'Those who know most': insider trading in 18$^{\text{th}}$ c. Amsterdam*

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Abstract

I use a natural experiment from financial history to study the process by which private information is incorporated into prices. I look at the market for British securities in the Netherlands during the 1770s and 1780s. Anecdotal evidence suggests that British insiders traded actively on their private signals, both in London and in Amsterdam. I reconstruct the arrival of sailing boats in the Netherlands by which information from London to Amsterdam was transmitted. I show that the specific price dynamics of the English securities in Amsterdam is consistent with an important role for private information. More specifically I provide evidence consistent with Kyle (1985) that insiders traded on their private signals in a strategic way and that private information was only slowly revealed to the market as a whole. I show that the speed of information revelation in Amsterdam crucially depended on how long insiders expected it would take for the private signal to be publicly revealed. In addition, I show that under a specific set of conditions, London prices responded to the price discovery process in Amsterdam.

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Asymmetric information plays a key role in many models that seek to explain the behavior of asset prices (seminal contributions are Kyle 1985; Glosten and Milgrom 1985). Many papers in this literature follow Kyle's (1985) basic framework.[1] Arguably the most important element of these "Kyle-type" models is the strategic behavior of insiders. Insiders take the impact of their own actions into account and this drives many of these models' predictions. To give a simple example, if one assumes that private information is generated at the beginning of the trading day, the classical Kyle model would predict that volatility should slowly decrease over the day. This result largely hinges on the strategic behavior of insiders. Since private information and privately informed trading are by definition unobservable[2], direct empirical evidence for this strategic behavior is difficult to obtain.

In this paper I use a natural experiment from financial history in which the process by which private information is incorporated into prices can be analyzed in unique detail. This setting provides a natural way to study the strategic behavior of insiders. I look at the market for British securities in the Netherlands in the 1770s and 1780s. The "English funds" were both traded in London, its primary market, and Amsterdam, the most important international capital market of the period (Neal 1990). Most, if not all, relevant information about the company was generated in England (Koudijs 2011). There is plenty of anecdotal evidence that British insiders actively traded on their private signals. They would not only do this in London, they would also share this information with their agents in Amsterdam who then tried to benefit from the same informational advantage. This information was transmitted by sailing boats. Twice a week so-called packet boats would cross the North Sea to deliver "the English letters", which would include private dispatches from English insiders to their Amsterdam agents. The newspapers of the time meticulously reported when these boats arrived in the Netherlands and I can identify exactly when information arrived in Amsterdam. I show that the specific price dynamics of English securities in Amsterdam between the arrival of boats is consistent with an important role for private information.

More specifically I provide evidence consistent with Kyle (1985) that insiders traded on their private signals in a strategic way and that private information was only slowly revealed to the market as a whole. I show that the speed of the revelation of information in Amsterdam crucially depended on how long insiders expected it would take for the private signal to be publicly revealed.

To guide the empirical analysis I present a simple two period model of private information in the vein of Kyle (1985). In the first period of the model a private signal arrives and a privately informed agent has the opportunity to trade. In the second period of the model no new information

[1] A non-exhaustive list of papers includes Admati and Pfleiderer 1988; Foster and Viswanathan 1990, 1996; Chowdry and Nanda 1991; Holden and Subrahmanyam 1992, 1994; Spiegel and Subrahmanyam 1992; George et al. 1994; Chordia, Roll and Subrahmanyam 2002; Baruch 2002; Back and Baruch 2004; Mendelson and Tunca 2004; Chau and Vayanos 2008; Caldentey and Stacchetti 2010.

[2] An exception are papers such as Cohen et al. (2011) that use data from insider trading records.

arrives, but there is an additional opportunity to trade. The main prediction of the benchmark Kyle model is that because of the multiple trading opportunities, private information will only be slowly revealed over time. In this context this means that, even when no new information arrives in Amsterdam, price changes in Amsterdam should still be correlated with those in London. This follows from the slow revelation of private information in both markets.

The empirical evidence supports this prediction. I also provide evidence that this co-movement between Amsterdam and London led to permanent price changes. Amsterdam and London didn't simply co-move because of correlated noise or liquidity shocks. In addition, I show that English security prices in London and Amsterdam also moved in the same direction during periods of bad weather in which it was impossible for sailing boats to cross the North Sea. This suggests that these results are not driven by the slipping through of other boats carrying public information that I do not observe.

I explicitly model the risk that private information is revealed before any second period trade can take place (compare Caldentey and Stacchetti 2010). To be clear, mail packetboats perform two functions in this setting. First of all, they transmit the private signal. Secondly, they will of course also transmit any public news, including London security prices, that will likely reveal some (if not all) of the old private signal. For example, price discovery in London will have (partially) revealed the private signal in that market. Alternatively, the private information may have been publicly revealed by the time the next boat departs for Amsterdam. If this next boat sails in quickly, the informed agent will have fewer opportunities to trade on his information. I model this as the insider having only one period to trade. This forces him to trade more aggressively right away, which leads to stronger revelation of private information in the first period of the model. Similarly, if the next boat is delayed, the insider will have two periods to trade and this will constrain his trading behavior in the first period, leading to less information revelation.

I use information about the sailing schedule and historical weather data from an observatory close to Amsterdam to approximate the insider's expectation about how long the next boat would take to arrive. I show that when the next boat is expected to arrive relatively soon, private information is revealed more quickly. This is fully consistent with the insider behaving strategically.

An advantage about this historical setup is that the departure dates of packetboats were fixed by the sailing schedule. In addition, sailing times were completely determined by weather conditions. The flow of information was therefore independent of private (or public) signals in the market. It is therefore unlikely that the strategic behavior result is somehow endogenous to other factors.

Private information not only mattered in a qualitative but also in a quantitative sense. I estimate the model structurally using GMM. Apart from confirming the previous results, the GMM estimates suggest that around 35% of all price movements in Amsterdam can be explained by private information. Finally, I show that price discovery in Amsterdam had a (conditional) feedback effect

on London. Conditional on its own past price changes, the London market updated its beliefs based on the price change it observed in Amsterdam. The empirical evidence suggests that this feedback effect was also conditional on the time it took for the private signal to "bounce off" from Amsterdam. The longer it took for the private signal to effectively make its way back to London, the less informative the Amsterdam price change was and the smaller the feedback effect. This makes it unlikely that this result is driven by other fundamental information originating in Amsterdam apart from the revelation of private information.

This paper is related to two strands in the existing literature. First of all, this paper is related to a broad empirical literature on the importance of private information for asset price movements. Most empirical work takes the price impact of transactions or order flow imbalance as evidence for the relevance of private information (Easley and O'Hara 1987; Hasbrouck 1991; Madhavan, Richardson and Roomans 1997; and related papers). Recently this interpretation has attracted some criticism (Duarte and Young 2009) and a number of papers have started using different approaches to study the impact of private information (Pasquariella and Vega 2007; Colla and Marin 2010; Tetlock 2010; Kelly and Ljungqvist 2011; Boulatov, Hendershott and Livdan 2011; Cohen, Malloy and Pomorski 2011).

Secondly, this paper is related to the question how fast we can private information to get incorporated into prices. Some contributions argue that this may take quite a while (Kyle 1985; Glosten and Milgrom 1985; Holden and Subrahmanyam 1992), while others point to reasons why this could happen very quickly (Holden and Subrahmanyam 1994; Foster and Viswanathan 1996; Chau and Vayanos 2008; Caldentey and Stacchetti 2010). Because private information is by definition unobservable, there is very little empirical evidence on this point. Notable exceptions are Dahya, Shi and Van Bommel (2010) and Boulatov, Hendershott and Livdan (2011).

Relative to this literature I make the following contributions. First of all I show that private information is slowly absorbed into prices, confirming the predictions from Kyle (1985) and related contributions. Moreover, I provide evidence that insiders took the time until their private signals would be (partially) revealed into consideration and acted in a strategic way.

The rest of the paper is organized as follows. Section 1 discusses the historical background and context of this paper in more detail. I provide further details about the microstructure of the Amsterdam market and I provide anecdotal evidence about the relevance of private information and market participants' limited risk bearing capacity. The theoretical framework is discussed in section 2. Section 3 provides empirical evidence supporting the model's predictions. Section 4 provides a number of extensions. Section 5 concludes.

1 Historical background

In separate work (Koudijs 2011, sea also Neal 1990) I provide a more detailed overview of the market for English stocks in Amsterdam in the 1770s and 1780s. In this section I will summarize this historical background, but I will give ample attention to the microstructure of this market.

1.1 Stock and sample period

The data necessary for this paper's analysis are available for three different English securities, British East India Company (EIC) stock, Bank of England (BoE) stock and a government bond, the 3% Annuities.[3] The empirical analysis in the main text focuses on the EIC. Results for the other two securities, which are overall very similar, are presented in Appendix B. The EIC was a trading company that held large possessions in what is today's India. The company's prospects were to a large extent determined by conditions in India. However, during the second half of the 18$^{\text{th}}$ century political developments in England started to become of key importance. There was a constant discussion inside and outside the British Parliament about the semi-private character of the company and its public function. In addition, the company required regular bailouts from the English government to stay on its feet. As a result, political gyrations had an important impact on the company's share price (Sutherland 1952). The BoE operated to help finance the British government debt. The BoE was set up in 1694 to function as the government's banker. In addition, the BoE also provided large scale credit to the EIC. Finally, it discounted commercial bills, but on a relatively modest scale (Clapham 1944).

The analysis of this paper rests on the assumption that all relevant information about the English securities was generated in England. This is not necessarily true for the entire 18$^{\text{th}}$ century (see Dempster et al. 2000). The period was filled with European continental wars or the threat of a war breaking out, and England was involved in nearly all of them (Neal 1990). I therefore limit the empirical analysis to the sample periods 1771-1777 and 1783-1787. In Koudijs (2011) I show that the evidence strongly suggests that during these two periods most relevant information about the English securities did originate in England. Figure 13 in Appendix B I present the impulse response functions of price changes of EIC stock in Amsterdam responding to London and vice versa. The figure shows that Amsterdam responded strongly to London, with hardly anything going in the other direction. Both periods are characterized by peace on the European continent. The starting point of the first period, September 1771, is determined by data limitations. The period stops in December 1777 as tensions between France and England increased, eventually leading to outright naval war in July 1778. The second sample period starts in September 1783, right after the signing of an official peace treaty between France and England. There had been an

[3] In addition to these three, South Sea Company stock and 4% Annuities were also widely traded in Amsterdam. However, there is no frequent price data from London available for these securities.

armistice between France and England since January 1783 and the official peace treaty meant the return to normality. The second sample period stops in March 1787 when domestic tensions in the Netherlands rose, eventually leading to minor skirmishes in May 1787 and an intervention by the Prussian army in September 1787.

1.2 The flow of information between London and Amsterdam

How exactly did the English news reach Amsterdam? England and the Dutch Republic were connected through a system of sailing ships, at the time referred to as packet boats. The system was organized between Harwich and Hellevoetsluys, a important harbor close to Rotterdam (see figure 1). Since Amsterdam did not have a direct connection with the North Sea (boats had to sail across the isle of Texel), this was the fastest way information from London could reach Amsterdam (Hemmeon 1912; Ten Brink 1969; Hogesteeger 1989; OSA 2599).

[FIGURE 1 ABOUT HERE]

Each packet boat brought in newspapers and other public newsletters with information about the recent developments in London, including the most recent stock prices. In addition, the packet boats brought in private letters. These could be simple letters from London correspondents with political and economic news and updates about stock market conditions[4]. They could also be private letters from London insiders to their agents in Amsterdam; the focus of this paper.

The packet boats were scheduled to leave on fixed days: Wednesday and Saturday. The sailing ships frequently encountered adverse winds and as a result there was considerable variation in the time it took for the packet boats to reach Hellevoetsluys. The median sailing time was 2 days (including the day of departure), but a trip could take considerably longer. As a result there is considerable variation in the time in Amsterdam between the arrival of boats. In the empirical section I make explicit use of this. It took some additional time to transport the news over land, making the total median travelling time between Amsterdam and London 4 days (including the day of departure). This is indicative of how bad roads were during the period. As far as I was able to tell, travelling time over land did not vary though.

The packet boat system was the main source of English information for investors in Amsterdam, including insiders. The Dutch newspapers of the time all relied on the packet boat service to get news from England (*Amsterdamsche Courant*; *Opregte Haerlemsche Courant*; *Rotterdamsche Courant*). During the sample period, all articles in the *Amsterdamsche Courant* with new information from London can be retraced to the arrival of a specific packet boat, except for a number

[4] Wilson (1941, pp. 74-75) gives a number of examples where people with an interest in the English stocks received private correspondence from London. For other examples of such letters see the correspondences the Amsterdam broker Robert Hennebo and the bankers Hope & Co maintained with their agents in London (Van Nierop 1931, passim and SAA 734; 78,79, 115 and 1510) and the estate of the Jewish broker Abraham Uziel Cardozo (SAA 334; 643).

of exceptions I discuss below.

Furthermore, evidence points out that private letters were sent through the packet boat system as well. Even Hope & Co., one of the biggest Dutch banks of the period, with strong connections in London and heavily engaged in insider trading in Amsterdam (see p. 9) seems to have solely relied on the packetboat system to receive its private dispatches from London. Most English letters in the Hope archive mention both the date a letter was written in London and the date it was received and opened in Amsterdam. I found 112 letters that Hope received from London. For 83 out of these 112 letters, I could identify on what day Hope received and opened these letters. Out of these 83 letters, 73 were received on days the mail packet arrived in Amsterdam. Five letters were opened one day late, after the news had arrived in the evening of the previous day. The final five letters were for some reason only opened a number of days later (Hope & Co, SAA 735: 78,79, 115 and 1510)[5].

At times, during periods of particularly bad weather, the English news could arrive in Amsterdam through the harbor of Ostend in today's Belgium, which had a regular packet boat service with Dover in England. During such episodes it was impossible for the packets to sail between Harwich and Hellevoetsluys but other packets seem to have managed to get across to Ostend. With a total of nine times this happened only infrequently during the entire sample period. These episodes were meticulously reported by the Dutch newspapers and I account for them in the empirical analysis.[6]

The packet boats were of course not the only ships that sailed between London and Amsterdam. Each week ships coming from England would dock in the Amsterdam harbor. However in terms of keeping up with current affairs these ships were always behind the packet boats. As said, they had to sail via the isle of Texel which would take a number of additional days. It therefore comes as no surprise that both individuals and the public newspapers had to rely on the packet boat service to get the most recent news from London.

Although the packet boat service seems to have been the most important source of information for Dutch investors, the flow of news through alternative channels can never be completely ruled out. It is possible that investors set up private initiatives to get information from London. For example, market participants may have used carrier pigeons to get information from London. The use of pigeons can be retraced to antiquity. However the historical record suggests that people started to use them intensively after 1800 only (Levi 1977). In Koudijs (2011) I found no evidence for their use in 1770s and 1780s. Specifically, carrier pigeons could only be used in the summer months and I found no differences in price patterns between summer and winter.

A more relevant possibility could be that investors would hire private boats to transmit infor-

[5]Of the total of 112 letters, 99 were dated on mail days and were specifically written right before the next mail packet would leave.

[6]I did not find a single reference to English letters received over Calais. Apparently, from a Dutch perspective, the Ostend connection always beat the Calais one.

mation from London to Amsterdam. For example, there are rumors from the South Sea bubble in 1720 that Dutch investors chartered their own fishing ships to get the most recent information from London (Smith 1919; Jansen 1946).[7] However it seems reasonable to assume that if the official packet boats could not sail because of adverse weather conditions it would have been extremely difficult for other boats to cross the North Sea. Later on in the paper I will use this logic to perform a number of robustness checks on the main results.

1.3 Market microstructure

During the 18th century the stock trade in Amsterdam took place in a decentralized fashion. Around noon there were two official trading hours in front of the Exchange building (Spooner 1983; Hoes 1986). However, trade continued outside these official hours in coffee shops and even in front of Jewish synagogue (many traders were Jewish). Trading seems to have continued into the evening. A central clearing mechanism for the stock trade was missing and most trades took place through the direct matching of buying and selling parties (Van Nierop 1931).

This matching was done by a relative small group of brokerage firms. Smith (1919) argues that in 1764 41 brokerage firms were dominating the market. The correspondence of broker Robert Hennebo published in Van Nierop (1931) indicates that the market was driven by limit orders. Principals would transmit these orders to their brokers, who then tried to execute these orders to the best of their ability.

This has an interesting implication for the prices we observe. The prices that were reported most likely reflected the equilibrium price at which most limit orders could be cleared. The correspondence in Van Nierop (1931) suggests that prices were indeed interpreted this way.

By the second half of the 18th century a significant fraction of trade in the English stocks in Amsterdam was concentrated in the futures market. This has the important implication that it was relatively easy for market participants to go short as well as long[8].

1.4 Private information

There is ample anecdotal evidence that London insiders used the Amsterdam market extensively to benefit from their private information. Insider trading in London and Amsterdam wasn't banned until the 1930's and especially EIC stock featured frequent insider trading. In a letter to one of his clients from January 1731 Amsterdam broker Robert Hennebo mentioned that there had been some active buying of EIC stock on the exchange and that

[7] Jansen could not find any evidence supporting these rumors.

[8] For example, in the beginning of 1772 Alexander Fordyce, a London investor, had built up a considerable short position in EIC stock through the Amsterdam futures market. When prices continued to rise, this created a spectacular bankruptcy. Wilson (1941) and Hope & Co., SAA 735; 1510

> 'if I am not mistaken, these orders came from London, from one of the directors of the EIC, John Bance (. . .), making it likely that the share price will rise some more'.[9]

There is also evidence that EIC directors James Cockburn and George Colebrooke were 'bulling' the Amsterdam market during 1772 (Sutherland 1952, p. 228; SAA Hope, Journal 1772). One of his contemporaries would later describe Colebrooke as he, 'who was in the secret, knowing when to sell for his own advantage' (quoted in Sutherland 1952, p. 234). Such practices were not restricted to directors of the EIC. At times, political developments had a profound impact on the Company's prospects and as a result British politicians would engage in insider trading as well. During the 1760's a group of MP's, amongst whom Lord Shelburne, a later prime-minister, and Lord Verney, member of the Privy Council, speculated in EIC stock on the Amsterdam exchange. The big advantage of trading in Amsterdam was that the risk of reputation loss due to insider trading would be minimized. Profiting from Amsterdam investors was far less of a sin than taking advantage of fellow countrymen (Sutherland 1952, pp. 206-8).

The clearest example of informed trading in Amsterdam originates from the archives of Hope & Co. In the fall of 1772 Hope went into business with Thomas Walpole to speculate on EIC stock. Walpole was a London banker and, as the nephew of former Prime-Minister Robert Walpole, a prominent Member of Parliament (Sutherland 1952, pp. 101 and 109). Walpole was clearly a political insider. On the 22$^{\text{nd}}$ of December 1772 Hope received a letter from Walpole dated the 18$^{\text{th}}$ which was labeled 'private' and read:

> 'A report is made [on the poor state of the EIC] and we shall soon judge of its effect upon the stock. Those who know most think the stock will fall and we are of that opinion. You may therefore resume your sales to such extent as you think proper and with the usual dex[t]erity. (. . .) There appears no risk in selling from 170% to about 166% [prices in % of nominal value]. One wouldn't go lower, for though it is probable the stock will fall to 150%, yet at that price or higher people may begin to speculate for the rise which will undoubtedly take place when any plan shall be fixed for the relief of the company. Whenever therefore the price falls to 154% or thereabouts, we should not only settle our positions but purchase more with a view to the rise as circumstances may make it advisable'.[10]

Walpole's intelligence proved to be accurate. On January 14, 1773 the Directors of the EIC asked for a government loan and concessions to export tea to all British colonies, both of which were granted (Sutherland 1952, pp. 249-251). Most importantly, Walpole's prediction on the price

[9] Hier is gisteravont veel premy voor de reysing gegeven, en vandaag waren hier koopers tot 169. So ik niet mis heb komt die order van London, van een der directeurs, Mr. John Bance, sodat, gelyk ik Ued meermaals gesegt en geschreeven heb, de apparentie grooter voor een reysing dan voor een daling is'. Van Nierop (1931), p. 68.

[10] Private letter from Walpole to Hope, Hope & Co., SAA 735; 115.

trajectory largely came true. The price of EIC stock in Amsterdam fell from 169.5% to 161%[11] on December 30, reaching its lowest point on January 4, 1773 at 157.50%[12]. After that, the price of EIC rose back to 169.5% on January 29, 1773.

Another interesting point is the reference to 'the usual dex[t]erity' Hope had to apply when executing the transactions. Most likely Hope had to be careful not to trade too conspicuously and reveal the information to other market participants. Hope probably did this by going through intermediaries. Hope's bookkeeping indicates that all share transactions on the Amsterstam exchange were handled by the brokerage firm David Pereira and Sons (SAA 734).

Unfortunately it is not possible to exactly reconstruct the profits Hope and Walpole managed to make by trading in Amsterdam. However, there are quarterly profit and loss statements available that indicate that on Februari 15, 1773 Hope credited Walpole £679:7:6 for profits on a short position in EIC stock of £18,500 nominal in the Amsterdam futures market (SAA 734). This short position must have run somewhere between 15 December 1772 and 15 February 1773. Assuming that Hope & Walpole shared the proceeds of this transaction 50/50, the profit from this short position is consistent with a price fall of -7.3 %-point (so for example from 165% to 157.7%).[13]

1.5 Data

The empirical analysis of this paper is based on detailed price data from the Amsterdam and London markets and information about the arrival of packet boats in Hellevoetsluys. Data on British stock prices in Amsterdam were hand collected from the *Amsterdamsche Courant* and where necessary supplemented by the *Opregte Haerlemsche Courant*. Three prices a week are available for Monday, Wednesday and Friday.[14] The Amsterdam market traded English stocks in Pounds Sterling and prices were therefore reported in Pounds (as the percentage of nominal value). The Amsterdam prices the Dutch papers published were supplied at the end of the afternoon by a committee of so-called sworn brokers who were officially responsible for the reporting of these prices (Smith 1919, p. 109; Jonker 1994, p. 147). Price data from London are available on a daily frequency (Monday - Saturday) and are taken from Neal (1990), where necessary supplemented from Rogers (1902).

By the second half of the 18th century, a significant fraction of trade in the English stocks in Amsterdam was concentrated in the futures market (Van Dillen 1931). As a result all available price data for the Amsterdam market refers to futures prices[15]. Prices in London are spot. In order

[11] In the 18th century prices prices were generally reported in % of nominal/face value. To facilitate bookkeeping, even stocks were assigned such a face or nominal value.

[12] In London the EIC stcok price did fall to 154 on January 16th.

[13] Reputable players like Hope could get non-collateralized positions in the futures markets. So this return did not require any capital outlays.

[14] Previous research by Neal (1990) and Dempster et al. (2000) use Amsterdam prices with a frequency of 2 observations a month.

[15] A future contract could have 4 possible expiration dates: February 15, May 15, August 15, or November 15.

to facilitate comparison between London and Amsterdam prices, I converted Amsterdam future prices into spot prices (for details see Koudijs 2011).

The arrival dates of boats in Hellevoetsluys were hand collected from the *Rotterdamsche Courant*. The newspaper reports on what day a specific boat arrived and whether it arrived before or after 12 p.m. This data can be used to determine when news from England must have arrived in Amsterdam. It took approximately 16 hours for news from Hellevoetsluys to be transported to Amsterdam (Stitt Dibden 1965, p. 9). This generally means that the information brought in on a certain day was only available to Amsterdam investors during the next day.[16] The *Rotterdamsche Courant* not only mentions the day a specific boat arrived but also the date of the news it carried. This information can be used to reconstruct what London price information was available to Amsterdam investors at certain points in time.

Finally I use data on weather conditions from the observatory of Zwanenburg, a town close to Amsterdam (10 kms from the city centre). This data provides three observations a day on the wind direction and other weather variables. This data comes from the *KNMI*.

2 Model

The model features the trade of a single risky asset in two different markets, London (L) and Amsterdam (A). I fully abstract from public information (in the empirical setting it will be simple to reintroduce this) and focus on private signals. The full model consists of a infinite number of episodes, indexed with k. Each individual episode k is represented in figure 2. At the beginning of episode k nature determines the true value of the asset v_k, where v_k is a random walk, i.e. $v_k = v_{k-1} + \epsilon_k$ with $\epsilon_k \sim N\left(0; \ {}^2_\varepsilon\right)$. ϵ_k is not known to the wider public but is privately observed by a single agent, the London insider, at the beginning of the episode. At the end of the episode, ϵ_k is publicly revealed in London and the next episode $k + 1$ begins.

[FIGURE 2 ABOUT HERE]

The model is focussed on developments in Amsterdam. I assume that right after the moment nature decides on ϵ_k, before any trade takes place in London, the London insider sends this signal to a trusted agent in Amsterdam. At the same time the revelation of ϵ_{k-1} is also transmitted to Amsterdam. Likewise, when ϵ_k is revealed and a new signal ϵ_{k+1} is generated, this information is also sent to Amsterdam immediately. Depending on the weather conditions, this news can take one or two periods to arrive in Amsterdam, indexed as $t = 1$ and $t = 2$. The probability of the news arriving right after $t = 1$ is $1 - \ {}_k$. The probability of it arriving after $t = 2$ is $\ {}_k$. If news

Prices reported were for the future contract ending at the nearest date.

[16] There are some exceptions, if a boat arrived in Hellevoetsluys very early in the morning, it sometimes happened that the information from London was already available in Amsterdam on the same day. I use the publication dates of English news in the *Amsterdamsche Courant* and *Rotterdamsche Courant* to identify these cases.

travels fast, there is only one period to trade on private signal ε_k, whereas if news travels slowly there are two periods.[17] Period $t = 1$ of the model corresponds to periods in Amsterdam right after the arrival of a boat. Period $t = 2$ of the model corresponds to subsequent non-news periods. Note that I assume that boat k fully reveals the private signal.

The price that results after trade in $t = 1, 2$ is given by $p_{k,t}$. Note that in general $p_{k,1} \neq v_{k-1}$, as $p_{k,1}$ will already be affected by private signal ε_k (see table 1). From now27(;t) ee alrus330(1)-1scripTJ/F7210.

Proposition 1 *A unique linear equilibrium exists and has the following form:*

$$\begin{aligned} \boldsymbol{x}_1 &= {}_1\," && (1)\\ \boldsymbol{x}_2 &= {}_2\,[" - (\boldsymbol{p}_1 - \boldsymbol{v}_0)] && (2)\\ \boldsymbol{p}_1 &= \boldsymbol{v}_0 + {}_1\,(\boldsymbol{x}_1 + \boldsymbol{u}_1) && (3)\\ \boldsymbol{p}_2 &= \boldsymbol{p}_1 + {}_2\,(\boldsymbol{x}_2 + \boldsymbol{u}_2) && (4) \end{aligned}$$

with

$$\begin{aligned} {}_1 &= \frac{1}{2\,{}_1}\,\frac{{}_2 - \frac{1}{2}\,{}_1}{{}_2 - \frac{1}{4}\,{}_1} && (5)\\ {}_2 &= \frac{1}{2\,{}_2} = \sqrt{\frac{{}^2_{u_2}}{(1 - {}_1\,{}_1)\,{}^2_{\varepsilon}}} && (6)\\ {}_1 &= \frac{{}_1\,{}^2_{\varepsilon}}{{}^2_1\,{}^2_{\varepsilon} + {}^2_{u_1}} && (7)\\ {}_2 &= \frac{{}_2\,(1 - {}_1\,{}_1)\,{}^2_{\varepsilon}}{{}^2_2\,(1 - {}_1\,{}_1)\,{}^2_{\varepsilon} + {}^2_{u_2}} = \sqrt{\frac{(1 - {}_1\,{}_1)\,{}^2_{\varepsilon}}{4\,{}^2_{u_2}}} && (8) \end{aligned}$$

Proof. see appendix A. ■

This equilibrium is very similar to the one in Kyle (1985). The first key result is summarized by the following two corollaries (compare Chowdry and Nanda 1991).

Corollary 2 $\boldsymbol{cov}(\boldsymbol{p}_1 - \boldsymbol{v}_0; ") > 0$

Proof. see appendix A. ■

Corollary 3 $\boldsymbol{cov}(\boldsymbol{p}_2 - \boldsymbol{p}_1; ") > 0$

Proof. see appendix A. ■

These corollaries state that price changes in Amsterdam in both periods $\boldsymbol{t} = 1$ and $\boldsymbol{t} = 2$ should be correlated with the private signal $\boldsymbol{"}$. The monopolistic behavior of the insider leads to a slow revelation of the private signal. The insider takes his own price impact (Kyle's) into account and this constrains his behavior. In other words, the equilibrium of $\boldsymbol{t} = 1$ is not fully revealing and asymmetric information is persistent. As a result there is additional price discovery going on in $\boldsymbol{t} = 2$.

In this specific historical context this means that price changes in London after the departure of a boat (to be clear, these are price changes not yet communicated to Amsterdam) should be positively correlated with returns in Amsterdam after the arrival of that boat. In the model this

either happens because ε_k is publicly revealed in London by the time the next boat k departs for England or by a process of price discovery of the private signal in London.[18] This co-movement should both be observable for Amsterdam news returns (period $t = 1$ of the model) and Amsterdam non-news returns (period $t = 2$ of the model).

In line with Kyle's results, there is no auto-correlation between price changes in Amsterdam in $t = 1$ and $t = 2$. This may seem counter-intuitive. The intuition comes from market efficiency. If there is positive auto-correlation, the price change in $t = 1$ would not fully incorporate all relevant information. The market maker would be able to predict the price change in $t = 2$ based on the price change in $t = 1$. This would be inconsistent with risk neutral and competitive behavior.

The second key result is summarized by the following corollary

Corollary 4 $\frac{\delta cov(p_1 - v_0, \varepsilon)}{\delta \pi} < 0$

Proof. see appendix A. ■

This corollary states that the co-movement between the price change in $t = 1$ and ε should be decreasing in . The intuition for this result follows from the trade-off the informed agent faces between profits from trading in $t = 1$ and $t = 2$. If the insider only had one period available to trade on his private signal, he would balance the price impact of his trade (the more he trades, the bigger the price impact) with the volume of trades he can get executed. One specific price impact-volume combination maximizes profits. If he gets a second period to trade, this optimal price impact-volume combination would change. The insider would now prefer to have less price impact in period $t = 1$ so that he reveals less of his private information and he can obtain more profits in period $t = 2$. In the model period $t = 2$ only occurs with probability . If is high the insider would like to trade less aggressively in $t = 1$ to save informational advantage for $t = 2$. However if is small, the optimal strategy would be to trade more aggressively in $t = 1$. As a result, co-movement with ε (and thus with London) will be stronger.

3 Empirical evidence

3.1 Introduction

In this section I present empirical evidence for the model's predictions. First of all, the model predicts that returns in Amsterdam should foreshadow developments in London, as the same underlying private signal gets incorporated into prices in both cities. This should be true for both $t = 1$, the news period right after the arrival of a boat, and $t = 2$, the subsequent non-news period.

[18] Even in the latter case I can leave this unmodeled because I assume that ε_k will be publicly revealed by the time the next boat departs for Amsterdam. As a result the price discovery process in London has no impact on informed profits in Amsterdam.

Secondly, the model predicts that this co-movement with London in period $\boldsymbol{t} = 1$ should be stronger if the next boat is expected to arrive relatively quickly.

To guide the empirical discussion, let me lay out a simple framework in figure 6. This figure applies the setup of the model from figure 2 to the empirical setting. There are two time-axes in the diagram, one for London and one for Amsterdam.

[FIGURE 6 ABOUT HERE]

As discussed, the time it took for boats to get across the North Sea depended on the weather conditions. There are two boat crossings of relevance here. The first crossing transmits the private signal $''_k$ (and partially or fully reveals the previous private signal $''_{k-1}$). The second crossing partially or fully reveals private signal $''_k$ (and brings in new private signal $''_{k+1}$). To simplify matters I fix the sailing time of the first crossing. I allow the time until the next boat arrives to vary. With probability $1 -$ this next boat will arrive relatively soon, with probability it will arrive relatively late.

I define Amsterdam and London returns as follows. $\boldsymbol{R}_k^L$ is the return in London that takes place after the departure of the first boat. I loosely refer to this as the London post-departure return. To be clear, information about this return is not publicly transmitted by the first boat. I calculate this return over different periods (2, 3, 4, and 5 days). I use the 3 day return as benchmark.

$\boldsymbol{R}_{k,t=1}^A$ is the return in Amsterdam that takes place immediately after the arrival of this boat. I refer to this as the Amsterdam news return. In terms of the model, this is the return that takes place over period $\boldsymbol{t} = 1$. Since I only have 3 prices a week available for Amsterdam (Monday, Wednesday and Friday), this return is calculated over 2 or 3 day periods, depending on the day of the week. Finally, $\boldsymbol{R}_{k,t=2}^A$, if it occurs, is the return in Amsterdam that takes place over the subsequent period without news, the so-called Amsterdam no-news return. This corresponds to period $\boldsymbol{t} = 2$ of the model.

Returns are calculated as log returns in percentages. The returns that are calculated for Friday to Monday (3 instead of 2 days) are not scaled down. The reason for not doing so that is that trading was restricted in the weekend. Jewish traders woudl not trade on the Sabbat, while Christians would not on Sundays (Spooner 1983). As an approximation, I therefore treat the 3 day weekend return the same as the 2 day week returns.

So far I have completely abstracted from public information. Let me reintroduce public news shocks here. It is clear that the first and the second boat in figure 6 do not only carry information pertaining to the private signals, they also carry information about public news shocks. These public information shocks will drive some of the return volatility in both Amsterdam and London. However, they should not affect the co-movement patterns of interest here. They could add additional noise to the estimates though, so where necesarry returns are corrected for these public news shocks (see below for details).

3.2 Benchmark results

How well do the corollaries established by the model hold up? Let's first look at the impact of insider trading and the resulting co-movement of London and Amsterdam returns. Corollaries 2 and 3 state that returns in Amsterdam, both right after the arrival of news from London and during subsequent periods without any new information, should predict developments in London that will take place right after the departure of the news to Amsterdam. Or in terms of figure 6 (see page 41) both $\boldsymbol{R}^A_{k,t=1}$ (the Amsterdam news return) and $\boldsymbol{R}^A_{k,t=2}$ (the Amsterdam no-news return) should be correlated with $\boldsymbol{R}^L_k$ (the London post-departure return).

Figures 7 and figures 8 graphically present these correlations for EIC stock. Figure 7 shows that $\boldsymbol{R}^A_{k,t=1}$ is positively correlated with London return $\boldsymbol{R}^L_k$ (calculated over the three days after the boat departure). Likewise, figure 8 shows that $\boldsymbol{R}^A_{k,t=2}$ is also correlated with $\boldsymbol{R}^L_k$. This implies that price changes in Amsterdam predict the contemporaneous (but as of yet unreported) return in London – news of which will only arrive in the future. Note that Amsterdam and London returns are corrected for public news shocks. Also note that these positive correlations cannot be the result of the generation of relevant news in Amsterdam. The time lags involved in getting news from Amsterdam to London make it nearly impossible that London returns $\boldsymbol{R}^L_k$ are influenced by developments in Amsterdam during episode $\boldsymbol{k}$.

[TABLE 3 ABOUT HERE]

In table 3 I estimate these correlations in a formal econometric framework, again for EIC stock (see tables 13 and 14 for similar tables for BoE stock and the 3% Annuities). I correlate $\boldsymbol{R}^L_k$ (again calculated over the three days after the departure of the boat) with $\boldsymbol{R}^A_{k,t=1}$ and $\boldsymbol{R}^A_{k,t=2}$. I condition on $\boldsymbol{P}^L_{k-1} - \boldsymbol{P}^A_{k-1}$, the difference between the London departure price and the Amsterdam pre-arrival price. This measures the public news shock arriving in Amsterdam with the packetboat. Inclusion of this variable should both tighten the co-movement estimates and correct for any momentum that might be present in the return series.

Results in table 3 suggest that the co-movement with London post-departure returns is especially strong for returns taking place right after the arrival of a boat from England. However, the difference between the two coefficients is not significant at standard confidence levels. In addition, the reverse seems to be true for BoE stock and the 3% Annuities (see tables 13 and 14), although differences here are not statistically significant either. It can be shown that the model has no strict predictions about the difference in co-movement between periods $\boldsymbol{t} = 1$ and $\boldsymbol{t} = 2$. It all depend on the variance of the noise trading shocks in the two periods.

I perform two simple robustness tests. First of all, I calculate the London post-departure return $\boldsymbol{R}^L_k$ for different periods (2, 4 and 5 days after a boat departure). Results for EIC stock are presented in table 11 in Appendix B. Varying the period over which to calculate $\boldsymbol{R}^L_k$ does not matter substantially for the estimates. In addition, I excluded the first day of the London post-departure

return to make sure that the positive co-movement between $\boldsymbol{R}_k^L$ and $\boldsymbol{R}_{k,t=1}^A$ is not just driven by the fact that the boat carried slightly more recent public information than indicated in my data. Table 12 in Appendix indicates that this is not the case.

3.3 Expectation next boat

How well does corollary 4 hold up? Remember that corollary 4 stated that the co-movement with London in period $\boldsymbol{t} = 1$ should be stronger if the next boat is expected to arrive relatively quickly. This is the most crucial prediction of the model. Evidence in favor of this corollary would support the view that insiders act strategically.

Before going into the empirical tests let me first discuss how I estimate the crucial parameter $_k$. This $_k$ is the probability that a second period of trade ($\boldsymbol{t} = 2$) occurs within episode $\boldsymbol{k}$ (see figure 6). I allow $_k$ to differ over time. To generate an empirical equivalent of $_k$ I estimate how many days, in expectation, there will be between the arrival of two boats. Effectively, this is the length of episode $\boldsymbol{k}$ in Amsterdam. The longer this period, the more trading opportunities the informed agent will have. I calculate this expectation in two ways.

To begin with, I simply add the median travelling time to the departure date of the next news dispatch that is expected. For example, if the next expected news dispatch is scheduled to leave London on March 24, 1773, I take March 27, 1773 as the next day news from London is expected to arrive in Amsterdam (median travelling time is 4 days, with the day of departure as day 1).

Once I know the date that the next news shipment is expected to arrive, I calculate how many days this is away from the arrival of the previous news shipment. In the previous example this arrived on March 24, so the expected number of days between the arrival of the two news shipments is 3 in this case. In other words, right after the arrival of the last news shipment insiders would expect the next news from England to arrive in 3 days. Two boats a week were set to sail between England and Holland, so the unconditional expectation of this number 3.5. If the expectation is less than 3.5, as in this specific example. I count this observation as having a low $_k$. In other words, insiders will expect to have relatively little trading opportunities. If the next news shipment is more than 3.5 days away I count this as a high $_k$.

As an alternative, I model the expected travelling time in a duration framework. Depending on weather conditions and the time of the year I allow the expected travelling time to differ. I then add this conditionally expected travelling time to the date of departure. I then follow the procedure above to come up with an alternative set of high and low $_k$'s.

Specifically I estimate a duration model with a flexible Gamma distribution explaining the expected arrival of the next news shipment. I condition on multiple factors. The first thing to note is that sailing boats had trouble crossing the North Sea from England to Holland when the wind was blowing from an eastern direction. When the sailing direction gets too close to the wind

direction, sails cannot be adjusted anymore and a sailing boat would enter the so-called no-go zone; see figure 3. If the boat's direction lies within this no-go zone, it will have to tack to keep moving. In other words, it will constantly have to change direction, leading to longer sailing times.[19] I have data available on wind directions from the observatory of Zwanenburg (close to Amsterdam) for 2 or 3 observations a day. For every observation I determine whether a sailing boat sailing east would face a no-go zone. For modern sailing boats this no-go zone lies around 30 to 50 degrees from the wind-direction. I assume that the 18$^{\text{th}}$ century packet boats had a no-go zone of 55 degrees around the prevailing wind direction. For every day I calculate what fraction of available observations featured a no-go zone, $\{0; \frac{1}{3}; \frac{1}{2}; \frac{2}{3}; 1\}$. I include this information as dummy variables which I include for lags $t-1$ and $t-2$. Other variables I condition on are a dummy for temperatures below 3 degrees Celcius to capture the possible presence of ice (also included for $t-1$ and $t-2$).[20] In addition, I include month dummies to condition on the season. In unreported results I find that the volatility of stock prices in London does not significantly differ accross months. This suggests that these month dummies should not be related to a different underlying price process.

[FIGURE 3 ABOUT HERE]

The correlation between the actual number of days until the next boat arrival and the estimated expectation is about 0.36 for the simple model and 0.52 for the extended model. Figures 4 and 5 present these results graphically. Both figures plot Kaplan-Meier estimates of the fraction of news shipments that have not yet arrived t days after the arrival of the previous news shipment. I differentiate between high and low $_k$ as explained above. If the estimation was perfect, we would expect all observations with a high $_k$ to be still "at risk" at 3.5 days. All observations with a low $_k$ should have "failed" by 3.5 days. Obviously this is not the case. However, both the simple and the extended procedures come up with reasonable estimates of $_k$, where the extended model does slightly better.

[FIGURES 4 AND 5 ABOUT HERE]

Now that we have defined $_k$, we can move to actually testing corollary 4. In table 4 I estimate whether Amsterdam post-arrival news returns ($R^A_{k,t=1}$) on EIC stock co-move more strongly with London post departure returns R^L_k if the next news shipment is expected to arrive within less than 3.5 days, i.e. when $_k$ is low. I test this through interaction effects and I use both the simple definition of $_k$ and the one derived from the extended duration model. In both cases the interaction effect is positive and statistically significant, either at the 5 or 10% level. Economically it is also significant, as co-movement almost doubles if the next boat is expected to arrive within 3.5 days. (Figures 16 to 19 in appendix B present these estimates graphically.) Tables 16 and 17

[19] The packet boats were rigged as two masted schooners (Stitt Dibden 1965, p. 11). If schooners have to tack, they can only use the sails on the front mast.

[20] Hellevoetsluys was situated in the mouth of several rivers. Ice floating downstream could make it hard to reach the harbor.

present these estimates for BoE stock and the 3% Annuities. Results are virtually the same. Table 4 calculates London returns over 3 days after the departure of a boat. In table 15 in Appendix B I redo these estimates, using different periods over which to calculate the London return (2, 4, 5 days). Again, in an economic sense the results hardly change, although the interaction effects are only statistically significant for the 5 day London returns. All in all, these estimates are supportive of the model's prediction that co-movement should be stronger if the insider expects to have less time to benefit from his private signal.

[TABLE 4 ABOUT HERE]

3.4 Robustness checks

Some of the empirical findings can be driven by other factors than private information. In this subsection I will discuss three alternative explanations, the slipping through of public news through alternative channels, correlated liquidity shocks and slow processing of public information.

3.4.1 Slipping through of news

The first finding regards the positive correlation between London and Amsterdam returns in the absence of news (Amsterdam no-news returns) that was presented in figure 8 and table 3. In the previous section I have already shown that this relation is unlikely to be driven by momentum in the return series. An alternative explanation could be the fact that some news may simply have arrived in Amsterdam outside of the official packet boat system.[21] I have argued before that it is unlikely that alternative news channels played an important role, but it is not impossible. To test for this possibility I look at the degree of co-movement during periods where the weather was particularly bad so that the packet boats were seriously delayed or could not sail out at all. The idea is that under these circumstances other boats must have found it difficult as well to make their way across the North Sea. If the slipping through of news was the main driver behind the positive correlation between Amsterdam and London returns in the absence of news, this correlation should be close to zero during periods of bad weather.

I construct bad and good weather samples in three different ways. First of all I distinguish between no-news periods that were purely the result of the sailing schedule and those that were the result of bad weather. I combine the sailing schedule with a median travelling time of 4 days I then check for every no-news observation whether the sailing schedule predicted this to be a non-news observation or not. If not, I include this observation in the bad weather sample A.

Bad weather sample B is based on wind directions. Remember that returns in Amsterdam

[21] Note that this would not disqualify the presence of private information. The co-movement between R_k^L and $R_{k,t=1}^A$ would still point into the direction of insider trading. In addition, the interaction effect with my estimates of high and low π would still point in the direction of strategic behavior of the insider.

are measured over 2 or 3 day periods. For every return I determine what the average daily wind direction was during this 2 or 3 day period. If the average wind condition was east (from 0 to 180 degrees) on every single day, I include the observation in bad weather sample B. I do something similar for bad weather sample C. Here I look at the no-go zones (see figure 3). For every day of a 2 or 3 day period, I check how many wind observations within that day (out of a total of 2 or 3) featured a no-go zone. If for every day at least 2 of these daily wind observations feature a no-go zone, I include this return in bad weather sample C.

[FIGURES 9 TO 11 ABOUT HERE]

[TABLE ABOUT HERE]

Figures 9 to 11 plot EIC returns $\boldsymbol{R}^{A}_{k,t=1}$ against $\boldsymbol{R}^{L}_{k}$ for the three restricted bad weather samples. The figures show that during periods when its was difficult to get news across the North Sea, there was still a positive correlation between returns in London and Amsterdam. Table 5 presents the corresponding regression results. The impact of bad weather observations is analyzed by ways of an interaction term between $\boldsymbol{R}^{L}_{k}$ and a bad weather dummy. The table shows that the degree of co-movement was equally strong or even slightly stronger (and not weaker) in periods of bad weather. Tables 19 and 20 in Appendix B present the same estimates for BoE stock and the 3% Annuities and results are almost identical. In table 18 in Appendix B I redo these estimations for EIC stock, calculating London returns over 2, 4 or 5 days after the departure of a boat, focusing on bad weather definition A. Again, results remain virtually the same.

To summarize, these results indicate that even under adverse weather conditions there is still co-movement between London and Amsterdam. This suggest that the co-movement between Amsterdam and London returns is not simply driven by news slipping through the official packet boat system. Moreover, I actually find no evidence for stronger co-movement during periods of good weather. This suggests that market participants did not structurally use good weather episodes to hire a private boat to transmit information outside of the official packet boat system. There may have been some episodes where did this happen, but this does not seem to affect overall patterns. At first sight this is surprising. One would assume that market participants would try to seize these arbitrage opportunities. One possible explanation could be that the costs of equipping a private boat were too high compared to the informed profits that could be made. Unfortunately I have too little information available about the market's liquidity to say something about this trade-off.

3.4.2 Permanent price changes?

One worry might be that price changes in Amsterdam that can be explained by the co-movement with prices in London have a transitory nature. In that case, the co-movement would not reflect the revelation of private information about the fundamental for which the price movement should be permanent. Rather it is more likely that the co-movement between Amsterdam and London reflects

the price impact of correlated liquidity shocks (or other type of transitory "sentiment" shocks) for which the price impact is expected to be temporary.

To test this, I run a series of predictive regression where I correlate the Amsterdam return over different future time horizons after the conclusion of episode $\boldsymbol{k}$ with the London post-departure returns of this episode $\boldsymbol{k}$. If the co-movement between Amsterdam and London is driven by transitory liquidity shocks, then London post-departure returns should be able to predict future Amsterdam returns. For example, if the London post departure return was negative then we would expect Amsterdam prices that initially followed this negative path, to rise over time. In the same manner we would predict positive London post-departure returns to be followed by a fall in Amsterdam prices.

I present these estimates in table 6 in Appendix B. I correlate Amsterdam returns over 2/3 and 4/5 day and 1, 2, 3 and 4 week periods after the conclusion of episode $\boldsymbol{k}$ with the London post-departure return of this same episode $\boldsymbol{k}$. The estimates show no significant predictive power. If anything, these estimates indicate the presence of momentum (for which I explicitly corrected in the previous regressions) rather than reversals. In other words, the evidence suggests that the co-movement between Amsterdam and London reflects permanent price changes rather than transitory shocks.

3.4.3 Slow processing of news

It is possible that some of the co-movement patterns that I presented are driven by slow processing of news (see Hong and Stein 2002; Duffie 2010 and references therein). If investors in Amsterdam and London simply need time to process complicated public information shocks, prices in both markets would move in the same direction, even when no information is flowing between the two markets. The first thing to note is that this explanation would not explain why Amsterdam post-arrival news returns would co-move more strongly if the next boat is expected to arrive relatively quickly.

Nevertheless this would provide an alternative explanation for the general co-movement patterns I documented. One way to test for this hypothesis is to check whether the co-movement between London post-departure returns and Amsterdam post-arrival returns is weaker when there are no/small public information shocks. Specifically if the return in London that takes place **before** the departure of a boat is zero (or close to zero) it would be hard to argue that there has been a large public information shock. Under this alternative hypothesis we would therefore not expect any correlation between $\boldsymbol{R}_k^L$ and $\boldsymbol{R}_{k,t=1,2}^A$.

[TABLE 7 ABOUT HERE]

In table 7 I test this econometrically for EIC stock returns. I interact $\boldsymbol{R}_k^L$ with either zero public news returns (note that public news returns are given by $\boldsymbol{R}_{k-1}^L$) or public news returns in

the second or third quartile of the return distributions. The coefficient on the interaction effect is very close to zero (even positive in most specifications) and insignificant. Tables 21 and 22 in present these returns for BoE stock and the 3% Annuities. Results are almost identical. Overall, this suggests that it is unlikely that the co-movement between London post-departure and Amsterdam post-arrival returns are driven by slow processing of news.

4 Extensions

The previous sections are consistent with an important qualitative role for private information. How much did private information matter quantitatively? I approach this question in two different ways. First of all I estimate the model structurally using GMM. This exercise allows me to determine what fraction of overall return volatility in Amsterdam is related to the revelation of private information. In addition, I can determine how important private information was compared to public information. Secondly, I test whether the revelation of private information in Amsterdam had any (conditional) feedback effects in London. This also provides an additional "out of sample" test on the validity of the private information explanation pursued in this paper.

4.1 Estimating the model with GMM

Without imposing more structure on the data, the regression coefficients of the previous section have relatively little to say about much private information mattered quantitatively compared to public information shocks. To provide some insight into this issue, I use GMM to match the model's predictions to the data. This way I can uncover the structural parameters of the model. In addition I can use overidentifying moment conditions to test the overall fit of the model.

4.1.1 Simple analyis

As a first step I refine the setup of the model of section 3 to include a public information shock $\;_k$.

$$\boldsymbol{v}_k = \boldsymbol{v}_{k-1} + "_k + \;_k$$

Table 2 summarizes what information investors in Amsterdam have available at certain moments in time.

Table 2: Setup model - public info

		Episode $\boldsymbol{k}$ in Amsterdam	
		$\boldsymbol{t} = 1$	$\boldsymbol{t} = 2$
$\boldsymbol{E}[\boldsymbol{v}_k]$	before observing $\boldsymbol{y}_{k,t}$	$\boldsymbol{v}_{k-1} + \;_k$	$\boldsymbol{p}_{k,1}$
	after observing $\boldsymbol{y}_{k,t}$	$\boldsymbol{p}_{k,1}$	$\boldsymbol{p}_{k,2}$

In this setting prices in Amsterdam will immediately change after the arrival of a boat, before any trade takes place. This price change will reflect two pieces of information that are now public in Amsterdam: first of all the public information shock $_k$, secondly the revelation of the residual of $''_{k-1}$ that wasn't revealed before. To build intuition, I start the analysis by combining these two pieces of information into one public news shock $\tilde{}_k$. In the second-next I split $\tilde{}_k$ up into its seperate components. As an other simplification I assume that is a constant. In the next sub-section I allow for some variation in over time.

In estimating the model I will only use covariances between the two markets and no variances or auto-covariances. The reason for doing so, is that it is likely that apart from information shocks, other 'noise' shocks (for example shocks to trading demand, Grossman and Miller 1988) also drive price changes. If that is the case, variances and auto-covariances will reflect these non-information shocks. I leave these unmodelled in the GMM analysis. With the GMM estimates in hand, I can then determine how well information based shocks alone can explain overall volatility and how important these other shocks must be.

Corollary 5 *Assume that all public information shocks are summarized by* $\tilde{}_k$. *In addition assume that parameter*

The variance of price changes driven by public information information is given by

$$\boldsymbol{var}\left(\boldsymbol{R}^{A}_{k,t=1}|\text{"}_{k}\right) = \;{}^{2}_{\tilde{\eta}}$$

Proof. see Appendix A. ■

Estimates are provided in column 1 of table 8. All estimates in table refer 8 to EIC stock only. The final rows show what percentage of the actual return variance can be attributed to public information, private information and noise shocks. The model has a surprisingly good fit for Amsterdam news returns on EIC stock. Around 91% of overall return variance can be attributed to news, 34% to private information and 57% to public information. The explanatory power of the estimated model is a lot less for Amsterdam non-news returns. $\boldsymbol{var}\left(\boldsymbol{R}^{A}_{k,t=1}|\tilde{}_{k}\boldsymbol{;}\,\boldsymbol{noise}\right)$ and $\boldsymbol{var}\left(\boldsymbol{R}^{A}_{k,t=2}|\boldsymbol{noise}\right)$ lie very close to each other. Nevertheless, 65% of non-news returns cannot be explained by the model and seems to be related no non-informational noise. Unreported results also indicate that Amsterdam no-news returns have a larger tendency to revert themselves in next trading periods than news returns, even after they are corrected for public and private news shocks. These two findings suggest that either there is more noise trading in no-news periods or that the (temporary) price impact of noise trades is significantly higher in no-news periods. Transaction data in Koudijs (2011) suggest that the market was not thinner on days without news. This would suggest that the relative importance of noise trading must have been higher on no-news days.

4.1.2 Time varying probability of boat arrivals

The first extension is to allow to vary over time. In the data I approximate with the expected number of days until the next boat arrival. In principal every different realization of (different number of expected days until the arrival of a boat) will lead to different moment conditions (10) and (10). To keep matters simple I allow to have a high or a low value. To determine which observation has a high or low I follow the same procedure as in section 3. If the number of expected days until the next boat arrival is below (above) the unconditional mean of 3.5 days, I count this as a low (high) observation.

Corollary 7 *If can either take a high or a low value, the moment conditions implied by the model are given by:*

$$\begin{aligned}
\boldsymbol{cov}\left(\boldsymbol{R}^{A}_{k,t=1}\boldsymbol{;}\,\boldsymbol{p}^{L}_{k-1}-\boldsymbol{p}^{A}_{k-1}\right) &= \;{}^{2}_{\tilde{\eta}} && (14)\\
\boldsymbol{cov}\left(\boldsymbol{R}^{A}_{k,t=1}\boldsymbol{;}\,\boldsymbol{R}^{L}_{k}|\quad\boldsymbol{high}\right) &= \;{}^{h}_{1}\;{}^{h}_{1}\;{}^{2}_{\varepsilon} && (15)\\
\boldsymbol{cov}\left(\boldsymbol{R}^{A}_{k,t=1}\boldsymbol{;}\,\boldsymbol{R}^{L}_{k}|\quad\boldsymbol{low}\right) &= \;{}^{l}_{1}\;{}^{l}_{1}\;{}^{2}_{\varepsilon} && (16)\\
\boldsymbol{cov}\left(\boldsymbol{R}^{A}_{k,t=2}\boldsymbol{;}\,\boldsymbol{R}^{L}_{k}|\quad\boldsymbol{high}\right) &= \frac{1}{2}\left(1-\;{}^{h}_{1}\;{}^{h}_{1}\right)\;{}^{2}_{\varepsilon} && (17)\\
\boldsymbol{cov}\left(\boldsymbol{R}^{A}_{k,t=2}\boldsymbol{;}\,\boldsymbol{R}^{L}_{k}|\quad\boldsymbol{low}\right) &= \frac{1}{2}\left(1-\;{}^{l}_{1}\;{}^{l}_{1}\right)\;{}^{2}_{\varepsilon} && (18)
\end{aligned}$$

Estimates are presented in the second column of table 8. In line with the model's predictions and the empirical analysis in section $\ _1^h \ _1^h < \ _1^l \ _1^l$. The difference between the two parameters is statistically significant with a p-value of 0.058. This system of moment conditions is overidentified. Essentially, $\ _\varepsilon^2$ could be estimated twice. This allows me to test the validity of the model with Hansen's J-test. This test fails to reject the validity of the model with a p-value close to 1. To summarize, the GMM analysis not only lends support to an important role of private information in the Amsterdam market, the evidence is also consistent with the strategic use of private information by the insider.

4.1.3 Differentiating between public news shocks and private information revelation

Public news shocks in Amsterdam contain two seperate pieces of information. First of all it reflects fully public innovation $\ _k$, secondly it contains information about private signal $"_{k-1}$ that is revealed in London but is not yet incorporated in in the Amsterdam price. The GMM framework can be used to discriminate between these two sources of information. The identifying assumption comes from whether the previous episode $k-1$ featured a non-news trading period in Amsterdam or not (period $k-1; t=2$ did or did not occur). If this no-news trading period did occur, more private information would have been revealed to the Amsterdam market. As a result, the public news shock $\ _k$ should, in relative terms, dominate overall news from London $\tilde{\ }_k$. On the other hand, if this no-news period did not occur, less private information would have been revealed in Amsterdam and more of the news shock would be driven by London news about $"_{k-1}$.

Corollary 8 *If we take into account whether episode $k-1$ featured a no-news trading period ($t=2$) or not, the moment conditions implied by the model, assuming a constant , are given by*

$$\begin{aligned}
cov\left(R^A_{k,t=1}; p^L_{k-1} - p^A_{k-1} | no\ k-1; t=2\right) &= \ _\eta^2 + (1 - \ _1 \ _1) \ _\varepsilon^2 && (19)\\
cov\left(R^A_{k,t=1}; p^L_{k-1} - p^A_{k-1} | \ k-1; t=2\right) &= \ _\eta^2 + \frac{1}{2}(1 - \ _1 \ _1) \ _\varepsilon^2 && (20)\\
cov\left(R^A_{k,t=1}; R^L_k\right) &= \ _1 \ _1 \ _\varepsilon^2 && (21)\\
cov\left(R^A_{k,t=2}; R^L_k\right) &= \frac{1}{2}(1 - \ _1 \ _1) \ _\varepsilon^2 && (22)
\end{aligned}$$

Proof. see Appendix A. ■

Results are presented in the third column of table 8. The estimate of $\ _1 \ _1$ is very much in line with the simple estimates from the first column. Not surpisingly, the variance $\ _\eta^2$ is significantly smaller than $\ _{\tilde{\eta}}^2$. This suggests that a large fraction of the news Amsterdam investors responded to was in fact the revelation of private information $"$ in London. All in all, results imply that 80% of relevant information generated in London was originally private in nature. This system of moment conditions is again overidentified. Hansen's J-test fails to reject the validity of the model with a

p-value of 0.66. This again indicates the model has a good fit in the data. The fourth column of table 8 combines the two extensions. The estimates are in line with the previous results.

To sum up, the GMM estimates suggest that the model has a good fit with the data. Overall, private information matters significantly for asset returns in Amsterdam. In addition, the analysis supports the prediction that insiders acted strategically on their information and traded more (less) aggressively when they expected the next boat to arrive quickly (slowly).

[Discuss assumption full " revealed and impact on estimates]

4.2 Feedback effects in London

So far the analyis has focused on Amsterdam alone. However, the presence of private information also implies a number of testable predictions for price discovery in London. Specifically, there may be feedback effects of the London private signal through the Amsterdam market. If there is a noisy price discovery process going on in both markets, and noise is not perfectly correlated, then the price changes in both cities together should provide information about the private signal that is superior to individual price signals on their own. In the end, London prices should respond to Amsterdam to reflect this "double" price discovery.

In the theoretical model of section 3 I assume that the private signal " in London was revealed relatively quickly. This is an approximating assumption to facilitate the analysis of the price discovery process in Amsterdam. However in reality it is possible that private information in London was longer lived. If that is true, than, under certain conditions, the revelation of private information in Amsterdam could have facilitated price discovery in London.

Figure 12 illustrates this situation. At London time t^* a boat with private signal " sets sail to Amsterdam. There this information is received at Amsterdam time t. a days later a boat departs again for London, carrying information about the price at time $t+a$. The concrete price signal this boat carries is a function of $p^A_{t+a} - p^L_{t*}$. This information reaches London at time $t^* + l$. Between t^* and $t^* + l$ the London market observed a London signal leading to the price change $p^A_{t^*+l} - p^L_{t^*}:$ At time $t^* + l$ the London market maker updates his beliefs based on these two signals. This will lead to a new London price $p^L_{t^*+l+1}$.

Suppose that the Amsterdam and London signals have the following form

$$
\begin{aligned}
{}^{A} &= " + \\
{}^{L} &= " +
\end{aligned}
$$

where everything is normally distributed. Based on the results from section 4, I assume that $0 < cov\left({}^{A}; {}^{L}\right) < var\left({}^{i}\right)$ for $i = A; L$. This means that the covariance between the two noise components can be positive, as long as they are not perfectly correlated (in which case $cov\left({}^{A}; {}^{L}\right) = var(\ )$). In addition, this means that $cov(\ ;\ )$ can also be negative, as long as it is

stricly bigger than $-\ {}^{2}_{\varepsilon}$. Assuming away any additional innovations in the price process (later on I will return to this assumption), security prices can be written as

$$
\begin{aligned}
p^{L}_{t^*+l} - p^{L}_{t^*} &= {}^{L}\ {}^{L} \\
p^{A}_{t+a} - p^{L}_{t^*} &= {}^{A}\ {}^{A} \\
p^{L}_{t^*+l+1} - p^{L}_{t^*} &= {}^{A|L}\ {}^{A} + {}^{L|A}\ {}^{L}
\end{aligned}
$$

where

$$
{}^{i} = \frac{cov\left(";\ {}^{i}\right)}{var\left(\ {}^{i}\right)} = \frac{{}^{2}_{\varepsilon}}{var\left(\ {}^{i}\right)} \tag{23}
$$

$$
{}^{i|j} = {}^{i} - {}^{j|i}\frac{cov\left(\ {}^{i};\ {}^{j}\right)}{var\left(\ {}^{i}\right)}, \text{ for } i;j = A;L \tag{24}
$$

Again, assuming away any noise, this implies that

$$
\begin{aligned}
{}^{L} &= \frac{p^{L}_{t^*+l} - p^{L}_{t^*}}{{}^{L}} \\
{}^{A} &= \frac{p^{A}_{t+a} - p^{L}_{t^*}}{{}^{A}}
\end{aligned}
$$

and that

$$
\begin{aligned}
p^{L}_{t^*+l+1} - p^{L}_{t^*+l} &= {}^{A|L}\ {}^{A} - \left({}^{L} - {}^{L|A}\right) {}^{L} \\
&= \frac{{}^{A|L}}{{}^{A}}\left(p^{A}_{t+a} - p^{L}_{t^*}\right) - \frac{\left({}^{L} - {}^{L|A}\right)}{{}^{L}}\left(p^{L}_{t^*+l} - p^{L}_{t^*}\right)
\end{aligned} \tag{25}
$$

Under the assumption that $0 < cov\left(\ {}^{A};\ {}^{L}\right) < var\left(\ {}^{i}\right);$equation 25 has three testable predictions.

Prediction 1: *The price change in London* $\left(p^{L}_{t^*+l+1} - p^{L}_{t^*+l}\right)$ *should respond positively to price changes in Amsterdam:* $\frac{\rho^{A|L}}{\rho^{A}} > 0$*. In addition,* $\left(p^{L}_{t^*+l+1} - p^{L}_{t^*+l}\right)$ *should respond negatively to the previous London price change:* $\left({}^{L} - {}^{L|A}\right) > 0$

Proof. see appendix A. ■

The intuition for this results follows from simple bivariate statistics. If the Amsterdam and London signal are both correlated with ", and are not perfectly correlated with each other, then the London market maker can learn from the Amsterdam signal. At the same time, the London market maker will put less weight on the London signal in $t^* + l + 1$ (after the arrival of the Amsterdam boat) than he did in $t^* + l$ (before the arrival of the boat). He does so because, by assumption, price changes in Amsterdam and London are positively correlated and putting more weight on one signal automatically implies putting less weigth on the other. This second part of this result is not trivial. If price changes in Amsterdam would simply reflect some fundamental

news unrelated to private information, there would be no reason why London price changes would partially revert after the arrival of a boat from Amsterdam.

Prediction 2: *In the empirical estimation* $\frac{\rho^{A|L}}{\rho^{A}}$ *will be larger when the response of* $\left(\boldsymbol{p}^{L}_{t^*+l+1} - \boldsymbol{p}^{L}_{t^*+l}\right)$ *on* $\left(\boldsymbol{p}^{A}_{t+a} - \boldsymbol{p}^{L}_{t^*}\right)$ *is made conditional on the London price change* $\left(\boldsymbol{p}^{L}_{t^*+l} - \boldsymbol{p}^{L}_{t^*}\right)$*.*

Proof. follows from omitted variable bias. ■

The intuition for this result again follows from $(\ {}^{L} - \ {}^{L|A}) > 0$ and the fact that, by assumption, price changes in London and Amsterdam are positively correlated. If one of these variables is omitted in the regression analysis this will lead to a downward bias in the size of $\frac{\rho^{A|L}}{\rho^{A}}$. This is not a trivial result either. If London prices would simply respond to news about fundamentals from Amsterdam that is unrelated to the private information, the size of $\frac{\rho^{A|L}}{\rho^{A}}$ should not depend on the inclusion of $\left(\boldsymbol{p}^{L}_{t^*+l} - \boldsymbol{p}^{L}_{t^*}\right)$.

Prediction 3: *Finally,* $\frac{\rho^{A|L}}{\rho^{A}}$ *should be increasing in the precision of signal* $\ {}^{A}$ and decreasing in the precision of signal $\ {}^{L}$.

Proof. See appendix A. ■

This is an intuitive result. The more precise the Amsterdam signal is, the more weight the market maker will put on it. Figure 12 suggests that this precision actually varies over time and can be measured. First of all, when the time between the arrival of news and the sailing of the next boat ($\boldsymbol{a}$) takes relatively long, then Amsterdam prices are probably **more** informative. More trade has taken place and most likely more of the private signal has been revealed. Longer periods $\boldsymbol{a}$ occur when the London news has arrived right after the previous boat had departed (and it takes 3 or 4 days for the next boat to sail out). Alternatively, longer periods happen when weather conditions are such that boats can not set their sails for England. In the same vein, if the time in London between the initial departure of the boat and the eventual arrival of news from Amsterdam ($\boldsymbol{l}$) is long, then in relative terms, Amsterdam prices are **less** informative. In this case London prices would probably reveal a large share of the private information. Longer periods $\boldsymbol{l}$ occur when $\boldsymbol{a}$ is long (creating a identification problem, see discussion below), or when sailing times on the North Sea (in either direction) happened to be long.

To test these predictions I estimate the following regression, including interaction effects between Amsterdam returns and $\boldsymbol{a}$ and $\boldsymbol{l}$ to pick up the effect the two different signals' precision.

$$
\begin{aligned}
\boldsymbol{p}^{L}_{t^*+l+1} - \boldsymbol{p}^{L}_{t^*+l} &= \ {}_{0} + \ {}_{1}\left(\boldsymbol{p}^{A}_{t+a} - \boldsymbol{p}^{L}_{t^*}\right) + \ {}_{2}\left(\boldsymbol{p}^{L}_{t^*+l} - \boldsymbol{p}^{L}_{t^*}\right) \\
&+ \ {}_{3}\left(\boldsymbol{p}^{A}_{t+a} - \boldsymbol{p}^{L}_{t^*}\right) \times \boldsymbol{a} + \ {}_{4}\left(\boldsymbol{p}^{A}_{t+a} - \boldsymbol{p}^{L}_{t^*}\right) \times \boldsymbol{l} \\
&+ \ {}_{1}\boldsymbol{a} + \ {}_{2}\boldsymbol{l}
\end{aligned} \tag{26}
$$

Predictions 1-3 predict that $_1 > 0$, $_2 < 0$, $_3 > 0$ and $_4 < 0$. Before turning to the regression results, let me first reiterate that I had to make an important assumption to arrive at (25) and (26), namely that no additional shocks affect the price process. This is obviously not true. Price change $\left(\boldsymbol{p}^A_{t+a} - \boldsymbol{p}^L_{t^*}\right)$ may include additional noise. In addition, $\left(\boldsymbol{p}^L_{t^*+l} - \boldsymbol{p}^L_{t^*}\right)$ may also include new private and public information shocks. In other words, I only observe ^{L} and ^{A} with an error. As a result there will be attenuation bias in estimating the regression coefficients from (26). However, predictions 1-3 should still remain valid. Coefficients (and differences between coefficients) should simply be smaller.

Table 10 presents the regression results from estimating 26 step by step. Table 10 presents results for the EIC. The observations included in these regressions are constructed as follows (see figure 12 for reference). For every news shipment from Amsterdam that arrived in London, I check when this news left Amsterdam. I then check what the most recent date of the English news was in Amsterdam the moment this boat departed. I calculate $\boldsymbol{a}$, the number of days between the arrival of this news and the departure of the present boat. I then finally check on what date this English news had been sent from London. That way I can calculate $\boldsymbol{l}$. In addition prices $\boldsymbol{p}^L_{t^*}$, $\boldsymbol{p}^A_{t+a}$, $\boldsymbol{p}^L_{t^*+l}$ and $\boldsymbol{p}^L_{t^*+l+1}$ are easy to recover. $\boldsymbol{p}^L_{t^*}$ and $\boldsymbol{p}^L_{t^*+l}$ are the most recent prices before a boat departed/arrived. $\boldsymbol{p}^L_{t^*+l+1}$ is the most recent price two days after the news arrived from Amsterdam.[22]

In the first column I estimate $_1\,(\frac{\rho^{A|L}}{\rho^A})$ individually. There seems to be some response in London to developments in Amsterdam. However, consistent with the impulse responses in figure 13, $_1$ is small. Unconditionally, price changes in Amsterdam have little impact on prices in London.

Consistent with prediction 2, this reponse increases with about 50% to 0:1 when the previous return in London is included in the estimation (a 1% increase in the Amsterdam price leads to a 0:1% increase in London prices). This difference is statistically significant with a p-value of 0.089. Consistent with prediction 1 $_2\,(-\frac{(\rho^L - \rho^{L|A})}{\rho^L})$ is negative and significant. These results suggest that the London reaction to news from Amsterdam is not just simply related to some other fundamental shocks but is really the result of the feedback effect of private information.

Colums 3 and 4 include the interaction effects with $\boldsymbol{a}$ and $\boldsymbol{l}$ individually. Both $\boldsymbol{a}$ and $\boldsymbol{l}$ are introduced as deviations from the median. This means that coefficient $_1$ is estimated at median values for $\boldsymbol{a}$ (3 days) and $\boldsymbol{l}$ (11 days). The interaction effects measure the impact on $_1$ when moving away from this median. Neither interaction effect, economically nor statistically, is significant on its own. This is not unexpected. It is obvious from figure 12 that $\boldsymbol{a}$ and $\boldsymbol{l}$ are positively correlated (correlation of 0.73). The two interaction effects actually have opposite expected coefficients ($_3 > 0$ and $_4 < 0$). This means that they might cancel each other out if they are introduced individually. In column 5 they are introduced jointly and in this specification they do have statistically significant coefficients. The signs on the coefficients are as predicted. A longer $\boldsymbol{l}$ leads to smaller response of

[22] A period of two days was chosen to minimize the number of missing observations. Using a horizon of one day leads to similar results, but, as expected, to larger standard errors.

the London price to Amsterdam price changes. A longer $\boldsymbol{a}$ leads to a larger response.

The economic impact of the interaction effects is considerable. The 75th (90th) percentile of the distribution of $[\boldsymbol{a} - \boldsymbol{median}(\boldsymbol{a})]$ is at 1 (2) days. This means that moving from the median to the 75th (or 90th) percentile increases the response coefficient from 0.111 to 0.177 (0.245).The 25th (10th) percentile of the distribution of $[\boldsymbol{l} - \boldsymbol{median}(\boldsymbol{l})]$ is at -2 (-3) days. This means that moving from the median to the 25th (or 10th) percentile increases the response coefficient from 0.111 to 0.213 (0.264).

To summarize, the empirical evidence is consistent with a feedback effect of English private information. The price discovery process in Amsterdam affects London prices the moment the London market observes how the market in Amsterdam has moved. This effect does not seem to be driven by fundamental shocks originating in Amsterdam that are unrelated to the private information. London's response to Amsterdam increases substantially when I condition on past London price changes. This is inconsistent with independent fundamental shocks coming from Amsterdam. In addition, the feedback effect is significantly larger when there was more time to trade in Amsterdam or when the overall time the private signal needed to "bounce off" was relatively short. Again, this is consistent with a feedback effect of private information, but inconsistent with the arrival of independent fundamental news from Amsterdam.

5 Conclusion

In this paper I present a unique historical case in which the impact of privately informed trading on security price movements can be analyzed. I look at the market for British securities in Amsterdam during the 1770s and 1780s. Back then communication took place through the sailing of mail packetboats. There is ample anecdotal evidence that London insiders not only traded on their private information in London, but also used the Amsterdam market to profit from their privileged knowledge. Private signals would be communicated between London and Amsterdam through this packetboat service. The same boats would also transmit the public information that, in the end, would reveal this private information to the wider public in Amsterdam. I use information about security returns in London and Amsterdam and the sailing of the packet boats to identify the impact of private information and the strategic behavior of insiders.

To guide the empirical discussion I use a two period model based on Kyle (1985). In the model an informed agent unveils his information slowly over time and price changes in both periods reflect some of his signal. The rate at which private information is revealed depends on the expectation about how long it will take for the private signal to be publicly revealed.

Empirical results are consistent with the model's predictions. Price movements in Amsterdam are correlated with the contemporaneous (but as of yet unreported) returns in London. This is consistent with the presence of a private signal that is incorporated into the price series of both

markets. In addition, I show that this correlation is stronger when the next boat is expected to arrive quickly. If this next boat reveals a significant fraction of the private signal, this is consistent with strategic behavior of the insider. He simply adjusts his trading strategy based on how much time he has to benefit from his informational advantage. If this time is limited, he will trade more aggressively and this will lead to more information revelation.

I provide evidence that the co-movement between Amsterdam and London was permanent. This means that it is unlikely that this co-movement is driven by correlated liquidity or other transitory shocks. Structural estimation of the model indicates that around 35% of overall stock price volatility in Amsterdam can be explained by private information *[Add comparison to more current estimates]*. The importance of private information for these historical markets is further demonstrated by the feedback effect that exists between Amsterdam and London. The revelation of the private signal in Amsterdam has some impact on the London market. This effect is only present under certain specific conditions that are consistent with private information but not with independent fundamental shocks originating from Amsterdam.

To what extent can the historical findings from this paper be generalized to today's financial markets? There is no obvious reason why insider trading would be less important today than it was in 18$^{\text{th}}$ century Amsterdam. In contrast to the past, insider trading today has become illegal. However the depth and anonymity of today's markets create many more opportunities to benefit from inside information than existed over two centuries ago. The model of insider trading developed in this paper is based on a number of assumptions that are similar to those often made in the market microstructure literature (e.g. Kyle 1985). Crucially, I assume that the insider is a monopolist over his signal, and that private information is long-lived, and arrives to the market in a non-continuous way. Although these assumptions fit well with the historical evidence, it is possible that private information in today's financial markets has different characteristics. Nevertheless, since private information or insider trading is by definition difficult to observe, any evidence on how it might influence the dynamics of trading is of interest.

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Figures

Figure 1: Map North Sea area

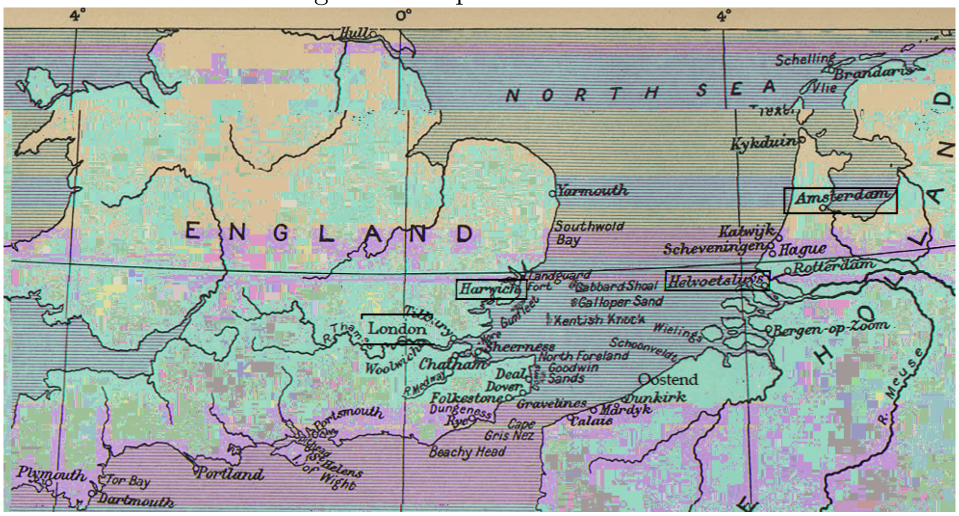


Figure 2: Setup model

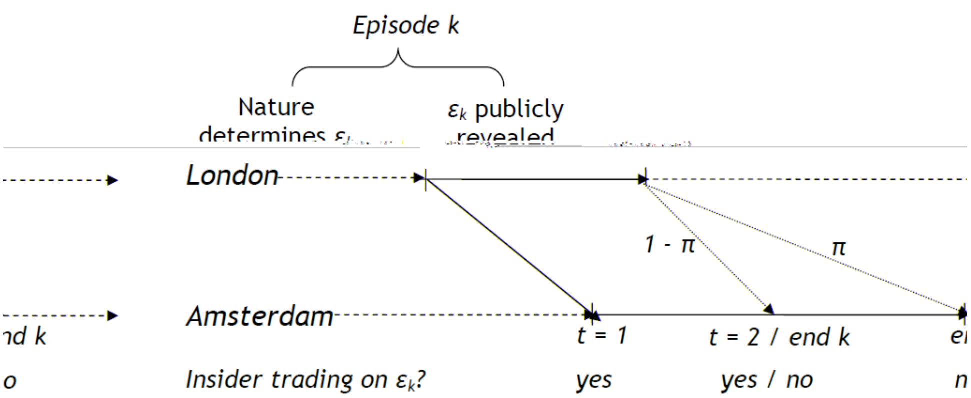


Figure 3: Points of sail (shaded area no-go zone)

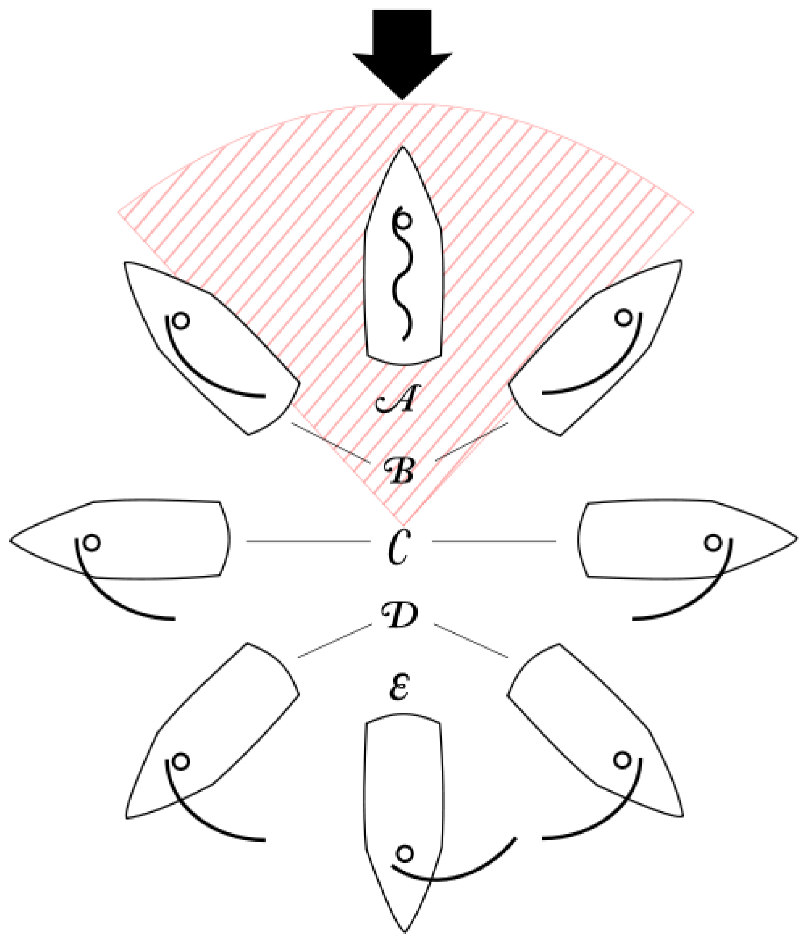
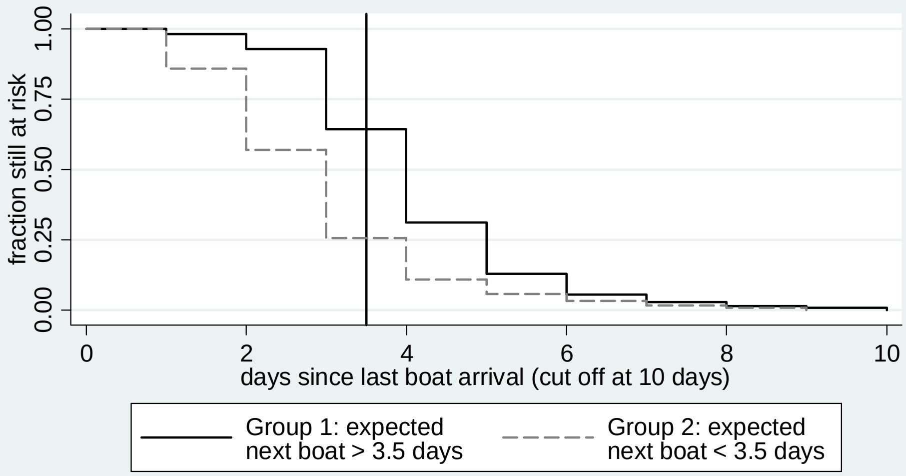
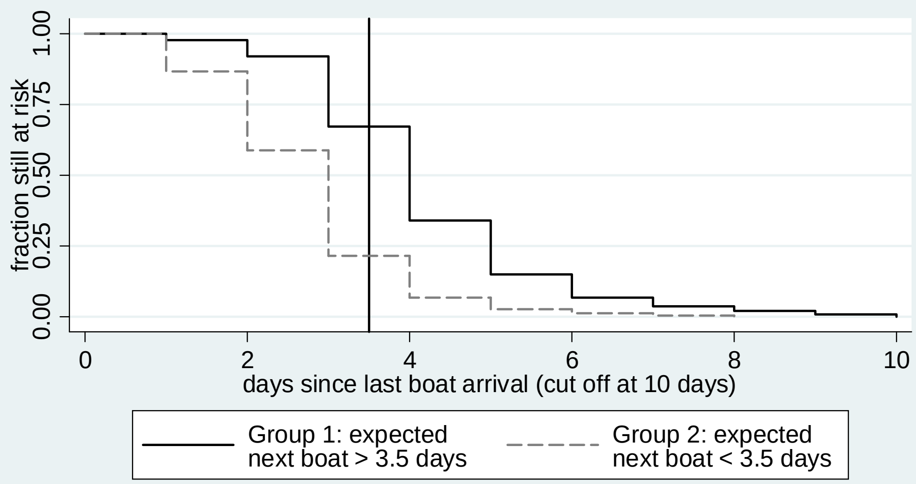


Figure 4: Kaplan-Meier estimates - arrival next boat (simple model)



Expected arrival of next boat estimated by simply adding the median sailing time to the date a boat was scheduled to depart.
The vertical black line indicates the unconditionally expected arrival time of 3.5 days.
If the empirical model has a perfect fit, we would expect all group 1 observations to be still at risk at 3.5 days, and all group 2 observations to have failed at 3.5 days.

Figure 5: Kaplan-Meier estimates - arrival next boat (extended duration model)



Expected arrival of next boat estimated using a duration model with a Gamma distribution including month dummies and a range of weather variables (see text).
The vertical black line indicates the unconditionally expected arrival time of 3.5 days.
If the empirical model has a perfect fit, we would expect all group 1 observations to be still at risk at 3.5 days, and all group 2 observations to have failed at 3.5 days.

Figure 6: Setup - empirical analysis

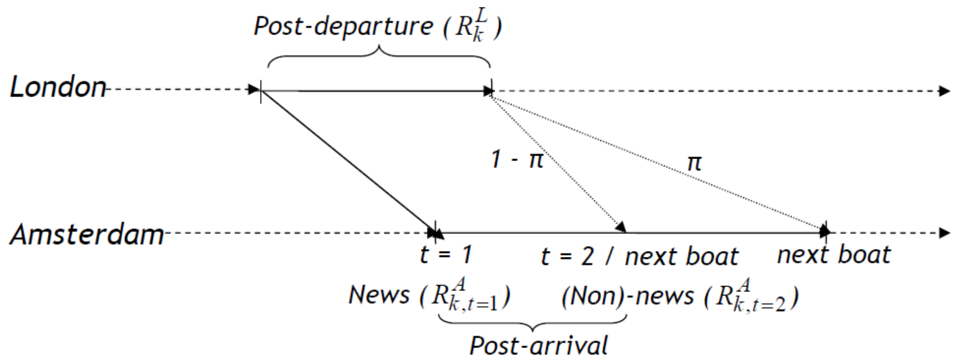
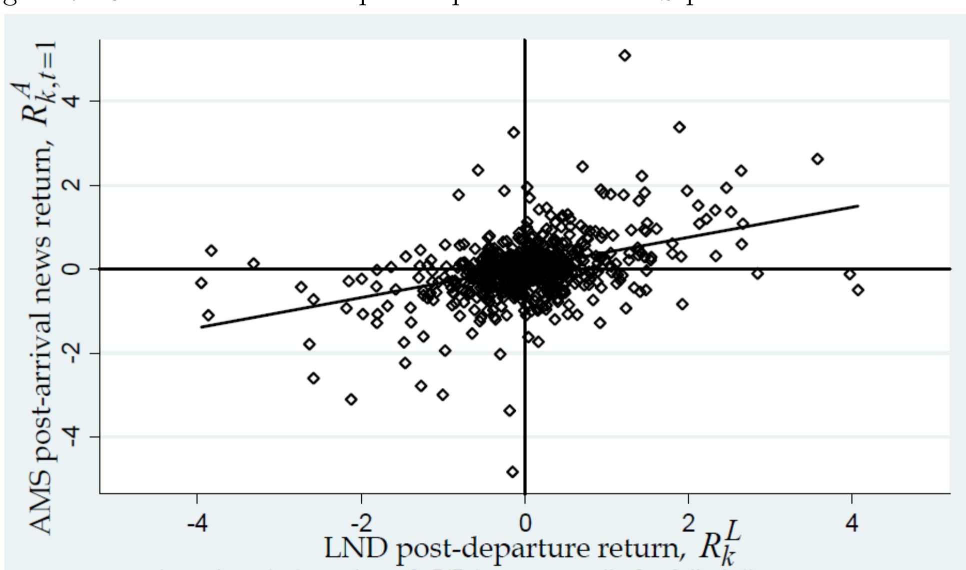


Figure 7: Co-movement LND post-departure and AMS post-arrival news returns



x and y axis cut at a value of -5/5 (see appendix for full plot)
Amsterdam and London returns are corrected for the difference between the London departure price and the Amsterdam pre-arrival price.
London post-departure returns are calculated over the three days after departure.

Figure 8: Co-movement LND post-departure and AMS post-arrival non-news returns

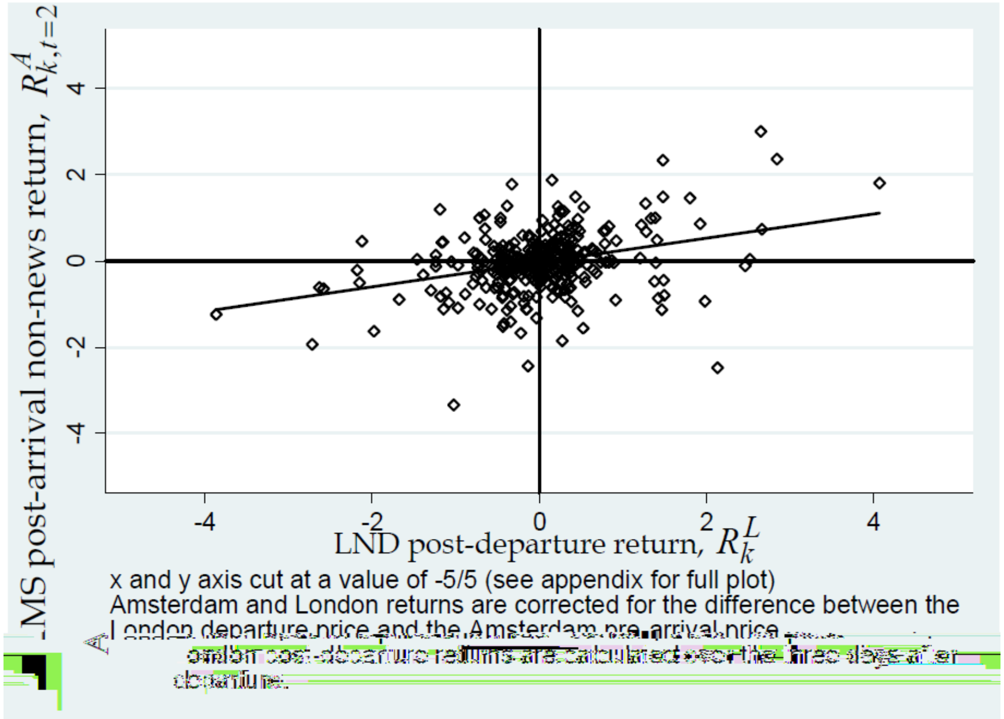


Figure 9: Co-movement LND post-departure and AMS post-arrival non-news returns - bad weather (A)

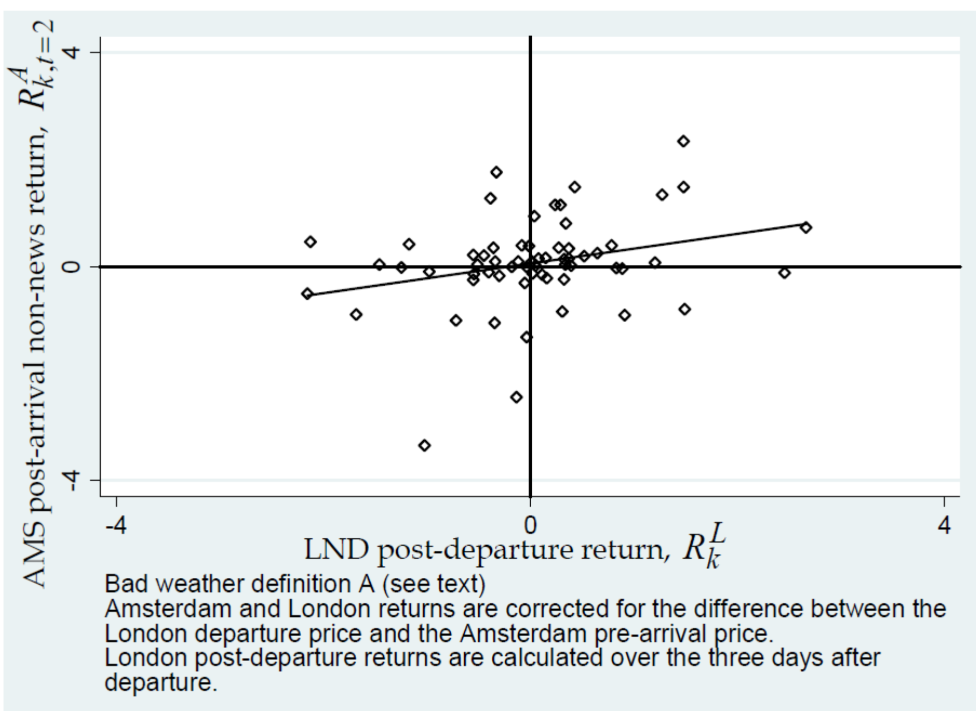


Figure 10: Co-movement LND post-departure and AMS post-arrival non-news returns - bad weather (B)

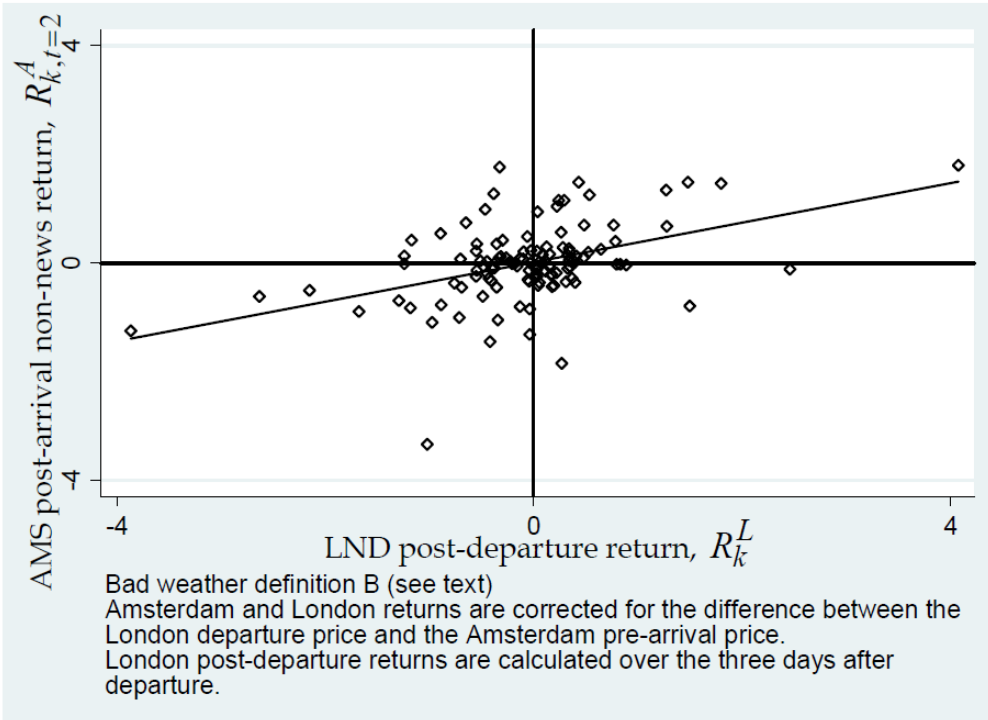


Figure 11: Co-movement LND post-departure and AMS post-arrival non-news returns - bad weather (C)

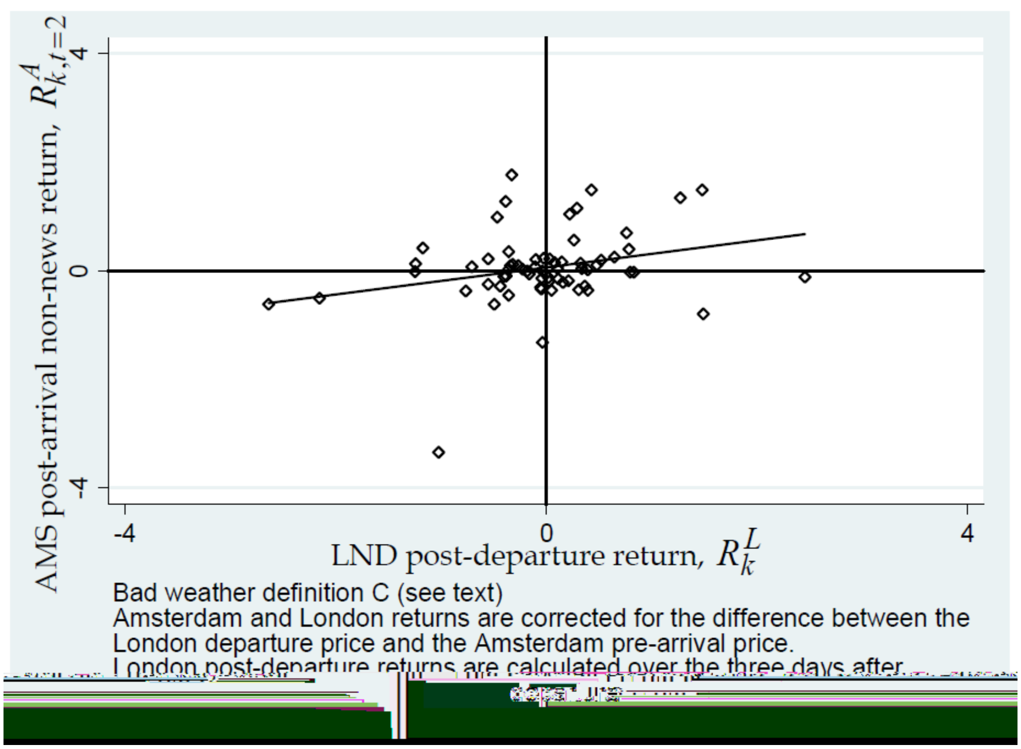
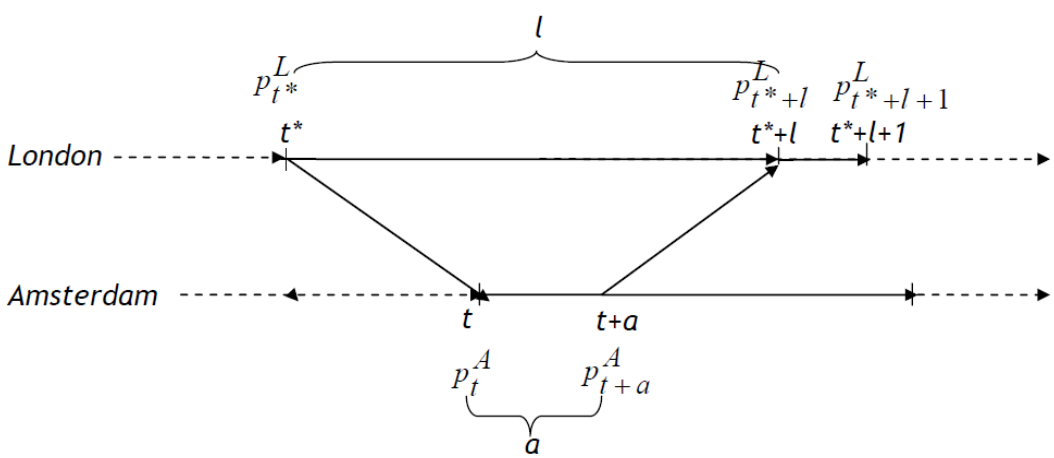


Figure 12: Feedback effects - setup



Tables

Table 3: Co-movement of returns - EIC

	(1) AMS post-arrival news return, $\boldsymbol{R}^A_{k,t=1}$	(2) AMS post-arrival non-news return, $\boldsymbol{R}^A_{k,t=2}$
LND post-departure return, $\boldsymbol{R}^L_k$	0.338	0.220
	(0.048)***	(0.062)***
Difference London departure and Amsterdam pre-arrival price, $\boldsymbol{P}^L_{k-1} - \boldsymbol{P}^A_{k-1}$	0.441	0.077
	(0.040)***	(0.038)**
Constant	0.005	-0.023
	(0.026)	(0.030)
Obs	666	355
R2	0.36	0.10
$\boldsymbol{Chi}^2$ test	2.27	
(p-value)	(0.132)	

Estimates of co-movement between London post-departure and Amsterdam post-arrival returns. Estimates are adjusted for possible momentum of the public news innovation by including the difference between the London departure and the Amsterdam pre-arrival price.
See figure ... for exact definitions of returns. London post-departure returns are calculated over the three days after a boat departure. A $\boldsymbol{Chi}^2$ test is performed on the equality of the $\boldsymbol{R}^L_k$ coefficients in columns (1) and (2).

***,** denotes statistical significance at the 1, 5% level. Robust, bootstrapped standard errors (1000 replications) are reported in parentheses.

Table 4: Co-movement EIC, different expectations next boat

	AMS post-arrival news return, $\boldsymbol{R}^A_{k,t=1}$	
London post-departure return, $\boldsymbol{R}^L_k$	0.242 (0.060)***	0.282 (0.063)***
$\boldsymbol{R}^L_k \times \boldsymbol{E}[\boldsymbol{A}\vert \boldsymbol{simple}] < 3{:}5$	0.232 (0.094)**	
$\boldsymbol{E}[\boldsymbol{A}\vert \boldsymbol{simple}] < 3{:}5$	0.008 (0.055)	
$\boldsymbol{R}^L_k \times \boldsymbol{E}[\boldsymbol{A}\vert \boldsymbol{extended}] < 3{:}5$		0.174 (0.097)*
$\boldsymbol{E}[\boldsymbol{A}\vert \boldsymbol{extended}] < 3{:}5$		-0.016 (0.056)
Difference London departure and Amsterdam pre-arrival price, $\boldsymbol{P}^L_{k-1} - \boldsymbol{P}^A_{k-1}$	0.472 (0.035)***	0.471 (0.039)***
Constant	-0.007 (0.038)	0.006 (0.041)
Obs	627	627
R2	0.39	0.38

Estimates of co-movement between London post-departure and Amsterdam post-arrival returns. $\boldsymbol{E}[\boldsymbol{A}]$ stands for the expected number of days until the next boat arrival. $\boldsymbol{E}[\boldsymbol{A}|\boldsymbol{simple}]$ is calculated by adding the median sailing time to the departure date of the next boat. $\boldsymbol{E}[\boldsymbol{A}|\boldsymbol{extended}]$ is calculated in a similar way, but here the expected sailing time is estimated in a duration model using a Gamma distribution, including a wide range of weather variables and month dummies (see text).
See figure ... for exact definitions of returns. London post-departure returns are calculated over three days after a boat departure. The observation of 20 November 1772 is dropped from the regression analysis to make sure that this outlier does not drive the positive interaction effect (see figure ... in appendix ...). Inclusion of this datapoint leads to slightly higher estimates of the interaction effect.

***, **, * denotes statistical significance at the 1, 5, 10% level. Robust, bootstrapped standard errors (1000 replications) are reported in parentheses.

Table 5: Co-movement EIC, bad weather

	AMS post-arrival no-news return, $\boldsymbol{R}^A_{k,t=2}$		
London post-departure return, $\boldsymbol{R}^L_k$	0.258 (0.074)***	0.223 (0.089)***	0.266 (0.073)***
$\boldsymbol{R}^L_k \times \boldsymbol{badweather}(\boldsymbol{A})$	0.012 (0.148)		
$\boldsymbol{badweather}(\boldsymbol{A})$	0.119 (0.111)		
$\boldsymbol{R}^L_k \times \boldsymbol{badweather}(\boldsymbol{B})$		0.115 (0.116)	
$\boldsymbol{badweather}(\boldsymbol{B})$		0.067 (0.072)	
$\boldsymbol{R}^L_k \times \boldsymbol{badweather}(\boldsymbol{C})$			-0.020 (0.154)
$\boldsymbol{badweather}(\boldsymbol{C})$			0.130 (0.094)
Difference London departure and Amsterdam pre-arrival price, $\boldsymbol{P}^L_{k-1} - \boldsymbol{P}^A_{k-1}$	0.120 -(0.067)***	0.126 (0.045)***	0.120 (0.043)***
Constant	-0.068 (0.034)	-0.067 (0.040)	-0.071 (0.037)
Obs - total	363	363	363
Obs - $\boldsymbol{badweather}(\boldsymbol{A})$	65		
Obs - $\boldsymbol{badweather}(\boldsymbol{B})$		117	
Obs - $\boldsymbol{badweather}(\boldsymbol{C})$			67
R2	0.12	0.12	0.12

Estimates of co-movement between London post-departure and Amsterdam post-arrival non-news returns, conditional on good or bad weather conditions. See the text for a description of the three definitions (A, B, and C) of bad weather.

See figure ... for exact definitions of returns. London post-departure returns are calculated over three days after a boat departure.

*** denotes statistical significance at the 1% level. Robust, bootstrapped standard errors (1000 replications) are reported in parentheses.

Table 6: Permanent price changes?

	Amsterdam return over period T after episode k (R^A_{k+T})					
	$2/3$ *days*	$4/5$ *days*	1 *week*	2 *weeks*	3 *weeks*	4 *weeks*
London post-departure	0.050	0.013	0.086	0.112	0.144	0.288
return (R^L_k)	(0.042)	(0.064)	(0.065)	(0.095)	(0.121)	(0.135)
Constant	-0.024	-0.005	0.052	0.093	0.079	0.133
	(0.033)	(0.042)	(0.051)	(0.070)	(0.093)	(0.106)
N	736	735	733	728	719	716
Adj. R^2	0.00	-0.00	0.00	0.00	0.00	0.01

Estimates from predictive regressions of London post-departure returns (R^A_{k+T}) on Amsterdam returns taking place after the conclusion of episode k. Estimates for different horizons: from 2/3 days to 4 weeks.

Robust, bootstrapped (1000 reps) standard errors in parantheses. None of the coefficients is statistically significant.

Table 7: Co-movement under different public news shocks, EIC

	Amsterdam post-arrival news return, $\boldsymbol{R}^A_{k,t=1}$		Amsterdam post-arrival non-news return, $\boldsymbol{R}^A_{k,t=2}$	
London post-departure return, $\boldsymbol{R}^L_k$	0.335 (0.055)***	0.366 (0.072)***	0.205 (0.060)***	0.187 (0.069)***
Zero past London post-departure return ($\boldsymbol{R}^L_{k-1} = 0$)	0.001 (0.071)		0.050 (0.084)	
$\times$ London post-departure return, $\boldsymbol{R}^L_k$	0.079 (0.144)		0.062 (0.165)	
Past London post-departure return ($\boldsymbol{R}^L_{k-1}$) in 2nd/3rd quartile		-0.016 (0.055)		0.060 (0.059)
$\times$ London post-departure return, $\boldsymbol{R}^L_k$		-0.089 (0.097)		0.129 (0.103)
Difference London departure and Amsterdam pre-arrival price, $\boldsymbol{P}^L_{k-1} - \boldsymbol{P}^A_{k-1}$	0.468 (0.039)***	0.465 (0.042)***	0.056 (0.034)	0.056 (0.035)
Constant	0.002 (0.031)	0.010 (0.044)	-0.033 (0.031)	-0.055 (0.047)
Obs - total	627	627	326	326
Obs - zero returns	76		39	
Obs - returns in 2nd/3rd quartile		300		147
R2	0.38	0.38	0.10	0.09

Estimates of co-movement between London post-departure and Amsterdam post-arrival non-news returns, conditional on a high or low volatility regime. Low (high) volatility regimes are proxied by $\boldsymbol{R}^L_{k-1}$ (past London post-departure returns) that are (non)zero or are in the 2nd and 3rd (1st and 4th) quartiles.
See figure ... for exact definitions of returns. London post-departure returns are calculated over three days after a boat departure. The observations of 25 November 1772 and 30 January 1784 are dropped from the regression analysis to make sure that these outliers do not bias the interaction effect upwards. Inclusion of these datapoints leads to slightly higher estimates of the interaction terms.

*** denotes statistical significance at the 1% level. Robust, bootstrapped standard errors (1000 replications) are reported in parentheses.

Table 8: GMM estimates

Parameters	Simple	Time varying	Public vs private news	Both
$^{2}_{\tilde{\eta}}$	0:434	0:438		
	(0:078)***	(0:078)***		
$^{2}_{\eta}$			0:152	0:169
			(0:082)*	(0:074)**
$^{2}_{\varepsilon}$	0:600	0:566	0:588	0:552
	(0:153)***	(0:132)***	(0:152)***	(0:140)***
$_1 \; _1$	0:430		0:415	
	(0:094)***		(0:092)***	
$^{l}_{1} \; ^{l}_{1}$		0:607		0:589
		(0:132)***		(0:133)***
$^{h}_{1} \; ^{h}_{1}$		0:331		0:298
		(0:112)***		(0:107)***
Z-test $^{l}_{1} \; ^{l}_{1} = \; ^{h}_{1} \; ^{h}_{1}$		$-1{:}87$		$-1{:}91$
(p-value)		(0:062)*		(0:056)*
Hansen's J-test		0:001	0:485	0:785
(p-value)		(0:980)	(0:486)	(0:675)
$\boldsymbol{var}\left(\boldsymbol{R}^{A}_{k,t=1}\right)$	0:756	0:756		
$\boldsymbol{var}\left(\widehat{\boldsymbol{R}^{A}_{k,t=1}\lvert\text{''}; \boldsymbol{noise}}\right)$	0:434 (57%)	0:438 (58%)		
$\boldsymbol{var}\left(\widehat{\boldsymbol{R}^{A}_{k,t=1}\lvert\tilde{}_{k}; \boldsymbol{noise}}\right)$	0:260 (34%)	0:265 (35%)		
$\boldsymbol{var}\left(\boldsymbol{R}^{A}_{k,t=2}\right)$	0:489	0:489		
$\boldsymbol{var}\left(\widehat{\boldsymbol{R}^{A}_{k,t=2}\lvert\boldsymbol{noise}}\right)$	0:170 (35%)	0:150 (27%)		

Estimations of the different GMM models described in the test that fit the data to theoretical model developed in section 3 (see text for further details). The final rows calculate what fraction of overall return volatility can be explained by private and public information.

*,**, *** indicate significance at the 1, 5, and 10% level.

Table 9: Observations different moment conditions

Moment conditions	Observations
$\boldsymbol{cov}\left(\boldsymbol{R}^{A}_{k,t=1}; \boldsymbol{P}^{L}_{k-1} - \boldsymbol{P}^{A}_{k-1}\right)$	727
$\boldsymbol{cov}\left(\boldsymbol{R}^{A}_{k,t=1}; \boldsymbol{P}^{L}_{k-1} - \boldsymbol{P}^{A}_{k-1} \vert \text{no } \boldsymbol{k} - 1; \boldsymbol{t} = 2\right)$	348
$\boldsymbol{cov}\left(\boldsymbol{R}^{A}_{k,t=1}; \boldsymbol{P}^{L}_{k-1} - \boldsymbol{P}^{A}_{k-1} \vert\ \boldsymbol{k} - 1; \boldsymbol{t} = 2\right)$	437
$\boldsymbol{cov}\left(\boldsymbol{R}^{A}_{k,t=1}; \boldsymbol{R}^{L}_{k}\right)$	632
$\boldsymbol{cov}\left(\boldsymbol{R}^{A}_{k,t=1}; \boldsymbol{R}^{L}_{k} \vert \quad \boldsymbol{high}\right)$	367
$\boldsymbol{cov}\left(\boldsymbol{R}^{A}_{k,t=1}; \boldsymbol{R}^{L}_{k} \vert \quad \boldsymbol{low}\right)$	304
$\boldsymbol{cov}\left(\boldsymbol{R}^{A}_{k,t=2}; \boldsymbol{R}^{L}_{k}\right)$	370
$\boldsymbol{cov}\left(\boldsymbol{R}^{A}_{k,t=2}; \boldsymbol{R}^{L}_{k} \vert \quad \boldsymbol{high}\right)$	285
$\boldsymbol{cov}\left(\boldsymbol{R}^{A}_{k,t=2}; \boldsymbol{R}^{L}_{k} \vert \quad \boldsymbol{low}\right)$	85

Table 10: Feedback effects

	London returns between $t^* + l + 1$ and $t^* + l$ ($p^L_{t^*+l+1} - p^L_{t^*+l}$)				
	(1)	(2)	(3)	(4)	(5)
Amsterdam news returns	0:066	0:100	0:100	0:107	0:111
($p^A_{t+a} - p^L_{t^*}$)	(0:034)*	(0:039)***	(0:038)***	(0:039)***	(0:039)***
London pre-news returns		−0:073	−0:073	−0:072	−0:066
($p^L_{t^*+l} - p^L_{t^*}$)		(0:041)*	(0:041)*	(0:041)*	(0:041)*
Amsterdam period a			−0:027		−0:046
			(0:023)		(0:035)
$a \times (p^A_{t+a} - p^L_{t*})$			0:011		0:067
			(0:019)		(0:031)**
London period l				−0:004	0:022
				(0:013)	(0:020)
$l \times (p^A_{t+a} - p^L_{t^*})$				−0:013	−0:051
				(0:011)	(0:019)***
constant	0:054	0:049	0:042	0:050	0:043
	(0:037)	(0:036)	(0:037)	(0:036)	(0:038)
^{2} test $(p^A_{t+a} - p^L_{t*})$: (1) = (2)		2:89			
(p-value)		(0:089)*			
N	696	695	695	695	695
Adj. R^2	0:01	0:02	0:02	0:02	0:03

This table provides estimates of the feedback effect of private information in London using iterative GMM. The weighted matrix is calculated using a heteroskedasticity- and autocorrelation-consistent weight matrix using the Newey-West kernel with optimal number of lags. See figure 12 for a definition of the timing.

Interaction effects estimated at the median. This means that the benchmark coefficient on $P^A_{t+a} - P^L_{t*}$measures the impact of Amsterdam returns on London returns at the median values of a and l.

*,**, *** indicate significance at the 1, 5, and 10% level.

Appendix A

Proof. of proposition 1.

(1) Take equations (1) to (8) as given and check whether this equilibrium exists and is optimal.

(2) Solve for the informed agent's optimization problems in $t = 1$ and $t = 2$.

(2a)Start with $t = 2$

$$\max x_2 (v_0 + " - p_2)$$

with p_2 defined by (4). The first order condition results in (2) with $\ _2 = \frac{1}{2\lambda_2}$. The second order condition yields $\ _2 > 0$.

(2b)Move to $t = 1$.

$$\max x_1 (v_0 + " - p_1) + \ \ E [x_2 (v_0 + " - p_2)]$$

Plugging in for (3) and (4), $E [x_2 (v_0 + " - p_2)]$ can be rewritten as

$$\frac{1}{4\ _2} \left[(" - \ _1 x_1)^2 + \ _1^2 \ _{u_1}^2 \right]$$

The first order condition gives (1), with $\ _1$ given by (5). The second order condition yields

$$\frac{\ _1^2}{2\ _2} < 2\ _1$$

From the second order condition from $t = 2$, we know that $\ _2 > 0$. This implies that $\ _1 > 0$. In addition,

$$4\ _2 > \ \ _1$$

(3) Solve for the inference problems of the market maker.

(3a) Start in $t = 1$.

The only signal (apart from v_0) the market maker observes is $y_1 = \ _1 " + u_1$. Because $"$ and u_1 are independent and normally distributed,

$$E ["|y_1] = \ _1 y_1$$

with $\ _1$ given by (7). p_1 will be given by (3).

(3b) Move to $t = 2$.

In the second period the market maker has two signals available, $y_1 = \ _1 " + u_1$ and $y_2 = \ _2 [" - (p_1 - v_0)] + u_2$. If y_1 and y_2 are independent (proof of this follows), we can simply write

$$\begin{aligned} E ["|y_1; y_2] &= p_1 + E [" - (p_1 - v_0) |y_2] \\ &= p_1 + \ _2 y_2 \end{aligned}$$

with $\ _2 = \frac{\beta_2 var[\varepsilon|p_1 - v_0]}{\beta_2^2 var[\varepsilon|p_1 - v_0] + \sigma_{u_2}^2}$. Combining this with $\ _2 = \frac{1}{2\lambda_2}$ we arrive at (8) and (6).

Using simple properties of linear projection, it can be shown that

$$\textbf{\textit{var}}\,[\text{"}|\textbf{\textit{p}}_1 - \textbf{\textit{v}}_0] = (1 - {}_1\,{}_1)\;{}^2_\varepsilon$$

(3c) Proof of independence of $\textbf{\textit{y}}_1$ and $\textbf{\textit{y}}_2$

Note that

$$\textbf{\textit{cov}}\,(\textbf{\textit{y}}_1; \textbf{\textit{y}}_2) = {}_2\left[{}_1(1 - {}_1\,{}_1)\;{}^2_\varepsilon - {}_1\;{}^2_{u_1}\right]$$

Using (7) to rewrite $(1 - {}_1\,{}_1)$ it can be shown that $\textbf{\textit{cov}}\,(\textbf{\textit{y}}_1; \textbf{\textit{y}}_2) = 0$. ■

Proof. of corollary 2.

$\textbf{\textit{cov}}(\textbf{\textit{p}}_1 - \textbf{\textit{v}}_0; \text{"}) = {}_1\,{}_1\;{}^2_\varepsilon$

${}_1 > 0$ because of the second order conditions for the informed agent (see proof of proposition 1).

${}_1 > 0$ follows from (7) and ${}_1 > 0$. ■

Proof. of corollary 3.

$\textbf{\textit{cov}}(\textbf{\textit{p}}_2 - \textbf{\textit{p}}_1; \text{"}) = {}_2\,{}_2(1 - {}_1\,{}_1)\;{}^2_\varepsilon$

${}_2 > 0$ because of the second order conditions for the informed agent in $\textbf{\textit{t}} = 2$ (see proof of proposition 1).

${}_2 > 0$ follows from ${}_2 > 0$ and ${}_2 = \frac{1}{2\lambda_2}$.

$(1 - {}_1\,{}_1) > 0$ follows from

$${}_1\,{}_1 = \frac{1}{2}\,\frac{{}_2 - \frac{1}{2}\;{}_1}{{}_2 - \frac{1}{4}\;{}_1}$$

which indicates that ${}_1\,{}_1 < \frac{1}{2}$. ■

Proof. of corollary 4.

It is easy to show that

$$\frac{{}_1\,{}_1}{} < 0$$

■

Proof. of corollary 5.

Moment condition (9) follows directly from the setup of table 2.

Moment conditions (10) and () follow simply from the solution to the model in section ..., noting that $\textbf{\textit{var}}(\text{"}|\textbf{\textit{p}}_{k,1}) = (1 - {}_1\,{}_1)\;{}^2_\varepsilon$ and ${}_2\,{}_2 = \frac{1}{2}$. ■

Proof. of corollary 6.

Noting that ${}_1 = \frac{\beta_1 \sigma^2_\varepsilon}{\beta_1^2 \sigma^2_\varepsilon + \sigma^2_{u_1}}$, we can rewrite $\textbf{\textit{var}}\left(\textbf{\textit{R}}^A_{k,t=1}|\tilde{}_k; \textbf{\textit{noise}}\right) = {}^2_1\left({}^2_1\;{}^2_\varepsilon + {}^2_{u_1}\right)$ as (12).

In the same vein we arrive at (13). ■

Proof. of corollary 8.

It can be shown that in this setup

$$
\begin{aligned}
\boldsymbol{R}^A_{k,t=1} &= \boldsymbol{p}^A_{k,t=1} - \boldsymbol{p}^A_{k-1,t=1} \\
&= {}_k + (1 - {}_1\ {}_1)\, "_{k-1} - {}_1\boldsymbol{u}_{k-1,1} + \boldsymbol{:::}\ (\text{no } \boldsymbol{k} - 1\boldsymbol{;}\, \boldsymbol{t} = 2) \\
\boldsymbol{R}^A_{k,t=1} &= \boldsymbol{p}^A_{k,t=1} - \boldsymbol{p}^A_{k-1,t=2} \\
&= {}_k + (1 - {}_1\ {}_1)\,(1 - {}_2\ {}_2)\, "_{k-1} + \frac{1}{2}\ {}_1\boldsymbol{u}_{k-1,1} - {}_2\boldsymbol{u}_{k-1,2} + \boldsymbol{:::}\ (\boldsymbol{k} - 1\boldsymbol{;}\, \boldsymbol{t} = 2)
\end{aligned}
$$

In addition

$$
\begin{aligned}
\boldsymbol{p}^L_{k-1} - \boldsymbol{p}^A_{k-1} &= {}_k + (1 - {}_1\ {}_1)\, "_{k-1} - {}_1\boldsymbol{u}_{k-1,1}\ (\text{no } \boldsymbol{k} - 1\boldsymbol{;}\, \boldsymbol{t} = 2) \\
\boldsymbol{p}^L_{k-1} - \boldsymbol{p}^A_{k-1} &= {}_k + (1 - {}_1\ {}_1)\,(1 - {}_2\ {}_2)\, "_{k-1} + \frac{1}{2}\ {}_1\boldsymbol{u}_{k-1,1} - {}_2\boldsymbol{u}_{k-1,2}\ (\boldsymbol{k} - 1\boldsymbol{;}\, \boldsymbol{t} = 2)
\end{aligned}
$$

Suppose there was no period $\boldsymbol{k} - 1\boldsymbol{;}\, \boldsymbol{t} = 2$. In that case

$$
\boldsymbol{cov}(\boldsymbol{R}^A_{k,t=1}\boldsymbol{;}\, \boldsymbol{p}^L_{k-1} - \boldsymbol{p}^A_{k-1}) = {}^2_\eta + (1 - {}_1\ {}_1)^2\ {}^2_\varepsilon + {}^2_1\ {}^2_{u_1}
$$

Again using the fact that ${}_1 = \frac{\beta_1\sigma^2_\varepsilon}{\beta^2_1\sigma^2_\varepsilon + \sigma^2_{u_1}}$ it can be shown that

$$
{}^2_1\ {}^2_{u_1} = {}_1\ {}_1(1 - {}_1\ {}_1)\ {}^2_\varepsilon
$$

from which (19 follows directly. Using similar logic we arrive at (20). ■

Proof. of prediction 1

Part 1: $\frac{\rho^{A|L}}{\rho^A} \boldsymbol{>} 0$

${}^A \boldsymbol{>} 1$ follows directly from equation (23).

${}^{A|L}$ from equation (24) can be rewritten as

$$
{}^{A|L} = \Omega^L \left[\ {}^A\boldsymbol{var}\left(\ {}^A\right) - {}^L\boldsymbol{cov}(\ {}^A\boldsymbol{;}\ {}^B)\right] \tag{27}
$$

with

$$
\Omega^L = \frac{\boldsymbol{var}\left(\ {}^L\right)}{\boldsymbol{var}\left(\ {}^L\right)\boldsymbol{var}\left(\ {}^A\right) - \boldsymbol{cov}\left(\ {}^A\boldsymbol{;}\ {}^L\right)^2} \tag{28}
$$

$\Omega^L \boldsymbol{>} 0$ follows from $\boldsymbol{cov}\left(\ {}^A\boldsymbol{;}\ {}^L\right) \boldsymbol{<} \boldsymbol{var}\left(\ {}^i\right)$ for $\boldsymbol{i} = \boldsymbol{A}\boldsymbol{;}\,\boldsymbol{L}$.

Using (23) and rearranging, this means that ${}^{A|L} \boldsymbol{>} 0$ is equivalent to

$$
{}^2_\varepsilon\left(1 - \frac{\boldsymbol{cov}(\ {}^A\boldsymbol{;}\ {}^B)}{\boldsymbol{var}\left(\ {}^L\right)}\right) \boldsymbol{>} 0
$$

Note that as long as $\boldsymbol{cov}\left(\ {}^A\boldsymbol{;}\ {}^L\right) \boldsymbol{<} \boldsymbol{var}\left(\ {}^L\right)$ this condition is met.

Part 2: $\left(\ {}^L - {}^{L|A}\right) \boldsymbol{>} 0$

This follows directly from (24) and ${}^{A|L} \boldsymbol{>} 0$. ■

Proof. of prediction 3

Using, (23) equation (27) can be rewritten as

$$\frac{\ ^{A|L}}{\ ^{A}} = \Omega^L \mathbf{var}\left(\ ^{A}\right)\left[1 - \frac{\mathbf{cov}(\ ^{A};\ ^{B})}{\mathbf{var}\left(\ ^{L}\right)}\right]$$

Keeping $\mathbf{var}\left(\ ^{L}\right)$ constant, $\mathbf{var}(\ ^{A})$ can be interpreted as the precision of signal $\ ^{A}$.

$$\frac{\left[\frac{\rho^{A|L}}{\rho^{A}}\right]}{\mathbf{var}(\ ^{A})} = \left[1 - \frac{\mathbf{cov}(\ ^{A};\ ^{B})}{\mathbf{var}\left(\ ^{L}\right)}\right]\left[\Omega^L + \frac{\Omega^L}{\mathbf{var}\left(\ ^{A}\right)}\mathbf{var}\left(\ ^{A}\right)\right]$$

Using (28) it can be shown that

$$\begin{aligned}
\frac{\left[\frac{\rho^{A|L}}{\rho^{A}}\right]}{\mathbf{var}(\ ^{A})} &= \Omega^L\left[1 - \frac{\mathbf{cov}(\ ^{A};\ ^{B})}{\mathbf{var}\left(\ ^{L}\right)}\right]\left[1 - \mathbf{var}(\ ^{A})\Omega^L\right] \\
&= -\Omega^L\left[1 - \frac{\mathbf{cov}(\ ^{A};\ ^{B})}{\mathbf{var}\left(\ ^{L}\right)}\right]\frac{\mathbf{cov}\left(\ ^{A};\ ^{L}\right)^2}{\mathbf{var}\left(\ ^{L}\right)\mathbf{var}\left(\ ^{A}\right) - \mathbf{cov}\left(\ ^{A};\ ^{L}\right)^2}
\end{aligned}$$

As long as $\mathbf{cov}\left(\ ^{A};\ ^{L}\right) < \mathbf{var}\left(\ ^{i}\right)$, $\frac{\delta\left[\frac{\rho^{A|L}}{\rho^{A}}\right]}{\delta var(\theta^{A})} < 0$.

In a similar way it can be shown that $\frac{\delta\left[\frac{\rho^{A|L}}{\rho^{A}}\right]}{\delta var(\theta^{L})} > 0$. ∎

Appendix B - additional figures and tables

Figure 13: Impulse response functions AMS-LND, EIC

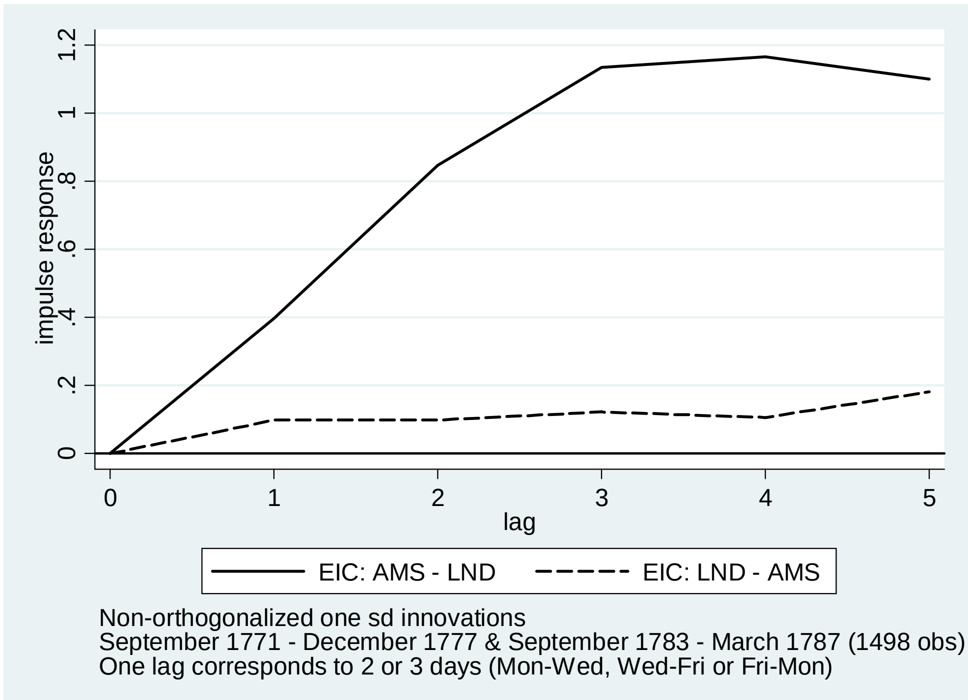
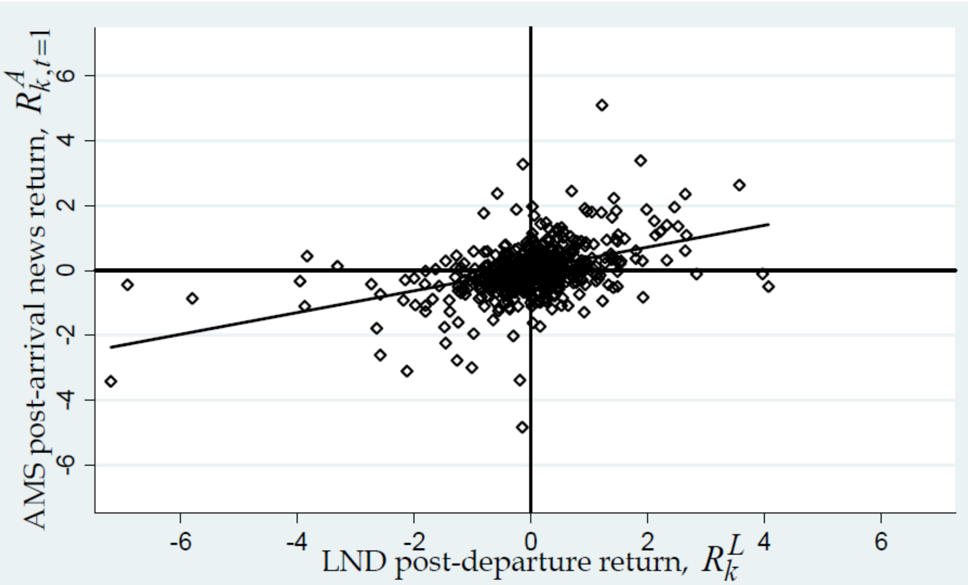
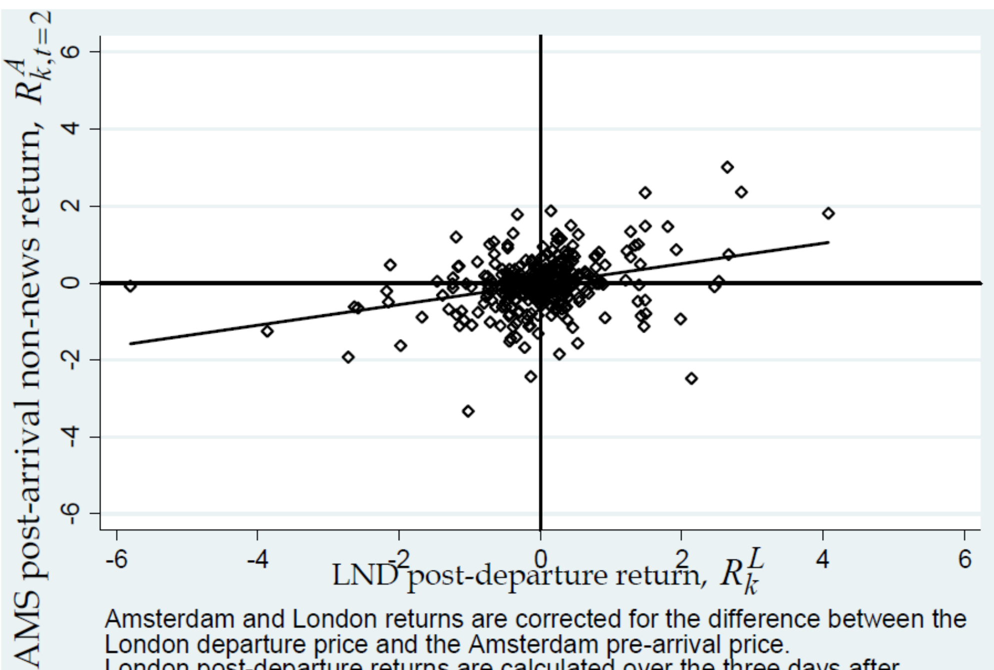


Figure 14: Co-movement LND post-departure and AMS post-arrival news returns



Amsterdam and London returns are corrected for the difference between the London departure price and the Amsterdam pre-arrival price.
London post-departure returns are calculated over the three days after departure.

Figure 15: Co-movement LND post-departure and AMS post-arrival non-news returns



Amsterdam and London returns are corrected for the difference between the London departure price and the Amsterdam pre-arrival price.
London post-departure returns are calculated over the three days after departure.

Figure 16: Co-movement LND post-departure and AMS post-arrival news returns - next boat $<$ 3.5 days

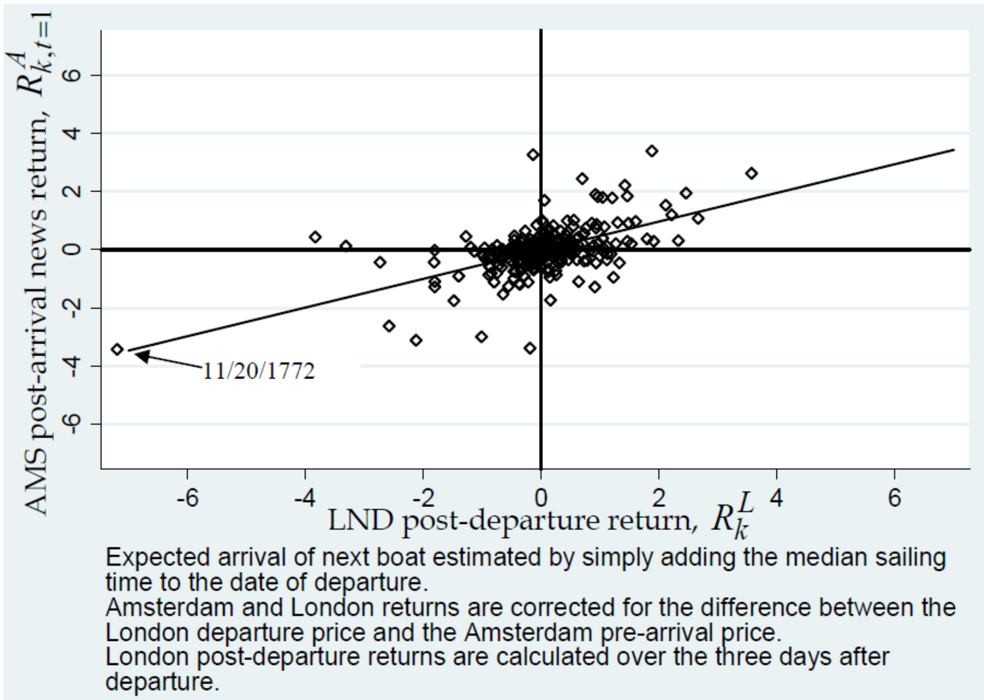


Figure 17: Co-movement LND post-departure and AMS post-arrival news returns - next boat $>$ 3.5 days

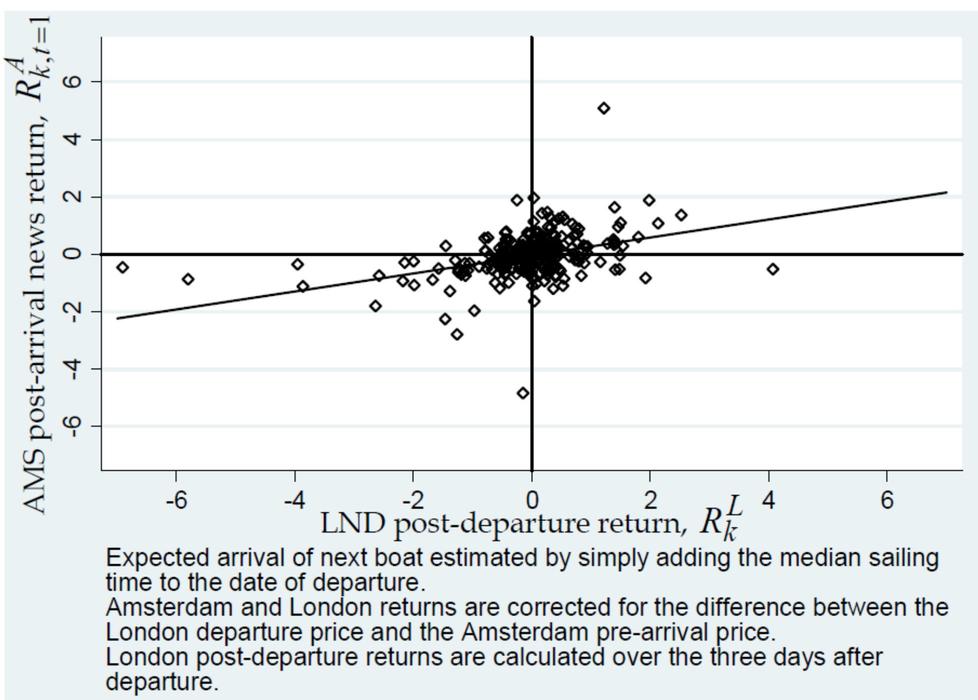
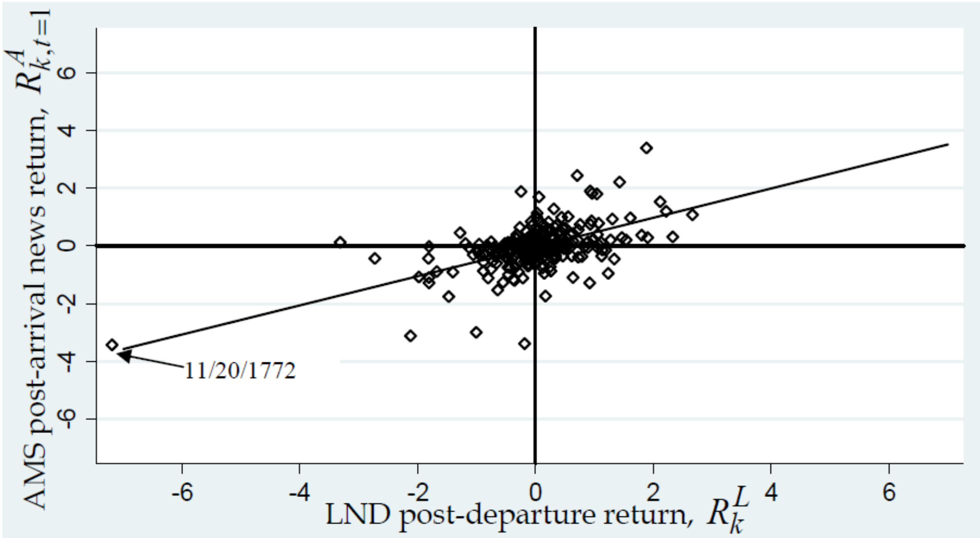
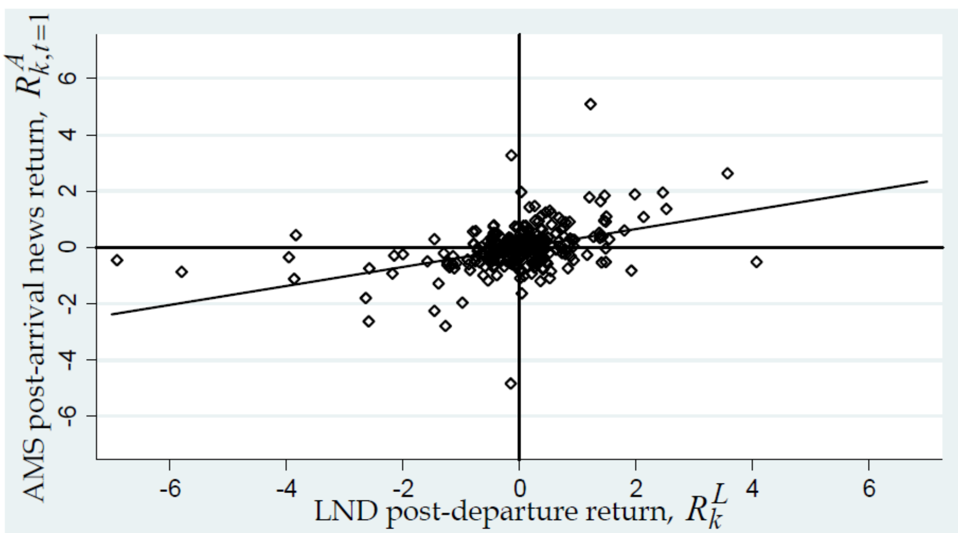


Figure 18: Co-movement LND post-departure and AMS post-arrival news returns - next boat $<$ 3.5 days



Expected arrival of next boat estimated using a duration model with a Gamma distribution including month dummies and a range of weather variables (see text). Amsterdam and London returns are corrected for the difference between the London departure price and the Amsterdam pre-arrival price. London post-departure returns are calculated over the three days after departure.

Figure 19: Co-movement LND post-departure and AMS post-arrival news returns - next boat $>$ 3.5 days



Expected arrival of next boat estimated using a duration model with a Gamma distribution including month dummies and a range of weather variables (see text). Amsterdam and London returns are corrected for the difference between the London departure price and the Amsterdam pre-arrival price. London post-departure returns are calculated over the three days after departure.

Table 11: Co-movement of returns, EIC (alternative $\boldsymbol{R}_k^L$ (1))

	AMS post-arrival news return, $\boldsymbol{R}_{k,t=1}^A$			AMS post-arrival non-news return, $\boldsymbol{R}_{k,t=2}^A$		
	(1a)	(2a)	(3a)	(1b)	(2b)	(3b)
LND post-departure return, $\boldsymbol{R}_k^L$						
2 days after departure	0.388			0.156		
	(0.066)***			(0.072)**		
4 days after departure		0.327			0.228	
		(0.044)***			(0.048)***	
5 days after departure			0.282			0.188
			(0.043)***			(0.035)***
Difference London departure and Amsterdam pre-arrival price, $\boldsymbol{P}_{k-1}^L - \boldsymbol{P}_{k-1}^A$	0.416	0.460	0.452	0.059	0.134	0.128
	(0.037)***	(0.039)***	(0.038)***	(0.040)	(0.040)***	(0.040)***
Constant	0.002	0.011	0.017	-0.032	-0.002	-0.003
	(0.030)	(0.026)	(0.024)	(0.035)	(0.030)	(0.029)
Obs	575	739	752	291	407	417
R2	0.33	0.38	0.37	0.03	0.11	0.12
$\boldsymbol{Chi}^2$ test	5.25	2.09	3.42			
(p-value)	(0.022)	(0.148)	(0.064)			

Estimates of co-movement between London post-departure and Amsterdam post-arrival returns. Estimates are adjusted for possible momentum of the public news innovation by including the difference between the London departure and the Amsterdam pre-arrival price.
See figure ... for exact definitions of returns. London post-departure returns are calculated over the two, four or five days after a boat departure. A $\boldsymbol{Chi}^2$ test is performed on the equality of the $\boldsymbol{R}_k^L$ coefficients in the (*a) and (*b) columns.

***,** denotes statistical significance at the 1, 5% level. Robust, bootstrapped standard errors(1000 replications) are reported in parentheses.

Table 12: Co-movement of returns, EIC (alternative $\boldsymbol{R}_k^L$ (2))

	AMS post-arrival news return, $\boldsymbol{R}_{k,t=1}^A$		
LND post-departure return, $\boldsymbol{R}_k^L$			
3 days after departure excluding the 1st day	0.335 (0.063)***		
4 days after departure excluding the 1st day		0.294 (0.056)***	
5 days after departure excluding the 1st day			0.258 (0.045)***
Difference London departure and Amsterdam pre-arrival price, $\boldsymbol{P}_{k-1}^L - \boldsymbol{P}_{k-1}^A$	0.432 (0.040)***	(0.444) (0.009)***	0.439 (0.039)***
Constant	-0.012 (0.030)	0.009 (0.027)	-0.016 (0.027)
Obs	580	715	736
R2	0.30	0.31	0.31

Estimates of co-movement between London post-departure returns and Amsterdam post-arrival news returns. Estimates are adjusted for possible momentum of the public news innovation by including the difference between the London departure and the Amsterdam pre-arrival price. See figure ... for exact definitions of returns. London post-departure returns are calculated over three, four and five days after a boat departure, excluding the first day.

***,** denotes statistical significance at the 1, 5% level. Robust, bootstrapped standard errors(1000 replications) are reported in parentheses.

Table 13: Co-movement of returns, BoE

	(1) AMS post-arrival news return, $\boldsymbol{R}^A_{k,t=1}$	(2) AMS post-arrival non-news return, $\boldsymbol{R}^A_{k,t=2}$
LND post-departure return, $\boldsymbol{R}^L_k$	0.224	0.268
	(0.046)***	(0.080)***
Difference London departure and Amsterdam pre-arrival price, $\boldsymbol{P}^L_{k-1} - \boldsymbol{P}^A_{k-1}$	0.375	0.116
	(0.037)***	(0.061)**
Constant	0.017	0.019
	(0.015)	(0.026)
Obs	629	315
R2	0.32	0.09
$\boldsymbol{Chi}^2$ test	0.21	
(p-value)	(0.648)	

Estimates of co-movement between London post-departure and Amsterdam post-arrival returns. Estimates are adjusted for possible momentum of the public news innovation by including the difference between the London departure and the Amsterdam pre-arrival price.
See figure ... for exact definitions of returns. London post-departure returns are calculated over the three days after a boat departure. A $\boldsymbol{Chi}^2$ test is performed on the equality of the $\boldsymbol{R}^L_k$ coefficients in columns (1) and (2).

***,** denotes statistical significance at the 1, 5% level. Robust, bootstrapped standard errors (1000 replications) are reported in parentheses.

Table 14: Co-movement of returns, 3% Ann.

	(1) AMS post-arrival news return, $\boldsymbol{R}^A_{k,t=1}$	(2) AMS post-arrival non-news return, $\boldsymbol{R}^A_{k,t=2}$
LND post-departure return, $\boldsymbol{R}^L_k$	0.220 (0.055)***	0.304 (0.081)***
Difference London departure and Amsterdam pre-arrival price, $\boldsymbol{P}^L_{k-1} - \boldsymbol{P}^A_{k-1}$	0.506 (0.044)***	0.176 (0.058)***
Constant	0.017 (0.0173)	0.004 (0.028)
Obs	779	432
R2	0.44	0.13
$\boldsymbol{Chi}^2$ test (p-value)	0.50 (0.480)	

Estimates of co-movement between London post-departure and Amsterdam post-arrival returns. Estimates are adjusted for possible momentum of the public news innovation by including the difference between the London departure and the Amsterdam pre-arrival price.
See figure ... for exact definitions of returns. London post-departure returns are calculated over the three days after a boat departure. A $\boldsymbol{Chi}^2$ test is performed on the equality of the $\boldsymbol{R}^L_k$ coefficients in columns (1) and (2).

*** denotes statistical significance at the 1% level. Robust, bootstrapped standard errors (1000 replications) are reported in parentheses.

Table 15: Co-movement EIC, different expectations next boat, alternative $\boldsymbol{R}_k^L$

	AMS post-arrival news return, $\boldsymbol{R}_{k,t=1}^A$					
London post-departure return, $\boldsymbol{R}_k^L$						
2 days after departure	0.311	0.335				
	(0.089)***	(0.082)***				
4 days after departure			0.265	0.300		
			(0.065)***	(0.093)***		
5 days after departure					0.210	0.230
					(0.049)***	(0.053)***
$\boldsymbol{R}_k^L \times \boldsymbol{E}[\boldsymbol{A}\|\boldsymbol{simple}] < 3.5$	0.145		0.145		0.178	
	(0.128)		(0.093)		(0.083)**	
$\boldsymbol{E}[\boldsymbol{A}\|\boldsymbol{simple}] < 3.5$	0.018		0.017		0.010	
	(0.059		(0.053)		(0.052)	
$\boldsymbol{R}_k^L \times \boldsymbol{E}[\boldsymbol{A}\|\boldsymbol{extended}] < 3.5$		0.127		0.093		0.156
		(0.127)		(0.087)		(0.074)**
$\boldsymbol{E}[\boldsymbol{A}\|\boldsymbol{extended}] < 3.5$		-0.002		-0.020		-0.039
		(0.062)		(0.052)		(0.050)
Difference London departure and Amsterdam pre-arrival price, $\boldsymbol{P}_{k-1}^L - \boldsymbol{P}_{k-1}^A$	0.441	0.441	0.493	0.493	0.488	0.488
	(-0.036)***	(0.036)***	(0.038)***	(0.038)***	(0.036)***	(0.038)***
Constant	-0.009	0.002	-0.003	0.012	0.006	0.025
	(0.041)	(0.047)	(0.036)	(0.037)	(0.035)	(0.036)
Obs	552	552	693	693	702	702
R2	0.35	0.35	0.40	0.40	0.41	0.40

Estimates of co-movement between London post-departure and Amsterdam post-arrival returns. $\boldsymbol{E}[\boldsymbol{A}]$ stands for the expected number of days until the next boat arrival. $\boldsymbol{E}[\boldsymbol{A}|\boldsymbol{simple}]$ is calculated by adding the median sailing time to the departure date of the next boat. $\boldsymbol{E}[\boldsymbol{A}|\boldsymbol{extended}]$ is calculated in a similar way, but here the expected sailing time is estimated in a duration model using a Gamma distribution, including a wide range of weather variables and month dummies (see text).
See figure ... for exact definitions of returns. London post-departure returns are calculated over the two, four or five days after a boat departure. The observation of 20 November 1772 is dropped from the regression analysis to make sure that this outlier does not drive the positive interaction effect (see figure ... in appendix ...). Inclusion of this datapoint leads to slightly higher estimates of the interaction effect.

***, ** denotes statistical significance at the 1, 5% level. Robust, bootstrapped standard errors (1000 replications) are reported in parentheses.

Table 16: Co-movement BoE, different expectations next boat

	AMS post-arrival news return, $\boldsymbol{R}^{A}_{k,t=1}$	
London post-departure return, $\boldsymbol{R}^{L}_{k}$	0.184 (0.065)***	0.213 (0.063)***
$\boldsymbol{R}^{L}_{k} \times \boldsymbol{E}[\boldsymbol{A}\vert\boldsymbol{simple}] < 3.5$	0.156 (0.087)*	
$\boldsymbol{E}[\boldsymbol{A}\vert\boldsymbol{simple}] < 3.5$	0.003 (0.055)	
$\boldsymbol{R}^{L}_{k} \times \boldsymbol{E}[\boldsymbol{A}\vert\boldsymbol{extended}] < 3.5$		0.105 (0.091)
$\boldsymbol{E}[\boldsymbol{A}\vert\boldsymbol{extended}] < 3.5$		0.015 (0.031)
Difference London departure and Amsterdam pre-arrival price, $\boldsymbol{P}^{L}_{k-1} - \boldsymbol{P}^{A}_{k-1}$	0.408 (0.038)***	0.409 (0.039)***
Constant	0.017 (0.022)	0.011 (0.021)
Obs	595	595
R2	0.36	0.35

Estimates of co-movement between London post-departure and Amsterdam post-arrival returns. $\boldsymbol{E}[\boldsymbol{A}]$ stands for the expected number of days until the next boat arrival. $\boldsymbol{E}[\boldsymbol{A}|\boldsymbol{simple}]$ is calculated by adding the median sailing time to the departure date of the next boat. $\boldsymbol{E}[\boldsymbol{A}|\boldsymbol{extended}]$ is calculated in a similar way, but here the expected sailing time is estimated in a duration model using a Gamma distribution, including a wide range of weather variables and month dummies (see text).
See figure ... for exact definitions of returns. London post-departure returns are calculated over three days after a boat departure.

***, * denotes statistical significance at the 1, 10% level. Robust, bootstrapped standard errors (1000 replications) are reported in parentheses.

Table 17: Co-movement 3% Ann., different expectations next boat

	AMS post-arrival news return, $\boldsymbol{R}^A_{k,t=1}$	
London post-departure return, $\boldsymbol{R}^L_k$	0.153 (0.079)***	0.183 (0.083)***
$\boldsymbol{R}^L_k \times \boldsymbol{E}[\boldsymbol{A}\|\boldsymbol{simple}] < 3{:}5$	0.256 (0.109)**	
$\boldsymbol{E}[\boldsymbol{A}\|\boldsymbol{simple}] < 3{:}5$	-0.001 (0.031)	
$\boldsymbol{R}^L_k \times \boldsymbol{E}[\boldsymbol{A}\|\boldsymbol{extended}] < 3{:}5$		0.165 (0.107)
$\boldsymbol{E}[\boldsymbol{A}\|\boldsymbol{extended}] < 3{:}5$		-0.004 (0.035)
Difference London departure and Amsterdam pre-arrival price, $\boldsymbol{P}^L_{k-1} - \boldsymbol{P}^A_{k-1}$	0.578 (0.047)***	0.577 (0.046)***
Constant	0.015 (0.023)	0.014 (0.026)
Obs	721	721
R2	0.51	0.38

Estimates of co-movement between London post-departure and Amsterdam post-arrival returns. $\boldsymbol{E}[\boldsymbol{A}|\boldsymbol{simple}]$ is calculated by adding the median sailing time to the departure date of the next boat. $\boldsymbol{E}[\boldsymbol{A}|\boldsymbol{extended}]$ is calculated in a similar way, but here the expected sailing time is estimated in a duration model using a Gamma distribution, including a wide range of weather variables and month dummies (see text).
See figure ... for exact definitions of returns. London post-departure returns are calculated over three days after a boat departure. The observation of 8 December 1777 is dropped from the regression analysis to make sure that this outlier does not drive the positive interaction effect (see figure ... in appendix ...). Inclusion of this datapoint leads to slightly higher estimates of the interaction effect.

***, ** denotes statistical significance at the 1, 5% level. Robust, bootstrapped standard errors (1000 replications) are reported in parentheses.

Table 18: Co-movement EIC, badweather, alternative $\boldsymbol{R}_k^L$

	AMS post-arrival no-news return, $\boldsymbol{R}_{k,t=2}^A$		
	(1)	(2)	(3)
LND post-departure return, $\boldsymbol{R}_k^L$			
2 days after departure	0.165		
	(0.097)*		
4 days after departure		0.264	
		(0.055)***	
5 days after departure			0.198
			(0.039)***
$\boldsymbol{R}_k^L \times \boldsymbol{badweather}(\boldsymbol{A})$	0.132	0.009	0.079
	(0.178)	(0.126)	(0.124)
$\boldsymbol{badweather}(\boldsymbol{A})$	0.090	0.102	0.092
	(0.142)	(0.104)	(0.103)
Difference London departure and Amsterdam pre-arrival price, $\boldsymbol{P}_{k-1}^L - \boldsymbol{P}_{k-1}^A$	0.106	0.180	0.169
	(0.046)**	(0.043)	(0.044)***
Constant	-0.079	-0.037	-0.038
	(0.035)	(0.032)	(0.032)
Obs - total	303	420	430
Obs - $\boldsymbol{badweather}(\boldsymbol{A})$	53	73	74
R2	0.14	0.14	0.14

Estimates of co-movement between London post-departure and Amsterdam post-arrival non-news returns, conditional on good or bad weather conditions. See the text for a description of bad weather sample (A). See figure ... for exact definitions of returns. London post-departure returns are calculated over two, four or five days after a boat departure.

***, **, * denotes statistical significance at the 1, 5, 10% level. Robust, bootstrapped standard errors (1000 replications) are reported in parentheses.

Table 19: Co-movement BoE, bad weather

	AMS post-arrival no-news return, $\boldsymbol{R}^{A}_{k,t=2}$		
London post-departure return, $\boldsymbol{R}^{L}_{k}$	0.309 (0.089)***	0.281 (0.109)***	0.330 (0.085)***
$\boldsymbol{R}^{L}_{k} \times \boldsymbol{badweather}(\boldsymbol{A})$	0.159 (0.213)		
$\boldsymbol{badweather}(\boldsymbol{A})$	0.021 (0.074)		
$\boldsymbol{R}^{L}_{k} \times \boldsymbol{badweather}(\boldsymbol{B})$		0.164 (0.169)	
$\boldsymbol{badweather}(\boldsymbol{B})$		0.035 (0.049)	
$\boldsymbol{R}^{L}_{k} \times \boldsymbol{badweather}(\boldsymbol{C})$			0.075 (0.306)
$\boldsymbol{badweather}(\boldsymbol{C})$			0.041 (0.051)
Difference London departure and Amsterdam pre-arrival price, $\boldsymbol{P}^{L}_{k-1} - \boldsymbol{P}^{A}_{k-1}$	0.179 (0.125)***	0.188 (0.061)***	0.182 (0.059)***
Constant	0.012 (0.028)	0.003 (0.035)	0.002 (0.033)
Obs - total	327	327	363
Obs - $\boldsymbol{badweather}(\boldsymbol{A})$	59		
Obs - $\boldsymbol{badweather}(\boldsymbol{B})$		106	
Obs - $\boldsymbol{badweather}(\boldsymbol{C})$			59
R2	0.15	0.16	0.12

Estimates of co-movement between London post-departure and Amsterdam post-arrival non-news returns, conditional on good or bad weather conditions. See the text for a description of the three definitions (A, B, and C) of bad weather.
See figure ... for exact definitions of returns. London post-departure returns are calculated over three days after a boat departure.

*** denotes statistical significance at the 1% level. Robust, bootstrapped standard errors (1000 replications) are reported in parentheses.

Table 20: Co-movement 3% Ann., bad weather

	AMS post-arrival no-news return, $\boldsymbol{R}^{A}_{k,t=2}$		
London post-departure return, $\boldsymbol{R}^{L}_{k}$	0.392 (0.122)***	0.357 (0.113)***	0.388 (0.092)***
$\boldsymbol{R}^{L}_{k} \times \boldsymbol{badweather}(\boldsymbol{A})$	-0.037 (0.173)		
$\boldsymbol{badweather}(\boldsymbol{A})$	0.093 (0.084)		
$\boldsymbol{R}^{L}_{k} \times \boldsymbol{badweather}(\boldsymbol{B})$		0.068 (0.193)	
$\boldsymbol{badweather}(\boldsymbol{B})$		0.050 (0.062)	
$\boldsymbol{R}^{L}_{k} \times \boldsymbol{badweather}(\boldsymbol{C})$			-0.057 (0.378)
$\boldsymbol{badweather}(\boldsymbol{C})$			0.052 (0.062)
Difference London departure and Amsterdam pre-arrival price, $\boldsymbol{P}^{L}_{k-1} - \boldsymbol{P}^{A}_{k-1}$	0.207 (0.059)***	0.210 (0.058)***	0.205 (0.060)***
Constant	-0.025 (0.030)	-0.022 (0.033)	-0.025 (0.033)
Obs - total	444	444	444
Obs - $\boldsymbol{badweather}(\boldsymbol{A})$	80		
Obs - $\boldsymbol{badweather}(\boldsymbol{B})$		135	
Obs - $\boldsymbol{badweather}(\boldsymbol{C})$			76
R2	0.16	0.16	0.12

Estimates of co-movement between London post-departure and Amsterdam post-arrival non-news returns, conditional on good or bad weather conditions. See the text for a description of the three definitions (A, B, and C) of bad weather.
See figure ... for exact definitions of returns. London post-departure returns are calculated over three days after a boat departure.

*** denotes statistical significance at the 1% level. Robust, bootstrapped standard errors (1000 replications) are reported in parentheses.

Table 21: Co-movement under different public news shocks, BoE

	Amsterdam post-arrival news return, $\boldsymbol{R}^A_{k,t=1}$		Amsterdam post-arrival non-news return, $\boldsymbol{R}^A_{k,t=2}$	
London post-departure return, $\boldsymbol{R}^L_k$	0.257 (0.058)***	0.250 (0.073)***	0.268 (0.074)***	0.263 (0.094)***
Zero past London post-departure return ($\boldsymbol{R}^L_{k-1} = 0$)	-0.018 (0.037)		0.021 (0.038)	
× London post-departure return, $\boldsymbol{R}^L_k$	-0.058 (0.114)		-0.007 (0.119)	
Past London post-departure return ($\boldsymbol{R}^L_{k-1}$) in 2nd/3rd quartile		-0.028 (0.032)		0.062 (0.045)
× London post-departure return, $\boldsymbol{R}^L_k$		-0.004 (0.089)		0.021 (0.137)
Difference London departure and Amsterdam pre-arrival price, $\boldsymbol{P}^L_{k-1} - \boldsymbol{P}^A_{k-1}$	0.411 (0.038)***	0.411 (0.038)***	0.089 (0.061)	0.086 (0.063)
Constant	0.019 (0.018)	0.032 (0.028)	0.004 (0.028)	-0.022 (0.038)
Obs - total	595	595	296	296
Obs - zero returns	91		41	
Obs - returns in 2nd/3rd quartile		317		148
R2	0.35	0.35	0.08	0.09

Estimates of co-movement between London post-departure and Amsterdam post-arrival non-news returns, conditional on a high or low volatility regime. Low (high) volatility regimes are proxied by $\boldsymbol{R}^L_{k-1}$ (past London post-departure returns) that are (non)zero or are in the 2nd and 3rd (1st and 4th) quartiles.
See figure ... for exact definitions of returns. London post-departure returns are calculated over three days after a boat departure.

*** denotes statistical significance at the 1% level. Robust, bootstrapped standard errors (1000 replications) are reported in parentheses.

Table 22: Co-movement under different public news shocks, 3% Ann.

	Amsterdam post-arrival news return, $\boldsymbol{R}^A_{k,t=1}$		Amsterdam post-arrival non-news return, $\boldsymbol{R}^A_{k,t=2}$	
London post-departure return, $\boldsymbol{R}^L_k$	0.256 (0.066)***	0.253 (0.082)***	0.290 (0.098)***	0.309 (0.113)***
Zero past London post-departure return ($\boldsymbol{R}^L_{k-1} = 0$)	0.026 (0.036)		-0.055 (0.061)	
$\times$ London post-departure return, $\boldsymbol{R}^L_k$	-0.075 (0.111)		-0.055 (0.061)	
Past London post-departure return ($\boldsymbol{R}^L_{k-1}$) in 2nd/3rd quartile		0.011 (0.036)		-0.068 (0.053)
$\times$ London post-departure return, $\boldsymbol{R}^L_k$		-0.013 (0.096)		-0.083 (0.154)
Difference London departure and Amsterdam pre-arrival price, $\boldsymbol{P}^L_{k-1} - \boldsymbol{P}^A_{k-1}$	0.575 (0.046)***	0.574 (0.048)***	0.124 (0.067)*	0.126 (0.072)*
Constant	0.005 (0.022)	0.004 (0.031)	0.015 (0.031)	-0.038 (0.045)
Obs - total	722	722	326	393
Obs - zero returns	130		39	
Obs - returns in 2nd/3rd quartile		367		193
R2	0.50	0.50	0.10	0.10

Estimates of co-movement between London post-departure and Amsterdam post-arrival non-news returns, conditional on a high or low volatility regime. Low (high) volatility regimes are proxied by $\boldsymbol{R}^L_{k-1}$ (past London post-departure returns) that are (non)zero or are in the 2nd and 3rd (1st and 4th) quartiles.
See figure ... for exact definitions of returns. London post-departure returns are calculated over three days after a boat departure.

***, * denotes statistical significance at the 1, 10% level. Robust, bootstrapped standard errors (1000 replications) are reported in parentheses.