right), \]

\[ E \equiv \left( \begin{array}{cc} I & -B_0 \\ 0 & I \end{array} \right), \quad \Gamma_i \equiv E^{-1} \left( \begin{array}{cc} A_i & B_i \\ C_i & D_i \end{array} \right) \]

\[ (4) \]

and rewrite Eq. (4) in a single error-correction equation that allows us to discuss information shares as in Hasbrouck (1995):

\[ \Delta y_t = \zeta + \alpha (\omega' y_{t-1}) + \Gamma_1 \Delta y_{t-1} + \cdots + v_t, \]

\[ \omega \equiv (-1 \ 1 \ 0 \ 0)', \]

\[ (5) \]

From this point onward, we follow Hasbrouck (1995, p. 1180–1183) and rewrite Eq. (5) in terms of a vector moving average (VMA) model:

\[ \Delta y_t = \Psi(L)v_t \]

\[ (6) \]

where \( \Psi \) is a polynomial in the lag operator. The cointegration of the midquote series implies that the top two rows of \( \Psi(1) \) are equal and we denote this common row vector by \( \psi \). Intuitively, \( \psi v_t \) constitutes the long-run impact of the midquote and order imbalance innovations. We can now define the “information share” of midquote and order imbalance innovations in each market as:

\[ S_j = \frac{([\psi F]_j)^2}{\psi \Omega \psi'} \]

\[ (7) \]

where \( F \) is the is the Cholesky factorization of \( \Omega \), which is the covariance matrix of \( v_t \), and \([\psi F]_j \) is the \( j \)th element of the row vector \( \psi F \). The factorization imposes a hierarchy that maximizes the information share of the first element of \( v_t \). We permute \( \psi \) and \( \Omega \) to find lower and upper bounds of each element’s information share.

In the implementation, we assume that order imbalance drives prices and not vice versa and, therefore, permute \( \psi \) and \( \Omega \) such that the order imbalance elements of \( v_t \) are always the top two elements and the midquote elements are the bottom two elements. We interpret the difference
between the lower and upper bound on information shares of order imbalance innovations as originating from the commonality in order imbalance. This difference must be caused by commonality as it is easily verified that this difference is zero if the order imbalance innovations are mutually uncorrelated (see also Hasbrouck, 1995, p. 1182). We do the same for midquote innovations.

**Results.** We determine the information shares for all quartiles of British stocks and for the Dutch stocks. We first standardize midquote changes and order imbalance in order to pool all stocks within a group. We then remove the first and last fifteen minutes of trading as they are contaminated by (idiosyncratic) trading at the open and close of a market. Finally, we estimate the error-correction model of Eq. (4). Before considering information shares, it is useful to examine impulse response functions to capture the transitional properties of the system.

**Figure 2** presents the impulse response functions for the focus groups: the top quantile of British stocks (Panel A) and the Dutch stocks (Panel B). Each panel shows four graphs corresponding to a one standard deviation impulse to either order imbalance innovations (top graphs) or midquote innovations (bottom graphs). All graphs show that midquotes are cointegrated as prices converge after shocks. Interestingly, the speed of convergence is considerably slower for the British stocks as compared to the Dutch stocks. We speculate that this is due to the British one-off tax of 150 basis points, which is charged when the share is converted to a US Depositary Receipt. This effectively widens the arbitrage bounds as US quotes do not trigger an arbitrage trade if they are within a window of roughly 0 to $+150$ basis points relative to British quotes (see Section 4.4 for details). It therefore takes longer for one market to adjust to quote updates in the other market.

Otherwise, the British and Dutch impulse response functions are strikingly similar. First, order imbalance innovations in the home market appear to have a more than double long-run impact than those originating in the NYSE market. Second, the speed of midquote adjustment to order imbalance innovations in the rival market is considerably faster than to midquote innovations in the rival market. That is, the lines in the order imbalance impulse graphs converge faster than in the midquote impulse graphs. Apparently, liquidity suppliers observe transactions in the rival market and are quick to condition on them, consistent with round 4 of the model in Section 2. These graphs, however, cannot give us any information on what the contribution is of the common component in either order imbalance innovations across markets or midquote innovations across markets. We, therefore, turn to information shares.

**Figure 3** depicts the information shares for all British quintiles and for the Dutch stocks. Panel A presents the order imbalance information shares and Panel B presents the midquote innovation information shares. These information shares sum to one by definition (see Eq. (7)).

The order imbalance information shares reveal an economically significant information share for the common component of Q1 British stocks and for the Dutch stocks. We find that their information share is, respectively, 8% and 12% (gray area). This information share for the other British quintiles is less than 3%. This reinforces the findings of Sections 4.1 and 4.2 that only the British Q1 and the Dutch stocks seem to support the predictions of the order-splitting equilibrium. Their significant information shares for the common component is consistent with order-splitters as informed traders who exploit their signal in two pools of liquidity in the overlap.

The information shares lead to some other interesting findings. First, we find that order imbalance matters for midquote changes and that its information share is highest for the British Q1 and Dutch stocks, 60–70%, and declines to less than 40% for British Q5 stocks. Second, the home market dominates the order imbalance information share (dark gray, 35–50%), but the contribution of the NYSE is not negligible (white, 2–10%). Third, panel B shows that the com-
These graphs depict the impulse response functions (IRFs) based on estimates of a vector-error correction model for five-minute midquote changes in the home market and the NYSE market (see Eq. (4)). We present these IRFs for the top quintile of British stocks in Panel A and for the Dutch stocks in Panel B. Each panel shows four graphs corresponding to a one standard deviation impulse to either order imbalance innovations (top graphs) or midquote innovations (bottom graphs).

Fig. 2. Impulse response functions top quintile British stocks and Dutch stocks.
These graphs depict “Hasbrouck” information shares for midquote and order imbalance innovations, according to a methodology that is inspired by Hasbrouck (1991, 1995). We describe the methodology in detail in Section 4.3. The intuition is that we decompose the overall variance of the long-term impact on prices of midquote and order imbalance innovations originating in both markets. Panel A depicts the information shares of order imbalance innovations. Panel B depicts the information shares of midquote innovations. The information shares sum to one i.e. the bars in Panels A and B sum to one. We interpret the white and black area as the information shares of the home market and the NYSE, respectively, and we interpret the gray area as the information share of the common component across markets.

Fig. 3. Information shares for all British quartiles and the Dutch stocks.

mon factor in midquote innovations (by construction this factor is orthogonal to order imbalance innovations) has high information share (gray, 15–50%). This is not surprising as we interpret midquote innovations as arriving from public information, which is easily observed by liquidity suppliers in both markets.

4.4. Discussion of results and further evidence of order-splitting

For the British Q1 and Dutch stocks, all results that we have presented thus far are consistent with the order-splitting equilibrium. In this section, we address two concerns one might still have. First, we consider the alternative hypothesis that the order imbalance correlation for these stocks is driven by local traders who receive the same private information and trade on it only in their own market. Second, one might be concerned that the intraday patterns can be explained by the well-documented market open and close effects.

Local traders exploit same private signal? To study this alternative hypothesis for positive order imbalance correlation across markets, we exploit the Stamp Duty Reserve Tax (SDRT) that British tax authorities impose on transactions in their markets. Such transaction tax does not exist for the Dutch and US market. The SDRT amounts to 50 basis points and is collected from the
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 a similar histogram for Dutch stocks. Both graphs are based five-minute snapshots for all stocks in the sample.

Fig. 4. Histogram log midquote differentials between the home market and the NYSE.

buy side of the transaction. And, to prevent order flow from migrating to the US, conversions to US Depositary Receipts (DR) are taxed a one-off of 150 basis points. For reverse transactions, a tax of 50 pence applies. We use the SDRT to sort our five-minute 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. Figure 4 illustrates this as it plots a histogram of midquote differentials for the British sample and for the Dutch sample as a benchmark.

In the implementation, we use exact conditions for arbitrage that also account for the 15 basis points conversion fee and the associated 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 (see Appendix B). If prices are beyond the “arbitrage bounds,” we label these “arbitrage” intervals. The unlabeled intervals, where prices are well within the “arbitrage bounds,” serve as controls that might exhibit positive correlation in order imbalance due to the alternative explanation of local traders in both markets trading on the same private information.

Panel A of Table 4 reports the conditional five-minute order imbalance correlations and finds that they are positive for all intervals, except for the arbitrage-opportunity intervals. The positive correlation for intervals without order-splitting opportunities shows that our benchmark corre-
Table 4
Order imbalance correlation conditional on order-splitting opportunities

**Panel A: Correlation Order Imbalance across Markets**

<table>
<thead>
<tr>
<th></th>
<th>Order-splitting opportunity</th>
<th>Arbitrage opportunity</th>
<th>Other</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Corr</td>
<td>σρ</td>
<td>#Obsv</td>
</tr>
<tr>
<td>UK Q1</td>
<td>0.20</td>
<td>0.03</td>
<td>2972</td>
</tr>
<tr>
<td>UK Q2</td>
<td>0.14</td>
<td>0.04</td>
<td>2763</td>
</tr>
<tr>
<td>UK Q3</td>
<td>0.11</td>
<td>0.02</td>
<td>3588</td>
</tr>
<tr>
<td>UK Q4</td>
<td>0.05</td>
<td>0.03</td>
<td>2672</td>
</tr>
<tr>
<td>UK Q5</td>
<td>0.00</td>
<td>0.04</td>
<td>1601</td>
</tr>
<tr>
<td>NL</td>
<td>0.26</td>
<td>0.01</td>
<td>6689</td>
</tr>
</tbody>
</table>

**Panel B: Cross-Sectional Regressions 5-Min Order Imbalance Correlations**

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Frequency NYSE small liquidity trades</td>
<td>0.023</td>
<td>0.027</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.63)</td>
<td>(1.10)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Relative frequency NYSE small liquidity trades</td>
<td>0.757*</td>
<td>0.675*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.06)</td>
<td>(1.81)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total number of trades (NYSE + London)</td>
<td>0.000</td>
<td>0.001</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.21)</td>
<td>(1.36)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Volatility London</td>
<td>0.473</td>
<td>0.423</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.48)</td>
<td>(1.41)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>R²</td>
<td>0.10</td>
<td>0.16</td>
<td>0.19</td>
<td>0.26</td>
</tr>
<tr>
<td>#Obsv</td>
<td>25</td>
<td>25</td>
<td>25</td>
<td>25</td>
</tr>
</tbody>
</table>

**Notes.** Panel A reports correlations of order imbalance across markets based on 5-min intervals. We report 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. We hypothesize that in the presence of order-splitting, the intervals with order-splitting opportunities show higher correlations than the “benchmark” remaining intervals. Panel B regresses the difference between these two correlations on NYSE small liquidity trading to test whether order-splitting is more prevalent for stocks with high NYSE small liquidity trading. We proxy for such trading by the frequency of NYSE trades after conditioning on times where NYSE traders would be strictly better off trading in London (see Appendix B). We use both absolute and relative NYSE small liquidity trades frequency, where we measure the latter relative to the overall small liquidity trading (i.e. we add the frequency of a similar proxy for London). We add the total number of trades and volatility as controls to account for, e.g., the level of information flow. In the analysis, we control for idiosyncratic opening and closing effects by excluding the first and last 15 minutes of the overlap. We report t-statistics in brackets.

* Significant at the 90% significance level.

The correlation should be nonzero. This could be interpreted as evidence of the alternative hypothesis of local traders who trade on the same private signal. But, we also find that relative to this benchmark correlation, order imbalance correlation is higher during the intervals with order-splitting opportunities, in particular for those quintiles where order-splitting is most likely. For example, for the Q1 quintile, we find that correlation is 0.20 relative to a 0.16 benchmark correlation.

Panel B of Table 4 finds that, cross-sectionally, the correlation for the order-splitting intervals relative to the control intervals increases with the amount of NYSE small liquidity trading. We find that this relationship is statistically significant for the share of NYSE small liquidity trading i.e. relative to home market small liquidity trading. The result remains significant after we add the total number of trades and volatility as control variables in the regression. We interpret this as further evidence of traders who concentrate their trades in the overlap and split orders.
Market open and close effects drive intraday patterns? Although the intraday patterns we document are consistent with the literature on market open and close effects, we consider the cross-sectional variation in the pattern as evidence in favor of the order-splitting equilibrium we propose. Figure 1, for example, illustrates for the British Q1 stocks that volatility and effective spread in the first half hour after the NYSE open are significantly lower than what we observe for the control stocks (40% and 30% lower, respectively). Clearly, the information asymmetry for the specialist, floor traders, and limit order submitters in New York is reduced as they benefit from home market prices ahead of the NYSE open. The literature on market opening documents the importance of pre-opening signals for price discovery during the opening of a market (see, e.g., Biais et al., 1995; Cao et al., 2000; Madhavan and Panchapagesan, 2000). As for a market close effect, Fig. 1 documents that, relative to control stocks, volume and volatility in New York drop and the effective spread rises after the home market closes. This pattern is consistent with, for example, Barclay and Hendershott (2003) who document less volume, less volatility, but more information per trade for the NASDAQ postclose trading hours. For our study, however, we emphasize the changes in the home market when the NYSE opens. The strongest evidence for the order-splitting equilibrium is that, cross-sectionally, these changes in the home market are consistent with such equilibrium and they are, along with the order imbalance correlation across markets, strongest for stocks with most NYSE small liquidity trading.

5. Conclusion

In this paper, we analyze 25 NYSE-listed British stocks along with single-listed control stocks and 4 NYSE-listed Dutch stocks to detect order-splitting. We extend the Chowdhry and Nanda (1991) model to allow large liquidity traders to time their trade in the spirit of Admati and Pfleiderer (1988). We find that the Nash equilibrium in which these traders concentrate their trades in the overlap and split their orders is the unique equilibrium when local “small liquidity trading” is sufficiently large. As a result, volume is higher in the overlap. Volatility is also higher, as market makers in both markets get an additional signal on the true value of the security by observing the transaction price in the rival market. And, these transaction prices are more revealing due to competition between the informed traders of both markets. Finally, it is the arrival of large liquidity trader volume and the lower profits of informed traders that make the market more liquid in the overlap.

We find considerable empirical support for the model. In the cross section of British stocks, we find that only the ones with highest NYSE small liquidity trading show intraday patterns that are consistent with the order-splitting Nash equilibrium: increased volume, increased volatility and (weakly) higher liquidity supply for the overlap relative to the nonoverlap. We document a similar pattern for Dutch stocks. We find further support for order-splitting as order imbalance is positively correlated across markets in the overlap and, in the cross-section of British stocks, it significantly increases with NYSE small liquidity trading. We further exploit the British tax regime to control for the alternative explanation that the positive correlation is due to local traders who exploit the same private signal locally. We find that the average correlation is higher for intervals with order-splitting opportunities as compared to intervals without such opportunities. Furthermore, in the cross-section, this difference increases with NYSE small liquidity trading.

In a Hasbrouck information share analysis, we find that the common component in order imbalance contains information. For the British stocks with most NYSE small liquidity trading and for Dutch stocks, it has an average 10% information share i.e. it explains 10% of the long-term variance of the stock price.
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Appendix A. Proofs of lemma and propositions

Summary results: We start with a summary of the equilibrium values for volume, volatility, liquidity supply, and order imbalance correlation for the Nash equilibrium where both large liquidity traders concentrate all demand in period 2. We report values for the overlap and the nonoverlap for only market $A$, as the model is symmetric in $A$ and $B$.

<table>
<thead>
<tr>
<th></th>
<th>volume</th>
<th>volatility</th>
<th>$\lambda$ (price impact)</th>
<th>$\rho$ (order imbalance)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Non-overlap</td>
<td>$\frac{1}{\sqrt{2\pi}} (4 + \sqrt{2}) \sigma_{d,A}$</td>
<td>$\frac{1}{2} \sigma_v^2$</td>
<td>$\frac{1}{\sigma_{u,A} \sigma_v}$</td>
<td></td>
</tr>
<tr>
<td>Overlap</td>
<td>$\frac{\sigma_{u,A}}{\sqrt{2\pi}} \left[ 1 + \sqrt{2\Theta + \beta \sqrt{1 + 2\Phi}} \right]$</td>
<td>$\frac{4}{5 + (\frac{2\Phi}{\Theta})} \sigma_v^2$</td>
<td>$\frac{\sqrt{\phi}}{\sqrt{1 + 2\Phi}} \frac{1}{\sigma_{u,A}} \sigma_v$</td>
<td>$\frac{2\Phi}{\Theta + 1}$</td>
</tr>
</tbody>
</table>

$\alpha \equiv 3 + \sqrt{2}$, $\beta \equiv \sqrt{2} (1 + \sqrt{3})$, $\Theta \equiv \frac{\sigma_{d,A} + \sigma_{d,B}}{\sigma_{u,A} + \sigma_{u,B}}$, $\Phi \equiv \frac{\sigma_{d,A} + \sigma_{d,B}}{(\sigma_{u,A} + \sigma_{u,B})^2}$

Preparation of Proofs of Lemma 1, Proposition 1, and Proposition 2: We first prove the results summarized in the table above for the overlap i.e. period 2.

1. We hypothesize linear pricing schedules for liquidity suppliers:

$$\Delta P_i = P_i - P = \lambda_i \omega_i$$  \hspace{1cm} (8)

2. We solve the optimization problem for the informed investors and the large liquidity traders.

The informed investor who originates in market $A$ has access to both markets during the overlap and, in each market, maximize their profit. The same goes for the informed investor of market $B$. Informed trader $A$ in market $i$, for example, solves the following optimization problem:

$$\max_{x_i^A} E \left[ x_i^A \left( v - \lambda_i (x_i^A + x_i^B + u_A + d_i^A + d_i^B) \right) \right]$$.  \hspace{1cm} (9)
She therefore sets:
\[ x_i^* = \frac{1}{2\lambda_i} v - \frac{1}{2} x_i^B. \]
(10)

Informed trader B solves the same problem in market i and we therefore find for the aggregate informed order flow in market i:
\[ x_i^* = x_i^A + x_i^B = \frac{4}{3} \left( \frac{1}{2\lambda_i} v \right). \]
(11)

The large liquidity traders originating in both markets minimize cost. Trader A, for example, solves (be aware that she concentrates all demand in this period so \( \text{var}(d^A) = 2\sigma^2_{d,A} \)) i.e. the sum of period 1 and 2 demand—we will prove this result later:
\[ \min \left\{ d^A_A, d^A_B \right\} \sum_{i=A,B} E\left[ d_i \cdot \lambda_i \cdot \omega_i \right] \text{ such that } d^A_A + d^A_B = d^A. \]
(12)

We find:
\[ d_i^* = \frac{\lambda_{j \neq i}}{\lambda_i + \lambda_{j \neq i}} d_i. \]
(13)

We find that the signed volume in market i originating from large liquidity traders is:
\[ d_i^* = d_i^A + d_i^B = \frac{\lambda_{j \neq i}}{\lambda_i + \lambda_{j \neq i}} (d^A + d^B). \]
(14)

(3) We use Eqs. (11) and (14) 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:
\[ \Delta P_A = E[v|\omega_A] = \lambda_A \cdot \omega_A \text{ with } \lambda_A = \frac{\text{cov}(\omega_A, v)}{\text{var}(\omega_A)}, \]
(15)

we compute the covariance and variance term, solve a system of two equations (for \( \lambda_A \) and \( \lambda_B \)), and find:
\[ \lambda_i = \sqrt{n} \frac{1}{\sqrt{\frac{8}{9} \sigma_{u,A} \sigma_{d,A}}} \sigma_v. \]
(16)

With this result, we calculate volume, volatility, and order imbalance correlation.

**Volume.** The variance of order imbalance \((\omega_i)\) 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 \( s_1, s_2, \ldots, s_n \), 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 \( S^+ = s_1^+ + \cdots + s_n^+ \) and \( S^- = s_1^- + \cdots + s_n^- \). The expected volume is
\[ E(\max(S^+, S^-)) = \frac{1}{2} \sum_{i=1}^n E|s_i| + \frac{1}{2} E\sum_{i=1}^n |s_i| = \frac{1}{\sqrt{2\pi}} \left( \sum_{i=1}^n \sigma_i + \sqrt{\sum_{i=1}^n \sigma_i^2} \right). \]
(17)

where \( \sigma_i \) is the standard deviation of \( s_i \) (see Admati and Pfleiderer, 1988). For our model we find:
\[ Volume_i = \frac{1}{\sqrt{2\pi}} \left( \sigma_{u,A} + k_i \sigma_{d,A} + k_i \sigma_{d,B} + c_i \sigma_v + \sigma_{\omega_i} \right) \]
\[ + \sqrt{\sigma^2_{u,A} + k^2_i \sigma^2_{d,A} + k^2_i \sigma^2_{d,B} + c_i^2 \sigma^2_v + \sigma^2_{\omega i}}, \]  
with \( c_i \equiv \frac{1}{2 \lambda_i}, \) \( k_i \equiv \frac{\lambda_{j \neq i} \lambda_i}{\lambda_{j \neq i} + \lambda_i}, \) \( \) and \( \sigma_{\omega i} = \sqrt{\sigma^2_{u,A} + k^2_i \sigma^2_{d,A} + k^2_i \sigma^2_{d,B} + c_i \sigma^2_v}. \) If we insert all constants, we find:

\[ \text{Volume}_i = \frac{\sigma_{u,A}}{\sqrt{2\pi}} \left[ 1 + \sqrt{2} \Theta + (\sqrt{2} + (1 + \sqrt{2}) \sqrt{3}) \sqrt{1 + 2 \Phi} \right]. \]  

Volatility. To calculate volatility, we follow the proof of Proposition 2 in Chowdhry and Nanda (1991):

\[ \text{Volatility} = \frac{4}{5 + \left( \frac{2 \Phi}{2 \Phi + 1} \right)} \sigma^2_v. \]  

Order imbalance correlation. To calculate order imbalance correlation, we follow the proof of Proposition 1 in Chowdhry and Nanda (1991):

\[ \rho(\omega_A, \omega_B) = \frac{9}{17} \left[ 1 + \left( \frac{2 \Phi}{2 \Phi + 1} \right) \right]. \]  

For the nonoverlap, the results trivially follow from the analysis so far, where we bear in mind that we only have one informed trader and one local liquidity trader (as the large liquidity trader has moved her demand to the overlap). We find \((i \in \{A, B\})\):

\[ \lambda_i = \frac{1}{2} \frac{\sigma_v}{\sigma_{u,i}}, \quad x_i = \frac{1}{2 \lambda_i} v, \quad \text{Volume}_i = \frac{1}{\sqrt{2\pi}} (4 + \sqrt{2}) \sigma_{u,A}, \quad \text{Volatility} = \frac{1}{2} \sigma^2_v. \]  

Proof of Lemma 1. Large liquidity traders prefer to concentrate their total liquidity demand (for large liquidity trader \(A\) this is \(d^A\) from period 1 and 2) in one trading period. Any other candidate solution where they split their total order across multiple periods will be dominated by concentrating it all in one of the periods they trade in. From Eqs. (12) and (13), it easily follows that her expected cost for the overlap equals \(\frac{1}{\sqrt{1 + 2 \gamma}} \gamma \sigma^2_{d,A}\), where \(\gamma\) is a constant that does not depend on the amount of large liquidity trading and \(\Phi\) is defined in the “summary results” at the start of the appendix and decreases in the amount of large liquidity trading (\(\sigma_{d,A}\) and \(\sigma_{d,B}\)). For the nonoverlap, it is straightforward to show that the expected cost is \(\lambda_i \sigma^2_{d,A}\), where \(\lambda_i\) also decreases in the amount of large liquidity trading. And, as the expected cost per unit of large liquidity trading variance decreases with the amount of large liquidity trading in all these periods, it follows that concentration in one period dominates other candidate solutions. □

Proof of Proposition 1. From Lemma 1, we know that large liquidity traders concentrate their trading in one period. We therefore restrict attention to nine potential equilibria \(a\) through \(i\).

<table>
<thead>
<tr>
<th>Trader (B) trades in:</th>
<th>Period 1</th>
<th>Period 2</th>
<th>Period 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Trader (A) trades in:</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Period 1</td>
<td>(a)</td>
<td>(b)</td>
<td>(c)</td>
</tr>
<tr>
<td>Period 2</td>
<td>(d)</td>
<td>(e)</td>
<td>(f)</td>
</tr>
<tr>
<td>Period 3</td>
<td>(g)</td>
<td>(h)</td>
<td>(i)</td>
</tr>
</tbody>
</table>

Equilibria \(c\) and \(g\) can be ruled out as Nash equilibria immediately. Suppose small liquidity trading is equal or higher in market \(A\). In this case, the large liquidity trader in period 3 will
move to period 1 in order to benefit from the presence of the small liquidity trader in market A and from the presence of the other large liquidity trader. The reason is that the expected cost for large liquidity traders depends on liquidity ($\lambda$), which improves with the total level of uninformed trading (see Eq. (22)). A similar reasoning goes for higher small liquidity trading in market B.

The other off-diagonal equilibria $b$, $d$, $f$, and $h$ can also be immediately ruled out as Nash. It is always optimal for the large liquidity trader who trades in the non-overlap to move to the overlap. Let us consider equilibrium $b$, where large liquidity trader A trades in period 1 and large liquidity trader B trades in the overlap. From Eqs. (12) and (13), we calculate the expected cost of trader A in case she moves to period 2 and compare it to the cost of staying in period 1:

\[
\text{Cost overlap} = E\left[\lambda_{A,2}\left(\frac{\lambda_{B,2}}{\lambda_{A,2} + \lambda_{B,2}} d^A\right)^2 + \lambda_{B,2}\left(\frac{\lambda_{A,2}}{\lambda_{A,2} + \lambda_{B,2}} d^A\right)^2\right]
\]

\[
= \frac{\lambda_{A,2} \lambda_{B,2}}{\lambda_{A,2} + \lambda_{B,2}} 2\sigma_{d,A}^2,
\]

\[
\text{Cost non-overlap} = E\left[\lambda_{A,1}(d^A)^2\right] = \lambda_{A,1} 2\sigma_{d,A}^2,
\]

where the subscripts indicate the market and the period, respectively. We find that the change in cost for trader A to move from period 1 to 2 equals:

\[
\Delta \text{Cost} = \left(\frac{\lambda_{A,2} \lambda_{B,2}}{\lambda_{A,2} + \lambda_{B,2}} - \lambda_{A,1}\right)\sigma_{d,A}^2
\]

\[
= \frac{1}{2} \left(\frac{\sqrt{8}}{9} \frac{1}{\sqrt{(\sigma_{u,A} + \sigma_{u,B})^2 + 2(\sigma_{d,A}^2 + \sigma_{d,B}^2)}} - \frac{1}{\sqrt{\sigma_{u,A}^2 + 2\sigma_{d,A}^2}}\right)\sigma_v 2\sigma_{d,A}^2 < 0.
\]

It is therefore optimal for her to move to period 2. A similar proof holds for showing that equilibria $d$, $f$, and $h$ cannot be Nash.

The diagonal options $a$, $e$, and $i$ remain as potential Nash equilibria. We first prove that equilibrium $e$ yields the lowest expected trading cost for both liquidity traders. Consider the cost difference for trader A of trading in period 2, equilibrium $e$, relative to trading in period 1, equilibrium $a$:

\[
\Delta \text{Cost} = \left(\frac{\lambda_{A,2} \lambda_{B,2}}{\lambda_{A,2} + \lambda_{B,2}} - \lambda_{A,1}\right)2\sigma_{d,A}^2
\]

\[
= \frac{1}{2} \left(\frac{\sqrt{8}}{9} \frac{1}{\sqrt{(\sigma_{u,A} + \sigma_{u,B})^2 + 2(\sigma_{d,A}^2 + \sigma_{d,B}^2)}} - \frac{1}{\sqrt{\sigma_{u,A}^2 + 2\sigma_{d,A}^2}}\right)\sigma_v 2\sigma_{d,A}^2 < 0.
\]

A similar argument holds for equilibrium $i$.

We further show that equilibrium $a$ is not a Nash equilibrium if it is optimal for one of the large liquidity traders to move to the second period (leaving the other large liquidity trader behind). The change in cost for large liquidity trader A to move is (“cost period 2–period 1”):

\[
\Delta \text{Cost} = \left(\frac{\lambda_{A,2} \lambda_{B,2}}{\lambda_{A,2} + \lambda_{B,2}} - \lambda_{A,1}\right)\sigma_{d,A}^2
\]
This cost is negative iff:

\[
\sigma_{u,B} + 2\sigma_{u,A}\sigma_{u,B} + \frac{1}{9}(2\sigma^2_{d,A} + 2\sigma^2_{d,B} + \sigma^2_{u,A}) > 2\sigma^2_{d,B}.
\] (27)

A similar condition holds for large liquidity trader B to move from period 1. If either large liquidity trader A or B has an incentive to move the potential Nash equilibrium of period 1 collapses. Following this argument, we arrive at the condition in Eq. (2) for \(i = B\). For equilibrium \(i\), we follow the same reasoning and find the condition of Eq. (2) with \(i = A\).

**Proof of Proposition 2.** The proof for proposition 2 follows from inspection of the equilibrium values derived at the start of the appendix. In this equilibrium, the volume difference comparing period 1 to period 2 is:

\[
\text{Volume}_{A,2} - \text{Volume}_{A,1} = \frac{\sigma_{u,A}}{\sqrt{2\pi}}(4 + \sqrt{2})
- (1 + \sqrt{2}\Theta + (\sqrt{2} + (1 + \sqrt{2})\sqrt{3})\sqrt{1 + 2\Phi}) > 0,
\] (28)

since \(\Theta\) and \(\Phi\) are greater or equal to zero. The volatility difference is:

\[
\text{Volatility}_{A,2} - \text{Volatility}_{A,1} = \left(\frac{8\Phi + 4}{12\Phi + 5} - \frac{1}{2}\right) > 0,
\] (29)

since \(\Phi\) is greater or equal to zero. The difference in price impact coefficients is:

\[
\lambda_{A,2} - \lambda_{A,1} = \frac{1}{2}\sigma_u \left(\frac{8}{9} \sqrt{\frac{1}{1 + 2\Phi}} - 1\right) < 0,
\] (30)

since \(\Phi\) is greater or equal to zero. This shows that markets are deeper during the overlap. The correlation in order imbalance equals:

\[
\rho(\omega_A, \omega_B) = \frac{9}{17} \left(1 + \frac{2\Phi}{2\Phi + 1}\right) > 0.
\] (31)

Comparing period 3 with period 2 yields the same results.

**Appendix B. Arbitrage and order-splitting conditions**

Arbitrage opportunities exist, when

\[
DR_{bid} > (1 + CF + 0.015) \cdot ORD_{ask} \cdot FX_{ask} \quad \text{(Buy London, Sell New York)},
\] (32)

\[
ORD_{bid} > (1 + CF) \cdot ADR_{ask} \cdot FX_{bid}^{-1} + 50p \quad \text{(Buy New York, Sell London)},
\] (33)

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 US Dollar. Opportunities for order-splitting exist, when

\[
DR_{bid} = (1 - CF) \cdot ORD_{bid} \cdot FX_{bid} \quad \text{(DR sellers split)},
\] (34)
**Table C.1**

NYSE-listed British and Dutch stocks and control stocks

<table>
<thead>
<tr>
<th>英国/荷兰</th>
<th>股票代码</th>
<th>股票名称</th>
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<th>英国控制股票</th>
<th>股票代码</th>
<th>股票名称</th>
<th>每月英国市场交易量（百万英镑）</th>
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注：英国交易量以英镑计，荷兰交易量以欧元计。
\[ \text{ORD}_{\text{bid}} = (1 - \text{CF}) \cdot \text{DR}_{\text{bid}} \cdot \text{FX}_{\text{ask}}^{-1} - 0.015 \cdot \text{ORD}_{\text{bid}} \quad (\text{ORD sellers split}), \tag{35} \]

\[ \text{DR}_{\text{ask}} = \text{ORD}_{\text{ask}} \cdot \text{FX}_{\text{ask}} \cdot (1 + \text{CF}) + 0.015 \cdot \text{ORD}_{\text{ask}} \cdot \text{FX}_{\text{ask}} \quad (\text{DR buyers split}), \tag{36} \]

\[ 1.005 \cdot \text{ORD}_{\text{ask}} = \text{DR}_{\text{ask}} \cdot \text{FX}_{\text{bid}}^{-1} \cdot (1 + \text{CF}) + 50p \quad (\text{ORD buyers split}), \tag{37} \]

where in Eqs. (35) and (36) the one-off tax of 150 basis points applies and in Eq. (37) the regular SDRT of 50 basis points applies as the ORD buyer has to pay, and, if buying in the US, the conversion fee of 50 pence applies.

Appendix C. NYSE-listed British and Dutch stocks and control stocks

Table C.1 presents (i) NYSE-listed British stocks and local market control stocks and (ii) NYSE-listed Dutch stocks. We include average 2003 monthly trading volume for the British stocks and 1997–1998 volume for the Dutch stocks. We emphasize that here we report overall volume (including, e.g., transactions in the dealer market), whereas in the remainder of the paper we consider limit order book activity only. We use a proxy for the number of NYSE small liquidity trades per hour to set up quintiles. This proxy counts all NYSE transactions at times when London prices are strictly better (see Appendix B). We follow Werner and Kleidon (1996) and assign control stocks to the cross-listed stocks based on volume.

References


