.

Appendices for online publication

Appendix A: Mathematical proofs

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Appendix A - mathematical proofs

Proof. of proposition 1.

(i) We conjecture equations (1) to (8) and verify whether this is a unique linear equilibrium.

(ii) Solve for the informed agent's optimization problem by backward induction.

(ii.a) Start in $t = 2$

$$\max_{x_2} x_2 \left(v_0 + \varepsilon - E\left[p_2|\varepsilon\right]\right)$$

The informed agent conjectures that p_2 is given by (4). The first order condition results in (2) with $\beta_2 = \frac{1}{2\lambda_2}$. The second order condition yields

$$\lambda_2 > 0 \tag{28}$$

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

$$\max_{x_1} x_1 \left(v_0 + \varepsilon - E\left[p_1|\varepsilon\right]\right) + \pi E\left[x_2\left(v_0 + \varepsilon - p_2\right)|\varepsilon\right]$$

Again, the agent conjectures that p_1 is given by (3). Plugging in for (2), (3) and (4) and solving for the expectations, this maximization problem can be rewritten as

$$\max_{x_1} x_1(\varepsilon - \lambda_1 x_1) + \frac{\pi}{4\lambda_2}\left[(\varepsilon - \lambda_1 x_1)^2 + \lambda_1^2 \sigma_{u_1}^2\right] \tag{29}$$

The first order condition of this problem yields (1), with β_1 given by (5). The second order condition implies

$$\frac{\pi \lambda_1^2}{2\lambda_2} < 2\lambda_1$$

From second order condition (28) we know that $\lambda_2 > 0$. This implies that $\lambda_1 > 0$ and

$$4\lambda_2 > \pi \lambda_1 \tag{30}$$

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

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

The only signal (apart from v_0) the market maker observes is $y_1 = x_1 + u_1$. He conjectures that $x_1 = \beta_1 \varepsilon$. Because ε and u_1 are independent and normally distributed,

$$v_0 + E\left[\varepsilon|y_1\right] = v_0 + \lambda_1 y_1$$

with λ_1 given by (7). The competitive risk neutral market maker sets prices equal to the expected value of $v_0 + \varepsilon$; this yields (3).

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

In the second period the market maker has two signals available, $y_1 = x_1 + u_1$ and $y_2 = x_2 + u_2$. Again, he guesses that $x_1 = \beta_1 \varepsilon$ and $x_2 = \beta_2 (v_0 + \varepsilon - p_1)$. Under the conjecture that y_1 and y_2 are independent (the proof of this follows under iii.c), we can simply write

$$\begin{aligned} v_0 + E[\varepsilon|y_1, y_2] &= p_1 + E[v_0 + \varepsilon - p_1|y_2] \\ &= p_1 + \lambda_2 y_2 \end{aligned} \tag{31}$$

with $\lambda_2 = \frac{\beta_2 var[\varepsilon|y_1]}{\beta_2^2 var[\varepsilon|y_1] + \sigma_{u_2}^2}$. Using the properties of linear projection, it can be shown that

$$var[\varepsilon|y_1] = (1 - \lambda_1 \beta_1) \sigma_\varepsilon^2 \tag{32}$$

Combining this with $\beta_2 = \frac{1}{2\lambda_2}$ we arrive at (8) and (6).

(iii.c) As a final step of the proof, we need to show that y_1 and y_2 are indeed independent.

Note that

$$cov(y_1, y_2) = \beta_2 \left[\beta_1 (1 - \lambda_1 \beta_1) \sigma_\varepsilon^2 - \lambda_1 \sigma_{u_1}^2\right] \tag{33}$$

Using (7) to rewrite $(1 - \lambda_1 \beta_1)$ as $\frac{\sigma_{u_1}^2}{\beta_1^2 \sigma_\varepsilon^2 + \sigma_{u_1}^2}$ and plugging in for (7), it is straightforward to show that $cov(y_1, y_2) = 0$. ■

Proof. of corollary 2.

(a) $cov(p_1 - v_0, \varepsilon) = \lambda_1 \beta_1 \sigma_\varepsilon^2$

$\lambda_1 > 0$ is a direct result of the informed agent's second order conditions (28) and (30); $\beta_1 > 0$ follows from expression (7) for λ_1 and the fact that $\lambda_1 > 0$.

(b) $cov(p_2 - p_1, \varepsilon) = \lambda_2 \beta_2 (1 - \lambda_1 \beta_1) \sigma_\varepsilon^2$

$\lambda_2 > 0$ follows from the informed agent's second order condition (28); $\beta_2 > 0$ follows from $\lambda_2 > 0$ and $\beta_2 = \frac{1}{2\lambda_2}$. Finally, we need to proof that $(1 - \lambda_1 \beta_1) > 0$. From (5) we can express $\lambda_1 \beta_1$ as

$$\lambda_1 \beta_1 = \frac{\lambda_2 - \frac{1}{2}\pi\lambda_1}{2\lambda_2 - \frac{1}{2}\pi\lambda_1} \tag{34}$$

which indicates that $\lambda_1 \beta_1 \leq \frac{1}{2}$.

(c) $cov(p_2 - p_1, p_1 - v_0) = 0$ follows directly from expressions (3) and (4) for p_1 and p_2 and expression (33). ■

Proof. of corollary 3.

The relevant covariance is given by

$$cov(p_1 - v_0, \varepsilon) = \lambda_1 \beta_1 \sigma_\varepsilon^2$$

It is sufficient to show that

$$\frac{\delta \sqrt{\lambda_1 \beta_1}}{\delta \pi} < 0$$

Start with expression (34) for $\lambda_1\beta_1$. We first multiply denominator and numerator by $\sqrt{\beta_1/\lambda_1}$. Plugging in expression (8) for λ_2 , and noting from (7) that $(1-\lambda_1\beta_1) = \frac{\sigma_{u_1}^2}{\beta_1^2\sigma_\varepsilon^2+\sigma_{u_1}^2}$, we can rewrite (34) as

$$z^2 = \frac{\kappa - \pi z}{2\kappa - \pi z} \tag{35}$$

with

$$z = \sqrt{\lambda_1\beta_1} = \sqrt{\frac{\beta_1^2\sigma_\varepsilon^2}{\beta_1^2\sigma_\varepsilon^2 + \sigma_{u_1}^2}} \tag{36}$$

and

$$\kappa = \sqrt{\sigma_{u_1}^2/\sigma_{u_2}^2} \tag{37}$$

Equation (35) can be rewritten as

$$\pi z^3 - 2\kappa z^2 - \pi z + \kappa = 0$$

Using implicit differentiation, we arrive at the following derivative

$$\frac{\delta\sqrt{\lambda_1\beta_1}}{\delta\pi} = \frac{\delta z}{\delta\pi} = \frac{z(1-z^2)}{\pi(3z^2-1) - 4\kappa z}$$

From expression (36) it is easy to see that $0 < z < 1$, so that the numerator has to be positive. Next, we multiply each side of the second order condition (30) with $\sqrt{\beta_1/\lambda_1}$ and, again noting that $(1-\lambda_1\beta_1) = \frac{\sigma_{u_1}^2}{\beta_1^2\sigma_\varepsilon^2+\sigma_{u_1}^2}$, it follows that

$$2\kappa > \pi z$$

Using this result, it is straightforward to show that

$$\pi\left[(3z^2-1) - \frac{4\kappa z}{\pi}\right] < \pi(z^2-1)$$

Again, from expression (36) we know that $0 < z < 1$, so that $\delta z/\delta\pi < 0$. ■

Proof. of prediction 1.

(a): $\rho^{A|L}/\rho^A > 0$

$\rho^A > 0$ follows directly from equation (15).

From equation (16), $\rho^{A|L}$ can be rewritten as

$$\rho^{A|L} = \Omega^L\left[\rho^A var\left(\theta^A\right) - \rho^L cov(\theta^A, \theta^L)\right] \tag{38}$$

with

$$\Omega^L = \frac{var\left(\theta^L\right)}{var\left(\theta^L\right) var\left(\theta^A\right) - cov\left(\theta^A, \theta^L\right)^2} \tag{39}$$

$\Omega^L > 0$ follows from the assumption that $cov\left(\theta^A, \theta^L\right) < var\left(\theta^i\right)$ for $i = A, L$.

Using (15) and rearranging, this means that $\rho^{A|L} > 0$ is equivalent to

$$\sigma_\varepsilon^2 \left(1 - \frac{cov(\theta^A, \theta^L)}{var\left(\theta^L\right)}\right) > 0$$

Because $cov\left(\theta^A, \theta^L\right) < var\left(\theta^L\right)$, this condition is always met.

(b): $(\rho^L - \rho^{L|A})/\rho^L > 0$

This follows directly from (15), (16) and the fact that $\rho^{A|L} > 0$. ■

Proof. of prediction 2 follows from standard results on omitted variable bias and the fact that $(\rho^L - \rho^{L|A}) > 0$ and $cov\left(p^A_{t+a} - p^L_{t^*}, p^L_{t^*+l} - p^L_{t^*}\right) > 0$. ■

Proof. of prediction 3.

(a) $\delta\left(\rho^{A|L}/\rho^A\right)/\delta\sigma_\zeta^2 < 0$

It is sufficient to show that $\delta\left(\rho^{A|L}/\rho^A\right)/\delta var(\theta^A) < 0$, keeping $var(\theta^L)$ and $cov(\theta^A, \theta^L)$ constant. Using (15), equation (38) can be rewritten as

$$\frac{\rho^{A|L}}{\rho^A} = \Omega^L var\left(\theta^A\right)\left[1 - \frac{cov(\theta^A, \theta^L)}{var\left(\theta^L\right)}\right]$$

where Ω^L is defined by (39). Taking derivatives,

$$\begin{aligned}
\frac{\delta\left(\rho^{A|L}/\rho^A\right)}{\delta var(\theta^A)} &= \left[1 - \frac{cov(\theta^A, \theta^L)}{var\left(\theta^L\right)}\right]\left[\Omega^L + \frac{\delta\Omega^L}{\delta var\left(\theta^A\right)} var\left(\theta^A\right)\right] \\
&= \Omega^L \left[1 - \frac{cov(\theta^A, \theta^L)}{var\left(\theta^L\right)}\right]\left[1 - var(\theta^A)\Omega^L\right] \\
&= -\Omega^L \left[1 - \frac{cov(\theta^A, \theta^L)}{var\left(\theta^L\right)}\right] \frac{cov\left(\theta^A, \theta^L\right)^2}{var\left(\theta^L\right) var\left(\theta^A\right) - cov\left(\theta^A, \theta^L\right)^2}
\end{aligned}$$

where the first step uses the fact that $\delta\Omega^L/\delta var\left(\theta^A\right) = -\left(\Omega^L\right)^2$. Since $cov\left(\theta^A, \theta^L\right) < var\left(\theta^i\right)$, it follows directly that $\delta\left(\rho^{A|L}/\rho^A\right)/\delta var(\theta^A) < 0$.

(b) $\delta\left(\rho^{A|L}/\rho^A\right)/\delta\sigma_\phi^2 > 0$

The proof of this part of the prediction is very similar to part (a) and is left to the reader. ■

Proof. of Lemma 4.

Start with the expression for Γ in equation (22).

(i) First note that the fractions of the different types of matches add up to 1

$$(1-\mu)^2 + 2\mu(1-\mu) + \mu^2 = 1$$

(ii) Second, from (21) we can express $n\gamma_n$ for $n \in \{2, 3, 4\}$ as

$$n\gamma_n = \frac{n\sigma_\varepsilon^2}{\sigma_\eta^2 + (n-1)\sigma_\varepsilon^2}$$

Since, by assumption $\sigma_\eta^2 > \sigma_\varepsilon^2$, it must be the case that $n\gamma_n < 1$ for any integer $n > 0$. In addition, as long as η_i conveys any information about ε, $n\gamma_n > 0$. ■

Proof. of Lemma 5 follows directly from Lemma 4. ■

Proof. of Lemma 6.

Start with the expression for Γ in equation (22). Taking the derivative with respect to μ yields

$$\frac{\delta\Gamma}{\delta\mu} = \begin{array}{c}(1-\mu)(3\gamma_3 - 2\gamma_2) \\ +\mu(4\gamma_4 - 3\gamma_3)\end{array}$$

It is straightforward to show that

$$n\gamma_n - (n-1)\gamma_{n-1} = \frac{\sigma_\eta^2 - \sigma_\varepsilon^2}{\sigma_\varepsilon^2}\gamma_n\gamma_{n-1} > 0 \text{ for any integer } n > 0$$

■

Proof. of Proposition 7.

We solve the model by backward induction.

(i) Start in $t = 2$ when no boat arrives. At that point the single market maker in $t = 1$ will have already provided liquidity to the market, effectively reducing the liquidity shock to $U + x_1$. In $t = 2$ (when no boat arrives) there are $N + 1$ liquidity providers. Because of risk neutrality, the objective function of the market maker who was already present in $t = 1$ is identical to the N new liquidity providers. Since the market makers are risk neutral and compete on quantities, their optimization problem is given by

$$\max_{x_{2,i}} x_{2,i}(v_0 - p_2^{A,nb}) \text{ for } i = 1, ..., N+1$$

where $p_2^{A,nb}$ is determined by the aggregate demand function of the long term investors

$$p_2^{A,nb} = v_0 + \varphi^A \left[(1-\delta)U + x_1 + \sum_{i=1}^{N+1} x_{2,i}^{nb}\right] \tag{40}$$

Imposing symmetry, the liquidity providers' first order condition implies that

$$x_{2,i}^{nb} = x_2^{nb} = -\frac{1}{N+2}\left[(1-\delta)U + x_1\right] \tag{41}$$

Plugging this into (40), we arrive at

$$p_2^{A,nb} = v_0 + \frac{\varphi^A}{N+2}\left[(1-\delta)U + x_1\right] \tag{42}$$

We can derive similar expressions for period $t = 2$ when a boat does arrive:

$$x_{2,i}^b = x_2^b = -\frac{1}{N+M+2}\left[(1-\delta)U + x_1\right] \tag{43}$$

$$p_2^{A,b} = v_0 + \frac{\varphi^A}{N+M+2}\left[(1-\delta)U + x_1\right] \tag{44}$$

(ii) Move back to $t = 1$. The single market maker's maximization problem is given by

$$\max_{x_1} x_1(v_0 - p_1^A) + E_1\left[x_{2,i}(v_0 - p_2^A)\right]$$

where the only source of uncertainty is whether a boat will arrive before or after $t = 2$ (with corresponding probabilities $1 - \pi$ and π). The expected profits for the single market maker from $t = 2$ are determined by prices $p_2^{A,nb}$ and $p_2^{A,b}$ and quantities x_2^{nb} and x_2^b, given by (42), (44), (41), and (43). Plugging those into the expression for expected profits, we arrive at the following maximization problem

$$\max_{x_1} x_1(v_0 - p_1^A) + \varphi^A \Psi\left[(1-\delta)U + x_1\right]^2$$

where Ψ is defined by (27) and price p_1^A is again determined by the aggregate demand function of the long term investors:

$$p_1^A = v_0 + \varphi^A\left[(1-\delta)U + x_1\right] \tag{45}$$

The first order condition of this problem implies that

$$x_1 = -(1-\delta)\frac{1-2\Psi}{2(1-\Psi)}U \tag{46}$$

After plugging (46) into (42), (44) and (45) we arrive at equilibrium prices (24), (25), and (26). ■

Proof. of corollary 8.

(a) $cov(p_1^A - p_0^A, p_1^L - p_0^L) > 0$

Starting from (23) and (24), it is straightforward to show that

$$p_1^A - p_0^A = -\varphi^A(1-\delta)\frac{1-2\Psi}{2(1-\Psi)}U \tag{47}$$

We can derive the price change in London over the same period by substituting δU for $(1-\delta)U$ and φ^L for φ^A, and setting $\pi = 1$ and $N = L$:

$$p_1^L - p_0^L = -\varphi^L\delta\frac{(L+2)^2 - 2}{2\left[(L+2)^2 - 1\right]}U \tag{48}$$

So that

$$cov(p_1^A - p_0^A, p_1^L - p_0^L) = \varphi^A\varphi^L\delta(1-\delta)\frac{1-2\Psi}{2(1-\Psi)}\frac{(L+2)^2 - 2}{2\left[(L+2)^2 - 1\right]}\Sigma^2 \tag{49}$$

It is sufficient to show that

$$\frac{1-2\Psi}{2(1-\Psi)} > 0$$

which follows directly from the fact that $0 < \Psi < 1/4$.

(b) $cov(p_2^{A,nb} - p_1^A, p_1^L - p_0^L) > 0$

Starting from (24) and (25), it is straightforward to show that

$$p_2^{A,nb} - p_1^A = -\varphi^A(1-\delta)\frac{N+1}{2(1-\Psi)(N+2)}U \tag{50}$$

Using (48), we get that

$$cov(p_2^{A,nb} - p_1^A, p_1^L - p_0^L) = \varphi^A \varphi^L \delta(1-\delta) \frac{N+1}{2(1-\Psi)(N+2)} \frac{(L+2)^2 - 2}{2\left[(L+2)^2 - 1\right]} \Sigma^2$$

It is sufficient to show that

$$\frac{N+1}{2(1-\Psi)(N+2)} > 0$$

which, again, follows directly from the fact that $0 < \Psi < 1/4$.

(c) $cov(p_2^{A,nb} - p_1^A, p_1^A - p_0^A) > 0$

This follows directly from (47), (50) and $0 < \Psi < 1/4$. ■

Proof. of corollary 9.

The covariance between $p_1^A - p_0^A$ and $p_1^L - p_0^L$ from (49) can be rewritten as

$$cov(p_1^A - p_0^A, p_1^L - p_0^L) = \frac{1-2\Psi}{2(1-\Psi)} \chi \Sigma^2$$

with

$$\chi = \varphi^A \varphi^L \delta(1-\delta) \frac{(L+1)(L+2)}{2\left[(L+2)^2 - 1\right]} > 0$$

It is straightforward to show that

$$\frac{\delta cov(p_1^A - p_0^A, p_2^L - p_1^L)}{\delta \pi} = -\frac{\chi \Sigma^2}{2(1-\Psi)^2} \frac{\delta \Psi}{\delta \pi}$$

and, from (27),

$$\frac{\delta \Psi}{\delta \pi} > 0$$

■

Proof. of corollary 10.

(a) $cov(p_0^L - v_0, p_1^A - p_0^A) < 0$

The price change in London in $t = 0$ is simply given by

$$p_0^L - v_0 = \varphi^L \delta U \tag{51}$$

Using (47), we arrive at

$$cov(p_0^L - v_0, p_1^A - p_0^A) = -\varphi^L \varphi^A \delta(1-\delta) \frac{1-2\Psi}{2(1-\Psi)} \Sigma$$

Since $0 < \Psi < 1/4$, this expression is negative.

(b) $cov(p_0^L - v_0, p_2^{A,nb} - p_1^A) < 0$

We now use (50) to arrive at

$$cov(p_0^L - v_0, p_2^{A,nb} - p_1^A) = -\varphi^L \varphi^A \delta(1-\delta) \frac{N+1}{2(1-\Psi)(N+2)} \Sigma$$

which, again, is negative since $0 < \Psi < 1/4$. ■

Appendix B - Construction dataset

Conversion of future prices into spots

While London security prices are for spot transactions, prices in Amsterdam refer to future contracts. This raises two issues. First, because of the cost-to-carry component in future prices, it is impossible to directly compare the price levels of spots and futures in the two markets. Second, Amsterdam prices always refer to the future contract ending on the nearest expiration date: February 15, May 15, August 15, or November 15. As a result, around an expiration date the maturity associated with a reported future price discretely jumps from 1 or 2 days to 3 months. This results in occasional spurious increases in future prices.

To solve these issues, I convert Amsterdam future prices into spots using the cost-to-carry rate. Unfortunately, information on short term interest rates (an important element of the cost-to-carry) is scarce. The only available information is based on bills of exchange; unsecured international short term loans (Flandreau et al. 2009). It is possible that counterparty risk differed between contracts. I therefore infer the cost-to-carry rate in an indirect way.

Start with the following expression for log future prices in Amsterdam

$$f_t^A = p_t^A + r_p(\tau)\tau \tag{52}$$

where p_t^A is the (unobserved) log spot price, $r_p(\tau)$ is the cost-to-carry rate during sample period $p \in \{\text{Sep. 1771 - Dec. 1777, Sep. 1783 - Mar 1787}\}$ and τ is the maturity of the futures contract in years ($\tau = \textit{days until expiration}/365$). The cost-to-carry rate $r_p(\tau)$ has a specific term structure that, for simplicity, is assumed to be time invariant within each sample period.[21] Note that this expression differs from the text-book definition as it excludes the dividend yield: in 18$^{\text{th}}$ century Amsterdam dividends accrued to the buyer rather than the seller.

We can approximate $r(\tau)$ using spot prices in London as they were observed in Amsterdam. Consider the price in Amsterdam right after the arrival of a boat from London

$$f_{k,t=1}^A = p_{k,t=1}^A + r_p(\tau)\tau \tag{53}$$

The Amsterdam price captures all information reflected in the London spot price p_{k-1}^L transmitted by that boat (details on timing and notation are in Figure 3). In other words

$$p_{k,t=1}^A = \alpha_0^p + p_{k-1}^L + u_{k,t=1} \tag{54}$$

where α_0^p captures any structural price difference between Amsterdam and London during subperiod p, and u_t is an iid error picking up transitory price differences arising from liquidity shocks or the (noisy) revelation of private information. Combining equations (53) and (54), we arrive at

$$f_{k,t=1}^A - p_{k-1}^L = \alpha_0^p + r_p(\tau)\tau + u_{k,t=1} \tag{55}$$

[21] Unreported results indicate that a time varying term structure leads to very similar results.

I estimate this equation by approximating the yield curve with a third order polynomial:

$$\widehat{r_p(\tau)} = \alpha_1^p + \alpha_2^p \tau + \alpha_3^p \tau^2 + \alpha_4^p \tau^3 \tag{56}$$

Estimates are in Table B.1 and differentiate between two different sample periods (1771-1777 and 1783-1787) and the three individual securities. The results indicate that α_0 is close to zero and tightly estimated. For example, between 1771 and 1777 the EIC price in Amsterdam was on average 0.3% higher than in London. The 95% interval lies between 0.15 and 0.44%. This indicates that structural price differences between the two markets were small. Average annualized cost-to-carry rates (for a period of 3 months) are in the ballpark of 2% (1771-1777) or 7% (1783-1787). The only exception are the 3% Annuities for which the cost-to-carry appears to be slightly negative between 1771 and 1777. The term structure is upward sloping. As a final step I use the estimated $\widehat{r_p(\tau)}$ to convert Amsterdam future prices into spots, i.e.:

$$\widehat{p_{k,t=1}^A} = f_{k,t=1}^A - \widehat{r_p(\tau)}\tau$$

The choice of specific conversion procedure does not affect the empirical results presented in the paper. As a case in point, Table B.2 replicates the results from Table 1 using non-adjusted future returns. As discussed before, the raw return series features spurious price increases on days that the maturity of the reported future contract changed. The regressions in Table B.2 include dummies to adjust for this. Panel (A) reports results for Amsterdam news returns, $R_{k,t=1}^A$. The regressions account for possible changes in the maturity of the futures contract during current period $k, t = 1$ and lagged period $k - 1$. Panel (B) looks at Amsterdam no-news returns, $R_{k,t=2}^A$. These regressions account for possible changes in the maturity during current period $k, t = 2$ and lagged period $k, t = 2$.

Results are very similar to those in Table 1 in the main text. The key coefficients on the London post-departure return R_k^L only differ marginally. As before, Amsterdam returns exhibit negative (rather than positive) autocorrelation, while there is some continuation of London news returns into no-news periods.[22]

Data cleaning procedures

Apart from the conversion of future into spot prices, the paper uses the raw data provided by the historical newspapers. There are two exceptions. First, whenever there was a clear typo in the newspaper the information was adjusted. For example, if a price changed from 138.5 to 188.25

[22] The dummies capturing maturity changes have coefficients that are (approximately) consistent with the cost-to-carry estimates from Table B.1. For example, for the EIC the average news return after a change in maturity from 1 or 2 days to 3 months is 0.7% between 1771 and 1777 and 2.7% between 1783 and 1787. This roughly translates into annualized cost-to-carry rates of 3.0 and 11.4% respectively. These are very close to the 2.5 and 8.2% reported in Table B.1.

and back to 138, I replace the 188.25 with 138.25. Similarly, whenever I find a date that clearly has the wrong year or month, I change this to the correct date. Second, for the EIC, I omit returns in Amsterdam and London associated with a speech English prime-minister Fox gave in Parliament on November 18, 1783, announcing that the EIC's finances were in a deplorable state and that no government bailout would be forthcoming. The impact on the EIC price in London and Amsterdam was dramatic, with an instantaneous price fall of 14%. This is 18 standard deviations from the mean of the EIC return distribution and a clear outlier in the regressions. See Koudijs (2015) for more details.

Additional References

Flandreau, M., Galimard C., Jobst, C., Nogues Marco, P. (2009). 'The Bell Jar: Commercial Interest Rates between Two Revolutions, 1688–1789', In: Atack, J., Neal, L. (eds). *The Origin and Development of Financial Markets and Institutions from the Seventeenth to Twenty-First Century.* Cambridge UP, pp. 161–208.

Table B.1: Cost-to-carry estimates

	Sep. 1771 - Dec. 1777			Sep. 1783 - Mar 1787		
	(1)	(2)	(3)	(4)	(5)	(6)
	EIC	BoE	3% Ann.	EIC	BoE	3% Ann.
α_1^p: time until maturity τ	-0.046	-0.058	-0.041	-0.028	0.052	0.103
	(0.048)	(0.027)**	(0.026)	(0.103)	(0.067)	(0.098)
α_2^p: $\tau * \tau$	1.108	1.247	0.718	1.542	-0.131	-1.251
	(0.886)	(0.507)**	(0.505)	(1.705)	(1.274)	(1.690)
α_3^p: $\tau * \tau^2$	-8.382	-8.225	-5.211	-8.764	0.781	9.804
	(5.862)	(3.476)**	(3.412)	(10.537)	(8.554)	(10.781)
α_4^p: $\tau * \tau^3$	20.327	17.554	11.559	17.422	-0.463	-21.674
	(12.507)	(7.614)**	(7.356)	(21.512)	(18.251)	(22.604)
Constant (α_0^p)	0.003	0.002	0.000	0.004	0.003	0.003
	(0.001)***	(0.000)***	(0.000)	(0.002)**	(0.001)**	(0.002)*
N	576	579	578	287	283	285
Adj R^2	0.013	0.019	0.036	0.363	0.274	0.333
$\widehat{r_p(\tau)}$: implied annualized interest rates at different maturities τ						
1.5 months	0.12	0.36	-1.01	6.18	4.69	5.75
3 months	2.47	1.40	-0.66	8.20	6.08	6.43

This Table presents cost-to-carry estimates from regressing price differences between Amsterdam future and London spot prices in logs ($f^A_{k,t=1} - p^L_{k-1}$) on the time until maturity in Amsterdam in years ($\tau = \textit{days until expiration}/365$, where τ lies between 1 day and 3 months). The estimated annualized cost-to-carry over a given period τ is given by $\widehat{r_p(\tau)} = \alpha_1^p + \alpha_2^p\tau + \alpha_3^p\tau^2 + \alpha_4^p\tau^3$ where the coefficients are allowed to differ across sample periods: $p \in \{$Sep. 1771 - Dec. 1777, Sep. 1783 - Mar 1787$\}$. The constant α_0^p captures any structural price level differences between Amsterdam and London. For example, between 1771 and 1777 Amsterdam EIC prices were on average 0.3% higher than in London. ***, **, * denote statistical significance at the 1, 5, and 10% level. Robust, bootstrapped standard errors are reported in parentheses.

Table B.2: Co-movement - non-adjusted returns

Panel (A): Dep. variable: Amsterdam post-arrival *news* returns, $R^A_{k,t=1}$						
	EIC		BoE		3% Annuities	
	(1)	(2)	(3)	(4)	(5)	(6)
London post-departure	0.288	0.300	0.185	0.229	0.220	0.245
returns, R^L_k	(0.060)***	(0.048)***	(0.078)**	(0.055)***	(0.104)**	(0.073)***
London pre-departure		0.400		0.487		0.600
returns, R^L_{k-1}		(0.049)***		(0.063)***		(0.066)***
Lagged London pre-		-0.023		0.055		0.082
departure returns, R^L_{k-2}		(0.044)		(0.055)		(0.055)
Lagged Amsterdam		-0.156		-0.317		-0.384
returns, R^A_{k-1}		(0.080)*		(0.057)***		(0.064)***
$Change\ maturity_{k,t=1}$	0.731	0.733	0.588	0.562	0.222	0.062
	(0.239)***	(0.236)***	(0.150)***	(0.158)***	(0.166)	(0.140)
$Change\ maturity_{k,t=1}$	2.005	2.207	1.707	1.642	1.884	2.117
$*post-1782$	(0.265)***	(0.250)***	(0.163)***	(0.171)***	(0.185)***	(0.152)***
$Change\ maturity_{k-1}$		-0.169		-0.205		-0.135
		(0.250)		(0.103)*		(0.111)
$Change\ maturity_{k-1}$		0.746		1.174		1.041
$*post-1782$		(0.398)*		(0.265)***		(0.278)***
$post-1782$	-0.086	-0.208	0.005	-0.043	0.026	-0.094
	(0.091)	(0.078)***	(0.067)	(0.056)	(0.083)	(0.056)*
Constant	0.057	0.061	0.013	0.012	0.030	0.020
	(0.039)	(0.030)**	(0.019)	(0.016)	(0.019)	(0.018)
Obs.	585	570	558	544	663	646
Adj. R^2	0.143	0.361	0.099	0.400	0.064	0.427

Table B.2 continued

Panel (B): Dep. variable: Amsterdam post-arrival *no-news* returns, $R^A_{k,t=2}$						
	EIC		BoE		3% Annuities	
	(1)	(2)	(3)	(4)	(5)	(6)
London post-departure	0.209	0.228	0.288	0.272	0.305	0.295
returns, R^L_k	(0.056)***	(0.052)***	(0.073)***	(0.063)***	(0.088)***	(0.081)***
London pre-departure		0.129		0.055		0.171
returns, R^L_{k-1}		(0.052)**		(0.063)		(0.071)**
Lagged Amsterdam		-0.110		-0.177		-0.149
returns, $R^A_{k,t=1}$		(0.067)*		(0.069)**		(0.067)**
$Change\ maturity_{k,t=2}$	0.159	0.126	0.303	0.306	-0.231	-0.230
	(0.132)	(0.122)	(0.182)*	(0.180)*	(0.090)**	(0.073)***
$Change\ maturity_{k,t=2}$	1.707	2.287	1.739	2.477	2.536	2.818
$*post-1782$	(0.726)**	(0.318)***	(0.839)**	(0.250)***	(0.677)***	(0.578)***
$Change\ maturity_{k,t=1}$		-0.151		-0.063		-0.124
		(0.211)		(0.123)		(0.178)
$Change\ maturity_{k,t=1}$		0.484		0.553		0.680
$*post-1782$		(0.271)*		(0.193)***		(0.308)**
$post-1782$	0.238	0.177	-0.019	-0.046	0.053	0.027
	(0.085)***	(0.085)**	(0.063)	(0.070)	(0.074)	(0.076)
Constant	-0.095	-0.081	-0.010	0.003	-0.030	-0.015
	(0.035)***	(0.036)**	(0.023)	(0.023)	(0.025)	(0.024)
Obs.	310	306	282	277	374	368
Adj. R^2	0.228	0.286	0.274	0.366	0.254	0.313

Estimates of co-movement between London post-departure and Amsterdam post-arrival returns. Figure 3 gives the exact definitions of returns. London post-departure returns are calculated over the three days after a boat departure. Amsterdam returns are non-adjusted future returns. The variable *Change maturity* is a dummy that turns on when the maturity of the reported future's contract changes from 1 or 2 days to 3 months. This captures a spurious positive return of 1/4 of the cost-to-carry rate. The interaction between *Change maturity* and the post-1782 dummy picks up any differences in the cost-to-carry rate between the two sample periods (1771-1777 and 1783-1787). ***,**, and * denote statistical significance at the 1, 5, and 10% level. Robust, bootstrapped standard errors are reported in parentheses.

Appendix C: Smugglers

Another alternative source of information could have been smuggling. Before 1784, there was rampant smuggling from Holland to England; especially in tea (up to 1784 England charged high tariffs on tea imports, Cole 1958). It is unclear whether Dutch smugglers were able to bring back information that was more current than the official news. To avoid being caught, they usually off-loaded their goods on remote beaches (Platt 2011). Local roads were in bad condition and news to these places travelled only slowly (Lewins 1865). Smugglers themselves seem to have relied on official packet boats to transmit information across the North Sea (Platt 2011, p. 30). Even if smugglers did bring in relevant information, it is not clear that this information reached Amsterdam before the official mail. Dutch smugglers were predominantly based in Flushing (Mui and Mui 1968) and getting a piece of news from Flushing to Amsterdam took more than 2 days (Le Jeune 1851, p. 247-252).

There is a simple way to test the impact of this potential channel. In 1784 the English decided to reduce tariffs on tea. This news became public in May 1784 (Mui and Mui 1961, p. 520). This significantly reduced smuggling between Holland and England (Cole 1958). If smuggling was an important information channel one would therefore expect that the co-movement of security prices in Amsterdam and London would fall after May 1784. I run the following regression

$$R^A_{k,t=2} = \alpha_0 + \alpha_1 R^L_k + \alpha_2 R^L_k \times post - tariffs + \alpha_3 post - tariffs + X_{k,t=2} + u_{k,t=2}$$

where the post-tariff dummy has a value of 1 starting in May 1784 and $X_{k,t=2}$ includes past returns in Amsterdam and London. Coefficient α_2 picks up the effect of the absence of smuggling. If smuggling was important before 1784, we would expect that $\alpha_2 < 0$. Table C.1 indicates that is not the case. If anything, co-movement was stronger after the reduction of tea duties.

Additional References

Cole, W.A., 'Trends in Eighteenth-Century Smuggling', in: *The Economic History Review*, 10-3 (1958)

Mui, H-C and L.H. Mui, 'William Pitt and the Enforcement of the Commutation Act', in: *The English Historical Review* (1961)

Mui, H-C and L.H. Mui, 'Smuggling and the British Tea Trade before 1784', in: *The American Historical Review*, 74-1 (1968)

Platt, R., *Smuggling in the British Isles: A History*, London: History Press Limited (2011)

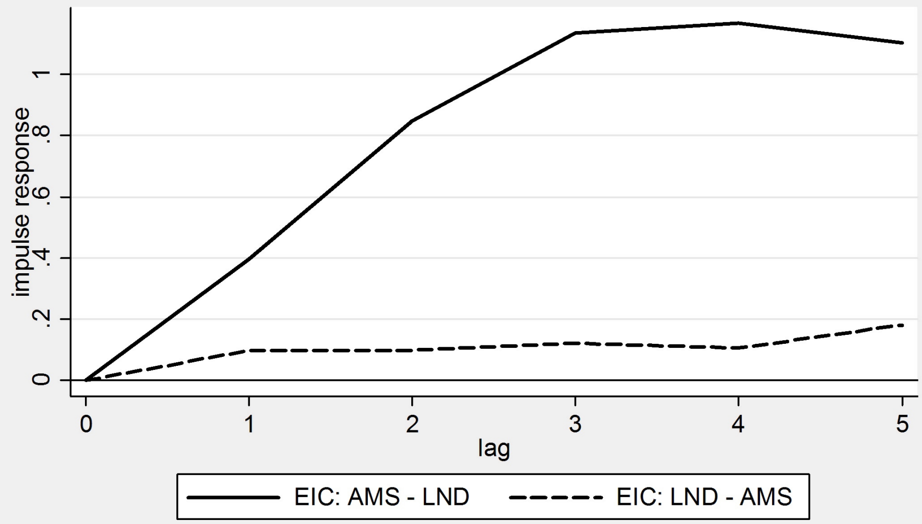
Table C.1: Co-movement - smugglers

Dep. variable: Amsterdam post-arrival no-news returns, $R^A_{k,t=2}$			
	EIC	BoE	3% Ann.
	(1)	(2)	(3)
London post-departure returns, R^L_k	0.204	0.277	0.268
	(0.057)***	(0.072)***	(0.099)***
$*post-tariffs$	0.198	0.066	0.051
	(0.162)	(0.170)	(0.189)
$post-tariffs$	0.207	0.103	0.160
	(0.084)**	(0.072)	(0.072)**
London pre-departure returns, R^L_{k-1}	0.136	0.087	0.184
	(0.053)**	(0.069)***	(0.077)***
Lagged Amsterdam returns, $R^A_{k,t=1}$	-0.136	-0.209	-0.188
	(0.066)**	(0.076)***	(0.072)***
Constant	-0.061	0.001	-0.015
	(0.034)*	(0.025)	(0.026)
Obs.	306	277	368
Adj. R^2	0.163	0.132	0.126

Estimates of co-movement between London post-departure and Amsterdam *no-news* returns. The table checks whether co-movement falls after the reduction in British tea duties in May 1784. This is captured by the interaction between R^L_k and the post-tariff dummy. ***,**, and * denote statistical significance at the 1, 5, and 10% level. Robust, bootstrapped standard errors are reported in parentheses.

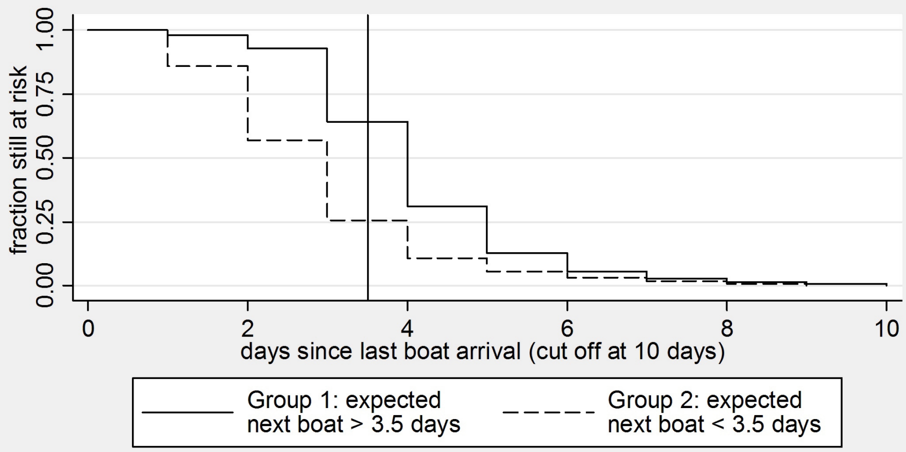
Appendix D - additional figures and tables

Figure D.1: Impulse response functions AMS-LND, EIC



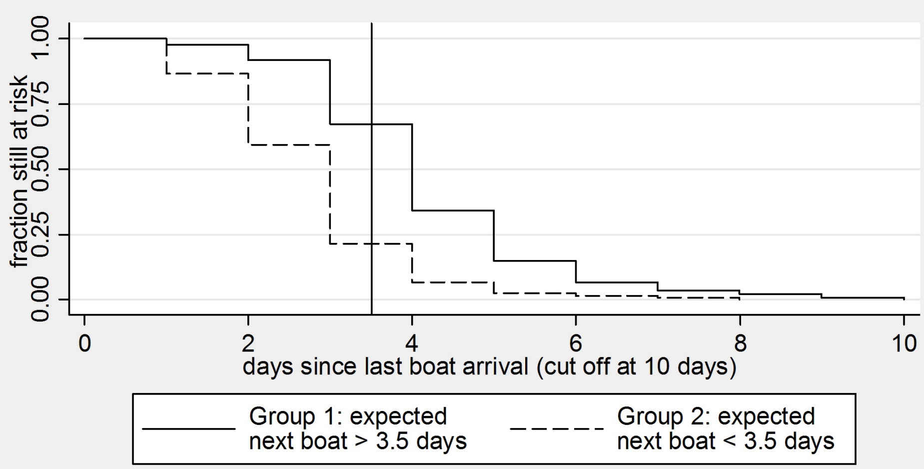
Impulse response estimates of innovations in London prices on Amsterdam prices and vice versa.
Non-orthogonalized one sd innovations, estimated in a VECM with 5 lags
September 1771 - December 1777 & September 1783 - March 1787 (1498 obs)
One lag corresponds to 2 or 3 days (Mon-Wed, Wed-Fri or Fri-Mon)

Figure D.2: Kaplan-Meier estimates - arrival next boat (simple model)



Evaluation precision estimate of the time until next boat arrival.
Expected arrival of next boat estimated by adding the median sailing time to the date a boat was scheduled to depart.
The vertical black line indicates the unconditionally expected time until the next boat arrival 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 D.3: Kaplan-Meier estimates - arrival next boat (extended duration model)



Evaluation precision estimate of the time until next boat arrival.
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 until the next boat arrival 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.

Table D.1: Co-movement EIC - different definitions A

Dep. variable:	Amsterdam post-arrival news returns, $R^A_{k,t=1}$ (EIC)			Amsterdam post-arrival no-news returns, $R^A_{k,t=2}$ (EIC)		
	(1)	(2)	(3)	(4)	(5)	(6)
London post-departure	0.341	0.257	0.217	0.206	0.217	0.167
returns, R^L_k	(0.068)***	(0.043)***	(0.040)***	(0.074)***	(0.048)***	(0.036)***
London pre-departure	0.391	0.397	0.388	0.137	0.155	0.142
returns, R^L_{k-1}	(0.043)***	(0.044)***	(0.043)***	(0.058)***	(0.052)***	(0.055)**
Lagged London pre-	-0.027	-0.018	-0.027			
departure returns, R^L_{k-2}	(0.046)	(0.041)	(0.043)			
Lagged Amsterdam	-0.118	-0.128	-0.116	-0.122	-0.085	-0.079
returns, R^A_{k-1} or $R^A_{k,t=1}$	(0.087)	(0.069)*	(0.068)*	(0.081)	(0.064)	(0.064)
Constant	0.046	0.051	0.056	-0.033	0.010	0.020
	(0.030)	(0.027)	(0.028)	(0.034)	(0.031)	(0.030)
Obs.	505	624	632	263	354	360
Adj. R^2	0.331	0.313	0.300	0.084	0.118	0.112

The table replicates the baseline estimates for EIC stock from Table 1, using different definitions for post-departure returns in London. They are calculated over different periods: cols 1 and 4: 2 days, cols 2 and 5: 4 days, columns 1 and 6: 5 days. ***,**, and * denote statistical significance at the 1, 5, and 10% level. Robust bootstrapped standard errors are reported in parentheses.

Table D.2: Co-movement EIC - different definitions B

Dep. variable:	Amsterdam post-arrival news returns, $R^A_{k,t=1}$ (EIC)			Amsterdam post-arrival no-news returns, $R^A_{k,t=2}$ (EIC)		
	(1)	(2)	(3)	(4)	(5)	(6)
London post-departure	0.290	0.210	0.180	0.301	0.215	0.167
returns, R^L_k	(0.064)***	(0.049)***	(0.045)***	(0.085)***	(0.058)***	(0.042)***
London pre-departure	0.393	0.403	0.393	0.112	0.133	0.129
returns, R^L_{k-1}	(0.052)***	(0.044)***	(0.046)***	(0.060)*	(0.055)**	(0.054)**
Lagged London pre-	-0.026	-0.019	-0.027			
departure returns, R^L_{k-2}	(0.048)	(0.043)	(0.042)			
Lagged Amsterdam	-0.132	-0.096	-0.091	-0.088	-0.042	-0.055
returns, R^A_{k-1} or $R^A_{k,t=1}$	(0.083)	(0.065)	(0.065)	(0.070)	(0.064)	(0.061)
Constant	0.041	0.049	0.055	-0.016	0.017	0.029
	(0.033)	(0.029)*	(0.027)**	(0.037)	(0.033)	(0.031)
Obs.	504	611	623	249	341	353
Adj. R^2	0.264	0.259	0.255	0.129	0.098	0.097

The table replicates the baseline estimates for EIC stock from Table 1, using different definitions for post-departure returns in London. They are calculated over different periods after a boat departure. In all cases the first day of a period is omitted. Cols 1 and 4: 3 days, cols 2 and 5: 4 days, cols 3 and 6: 5 days. ***,**, and * denote statistical significance at the 1, 5, and 10% level. Robust bootstrapped standard errors are reported in parentheses.

Table D.3: Co-movement - Amsterdam as source of information; different expectations next boat

Dep. variable: London post-arrival news returns, $R^L_{k,t=1}$						
	EIC		BoE		3% Annuities	
	(1)	(2)	(3)	(4)	(5)	(6)
Amsterdam post-departure	0.061	0.059	0.095	0.088	0.075	0.069
returns, R^A_k	(0.074)	(0.089)	(0.083)	(0.094)	(0.065)	(0.079)
$*E[A\|simple] < 3.5$ days	0.014		-0.037		-0.064	
	(0.110)		(0.097)		(0.073)	
$*E[A\|extended] < 3.5$ days		0.014		-0.018		-0.038
		(0.107)		(0.106)		(0.089)
$E[A\|simple] < 3.5$ days	0.044		0.027		0.074	
	(0.078)		(0.043)		(0.038)*	
$E[A\|extended] < 3.5$ days		0.003		-0.001		0.053
		(0.076)		(0.043)		(0.038)
Amsterdam pre-departure	0.046	0.047	0.134	0.132	0.108	0.109
returns, R^A_{k-1}	(0.044)	(0.044)	(0.056)**	(0.055)**	(0.037)***	(0.037)***
Lagged Amsterdam pre-	-0.001	-0.000	0.044	0.042	0.058	0.056
departure returns, R^A_{k-2}	(0.048)	(0.048)	(0.050)	(0.052)	(0.042)	(0.042)
Lagged London	-0.089	-0.089	-0.055	-0.053	-0.105	-0.102
returns, R^L_{k-1}	(0.090)	(0.089)	(0.085)	(0.087)	(0.059)*	(0.057)*
Constant	0.033	0.047	0.007	0.018	-0.020	-0.021
	(0.047)	(0.058)	(0.027)	(0.031)	(0.025)	(0.029)
Obs.	593	593	589	589	824	824
Adj. R^2	0.00	0.00	0.02	0.02	0.03	0.03

Estimates of co-movement between Amsterdam post-departure and London post-arrival *news* returns. $E[A]$ stands for the expected number of days until the next boat arrival. $E[A|simple]$ is calculated by adding the median sailing time to the departure date of the next boat. For $E[A|extended]$ the median sailing time is replaced by a conditionally expected sailing time which is estimated in a duration model, using a Gamma distribution, including a no-go zone dummy and month dummies (see main text). ***, **, and * denote statistical significance at the 1, 5, and 10% level. Robust, bootstrapped standard errors are reported in parentheses.

Table D.4: Co-movement - alternative definitions for favorable winds

Dep. variable: Amsterdam post-arrival no-news returns, $R^A_{k,t=2}$						
	EIC		BoE		3% Annuities	
	(1)	(2)	(3)	(4)	(5)	(6)
London post-departure	0.343	0.351	0.366	0.289	0.241	0.220
returns, R^L_k	(0.0.78)***	(0.111)***	(0.144)**	(0.101)***	(0.117)**	(0.131)*
$*favorable$ (B)	-0.140		-0.099		0.123	
	(0.109)		(0.164)		(0.175)	
$*favorable$ (C)		-0.124		0.010		0.145
		(0.133)		(0.126)		(0.178)
$favorable$ (B)	-0.076		-0.010		-0.033	
	(0.067)		(0.049)		(0.084)	
$favorable$ (C)		-0.233		-0.133		-0.084
		(0.091)**		(0.059)**		(0.076)
London pre-departure	0.151	0.154	0.107	0.105	0.202	0.194
returns, R^L_{k-1}	(0.057)***	(0.059)***	(0.072)	(0.073)	(0.080)**	(0.079)**
Lagged Amsterdam	-0.141	-0.133	-0.209	-0.204	-0.204	-0.194
returns, $R^A_{k,t=1}$	(0.073)*	(0.067)**	(0.077)***	(0.077)***	(0.073)***	(0.074)***
Constant	0.028	0.174	0.027	0.132	-0.007	0.089
	(0.057)	(0.084)	(0.041)	(0.052)	(0.049)	(0.070)
Obs.	306	306	277	277	368	368
Adj. R^2	0.143	0.153	0.124	0.134	0.114	0.116
Obs. with non-favorable	99	46	91	44	115	52

Estimates of co-movement between London post-departure and Amsterdam post-arrival *no-news* returns. Co-movement is made conditional on having favorable winds or not ("favorable"). The baseline coefficients measure co-movement during periods with non-favorable winds. The interaction term captures any additional co-movement during periods with favorable winds. The table uses definitions B and C for favorable winds (see main text for details). The table lists the number of observations with non-favorable wind conditions. The baseline coefficients are based on this (limited) number of observations. See Figure 3 for exact definitions of returns. London post-departure returns are calculated over three days after a boat departure. ***,**, and * denote statistical significance at the 1, 5, and 10% level. Robust, bootstrapped standard errors are reported in parentheses.

Table D.5: Co-movement - zero returns in Amsterdam

Dep. variable: Amsterdam post-arrival no-news returns, $R^A_{k,t=2}$			
	EIC	BoE	3% Ann.
	(1)	(2)	(3)
London post-departure returns, R^L_k	0.245	0.299	0.332
	(0.061)***	(0.073)***	(0.112)***
$*I(R^A_{k,t=1} = 0)$	0.123	0.020	-0.085
	(0.216)	(0.173)	(0.165)
$I(R^A_{k,t=1} = 0)$	-0.067	0.010	-0.057
	(0.093)	(0.048)	(0.050)
London pre-departure returns, R^L_{k-1}	0.146	0.099	0.200
	(0.054)***	(0.071)	(0.079)**
Lagged Amsterdam returns, $R^A_{k,t=1}$	-0.141	-0.212	-0.194
	(0.070)**	(0.076)***	(0.075)***
Constant	-0.017	0.018	0.035
	(0.033)	(0.028)	(0.033)
Obs.	306	277	368
Adj. R^2	0.133	0.121	0.114
Obs. with $R^A_{k,t=1} = 0$	45	67	106

This table presents co-movement estimates for Amsterdam *no-news* returns that are conditional on whether the preceding Amsterdam *news* return was zero or not: $I(R^A_{k,t=1} = 0)$. The interaction term measures whether there is less co-movement if $R^A_{t=1} = 0$. London post-departure returns are calculated over three day periods. The table reports the the number of observations associated with zero returns in Amsterdam. ***, **, and * denote statistical significance at the 1, 5, and 10% level. Robust, bootstrapped standard errors are reported in parentheses.

Table D.6: Likelihood of zero returns - expectations next boat

Dep. variable: Amsterdam post-arrival news returns zero or not, $R^A_{k,t=1} = 0$						
	EIC		BoE		3% Annuities	
	(1)	(2)	(3)	(4)	(5)	(6)
	Logit	Probit	Logit	Probit	Logit	Probit
$E[A\|extended] < 3.5$ days	-0.009	-0.009	0.025	0.025	0.015	0.041
	(0.028)	(0.028)	(0.035)	(0.035)	(0.039)	(0.109)
Obs.	591	591	591	591	591	591

Logit or probit estimates predicting whether an Amsterdam *news* return is zero depending on whether the next boat is expected to arrive within 3.5 days or not. Marginal effects: the estimates give the change in probability from moving from $E[A|extended] > 3.5$ days to $E[A|extended] < 3.5$ days. ***,**, and * denote statistical significance at the 1, 5, and 10% level. Robust, bootstrapped standard errors are reported in parentheses.

Table D.7: Co-movement - expectation next boat and weather conditions

Dep. variable: Amsterdam post-arrival news returns, $R^A_{k,t=1}$			
	EIC	BoE	3% Ann.
	(1)	(2)	(3)
London post-departure returns, R^L_k	0.286	0.261	0.317
	(0.135)**	(0.139)*	(0.190)*
$*E[A\|extended] < 3.5$ days	0.225	0.299	0.178
	(0.099)**	(0.101)***	(0.135)
∗Rain during at least 1 daily obs.	0.014	-0.058	-0.195
	(0.140)	(0.149)	(0.159)
∗Total daily rainfall	0.001	-0.003	0.033
	(0.020)	(0.037)	(0.038)
∗Max. wind speed during the day	-0.027	-0.030	-0.037
	(0.035)	(0.036)	(0.066)
$E[A\|extended] < 3.5$ days	-0.007	-0.041	-0.110
	(0.057)	(0.034)	(0.037)***
London pre-departure returns, R^L_{k-1}	0.397	0.493	0.607
	(0.043)***	(0.064)***	(0.064)***
Lagged London pre-departure returns, R^L_{k-2}	-0.029	0.061	0.081
	(0.043)	(0.051)	(0.055)
Lagged Amsterdam returns, $R^A_{k,t=1}$	-0.156	-0.320	-0.390
	(0.071)**	(0.056)***	(0.064)***
Constant	0.063	0.105	0.055
	(0.087)	(0.045)	(0.051)
Obs.	570	544	646
Adj. R^2	0.33	0.36	0.42

Estimates of co-movement between Amsterdam post-departure and London post-arrival *news* returns. $E[A|extended]$ stands for the expected number of days until the next boat. This is calculated using the sailing schedule and a duration model with a flexible Gamma distribution that includes a number of weather variables and month dummies (see main text for details). The regression includes interaction terms between London post-departure returns and three weather variables: whether there was rain during some point in the day, total daily rainfall (in mm, mean: 1.28; sd: 3.03 and the maximum wind speed (in Beaufort; mean: 2.85; st. dev.: 1.23). To preserve space, the level-coefficients on the weather variables are omitted. ***,**, and * denote statistical significance at the 1, 5, and 10% level. Robust, bootstrapped standard errors are reported in parentheses.

Appendix E - theoretical model feedback effects

In section 3.4 I analyze the impact of price discovery in Amsterdam on price changes in London in a simple reduced form model. This appendix presents a full-fledged theoretical model in which the London insider takes the impact of price discovery in Amsterdam into account when deciding how to trade. Under a number of reasonable assumptions, the predictions from both models are equivalent.

Predictions 1 and 2 of the reduced form model are general and hold for any setup in which price discovery in Amsterdam and London is not perfectly correlated. Prediction 3 is more ambiguous, especially part 3b. This states that the weight that the London market puts on price changes in Amsterdam should increase in the precision of that signal. It is not immediately obvious that this prediction holds in a full theoretical model.

The reasoning is as follows. The moment the price signal from Amsterdam becomes more informative, the incentives for the London insider change. Because news from Amsterdam will now reveal a large part of the insider's signal, the London insider will trade more aggressively before price changes in Amsterdam are communicated to the Amsterdam market. This makes London prices more informative and, as a result, the London market will put less weight on the Amsterdam signal. In other words, there are two counteracting effects. Keeping the London insider's trading rule constant, the London market will put more weight on the Amsterdam signal if it becomes more informative. However, if that is the case the London insider has an incentive to trade more aggressively and the London signal will also become more informative. This decreases the weight on the Amsterdam signal. It is unclear, ex ante, which of the two effects dominate.

The theoretical model shows that under reasonable parameter values the first effect dominates and prediction 3b of the simple reduced form model continues to hold. The intuition is as follows. Suppose that the profits for the London insider *after* the arrival of news from Amsterdam are relatively small to begin with. In that case, the additional updating of the London market based on the Amsterdam signal will only marginally affect the insider's overall profits. As a result, the optimal trading strategy of the London insider *before* the arrival of news from Amsterdam will not significantly change. Neither will the informativeness of London price changes before the arrival of news.

How reasonable is the assumption that profits after the arrival of news from Amsterdam are relatively small? Results in section 3.4 show that on average it took 10 days for a London private signal to "bounce off" from Amsterdam. The evidence also suggests that, after 12 days, the private information was fully incorporated into London prices. This suggests that, after the arrival of a boat from Amsterdam, the London insider had limited time to trade on the (remainder of) a given private signal. In relative terms, the insider profits that could be made during these final 3 days were probably small.

Setup model

A single asset with payoff $v_0 + \varepsilon$, where $\varepsilon \sim N(0, \Sigma_0)$, is traded in two markets: Amsterdam (A) and London (L). In both markets there are two periods of trade, $t = 1, 2$. Markets are imperfectly integrated. In both markets there is a single informed agent.

Figure D.4 illustrates the details of the model. (1) We start in London at the beginning of $t^L = 1$. Nature decides on the value of ε. This information is privately observed by a London insider who immediately transmits this information to his Amsterdam agent. He trades on his private information during the remainder of period $t^L = 1$. (2) The Amsterdam agent receives the private information at the beginning of period $t^A = 1$. During periods $t^A = 1, 2$ he trades on the private signal. Right after period $t^A = 1$, information about Amsterdam prices is sent to the London market. (3) This either arrives in London right after the conclusion of period $t^L = 1$ (probability $1-\pi$) or it delayed and arrives in London after a subsequent period $t^L = 2$ (probability $1-\pi$). The arrival of news from Amsterdam is a public event and is both observed by the London market maker and the London insider. (4) The London insider trades on the remainder of his private information during period $t^L = 2$. I write $t^L = 2^*$ if the Amsterdam signal is received *before* the start of this second period. The optimal trading strategy of the informed agent is different in $t^L = 2$ and $t^L = 2^*$. (5) After period $t^L = 2/t^L = 2^*$, the true value of ε is publicly revealed in London. This information is immediately transmitted to Amsterdam where it arrives after period $t^A = 2$.

[FIGURE D.4 ABOUT HERE]

Insiders submit trading orders x_t^i, where i denotes $\{A, L\}$. In addition to informed trading, there is a continuum of uniformed noise or liquidity traders who exogenously submit trading orders. Aggregate orders u_t^i are iid, uncorrelated and $u_t^i \sim N(0, \sigma^2_{u_t^i})$. Uninformed trades in London in $t = 2/t = 2^*$ are the same regardless of whether information arrived from Amsterdam or not. Informed and uninformed trades are submitted to a risk neutral competitive market maker who sets prices equal to the expected value of the asset, $p_t^i = v_0 + E\left[\varepsilon | I_t^i\right]$. See tables D.8 and D.9.

Table D.8: Setup model - Amsterdam

		$t^A = 1$	$t^A = 2$
$E\left[v \mid I_t^A\right]$	begin	v_0	p_1^A
	end	$p_1^A = v_0 + E\left[\varepsilon_t \mid x_1^A + u_1^A\right]$	$p_2^A = p_1^A + E\left[v_0 + \varepsilon_t - p_1^A \mid x_2^A + u_2^A\right]$

The most interesting updating rule for the market maker is the case where the London market receives information from Amsterdam right after period $t^L = 1$. Before period $t^L = 2^*$ begins, the market maker observes two different prices, p_1^L and p_1^A. The market maker weighs both signals with α^A and α^L. The main focus of this appendix is on the properties of α^A.

Table D.9: Setup model - London

			prob. π	prob. $(1-\pi)$
		$t^L = 1$	$t^L = 2$	$t^L = 2^*$
$E\left[v \mid I_t^L\right]$	begin	v_0	p_1^L	$p_{1*}^L = \alpha^A p_1^A + \alpha^L p_1^L$
	end	$p_1^L = v_0 +$ $E\left[\varepsilon_t \mid x_1^L + u_1^L\right]$	$p_2^L = p_1^L +$ $E\left[v_0 + \varepsilon_t - p_1^L \mid x_2^L + u_2^L\right]$	$p_{2*}^L = p_{1*}^L +$ $E\left[v_0 + \varepsilon_t - p_{1*}^L \mid x_{2*}^L + u_2^L\right]$

Equilibrium

I analyze the situation where both the London insider and his Amsterdam agent maximize profits for the two markets individually. This means that the Amsterdam agent does not take the impact of his trades on informed profits in London into account. This is a simplifying assumption. The results of this approximation should be close to a full fledged version of the model as long as the profits in London in period $t = 2/t = 2^*$ are relatively small. As discussed before, this is a reasonable assumption.

The equilibrium is constructed as follows. I first assume that a linear equilibrium exists in which the insider trades are linear in the information. More specifically

$$x_1^i = \beta_1^i \varepsilon \tag{57}$$

$$x_2^A = \beta_2^A \left(v_0 + \varepsilon - p_1^A\right) \tag{58}$$

$$x_2^L = \beta_2^L \left(v_0 + \varepsilon - p_1^L\right) \tag{59}$$

$$x_{2*}^L = \beta_{2*}^L \left(v_0 + \varepsilon - p_{1*}^L\right) \tag{60}$$

Given these linear policies, the market makers' optimal updating rules can be written as

$$p_1^i = v_0 + \lambda_1^i (x_1^i + u_1^i) \tag{61}$$

$$p_2^A = p_1^A + \lambda_2^A (x_2^A + u_2^A) \tag{62}$$

$$p_2^L = p_1^L + \lambda_2^L (x_2^L + u_2^L) \tag{63}$$

$$p_{1*}^L = \alpha^A p_1^A + \alpha^L p_1^L \tag{64}$$

$$p_{2*}^L = p_{1*}^L + \lambda_{2*}^L (x_{2*}^L + u_2^L) \tag{65}$$

where

$$\lambda_1^i = \frac{\beta_1^i \Sigma_0}{\left(\beta_1^i\right)^2 \Sigma_0 + \sigma_{u_1^i}^2}$$

$$\lambda_2^i = \frac{1}{2}\sqrt{\frac{\Sigma_1^i}{\sigma_{u_2^i}^2}}, \ \lambda_{2*}^L = \frac{1}{2}\sqrt{\frac{\Sigma_{1*}^L}{\sigma_{u_2^L}^2}}$$

$$\alpha^A = \frac{\Sigma_{1*}^L}{\Sigma_1^A}, \ \alpha^L = \frac{\Sigma_{1*}^L}{\Sigma_1^L} \tag{66}$$

Σ_1^i and Σ_{1*}^L indicate the uncertainty of the market maker's estimate of ε after observing the aggregate order flows:

$$\begin{aligned}
\Sigma_1^i &= var\left[p_1^i | I_1^i\right] = (1-\beta_1^i\lambda_1^i)\Sigma_0 \\
\Sigma_{1*}^L &= var\left[p_{1*}^L | I_1^A, I_1^L\right] = \frac{\Sigma_0\Sigma_1^A\Sigma_1^L}{\Sigma_0\left(\Sigma_1^A+\Sigma_1^L\right)-2\Sigma_1^A\Sigma_1^L}
\end{aligned} \tag{67}$$

We can now turn to the optimal behavior of the two insiders and check whether their optimal policies are indeed as described by equations (57) to (60). The Amsterdam agent maximizes

$$\max_{x_1^A, x_2^A} E\left[x_1^A\left(v_0+\varepsilon-p_1^A\right)+x_2^A\left(v_0+\varepsilon-p_2^A\right)|\varepsilon\right]$$

and the London agent maximizes

$$\max_{x_1^L, x_2^L, x_{2*}^L} E\left[x_1^L\left(v_0+\varepsilon-p_1^A\right)+\pi x_2^L\left(v_0+\varepsilon-p_2^L\right)+(1-\pi)\,x_{2*}^L\left(v_0+\varepsilon-p_{2*}^L\right)|\varepsilon\right]$$

Plugging in for prices from equations (61) to (65), it can indeed be shown that (57) to (60) hold with

$$\begin{aligned}
\beta_1^A &= \frac{1-\lambda_1^A\beta_2^A}{2\lambda_1^A-\left(\lambda_1^A\right)^2\beta_2^A} \\
\beta_1^L &= \frac{-1+\pi\lambda_1^L\beta_2^L+(1-\pi)\,\alpha^L\lambda_1^L\left(1-\alpha^A\lambda_1^A\beta_1^A\right)\beta_{2*}^L}{-2\lambda_1^L+\pi\left(\lambda_1^L\right)^2\beta_2^L+(1-\pi)\,(\alpha^L\lambda_1^L)^2\beta_{2*}^L} \\
\beta_2^i &= \sqrt{\frac{\sigma_{u_2^i}^2}{\Sigma_1^i}},\ \beta_{2*}^L=\sqrt{\frac{\sigma_{u_2^L}^2}{\Sigma_{1*}^L}}
\end{aligned}$$

Comparative statics

In what follows I revisit predictions 3a and 3b from the simple reduced form model of section 3.4. Prediction 3 relates the weight that the London market maker puts on the Amsterdam price signal (α^A) to the informativeness of p_1^L and p_1^L. The informativeness of these prices can be summarized by Σ_1^L and Σ_1^A. The smaller Σ_1^i the more informative prices are.

In the model Σ_1^i is determined by the relative size of $\sigma_{u_1^i}^2$ with respect to $\sigma_{u_2^i}^2$. For example, if $\sigma_{u_1^i}^2$ is relatively large, then potential informed profits from period $t^i=1$ are relatively large as well. There is more noise trading that the informed agent can benefit from. As a result, the informed agent trades aggressively in this period $t^i=1$ and saves only a small fraction of his informational advantage for period $t^i=2$, making prices after period $t^i=1$ become more informative.

Prediction 3a: α^A *should be decreasing in the informativeness of* p_1^L, $\delta\alpha^A/\delta\Sigma_1^L>0$.
Proof. Follows from expressions (66) and (67). ■

If the London signal becomes more informative, the London market maker will put less weight on the Amsterdam signal.[23]

Prediction 3b: α^A *should be increasing in the informativeness of* p_1^A*:* $\delta\alpha^A/\delta\Sigma_1^A < 0$.

The proof of this prediction is split up in a number of steps. First of all, keeping Σ_1^L constant ($\overline{\Sigma_1^L}$) it is easy to show that

Lemma 11

$$\frac{\delta\alpha^A(\overline{\Sigma_1^L})}{\delta\Sigma_1^A} < 0$$

Proof. Follows from expressions (66) and (67). ■

However, Σ_1^L is not constant and is affected by Σ_1^A. In fact it can be shown that

Lemma 12

$$\frac{\delta\Sigma_1^L}{\delta\Sigma_1^A} > 0$$

Proof. Numerical verification ■

The intuition for this result is that the London insider changes his trading behavior if p_1^A becomes more informative; potential insider profits from the second period $t^L = 2^*$ fall. As a result, the insider will save less of his informational advantage and trade more aggressively in period $t^L = 1$. This leads to a smaller Σ_1^L. For its part this will lead to a smaller α^A.

What is the net effect of these two lemmas?

Proposition 13 *As long as potential insider profits during period* $t = 2/t = 2^*$ *are relatively small (large* π*, large* $\sigma^2_{u_1^L}$*, and/or large* $\sigma^2_{u_1^A}$*) then*

$$\frac{\delta\alpha^A}{\delta\Sigma_1^A} < 0$$

Proof. Numerical results in figure D.5 ■

Potential insider profits from period $t = 2/t = 2^*$ are relatively small as long as $\sigma^2_{u_1^L}$ is large. In this case, the additional updating of the London market maker based on p_1^A will be relatively unimportant for the insider's optimal trading strategy in period $t^L = 1$: Lemma 10 dominates. If $\sigma^2_{u_1^A}$ is large, the Amsterdam signal will be highly informative to begin with and this decreases the potential insider profits from $t = 2^*$ even further. This reduces the level of $\sigma^2_{u_1^L}$ for which $\delta\alpha^A/\delta\Sigma_1^A < 0$.

[23] Note that in this (simplified) version of the model, Σ_1^A is effectively kept constant. The Amsterdam insider does not take his impact on London profits into consideration. If he would do so, changes in Σ_1^L would affect optimal informed trading in Amsterdam in period $t^A = 1$ and thus the informativeness of Amsterdam prices Σ_1^A. This effect is likely to be small if insider profits in London after the arrival of a boat are small.

[FIGURE D.5 ABOUT HERE]

Figure D.5 is drawn for $\pi = 0$. This is a scenario in which it is certain that the Amsterdam signal will arrive in London after $t^L = 1$. This is the case where the Amsterdam price has the biggest impact on the London insider's trading strategy in period $t^L = 1$. For larger values of π Amsterdam prices become less important and the parameter space in Figure D.5 where $\delta\alpha^A/\delta\Sigma_1^A < 0$ is larger.

Figure D.4: Setup - feedback model

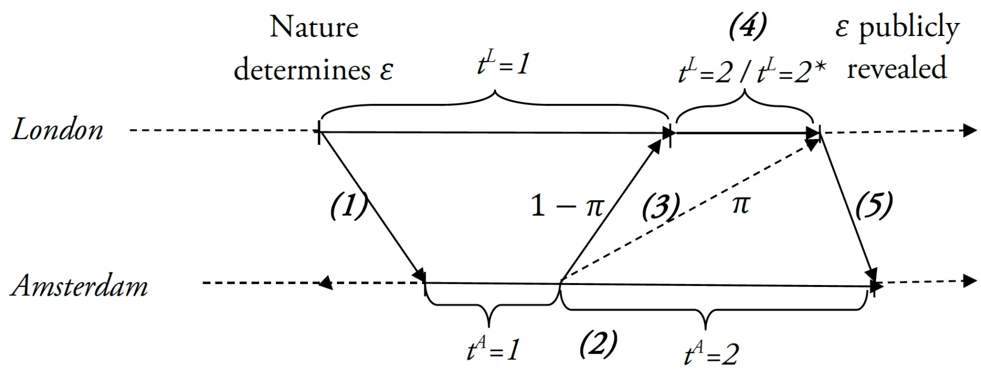


Figure D.5: Prediction 3B