Appendices for online publication

Appendix A: mathematical proofs

Appendix B: additional figures and tables

Appendix C: theoretical model feedback effects

Appendix A - mathematical proofs

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 $t = 2$

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

with p_2 defined by (4). The first order condition results in (2) with $\beta_2 = \frac{1}{2\lambda_2}$. The second order condition yields $\lambda_2 > 0$.

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

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

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

$$\frac{1}{4\lambda_2} \left[(\varepsilon - \lambda_1 x_1)^2 + \lambda_1^2 \sigma_{u_1}^2 \right]$$

The first order condition gives (1), with β_1 given by (5). The second order condition yields

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

From the second order condition from $t = 2$, we know that $\lambda_2 > 0$. This implies that $\lambda_1 > 0$. In addition,

$$4\lambda_2 > \pi \lambda_1 \tag{15}$$

(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 $y_1 = \beta_1 \varepsilon + u_1$. Because ε and u_1 are independent and normally distributed,

$$E [\varepsilon | y_1] = \lambda_1 y_1$$

with λ_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, $y_1 = \beta_1 \varepsilon + u_1$ and $y_2 = \beta_2 [\varepsilon - (p_1 - v_0)] + u_2$. If y_1 and y_2 are independent (proof of this follows), we can simply write

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

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

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

$$var [\varepsilon | p_1 - v_0] = (1 - \lambda_1 \beta_1) \sigma_\varepsilon^2$$

(3c) Proof of independence of y_1 and y_2

Note that

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

Using (7) to rewrite $(1-\lambda_1\beta_1)$ it can be shown that $cov\,(y_1, y_2) = 0$. ■

Proof. of corollary 2.

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

$\lambda_1 > 0$ because of the second order conditions for the informed agent (see proof of proposition 1).

$\beta_1 > 0$ follows from (7) and $\lambda_1 > 0$. ■

Proof. of corollary 3.

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

$\lambda_2 > 0$ because of the second order conditions for the informed agent in $t = 2$ (see proof of proposition 1).

$\beta_2 > 0$ follows from $\lambda_2 > 0$ and $\beta_2 = \frac{1}{2\lambda_2}$.

$(1-\lambda_1\beta_1) > 0$ follows from

$$\lambda_1\beta_1 = \frac{1}{2}\frac{\lambda_2 - \frac{1}{2}\pi\lambda_1}{\lambda_2 - \frac{1}{4}\pi\lambda_1}$$

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

Proof. of corollary 4.

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

It is sufficient to show that

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

Start with expression (5) for β_1. Using expressions (7) and (8) for λ_1 and λ_2 (and rearranging) this can be rewritten as

$$z^2 = \frac{\theta - \pi z}{2\theta - \pi z} \tag{16}$$

with

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

and

$$\theta = \sqrt{\frac{\sigma_{u_1}^2}{\sigma_{u_2}^2}}$$

Equation (16) can be rewritten as

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

Using implicit differentiation it can be shown that

$$\frac{\delta z}{\delta\pi} = \frac{z(1-z^2)}{\pi(3z^2-1) - 4\theta z}$$

By definition $0 < z < 1$, so the numerator is positive. Using expressions (7) and (8) for λ_1 and λ_2 (and rearranging) the second order condition from (15) can be rewritten as

$$\frac{\theta}{\pi} > \frac{1}{2}z$$

and it can be shown that

$$\pi\left[(3z^2-1)-4\frac{\theta}{\pi}z\right]<0$$

since

$$z^2<1$$

■

Proof. of prediction 1

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

$\rho^A>1$ follows directly from equation (11).

$\rho^{A|L}$ from equation (12) can be rewritten as

$$\rho^{A|L}=\Omega^L\left[\rho^A var\left(\theta^A\right)-\rho^L cov(\theta^A,\theta^B)\right] \tag{17}$$

with

$$\Omega^L=\frac{var\left(\theta^L\right)}{var\left(\theta^L\right)var\left(\theta^A\right)-cov\left(\theta^A,\theta^L\right)^2} \tag{18}$$

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

Using (11) and rearranging, this means that $\rho^{A|L}>0$ is equivalent to

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

Note that as long as $cov\left(\theta^A,\theta^L\right)<var\left(\theta^L\right)$ this condition is met.

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

This follows directly from (12) and $\rho^{A|L}>0$. ■

Proof. of predictions 3a and 3b

Using, (11) equation (17) can be rewritten as

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

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

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

Using (18) it can be shown that

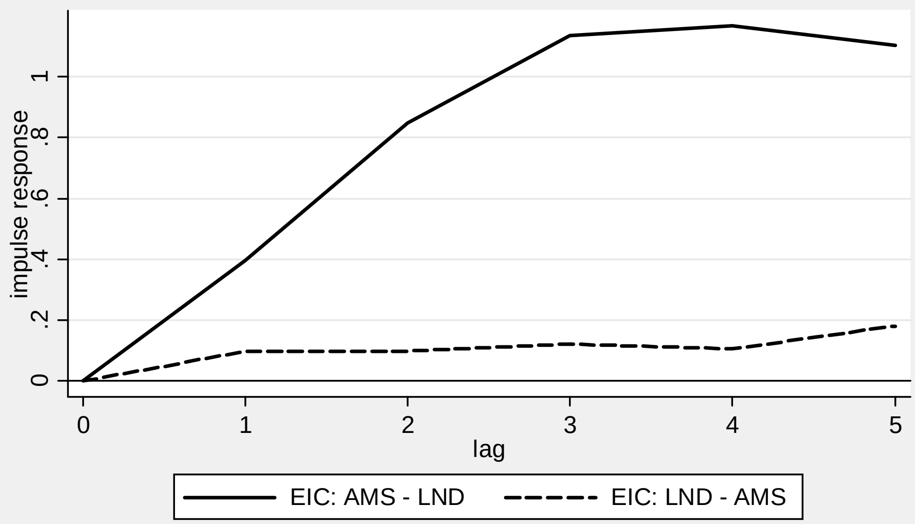
$$\begin{aligned}\frac{\delta\left[\frac{\rho^{A|L}}{\rho^A}\right]}{\delta var(\theta^A)} &= \Omega^L\left[1-\frac{cov(\theta^A,\theta^B)}{var\left(\theta^L\right)}\right]\left[1-var(\theta^A)\Omega^L\right]\\ &= -\Omega^L\left[1-\frac{cov(\theta^A,\theta^B)}{var\left(\theta^L\right)}\right]\frac{cov\left(\theta^A,\theta^L\right)^2}{var\left(\theta^L\right)var\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

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

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

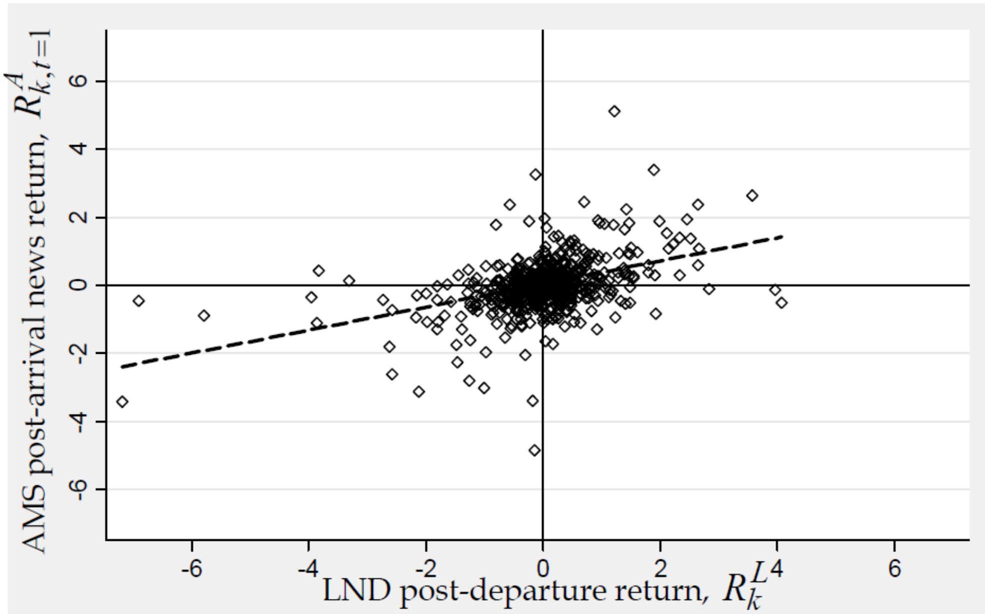
Appendix B - additional figures and tables

Figure 14: Impulse response functions AMS-LND, EIC



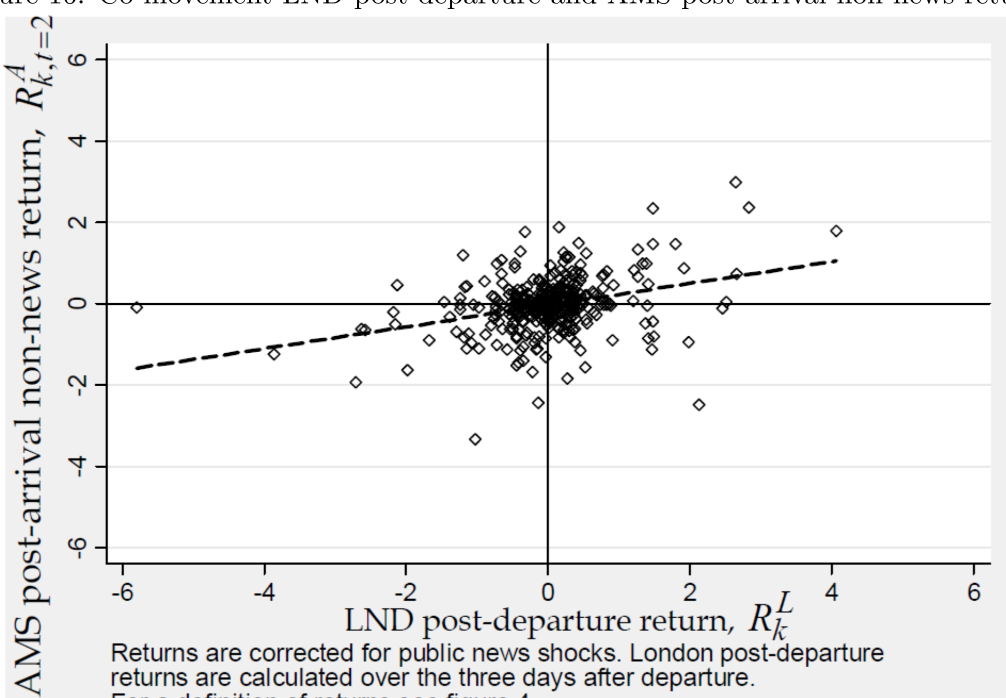
Impulse response estimates of innovations in London prices on Amsterdam prices and vice versa.
Non-orthogonalized one sd innovations, estimated in a VECM with 5 lags
September 1771 - December 1777 & September 1783 - March 1787 (1498 obs)
One lag corresponds to 2 or 3 days (Mon-Wed, Wed-Fri or Fri-Mon)

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



Returns are corrected for public news shocks. London post-departure returns are calculated over the three days after departure.
For a definition of returns see figure 4.

Figure 16: Co-movement LND post-departure and AMS post-arrival non-news returns



Returns are corrected for public news shocks. London post-departure returns are calculated over the three days after departure.
For a definition of returns see figure 4.

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

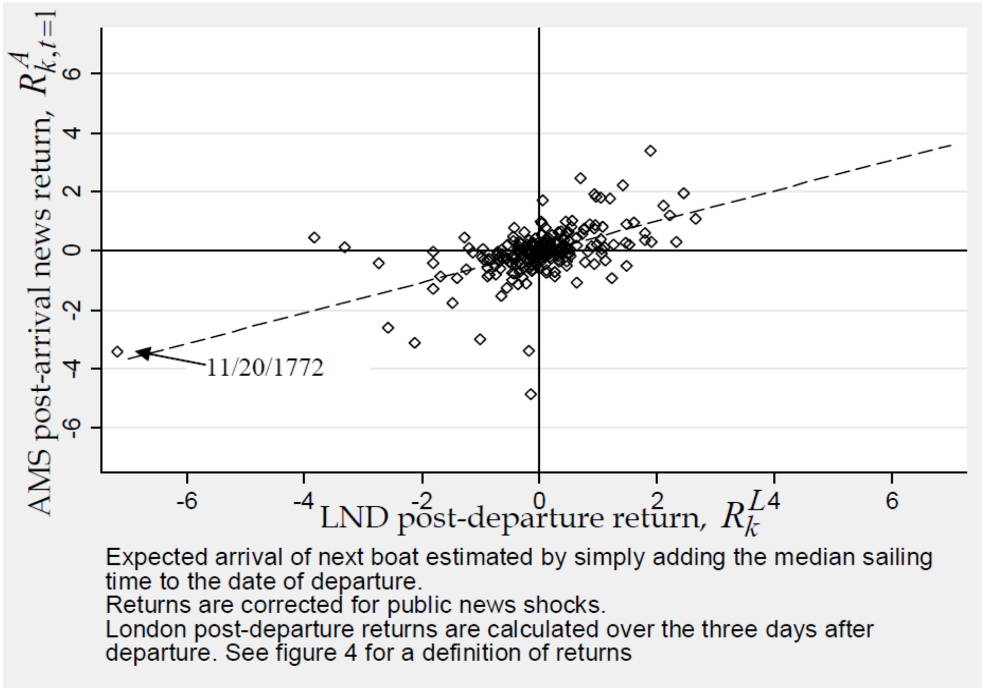


Figure 18: Co-movement LND post-departure and AMS post-arrival news returns - next boat > 3.5 days

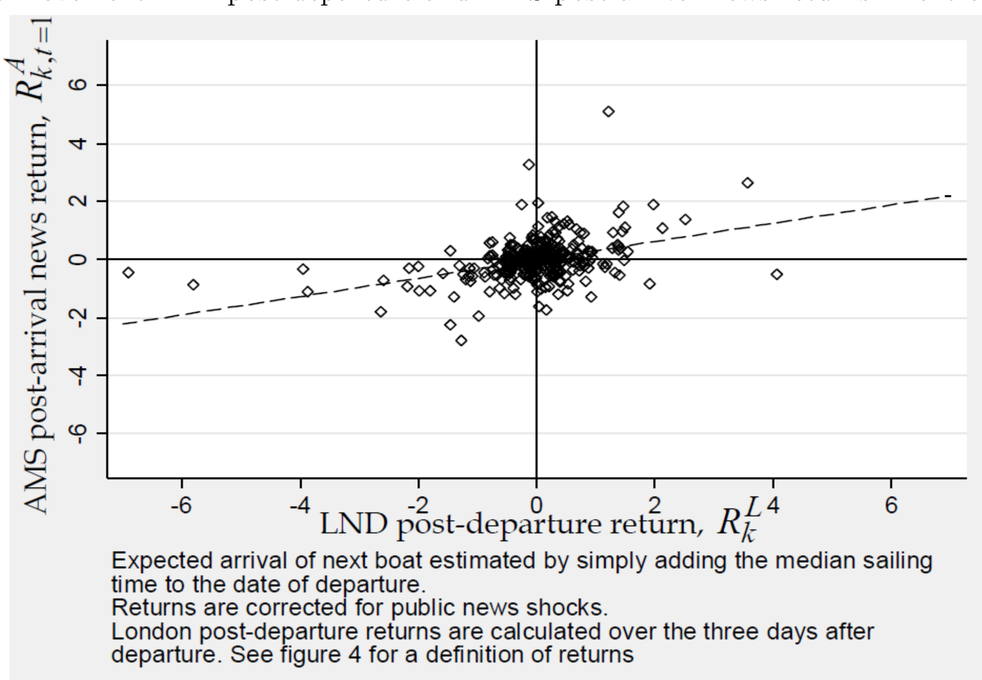


Figure 19: Co-movement LND post-departure and AMS post-arrival news returns - next boat < 3.5 days

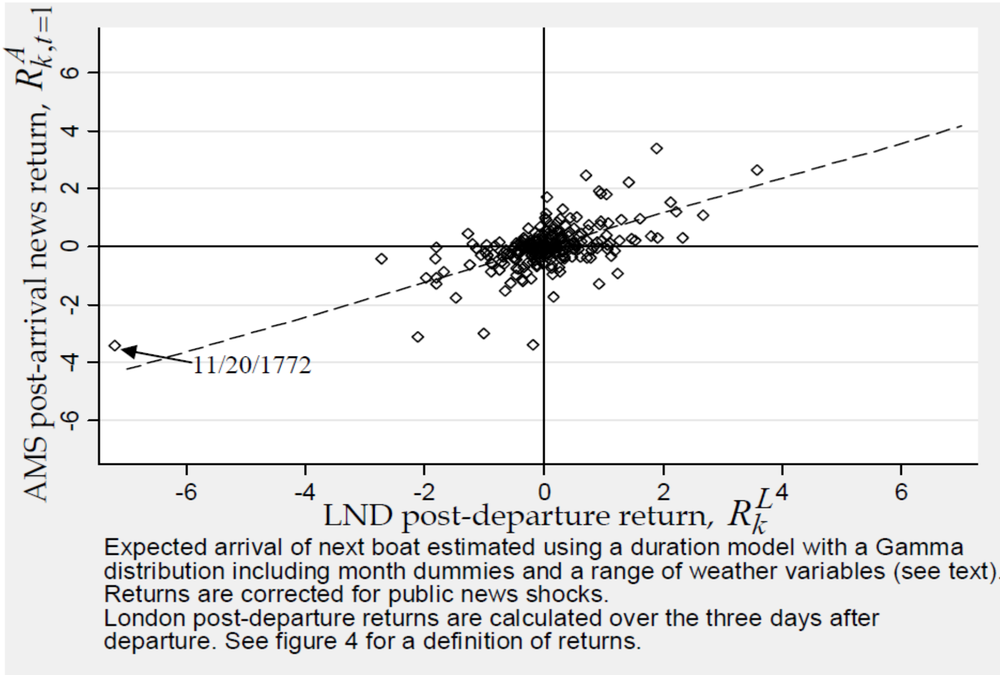


Figure 20: Co-movement LND post-departure and AMS post-arrival news returns - next boat > 3.5 days

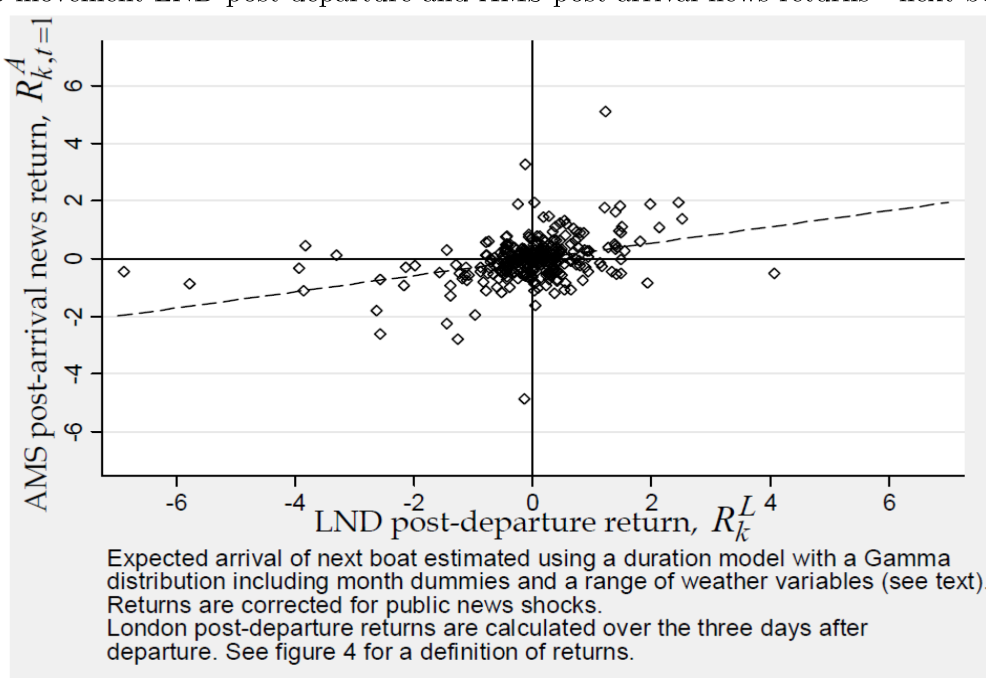


Table 7: Co-movement of returns, BoE

	(1) AMS post-arrival news return, $R^A_{k,t=1}$	(2) AMS post-arrival non-news return, $R^A_{k,t=2}$
LND post-departure return, R^L_k	0.224	0.268
	(0.046)***	(0.080)***
Public news shock, ΔN_{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
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 the possible continuation (momentum) of public news by including ΔN_{k-1}.
See figure 4 for exact definitions of returns. London post-departure returns are calculated over the three days after a boat departure. A Chi^2 test is performed on the equality of the 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 8: Co-movement of returns, 3% Ann.

	(1) AMS post-arrival news return, $R^A_{k,t=1}$	(2) AMS post-arrival non-news return, $R^A_{k,t=2}$
LND post-departure return, R^L_k	0.220	0.304
	(0.055)***	(0.081)***
Public news shock, ΔN_{k-1}-	0.506	0.176
	(0.044)***	(0.058)***
Constant	0.017	0.004
	(0.0173)	(0.028)
Obs	779	432
R2	0.44	0.13
Chi^2 test	0.50	
(p-value)	(0.480)	

Estimates of co-movement between London post-departure and Amsterdam post-arrival returns. Estimates are adjusted for the possible continuation (momentum) of public news by including ΔN_{k-1}.
See figure 4 for exact definitions of returns. London post-departure returns are calculated over the three days after a boat departure. A Chi^2 test is performed on the equality of the 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 9: Co-movement of returns, EIC (alternative R_k^L (1))

	AMS post-arrival news return, $R^A_{k,t=1}$			AMS post-arrival non-news return, $R^A_{k,t=2}$		
	(1a)	(2a)	(3a)	(1b)	(2b)	(3b)
LND post-departure return, 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)***
Public news shock,	0.416	0.460	0.452	0.059	0.134	0.128
ΔN_{k-1}	(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
Adj. R2	0.33	0.38	0.37	0.03	0.11	0.12
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 the possible continuation (momentum) of public news by including ΔN_{k-1}.

See figure 4 for exact definitions of returns. London post-departure returns are calculated over the two, four or five days after a boat departure. A Chi^2 test is performed on the equality of the 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 10: Co-movement of returns, EIC (alternative R_k^L (2))

	AMS post-arrival news return, $R^A_{k,t=1}$		
LND post-departure return, 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)***
Public news shock, ΔN_{k-1}	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 and Amsterdam post-arrival returns. Estimates are adjusted for the possible continuation (momentum) of public news by including ΔN_{k-1}.
See figure 4 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 11: Co-movement BoE, different expectations next boat

	AMS post-arrival news return, $R^A_{k,t=1}$	
London post-departure return, R^L_k	0.169 (0.062)***	0.207 (0.064)***
$R^L_k \times E[A\|simple] < 3.5$	0.213 (0.087)**	
$E[A\|simple] < 3.5$	-0.046 (0.032)	
$R^L_k \times E[A\|extended] < 3.5$		0.136 (0.095)
$E[A\|extended] < 3.5$		0.004 (0.031)
Public news shock, ΔN_{k-1}	0.411 (0.037)***	0.409 (0.039)***
Constant	0.040 (0.022)	0.014 (0.021)
Obs	595	595
R2	0.36	0.35

Estimates of co-movement between London post-departure and Amsterdam post-arrival 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 number of weather variables and month dummies (see main text).

See figure 4 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 12: Co-movement 3% Ann., different expectations next boat

	AMS post-arrival news return, $R^A_{k,t=1}$	
London post-departure return, R^L_k	0.191 (0.078)**	0.213 (0.078)***
$R^L_k \times E[A\|simple] < 3.5$	0.176 (0.115)	
$E[A\|simple] < 3.5$	-0.013 (0.035)	
$R^L_k \times E[A\|extended] < 3.5$		0.132 (0.106)
$E[A\|extended] < 3.5$		0.001 (0.034)
Public news shock, ΔN_{k-1}	0.577 (0.048)***	0.576 (0.046)***
Constant	0.018 (0.023)	0.010 (0.024)
Obs	722	722
R2	0.50	0.50

Estimates of co-movement between London post-departure and Amsterdam post-arrival returns. $E[A|simple]$ is calculated by adding the median sailing time to the departure date of the next boat. $E[A|extended]$ 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 4 for exact definitions of returns. London post-departure returns are calculated over three days after a boat departure.

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

Table 13: Co-movement EIC, different expectations next boat, alternative R_k^L

	AMS post-arrival news return, $R_{k,t=1}^A$					
London post-departure return, R_k^L						
2 days after departure	0.308	0.279				
	(0.080)***	(0.074)***				
4 days after departure			0.264	0.272		
			(0.060)***	(0.064)***		
5 days after departure					0.202	0.214
					(0.045)***	(0.051)***
$R_k^L \times E[A \vert simple] < 3.5$	0.178		0.161		0.204	
	(0.134)		(0.094)*		(0.082)**	
$E[A \vert simple] < 3.5$	-0.026		-0.040		-0.037	
	(0.062)		(0.053)		(0.054)	
$R_k^L \times E[A \vert extended] < 3.5$		0.289		0.161		0.203
		(0.116)***		(0.085)*		(0.074)***
$E[A \vert extended] < 3.5$		-0.017		-0.025		-0.043
		(0.061)		(0.053)		(0.051)
Public news shock,	0.447	0.443	0.498	0.495	0.493	0.489
ΔN_{k-1}	(0.037)***	(0.037)***	(0.036)***	(0.038)***	(0.036)***	(0.038)***
Constant	0.013	0.005	0.022	0.012	0.027	0.023
	(0.037)	(0.043)	(0.036)	(0.034)	(0.033)	(0.034)
Obs	552	552	693	693	702	702
R2	0.35	0.36	0.40	0.40	0.41	0.41

Estimates of co-movement between London post-departure and Amsterdam post-arrival 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 number of weather variables and month dummies (see main text).

See figure 4 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 November 20, 1772 is dropped from the regression analysis to make sure that this outlier does not drive the positive interaction effect (see figures 17 and 19 in appendix B). 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 14: Feedback effects - BoE

	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	0.052	0.064	0.065	0.068	0.079
$(p^A_{t+a} - p^L_{t^*})$	(0.050)	(0.049)	(0.049)	(0.049)	(0.049)
London pre-news returns		-0.043	-0.045	-0.039	-0.046
$(p^L_{t^*+l} - p^L_{t^*})$		(0.048)	(0.048)	(0.049)	(0.048)
Amsterdam period a			-0.013		-0.012
			(0.013)		(0.017)
$a \times \left(p^A_{t+a} - p^L_{t*}\right)$			0.010		0.056
			(0.021)		$(0.031)^{*}$
London period l				-0.007	0.000
				(0.008)	(0.011)
$l \times \left(p^A_{t+a} - p^L_{t^*}\right)$				-0.013	-0.042
				(0.014)	$(0.021)^{**}$
constant	0.018	0.020	0.017	0.018	0.018
	(0.019)	(0.019)	(0.019)	(0.019)	(0.020)
χ^2 test $\left(p^A_{t+a} - p^L_{t*}\right)$: (1) = (2)		0.70			
(p-value)		(0.403)			
N	684	684	684	684	684
Adj. R^2	0.00	0.01	0.01	0.01	0.02

This table provides estimates of the feedback effect of Amsterdam returns in London prices. See figure 10 for a definition of the timing and the returns. a measures the number of days between the arrival of a signal in Amsterdam and the departure of the next boat to London. l measures the number of days it takes for the private signal to "bounce off" from Amsterdam. Variation in a and l is driven by weather conditions. All estimates, including the benchmark coefficient on$(p^A_{t+a} - p^L_{t^*})$ are at median values of l (11 days) and a (3 days).

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

Table 15: Feedback effects - 3 % Annuities

	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	0.005	0.009	0.011	0.011	0.020
$(p^A_{t+a} - p^L_{t^*})$	(0.032)	(0.032)	(0.032)	(0.033)	(0.033)
London pre-news returns		-0.027	-0.031	-0.028	-0.032
$(p^L_{t^*+l} - p^L_{t^*})$		(0.037)	(0.037)	(0.037)	(0.038)
Amsterdam period a			-0.026		-0.034
			(0.012)		(0.018)$*$
$a \times \left(p^A_{t+a} - p^L_{t*}\right)$			0.021		0.039
			(0.013)		(0.020)*
London period l				-0.012	0.007
				(0.007)	(0.012)
$l \times \left(p^A_{t+a} - p^L_{t^*}\right)$				0.002	-0.019
				(0.009)	(0.014)
constant	0.007	0.008	0.001	0.005	0.001
	(0.018)	(0.018)	(0.019)	(0.018)	(0.019)
χ^2 test $\left(p^A_{t+a} - p^L_{t*}\right)$: (1) = (2)		0.70			
(p-value)		(0.403)			
N	845	845	845	845	845
Adj. R^2	0.00	0.00	0.01	0.00	0.01

This table provides estimates of the feedback effect of Amsterdam returns in London prices. See figure 10 for a definition of the timing and the returns. a measures the number of days between the arrival of a signal in Amsterdam and the departure of the next boat to London. l measures the number of days it takes for the private signal to "bounce off" from Amsterdam. Variation in a and l is driven by weather conditions. All estimates, including the benchmark coefficient on$(p^A_{t+a} - p^L_{t^*})$ are at median values of l (11 days) and a (3 days).

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

Table 16: Co-movement BoE, bad weather

	AMS post-arrival no-news return, $R^A_{k,t=2}$		
London post-departure return, R^L_k	0.309	0.281	0.330
	(0.089)***	(0.109)***	(0.085)***
$R^L_k \times badweather(A)$	0.159		
	(0.213)		
$badweather(A)$	0.021		
	(0.074)		
$R^L_k \times badweather(B)$		0.164	
		(0.169)	
$badweather(B)$		0.035	
		(0.049)	
$R^L_k \times badweather(C)$			0.075
			(0.306)
$badweather(C)$			0.041
			(0.050)
Public news shock	0.179	0.188	0.182
ΔN_{k-1}	(0.125)***	(0.061)***	(0.060)***
Constant	0.012	0.003	0.002
	(0.028)	(0.035)	(0.033)
Obs - total	327	327	363
Obs - $badweather(A)$	59		
Obs - $badweather(B)$		106	
Obs - $badweather(C)$			59
R2	0.15	0.16	0.15

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 4 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 17: Co-movement 3% Ann., bad weather

	AMS post-arrival no-news return, $R^A_{k,t=2}$		
London post-departure return, R^L_k	0.392	0.357	0.388
	(0.122)***	(0.113)***	(0.092)***
$R^L_k \times badweather(A)$	-0.037		
	(0.173)		
$badweather(A)$	0.093		
	(0.084)		
$R^L_k \times badweather(B)$		0.068	
		(0.193)	
$badweather(B)$		0.050	
		(0.062)	
$R^L_k \times badweather(C)$			-0.057
			(0.378)
$badweather(C)$			0.052
			(0.062)
Public news shock	0.207	0.210	0.205
ΔN_{k-1}	(0.059)***	(0.058)***	(0.060)***
Constant	-0.025	-0.022	-0.025
	(0.030)	(0.033)	(0.033)
Obs - total	444	444	444
Obs - $badweather(A)$	80		
Obs - $badweather(B)$		135	
Obs - $badweather(C)$			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 4 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 18: Co-movement EIC, badweather, alternative R_k^L

	AMS post-arrival no-news return, $R^A_{k,t=2}$		
	(1)	(2)	(3)
LND post-departure return, 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)***
$R_k^L \times badweather(A)$	0.132	0.009	0.079
	(0.178)	(0.126)	(0.124)
$badweather(A)$	0.090	0.102	0.092
	(0.142)	(0.104)	(0.103)
Public news shock,	0.106	0.180	0.169
ΔN_{k-1}	(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 - $badweather(A)$	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 4 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 after zero returns in London, BoE

	Amsterdam post-arrival news return, $R^A_{k,t=1}$	Amsterdam post-arrival non-news return, $R^A_{k,t=2}$
London post-departure return, R^L_k	0.237	0.285
	(0.056)***	(0.078)***
Zero London pre-departure return ($R^L_{k-1} = 0$)	-0.029	0.010
	(0.037)	(0.036)
$\times$ London post-departure return, R^L_k	0.074	-0.178
	(0.120)	(0.132)
Public news shock, ΔN_{k-1}	0.412	0.087
	(0.038)***	(0.063)
Constant	0.023	0.002
	(0.017)	(0.028)
Obs - total	595	296
Obs - zero returns	103	47
Adj-R2	0.35	0.09

This table provides additional tests whether co-movement was driven by trading costs or limits to arbitrage. Results in preceding tables show that co-movement was not driven by return continuation. This table tests whether co-movement between Amsterdam and London was stronger if past London returns (pre-departure returns $R^L_{k-1} = 0$) had been zero. This proxies for situations were trading costs or limits to arbitrage led to a delay in the incorporation of public information into prices (Lesmond et al 1999).
See figure 4 for exact definitions of returns. London post-departure returns are calculated over three days after a boat departure.

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

Table 20: Co-movement after zero returns in London, 3% Annuities

	Amsterdam post-arrival news return, $R^A_{k,t=1}$	Amsterdam post-arrival non-news return, $R^A_{k,t=2}$
London post-departure return, R^L_k	0.258	0.291
	(0.068)***	(0.099)***
Zero London pre-departure return	0.032	-0.060
($R^L_{k-1} = 0$)	(0.039)	(0.060)
$\times$ London post-departure return, R^L_k	-0.102	0.073
	(0.112)	(0.270)
Public news shock, ΔN_{k-1}	0.575	0.124
	(0.049)***	(0.068)*
Constant	0.004	0.016
	(0.021)	(0.031)
Obs - total	722	393
Obs - zero returns	135	69
Adj-R2	0.50	0.09

This table provides additional tests whether co-movement was driven by trading costs or limits to arbitrage. Results in preceding tables show that co-movement was not driven by return continuation. This table tests whether co-movement between Amsterdam and London was stronger if past London returns (pre-departure returns $R^L_{k-1} = 0$) had been zero. This proxies for situations were trading costs or limits to arbitrage led to a delay in the incorporation of public information into prices (Lesmond et al 1999).
See figure 4 for exact definitions of returns. London post-departure returns are calculated over three days after a boat departure.

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

Table 21: Permanent price changes? BoE

	Amsterdam return over period T after episode k ($p^A_{k+T} - p^A_{k,t=1}$)					
	2/3 days	*4/5 days*	*1 week*	*2 weeks*	*3 weeks*	*4 weeks*
London return (R^L_{k-1})	0.072	0.142	0.108	0.281	0.325	0.470
	(0.043)*	(0.069)**	(0.074)	(0.096)	(0.124)	(0.150)
Constant	0.026	0.054	0.078	0.144	0.247	0.306
	(0.016)*	(0.022)**	(0.026)***	(0.038)***	(0.050)***	(0.058)***
N	705	705	702	695	688	685
Adj. R^2	0.01	0.02	0.00	0.02	0.02	0.03

Estimates of regressions predicting future Amsterdam returns based on London returns.
The London return is defined as the London pre-departure return (R^L_{k-1}, see figure 4).
The Amsterdam return is calculated as the price change after the arrival of the boat
that brings this information ($p^A_{k,t=1}$) and the Amsterdam price T days into the future (p^A_{k+T}).
T varies between 2/3 days and 4 weeks.
Robust, bootstrapped (1000 reps) standard errors in parentheses.
*, **, *** indicates statistical significance at the 10, 5 and 1% level

Table 22: Permanent price changes? 3%Ann

	Amsterdam return over period T after episode k ($p^A_{k+T} - p^A_{k,t=1}$)					
	2/3 days	*4/5 days*	*1 week*	*2 weeks*	*3 weeks*	*4 weeks*
London return (R^L_{k-1})	0.081	0.155	0.129	0.255	0.317	0.497
	(0.052)	(0.061)**	(0.083)	(0.094)***	(0.117)***	(0.131)***
Constant	0.010	0.045	0.073	0.144	0.241	0.307
	(0.019)	(0.025)*	(0.029)**	(0.039)***	(0.050)***	(0.058)***
N	863	862	857	848	838	834
Adj. R^2	0.01	0.02	0.01	0.02	0.02	0.04

Estimates of regressions predicting future Amsterdam returns based on London returns.
The London return is defined as the London pre-departure return (R^L_{k-1}, see figure 4).
The Amsterdam return is calculated as the price change after the arrival of the boat
that brings this information ($p^A_{k,t=1}$) and the Amsterdam price T days into the future (p^A_{k+T}).
T varies between 2/3 days and 4 weeks.
Robust, bootstrapped (1000 reps) standard errors in parentheses.
*, **, *** indicates statistical significance at the 10, 5 and 1% level

Appendix C - theoretical model feedback effects

In section 3.4 I analyze the impact of price discovery in Amsterdam on price changes in London. The starting point for the analysis is a simple statistical model. In this appendix this is extended to a full 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 (realistic) conditions, the predictions from the statistical and theoretical model are equivalent.

Predictions 1 and 2 of the statistical model are general and hold in any setup in which price discovery in Amsterdam and London is not perfectly correlated. Prediction 3 may be 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 straightforward 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 all else equal, the London market will put more weight on the Amsterdam signal if it becomes more informative. However, all else is not equal and the London signal will also become more informative. This decreases the weight on the Amsterdam signal. It is ex ante unclear 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 statistical 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? In section 3.4 I show that it took around 11 days for a London private signal to "bounce off" from Amsterdam. I also provide evidence that after two weeks the private information was fully incorporated into London prices. This suggests that, after the arrival of a boat from Amsterdam, the London insider only 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 21 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 London 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 21 ABOUT HERE]

Insiders submit trading orders $x_t^i \left(x_1^A, x_2^A, x_1^L, x_2^L, x_{2*}^L\right)$, 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 $u_t^i \left(u_1^A, u_2^A, u_1^L, u_2^L\right)$ 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 23 and 24.

Table 23: Setup model - Amsterdam

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

Table 24: Setup model - London

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

The most interesting updating rule for the market maker is the case where the London market receives information from Amsterdam 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.

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 above, this it is reasonable to assume that this was the case.

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

$$
\begin{aligned}
x_1^i &= \beta_1^i \varepsilon && (19)\\
x_2^A &= \beta_2^A \left(v_0 + \varepsilon - p_1^A\right) && (20)\\
x_2^L &= \beta_2^L \left(v_0 + \varepsilon - p_1^L\right) && (21)\\
x_{2*}^L &= \beta_{2*}^L \left(v_0 + \varepsilon - p_{1*}^L\right) && (22)
\end{aligned}
$$

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

$$
\begin{aligned}
p_1^i &= v_0 + \lambda_1^i (x_1^i + u_1^i) && (23)\\
p_2^A &= p_1^A + \lambda_2^A (x_2^A + u_2^A) && (24)\\
p_2^L &= p_1^L + \lambda_2^L (x_2^L + u_2^L) && (25)\\
p_{1*}^L &= \alpha^A p_1^A + \alpha^L p_1^L && (26)\\
p_{2*}^L &= p_{1*}^L + \lambda_{2*}^L (x_{2*}^L + u_2^L) && (27)
\end{aligned}
$$

where

$$
\begin{aligned}
\lambda_1^i &= \frac{\beta_1^i \Sigma_0}{\left(\beta_1^i\right)^2 \Sigma_0 + \sigma_{u_1^i}^2}\\
\lambda_2^i &= \frac{1}{2}\sqrt{\frac{\Sigma_1^i}{\sigma_{u_2^i}^2}},\ \lambda_{2*}^L = \frac{1}{2}\sqrt{\frac{\Sigma_{1*}^L}{\sigma_{u_2^L}^2}}\\
\alpha^A &= \frac{\Sigma_{1*}^L}{\Sigma_1^A},\ \alpha^L = \frac{\Sigma_{1*}^L}{\Sigma_1^L} && (28)
\end{aligned}
$$

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

$$
\begin{aligned}
\Sigma_1^i &= var\left[p_1^i | I_1^i\right] = (1 - \beta_1^i \lambda_1^i)\Sigma_0\\
\Sigma_{1*}^L &= var\left[p_{1*}^L | I_1^A, I_1^L\right] = \frac{\Sigma_0 \Sigma_1^A \Sigma_1^L}{\Sigma_0\left(\Sigma_1^A + \Sigma_1^L\right) - 2\Sigma_1^A \Sigma_1^L} && (29)
\end{aligned}
$$

We can now turn to the optimal behavior of the two insiders and check whether their optimal policies are indeed as described by equations (19) to (22). 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 (23) to (27), it can indeed be shown that (19) to (22) hold with

$$\beta_1^A = \frac{1-\lambda_1^A\beta_2^A}{2\lambda_1^A - \left(\lambda_1^A\right)^2\beta_2^A}$$

$$\beta_1^L = \frac{-1+\pi\lambda_1^L\beta_2^L + (1-\pi)\,\alpha^L\lambda_1^L\left(1-\alpha^A\lambda_1^A\beta_1^A\right)\beta_{2*}^L}{-2\lambda_1^L + \pi\left(\lambda_1^L\right)^2\beta_2^L + (1-\pi)\,(\alpha^L\lambda_1^L)^2\beta_{2*}^L}$$

$$\beta_2^i = \sqrt{\frac{\sigma_{u_2^i}^2}{\Sigma_1^i}},\ \beta_{2*}^L = \sqrt{\frac{\sigma_{u_2^L}^2}{\Sigma_{1*}^L}}$$

Comparative statics

In what follows I revisit predictions 3a and 3b from the simple statistical 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 $t^i = 2$. As a result prices after period $t^i = 1$ become more informative.

Prediction 3a: α^A *should be decreasing in the informativeness of* p_1^L, $\frac{\delta\alpha^A}{\delta\Sigma_1^L} > 0$.

Proof. Follows from expressions (28) and (29). ■

If the London signal becomes more informative, the London market maker will put less weight on the Amsterdam signal.[39]

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

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 5

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

Proof. Follows from expressions (28) and (29). ■

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

Lemma 6

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

[39] 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.

Proof. Numerical verification ■

The intuition for this result is that the London insider changes his trading behavior if p_1^A becomes more informative. If this is the case, then potential insider profits from the second period $t^L = 2^*$ will 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 lemma's?

Proposition 7 *As long as potential insider profits during period $t = 2/t = 2^*$ are relatively small (large π, large $\sigma^2_{u_1^L}$, large $\sigma^2_{u_1^A}$) then*

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

Proof. Numerical results in figure 22 ■

The intuition is as follows. Potential insider profits from period $t = 2/t = 2^*$ are relatively small as long as $\sigma^2_{u_1^L}$ is large. If that is the 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 5 will dominate. 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. The lowers the level of $\sigma^2_{u_1^L}$ for which $\frac{\delta\alpha^A}{\delta\Sigma_1^A} < 0$.

[FIGURE 22 ABOUT HERE]

Note that figure 22 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 22 where $\frac{\delta\alpha^A}{\delta\Sigma_1^A} < 0$ is larger.

Figure 21: Setup - feedback model

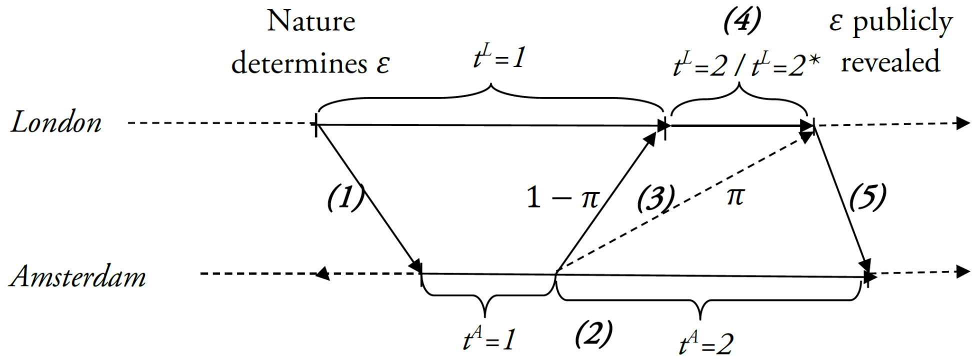


Figure 22: Prediction 3b