Internet Appendix

for

Preventing Information Leakage

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I: Additional analysis of the model

This section has two parts. First, it generates additional predictions regarding the informed trader's total trading size. Second, it provides a theoretical foundation for the empirical exercise performed in Section 6.4.

I.1 Predictions regarding trading size

During the trading, the informed trader's choice of brokers, n, has been fixed (see the discussion about timing in Remark 1). Therefore, taking it as given, the model yields result regarding the informed investor's trading size. Direct computation gives

$$\mathbb{E}[|\sum x_i|] = \mathbb{E}[|n\beta s|] = \sqrt{\frac{2}{\pi}}\sqrt{\mathbb{V}[\sum x_i]} = \sqrt{\frac{2}{\pi}}\sqrt{\frac{\sigma_u^2 + \gamma^2(n^2\sigma_\zeta^2 + n\sigma_\xi^2)}{(1+\gamma)^2}},$$

from which it can be immediately seen that the expected trading size is (i) monotone increasing in n; (ii) monotone in the noises, i.e., σ_u^2, σ_ζ^2, and σ_ξ^2; but (iii) ambiguous in γ, the severity of the leak.

The results (i) and (ii) are rather intuitive, consistent with standard intuition from informed trading theory, like Kyle (1985): If more brokers are used or if the noise is larger, the informed investor can better hide her private information and will therefore trade more.

The result (iii) is perhaps less obvious. To understand it, note that γ serves two purposes in the model. The leak from a broker is modelled as $\gamma(x_i + \zeta + \xi_i)$. That is, γ not only scales up the noises in the leaks but also the informative component x_i in the leak. That is, if she trades more, the leaks may tip off too much to the market maker, despite the added noises. Therefore, when the leak is more severe, whether the informed investor trades more aggressively depends on the net effect between the leak of her trade and the noises in the leak.

I.2 Heterogeneous brokers

The baseline model presented in Section 2 is specialized to generate the key predictions tested in Section 6.4 that if an institution (an informed trader) concentrates her trades in fewer brokers, the benefit of using multiple brokers would be lower. In particular, Section 6.4 tests whether there is a difference between the price impacts of trades with high vs low broker concentration HHI (Herfindahl-Hirschman Index).

I.2.1 A specialized model

To generate the above prediction, the baseline model is generalized in the following two aspects. We show that the resulting trading equilibrium nests the baseline as a special case. First, the magnitude of the leaks is allowed to be different across brokers. That is, instead of a constant

γ for all brokers, each broker i has a possibly different severity in the leaks: $\gamma_i(x_i + \zeta + \xi_i)$. This broker heterogeneity is necessary for the informed investor to optimally choose different quantities across different brokers, generating nontrivial HHI.

Second, instead of setting the competitive price $p = \mathbb{E}[v|\omega]$, where the aggregate order flow $\omega = \sum_{i=1}^{n}\big(x_i + \gamma_i(x_i + \zeta + \xi_i)\big) + u$, the market maker observes all n *separate* flows from the n brokers, i.e., $\omega_i = x_i + \gamma_i(x_i + \zeta + \xi_i) + z_i$, and then set the price at

$$p = \mathbb{E}[v|\omega_1, \dots, \omega_n].$$

Note that the broker-specific noise trading is written as z_i, which is i.i.d. normal with zero mean and variance $\mathbb{V}[z_i] = \sigma_z^2$. These noises can be thought of, but not necessarily, trading unrelated to the informed trader. In the baseline, they would contribute to the total noise trading u; for example, by setting $\sigma_z^2 = \sigma_u^2/n$, the total amount of noise trading remains the same as in the baseline.

This second modification is, first of all, a more realistic characterization of how prices are formed in our specific empirical setting. When the informed investor executes orders using multiple brokers, there will inevitably be some time differences. Therefore, the market will more realistically be able to see different orders (sent through different brokers) before forming the price competitively. Second, it is a technical adjustment because pricing based only on the lump order ω, i.e., letting $p = p(\omega)$, would allow for "statistical arbitrage." To see this, note that the informed investor's trading via broker i has a marginal price impact cost of $\mathbb{E}\left[\frac{dp(\omega)}{dx_i}\right] = \mathbb{E}\left[p'(\omega)\frac{d\omega}{dx_i}\right] = \mathbb{E}[p'(\omega)]\,(1 + \gamma_i)$. That is, so long as $\gamma_i \neq \gamma_{i'}$, the price impact costs can never be aligned between the two brokers. Consequently, the informed investor will optimally buy in one broker and sell the appropriate amount in another, annihilating price impact costs, to make riskless profit (hence statistical arbitrage). This is similar to the source of "quasi-arbitrage" pointed out by Huberman and Stanzl (2004). Allowing the market maker to price according to separate orders addresses this issue because the marginal price impact cost via broker i now becomes $\mathbb{E}\left[\frac{dp(\omega_1,\ldots,\omega_n)}{dx_i}\right] = \mathbb{E}\left[\frac{dp(\cdot)}{d\omega_i}\frac{d\omega_i}{dx_i}\right] = \mathbb{E}\left[\frac{dp(\cdot)}{d\omega_i}\right](1+\gamma_i)$, where $\mathbb{E}\left[\frac{dp(\cdot)}{d\omega_i}\right]$ can be different across i. Indeed, the informed trader will do so in equilibrium, as will be shown below, and the intuition is the same as why in the continuous time version of Kyle (1985) the price impact must be constant over time: if not, the informed trader will be better off trading more (less) aggressively when the price impact is low (high).

Finally, to simplify the notations, in the subsequent analysis, we let $n = 2$ and ignore the common component ζ in the leak noise, i.e., setting $\sigma_\zeta^2 = 0$. These simplifying assumptions are not necessary and are only for the ease of exposition. In particular, while the informed investor's optimal choice of brokers, n, can be endogenously solved like in the baseline, this internet appendix only focuses on the trading equilibrium and takes $n = 2$ as given. This is because the key prediction about order concentration and price impact can already be obtained with a fixed n. All other model elements remain the same as described in the baseline.

I.2.2 Equilibrium characterization

We conjecture and look for a linear-strategy trading equilibrium in the following form: The informed investor trades $x_i = \beta_i s$ via broker i, while the competitive market maker sets the price as $p = \sum_{i=1}^{n} \delta_i \omega_i$, and the coefficients β_i and δ_i will be determined endogenously.

Consider first the competitive pricing by the market maker, taking as given the order submission strategy of $x_i = \beta_i s$ and hence $\omega_i = (1+\gamma_i)x_i + \gamma_i \xi_i + z_i$:

$$p = \mathbb{E}[v|\omega_1, \omega_2] = \delta_1\omega_1 + \delta_2\omega_2,$$

where the coefficients δ_i following Bayes' theorem is given by

$$\delta_i = \frac{\frac{(1+\gamma_i)\beta_i \phi \sigma_v^2}{\sigma_i^2 + \gamma_i^2 \sigma_\xi^2}}{\phi + \sum_{j=1}^{2} \frac{(1+\gamma_j)^2 \beta_j^2 \sigma_v^2}{\sigma_j^2 + \gamma_j^2 \sigma_\xi^2}}. \tag{IA. 1}$$

This confirms the linear conjecture made earlier.

Now consider the informed investor's optimal trading. She solves the following problem:

$$\max_{\{x_1, x_2\}} \mathbb{E}\left[\left(v - p(\omega_1, \omega_2)\right)(x_1 + x_2)\middle|s\right]$$

where $p(\omega_1, \omega_2) = \delta_1 \omega_1 + \delta_2 \omega_2$. Her first-order derivative with respect to x_i is

$$\phi s - 2\delta_i(1+\gamma_i)(x_i + x_2).$$

A necessary equilibrium condition is that the above first-order derivatives across $i \in \{1,2\}$ must be equalized, because, as discussed earlier, statistical arbitrage would arise otherwise: The informed investor could buy via one broker and sell an appropriate amount via the other to completely eliminate price impact costs. This equality gives rise to the following equilibrium condition:

$$\phi s - 2\delta_1(1+\gamma_1)(x_1 + x_2) = \phi s - 2\delta_2(1+\gamma_2)(x_1 + x_2)$$

$$\Rightarrow \delta_1(1+\gamma_1) = \delta_2(1+\gamma_2), \tag{IA. 2}$$

where the expressions of δ_1 and δ_2 are given earlier in (IA.1). Just like in the baseline, the first-order condition then only determines the aggregate order size: $x_1 + x_2 = \frac{\phi s}{2\lambda}$. Under the conjectured linear strategy, $x_1 + x_2 = (\beta_1 + \beta_2)s$, yielding the following equilibrium conditions:

$$\beta_1 + \beta_2 = \frac{\phi}{2\delta_1(1+\gamma_1)} = \frac{\phi}{2\delta_2(1+\gamma_2)}. \tag{IA. 3}$$

Substituting δ_1 and δ_2 from (IA.1) to (IA.2) and (IA.3), we obtain a quadratic equation system of two unknowns, $\{\beta_1, \beta_2\}$, which in turn determine $\{\delta_1, \delta_2\}$. Only one pair of the roots satisfies the informed investor's second-order condition:

$$\beta_i = \frac{(1+\gamma_{-i})(\sigma_z^2 + 2\gamma_i^2\sigma_\xi^2)}{1+\gamma_i}\frac{\sqrt{\phi}}{\sigma_v\sqrt{2\Sigma}} \text{ and } \delta_i = \frac{(1+\gamma_{-i})\sigma_v\sqrt{\phi}}{\sqrt{2\Sigma}},$$

where γ_{-i} indicates the leak magnitude in the other broker and $\Sigma \coloneqq ((1+\gamma_1)^2 + (1+\gamma_2)^2)\sigma_z^2 + 2(\gamma_2^2(1+\gamma_1)^2 + \gamma_1^2(1+\gamma_2)^2)\sigma_\xi^2$. As a special case, setting $n = 2$, $\gamma_1 = \gamma_2 = \gamma$, and $\sigma_\zeta = 0$, we obtain the same coefficient β and $\lambda = \delta$ as in the baseline.

I.2.3 Prediction: concentration vs. price impact

We now explore the relation between the informed investor's order concentration (across brokers) and her price impact. To do so, we let $\gamma_1 \leq \gamma_2$ (which is without loss of generality) and exogenously vary γ_2 to examine how both objects change in equilibrium. The idea is to attribute the variation in cross-broker order concentration to brokers' different leak severity and examine the resulting differences in price impacts.

A parameter restriction. We begin by imposing the following intuitive requirement: the investor should trade less with a broker whose leak is more severe, i.e., $\beta_1 \leq \beta_2$ (since we assume $\gamma_1 \leq \gamma_2$). Directly evaluating $\beta_1 \leq \beta_2$ yields the following sufficient condition:

$$0 < \gamma_1 \leq \gamma_2 \leq \frac{\sigma_z^2}{2\sigma_\xi^2}. \tag{IA.4}$$

Concentration index. The HHI is computed as

$$\left(\frac{x_1}{x_1 + x_2}\right)^2 + \left(\frac{x_2}{x_1 + x_2}\right)^2 = \left(\frac{\beta_1}{\beta_1 + \beta_2}\right)^2 + \left(\frac{\beta_2}{\beta_1 + \beta_2}\right)^2 = \left(\frac{\beta_1}{\beta_1 + \beta_2}\right)^2 + \left(1 - \frac{\beta_1}{\beta_1 + \beta_2}\right)^2.$$

Hence, it suffices to examine how γ_2 affects the ratio of $\frac{\beta_1}{\beta_1+\beta_2}$. Direct computation shows that, under (IA.4), $\frac{d}{d\gamma_2}\left(\frac{\beta_1}{\beta_1+\beta_2}\right) \geq 0$. Note also that if $\gamma_2 \downarrow \gamma_1$, $\frac{\beta_1}{\beta_1+\beta_2} \to \frac{1}{2}$. That is, as γ_2 increases from γ_1, the ratio $\frac{\beta_1}{\beta_1+\beta_2}$ monotonically increases from $\frac{1}{2}$, and therefore the HHI monotonically increases from $\frac{1}{4}$ with γ_2.

Price impact. The informed investor's (average) price impact can be defined as

$$\lambda := \mathbb{E}\left[\frac{p}{x_1 + x_2}\right] = \mathbb{E}\left[\frac{\delta_1\omega_1 + \delta_2\omega_2}{x_1 + x_2}\right] = \mathbb{E}\left[\mathbb{E}\left[\frac{\delta_1\omega_1 + \delta_2\omega_2}{x_1 + x_2}\middle| x_1, x_2\right]\right]$$

$$= \mathbb{E}\left[\mathbb{E}\left[\frac{\delta_1(1 + \gamma_1)x_1 + \delta_2(1 + \gamma_2)x_2}{x_1 + x_2}\right]\right] = \delta_1(1 + \gamma_1),$$

where the last equality uses (IA.2). Using the closed-form solution of δ_1, we can directly compute and see that $\frac{d\lambda}{d\gamma_2} > 0$. That is, the price impact monotonically increases with γ_2.

Prediction: Since both the HHI and the price impact increase with γ_2, we expect to find that the informed investor experiences lower price impact when the HHI is low, i.e., when her trades are less concentrated. This gives rise to the empirical exercise in Section 6.4. The evidence, presented in Table A6 in Internet Appendix II, also supports this prediction.

II: Supplementary empirical results.

This section presents a set of supplementary empirical exercises that substantiate and extend the paper's main findings. First, we provide further evidence supporting our central claim that multi-broker trades are more informed by examining their ability to predict future returns. We also confirm our findings on execution costs by using an alternative measure, implementation shortfall, demonstrating the robustness of our results. Second, we investigate potential alternative mechanisms and confounders, in particular, whether anonymous trading operates as a substitute for multi-broker routing. Finally, we examine heterogeneity in the effectiveness of multi-broker strategies by testing for diminishing marginal returns to the number of brokers and by analyzing how the concentration of order flow across brokers influences execution outcomes. Together, these tests enhance the robustness of our conclusions and provide further insight into the strategic behavior of informed traders.

II.1 Return predictability

To rule out the possibility that trades with multiple brokers are driven by investors' liquidity needs, we test whether multi-broker trades are more likely to predict future stock returns than are one-broker trades. To test whether the return predictability of multiple brokers is statistically different from that of single-broker trades, we perform the following OLS regression model separately for net buy and net sell trades:

$$Ret[1, 5]_{i,t} \text{ or } Ret[1, 10]_{i,t} = a_0 + a_2 \mathbb{1}(\textit{Multi-broker Trades})_{i,j,t} \text{ or } \#Brokers_{i,j,t} + \gamma' X + \theta_i + \theta_j + \theta_t + \epsilon_{i,j,t}, \quad \text{(IA.5)}$$

where the dependent variable is $Ret[1, 5]_{i,t}$, the 5-days cumulative returns (i.e., t+1 to t+5). We also repeat the analysis using a 10-day cumulative returns (i.e., t+1 to t+10) dependent variable, $Ret[1, 10]_{i,t}$. We use both the indicator variable and the continuous variable to measure multi-broker trades. $\mathbb{1}(\textit{Multi-broker Trades})_{i,j,t}$ is an indicator variable that takes the value one if DMA firm *j* executes trades with more than one broker for stock *i* on day *t*, and zero otherwise. Alternatively, $\#Brokers_{i,j,t}$ is the number of brokers that DMA firm *j* uses to execute trades for stock *i* on day *t*. We expect a_2 to be positive (negative) if multi-broker net buy (net sell) trades are more informed than single-broker trades. *X* is the same set of control variables that are used in

Equation (3). Finally, we include stock fixed effects, θ_i, DMA firm fixed effects, θ_j, and trading day fixed effects, θ_t, and cluster standard errors by stock and day.

Table A1 presents the results. Columns (1) – (4) report the results when 𝟙(Multi-broker Trades) is the variable of interest, and columns (5) – (8) report the results when #Brokers is the variable of interest. Columns (1) – (2) and (5) – (6) present the regression results when the dependent variable is *Ret[1, 5]* and columns (3) – (4) and (7) – (8) report the results when the dependent variable is *Ret[1, 10]*. Columns (1), (3), (5), and (7) present the regression results when DMA trades are net buy and columns (2), (4), (6), and (8) report the results when DMA trades are net sell.

Insert Table A1 about Here

In columns (1) and (3), where DMA trades are net buy, we find that the coefficient on *𝟙(Multi-broker Trades)* is positive and statistically significant. The estimates are also economically significant. For example, for *Ret[1, 5]*, the coefficient on *𝟙(Multi-broker Trades)* is 0.135, implying that a five-day future cumulative return is 13.5 bps higher than that for one-broker trades. In contrast, we find that the coefficient is statistically insignificant when DMA trades are net sales. The "buy-sell" asymmetry here is consistent with the idea that informed traders are less worried about information leakage before negative events because informed agents face less competition before adverse events than positive events due to the constraint of share ownership and the cost of short selling (e.g., Baruch, Panayides, and Venkataraman (2017)). In columns (5) – (8), we find weak evidence that when a DMA firm's net buy trades are more informed about future stock, it uses more brokers to execute the trades.

Table A1 Trading with multiple brokers and return predictability. This table presents the results of OLS regressions examining the relation between multi-broker trading and return predictability. Columns (1), (3), (5), and (7) present the regression results when DMA trades at the stock-day level are net buy, and columns (2), (4), (6), and (8) report the results when DMA trades at the stock-day level are net sell. In columns (1) – (4), $\mathbb{1}$(Multi-broker Trades) is the measure of multi-broker trading, and in columns (5) – (8), #Brokers is the measure of multi-broker trading. The variables are defined in Appendix 2. T-statistics, based on standard errors clustered by stock and day, are in parentheses. *i* denotes stocks, *j* denotes DMA firms, and *t* denotes days.***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels

Table A1 Continued

	Ret [1, 5] $_{i,t}$	Ret [1, 5] $_{i,t}$	Ret [1, 10] $_{i,t}$	Ret [1, 10] $_{i,t}$	Ret [1, 5] $_{i,t}$	Ret [1, 5] $_{i,t}$	Ret [1, 10] $_{i,t}$	Ret [1, 10] $_{i,t}$
	Buy	Sell	Buy	Sell	Buy	Sell	Buy	Sell
Trading characteristics:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
𝟙(Multi-broker Trades) $_{i,j,t}$	0.135**	0.083	0.172*	0.100				
	(2.17)	(1.02)	(1.88)	(0.83)				
#Brokers $_{i,j,t}$					0.083*	0.062	0.094	0.045
					(1.82)	(1.07)	(1.29)	(0.54)
Log(Dollar Imbalance) $_{i,j,t}$	0.005	-0.002	-0.000	-0.005	0.005	-0.002	-0.000	-0.005
	(0.66)	(-0.24)	(-0.03)	(-0.41)	(0.67)	(-0.25)	(-0.00)	(-0.39)
Stock characteristics:								
Log(Market Cap) $_{i,t}$	-7.18***	-7.447***	-13.929***	-14.529***	-7.182***	-7.446***	-13.927***	-14.528***
	(-5.23)	(-5.49)	(-5.79)	(-6.18)	(-5.23)	(-5.48)	(-5.79)	(-6.18)
Price $^{-1}$ $_{i,t}$	6.202	0.182	10.717	1.318	6.203	0.182	10.719	1.317
	(1.25)	(0.04)	(1.16)	(0.13)	(1.25)	(0.04)	(1.16)	(0.13)
Quoted Spread $_{i,t}$	0.005	0.002	0.012	0.010	0.005	0.002	0.012	0.010
	(0.78)	(0.62)	(0.99)	(1.12)	(0.78)	(0.62)	(0.99)	(1.12)
Turnover $_{i,t}$	-0.321**	-0.321***	-0.410**	-0.393**	-0.321**	-0.321***	-0.410**	-0.393**
	(-2.53)	(-2.78)	(-2.39)	(-2.21)	(-2.54)	(-2.78)	(-2.39)	(-2.21)
Return $_{i,t}$	-0.029	-0.020	-0.027	-0.001	-0.029	-0.020	-0.027	-0.001
	(-0.82)	(-0.65)	(-0.57)	(-0.02)	(-0.82)	(-0.65)	(-0.57)	(-0.02)
Volatility $_{i,t}$	5.526	2.626	6.290	-0.791	5.530	2.629	6.296	-0.786
	(1.26)	(0.72)	(0.85)	(-0.15)	(1.26)	(0.72)	(0.85)	(-0.15)
𝟙(Pre News) $_{i,t}$	-0.281*	-0.136	-0.421**	-0.238	-0.281*	-0.136	-0.420**	-0.238
	(-1.75)	(-0.88)	(-2.17)	(-1.19)	(-1.75)	(-0.88)	(-2.17)	(-1.19)
𝟙(News) $_{i,t}$	-0.045	-0.108	0.010	-0.047	-0.045	-0.108	0.010	-0.047
	(-0.42)	(-0.95)	(0.06)	(-0.32)	(-0.42)	(-0.95)	(0.06)	(-0.32)
𝟙(Pre EA) $_{i,t}$	0.398*	0.332	0.338	0.189	0.398*	0.332	0.337	0.189
	(1.75)	(1.49)	(1.02)	(0.57)	(1.75)	(1.49)	(1.02)	(0.57)
𝟙(EA) $_{i,t}$	0.110	0.097	0.012	-0.013	0.110	0.097	0.012	-0.013
	(0.47)	(0.43)	(0.04)	(-0.05)	(0.47)	(0.43)	(0.04)	(-0.05)
Day FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
DMA FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	162,874	162,436	162,874	162,436	162,874	162,436	162,874	162,436
Adjusted R-squared	0.185	0.184	0.205	0.206	0.185	0.184	0.205	0.206

II.2 Implementation shortfalls

As a second test, we compare the implementation shortfall of multi-broker trades to those of the one-broker trades to examine whether using multiple brokers can prevent information leakage. If investors are able to use multiple brokers to successfully hide their information, the trades are less likely to move market prices away from the price at the start of the trade and the total cost of the day trades can be lower. The total costs associated with such a "string of trades within the day" are measured by the implementation shortfall measure. Thus, we expect a smaller implementation shortfall for multi-broker trades than for one-broker trades with similar information (proxied by trade size).

Following Malinova, Park, and Riordan (2018), we measure the implementation shortfall as:

$$IS_{i,j,t} = q_{i,j,t} \times (\$Vol_{i,j,t} - p_{i,j,0} \times Vol_{i,j,t}), \tag{IA.6}$$

where *i* denotes stock, *j* denotes DMA firm, and *t* denotes trading day. $q_{i,j,t}$ is 1 for a string of buys and -1 for a string of sales on day *t*. $\$Vol_{i,j,t}$ is the total dollar volume for the string of trades, $p_{i,j,0}$ is the prevailing price at the time of the first trade in the string of trades, and $Vol_{i,j,t}$ is the total share volume for the string of trades. For example, for a string of buys, $\$Vol_{i,j,t}$ captures the total cost of the trades, and $p_{i,j,0} \times Vol_{i,j,t}$ measures the hypothetical cost that the trader would have faced, had the entire quantity executed immediately at price $p_{i,j,0}$. A positive implementation shortfall indicates that prices move in the same direction as the start of trade and higher trading cost. We sum the implementation shortfalls for both sells and buys and then calculate the implementation shortfall per dollar traded by scaling the total implementation shortfall by the total dollar volume of all the trade strings. We winsorize this variable at the 1st and 99th percentiles.

We examine the effect of trading with multiple brokers on the implementation shortfall using the matching sample by executing the following regression model:

$$IS_{i,j,t} = \alpha + \beta_1 \mathbb{1}(Multi-broker\ Trades)_{i,j,t}\ or\ \#Brokers_{i,j,t} + \gamma' X + \theta_i + \theta_j + \theta_t + \varepsilon_{i,j,t}, \tag{IA.7}$$

where the subscripts denote stock *i*, DMA firm j, broker *k*, and date *t*, respectively. The variable $IS_{i,j,t}$ is the dollar-weighted implementation shortfall, expressed in basis points. *𝟙(Multi-broker Trades)*$_{i,j,t}$ is an indicator variable that takes the value one if DMA firm *j* executes trades with more than one broker for stock *i* on day *t*, and zero otherwise. *#Brokers*$_{i,j,t}$ is the number of brokers that DMA firm *j* uses to execute trades for stock *i* on day *t*. *X* is the same set of control variables that are used in Equation (3). We also include stock fixed effects, θ_i, DMA firm fixed effects, θ_j, and trading day fixed effects, θ_t, and cluster standard errors by stock and day.

Table A2 provides the results for the estimation of Equation (IA.7) using the matched samples.

Insert Table A2 about Here

Column (1) reports the results when *𝟙(Multi-broker Trades)* is the variable of interest, and column (2) reports the results when #Brokers is the variable of interest. The coefficient on *𝟙(Multi-broker Trades)* and on *#Brokers* is negative and statistically significant at the 1% level or higher in both columns. In summary, the results in Tables 5 and 6 are consistent with DMA firms successfully utilizing multiple brokers to mitigate information leakage and reduce trading costs.

Table A2: Trading with multiple brokers and implementation shortfalls, regression analysis on a matched sample. This table presents the results for the multivariate regressions examining the relationship between trading with multiple brokers and implementation shortfalls on a matched sample. In column (1), 𝟙(Multi-broker Trades) is the measure of multi-broker trading, and in column (2), #Brokers is the measure of multi-broker trading. The variables are defined in Appendix 2. T-statistics, based on standard errors clustered by stock and day, are in parentheses. *i* denotes stocks, *j* denotes DMA firms, and *t* denotes days. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels.

	Implementation Shortfall $_{i,j,t}$	
	(1)	(2)
Trading characteristics:		
𝟙(Multi-broker Trades) $_{i,j,t}$	-7.534***	
	(-6.97)	
#Brokers $_{i,j,t}$		-4.683***
		(-5.47)
Log(Dollar Imbalance) $_{i,j,t}$	0.569	0.591
	(1.41)	(1.44)
Stock characteristics:		
Log(Market Cap) $_{i,t}$	3.700	3.270
	(0.48)	(0.43)
Price $^{-1}_{i,t}$	56.493	57.846
	(1.02)	(1.05)
Quoted Spread $_{i,t}$	-0.031	-0.030
	(-1.22)	(-1.17)
Turnover $_{i,t}$	-2.368	-2.423
	(-0.82)	(-0.83)
Return $_{i,t}$	-0.286	-0.281
	(-0.54)	(-0.53)
Volatility $_{i,t}$	-157.688**	-158.428**
	(-2.50)	(-2.51)
𝟙(Pre News) $_{i,t}$	3.430**	3.389**
	(2.39)	(2.35)
𝟙(News) $_{i,t}$	2.337	2.354
	(1.53)	(1.55)
𝟙(Pre EA) $_{i,t}$	1.668	1.779
	(0.74)	(0.79)
𝟙(EA) $_{i,t}$	1.462	1.532
	(0.44)	(0.46)
Day FEs	Y	Y
Stock FEs	Y	Y
DMA FEs	Y	Y
Observations	13,875	13,875
Adjusted R-squared	0.035	0.034

Table A3: Determinants of the choice to trade with multiple brokers and anonymous trading. This table presents the probit regression results examining the determinants of 𝟙 (Multi-broker Trades), with Anonymous Trade Ratio added as an additional control. The variables are defined in Appendix 2. Z-statistics, based on standard errors clustered by stock and day, are in parentheses. *i* denotes stocks, *j* denotes DMA firms, and *t* denotes days. ***, **, and * denote significance at the 0.01, 0.05, and 0.10 levels.

	Pr(Multi-broker Trades=1) $_{i,j,t}$	
	Probit	Probit
	Coefficient	Marginal Effect
Trading characteristics:		
Anonymous Trade Ratio $_{i,j,t}$	0.026	0.003
	(0.52)	(0.52)
Log(Dollar Imbalance) $_{i,j,t}$	0.096***	0.010***
	(10.81)	(10.94)
Stock characteristics:		
Log(Market Cap) $_{i,t}$	0.003	0.000
	(0.19)	(0.19)
Price $^{-1}$ $_{i,t}$	0.493	0.051
	(1.43)	(1.43)
Quoted Spread $_{i,t}$	-0.002*	-0.000*
	(-1.74)	(-1.72)
Turnover $_{i,t}$	-0.013	-0.001
	(-0.60)	(-0.60)
Return $_{i,t}$	0.000	0.000
	(0.08)	(0.08)
Volatility $_{i,t}$	0.816**	0.084**
	(2.04)	(2.03)
𝟙(Pre News) $_{i,t}$	0.042*	0.004*
	(1.68)	(1.68)
𝟙(News) $_{i,t}$	0.003	0.000
	(0.25)	(0.25)
𝟙(Pre EA) $_{i,t}$	0.014	0.001
	(0.88)	(0.88)
𝟙(EA) $_{i,t}$	0.003	0.000
	(0.13)	(0.13)
Day FEs	N	
Stock FEs	N	
DMA FEs	N	
Obs.	325,788	
Pseudo R-squared	0.025	

Table A4: Anonymous trading and price impact: regression analysis on a matched sample. This table presents the regression results that examine the relationship between the Anonymous Trade Ratio, defined as the fraction of volume trades executed by a DMA firm using an anonymous broker ID, and price impacts. The variables are defined in Appendix 2. T-statistics, based on standard errors clustered by stock and day, are in parentheses. *i* denotes stocks, *j* denotes DMA firms, and *t* denotes days. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels.

Table A4 Continued

	Price Impact 5 min $_{i,j,t}$	Price Impact 15 min $_{i,j,t}$	Price Impact 30 min $_{i,j,t}$	Price Impact 5 min $_{i,j,t}$	Price Impact 15 min $_{i,j,t}$	Price Impact 30 min $_{i,j,t}$
Trading characteristics:	(1)	(2)	(3)	(4)	(5)	(6)
𝟙(Multi-broker Trades) $_{i,j,t}$	-3.856***	-10.139***	-15.933***			
	(-5.52)	(-8.84)	(-10.75)			
#Brokers $_{i,j,t}$				-2.389***	-6.560***	-10.081***
				(-4.32)	(-7.58)	(-9.04)
Anonymous Trade Ratio $_{i,j,t}$	-4.851***	-7.207***	-8.299***	-4.891***	-7.294***	-8.452***
	(-4.14)	(-4.60)	(-3.61)	(-4.18)	(-4.63)	(-3.67)
Log(Dollar Imbalance) $_{i,j,t}$	-0.200	-0.878***	-1.826***	-0.188	-0.827***	-1.764***
	(-0.81)	(-2.81)	(-4.74)	(-0.75)	(-2.63)	(-4.59)
Stock characteristics:						
Log(Market Cap) $_{i,t}$	2.492	14.573*	21.203**	2.266	14.010*	20.293**
	(0.46)	(1.85)	(2.13)	(0.42)	(1.77)	(2.03)
Price$^{-1}_{i,t}$	79.410	144.378**	151.885**	80.078	145.943**	154.500**
	(1.50)	(2.49)	(2.07)	(1.49)	(2.51)	(2.11)
Quoted Spread $_{i,t}$	0.083	0.117	0.063	0.083	0.118	0.066
	(0.84)	(0.93)	(0.39)	(0.85)	(0.95)	(0.41)
Turnover $_{i,t}$	-2.278	-2.381	2.256	-2.307	-2.443	2.146
	(-1.02)	(-0.87)	(0.62)	(-1.04)	(-0.88)	(0.59)
Return $_{i,t}$	0.235	0.294	-0.012	0.238	0.302	0.001
	(0.99)	(0.79)	(-0.02)	(1.00)	(0.82)	0.00
Volatility $_{i,t}$	58.797*	136.610***	223.277***	58.419*	135.788***	221.844***
	(1.96)	(3.13)	(3.73)	(1.94)	(3.11)	(3.70)
𝟙(Pre News) $_{i,t}$	-0.015	-1.022	-0.866	-0.036	-1.072	-0.951
	(-0.02)	(-0.70)	(-0.46)	(-0.04)	(-0.73)	(-0.51)
𝟙(News) $_{i,t}$	0.221	-0.098	0.682	0.23	-0.075	0.718
	(0.32)	(-0.09)	(0.44)	(0.34)	(-0.07)	(0.47)
𝟙(Pre EA) $_{i,t}$	0.069	-1.344	-0.388	0.125	-1.201	-0.159
	(0.06)	(-0.77)	(-0.18)	(0.12)	(-0.69)	(-0.08)
𝟙(EA) $_{i,t}$	-1.585	-4.220	-1.353	-1.549	-4.13	-1.208
	(-0.85)	(-1.66)	(-0.44)	(-0.83)	(-1.63)	(-0.39)
Day FEs	Y	Y	Y	Y	Y	Y
Stock FEs	Y	Y	Y	Y	Y	Y
DMA FEs	Y	Y	Y	Y	Y	Y
Obs.	13,875	13,875	13,875	13,875	13,875	13,875
Adj. R-squared	0.103	0.087	0.087	0.103	0.085	0.084

Table A5: Diminishing effect of multiple brokers and price impact: regression analysis on a matched sample. This table presents the results of regression analyses examining the marginal effect of using an additional broker. The variables are defined in Appendix 2. The analysis includes coefficients for each broker category, assessing their price impacts at 5-minute, 15-minute, and 30-minute intervals. T-statistics, based on standard errors clustered by stock and day, are in parentheses. *i* denotes stocks, *j* denotes DMA firms, and *t* denotes days. ***, **, and * denote significance at the 0.01, 0.05, and 0.10 levels.

	Price Impact 5 min $_{i,j,t}$	Price Impact $_{i,j,t}$ 15 min $_{i,j,t}$	Price Impact 30 min $_{i,j,t}$
Trading characteristics:	(1)	(2)	(3)
2 Brokers $_{i,j,t}$	-4.078***	-10.395***	-16.431***
	(-5.70)	(-8.73)	(-10.89)
3 Brokers $_{i,j,t}$	-3.180***	-10.459***	-14.807***
	(-2.78)	(-5.64)	(-6.57)
4 Brokers $_{i,j,t}$	-2.459	-5.417	-8.504*
	(-0.74)	(-1.41)	(-1.95)
>4 Brokers $_{i,j,t}$	-11.857	-15.928*	-21.882
	(-1.65)	(-1.90)	(-1.14)
Log(Dollar Imbalance) $_{i,j,t}$	-0.313	-1.053***	-2.061***
	(-1.20)	(-3.19)	(-5.08)
Stock characteristics:			
Log(Market Cap) $_{i,t}$	3.137	15.487*	22.311**
	(0.57)	(1.98)	(2.26)
Price$^{-1}_{i,t}$	83.020	149.339**	157.711**
	(1.55)	(2.56)	(2.15)
Quoted Spread $_{i,t}$	0.084	0.118	0.065
	(0.86)	(0.95)	(0.41)
Turnover $_{i,t}$	-2.181	-2.231	2.417
	(-0.98)	(-0.81)	(0.67)
Return $_{i,t}$	0.234	0.293	-0.016
	(0.98)	(0.79)	(-0.03)
Volatility $_{i,t}$	58.095*	135.566***	221.962***
	(1.96)	(3.11)	(3.71)
𝟙(Pre News) $_{i,t}$	0.041	-0.937	-0.768
	(0.04)	(-0.65)	(-0.41)
𝟙(News) $_{i,t}$	0.248	-0.059	0.724
	(0.36)	(-0.05)	(0.46)
𝟙(Pre EA) $_{i,t}$	0.122	-1.271	-0.318
	(0.11)	(-0.73)	(-0.15)
𝟙(EA) $_{i,t}$	-1.641	-4.301*	-1.454
	(-0.88)	(-1.67)	(-0.47)
Time FEs	Y	Y	Y
Stock FEs	Y	Y	Y
DMA FEs	Y	Y	Y
Observations	13,875	13,875	13,875
Adjusted R-squared	0.102	0.086	0.086

Table A6: Trade concentration and price impact: regression analysis on a matched sample. This table presents the results for multivariate regressions examining the relationship between trade concentration and price impacts using a matched sample. The dependent variables include the dollar-weighted price impacts at 5-minute, 15-minute, and 30-minute frequency. We construct a Herfindahl-Hirschman Index (HHI) of trade concentration across brokers for each DMA firm-stock-day observation where multiple brokers are used. A lower HHI indicates a more even distribution of trades across brokers. We create two dummy variables based on HHI. HighConcentration is set to 1 for each multi-broker trade with a HHI above the median, and 0 otherwise. LowConcentration is set to 1 for each multi-broker trade with a HHI equal or below the median, and 0 otherwise. The variables are defined in Appendix 2. T-statistics, based on standard errors clustered by stock and day, are in parentheses. *i* denotes stocks, *j* denotes DMA firms, and *t* denotes days. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels.

Table A6 Continued

	Price Impact 5 $min_{i,j,t}$	Price Impact 15 $min_{i,j,t}$	Price Impact 30 $min_{i,j,t}$
	(1)	(2)	(3)
Trading characteristics:			
HighConcentration $_{i,j,t}$	-2.899***	-9.363***	-14.891***
	(-3.62)	(-8.20)	(-10.16)
LowConcentration $_{i,j,t}$	-5.017***	-11.226***	-17.332***
	(-6.19)	(-8.17)	(-10.08)
Log(Dollar Imbalance) $_{i,j,t}$	-0.274	-0.999***	-1.964***
	(-1.10)	(-3.09)	(-4.93)
Stock characteristics:			
Log(Market Cap) $_{i,t}$	3.153	15.527**	22.309**
	(0.58)	(1.99)	(2.27)
$Price^{-1}_{i,t}$	83.542	150.167**	158.631**
	(1.54)	(2.57)	(2.15)
Quoted Spread $_{i,t}$	0.085	0.119	0.067
	(0.86)	(0.95)	(0.41)
Turnover $_{i,t}$	-2.159	-2.215	2.450
	(-0.97)	(-0.81)	(0.68)
Return $_{i,t}$	0.235	0.293	-0.012
	(0.98)	(0.79)	(-0.02)
Volatility $_{i,t}$	58.399*	135.907***	222.494***
	(1.96)	(3.12)	(3.71)
𝟙(Pre News) $_{i,t}$	0.034	-0.945	-0.779
	(0.03)	(-0.65)	(-0.42)
𝟙(News) $_{i,t}$	0.186	-0.115	0.654
	(0.27)	(-0.11)	(0.42)
𝟙(Pre EA) $_{i,t}$	0.124	-1.257	-0.289
	(0.11)	(-0.72)	(-0.14)
𝟙(EA) $_{i,t}$	-1.649	-4.308*	-1.456
	(-0.88)	(-1.67)	(-0.47)
Day FEs	Y	Y	Y
Stock FEs	Y	Y	Y
DMA FEs	Y	Y	Y
Observations	13,875	13,875	13,875
Adjusted R-squared	0.102	0.086	0.086

Table A7: Trading with multiple brokers and price impacts, regression analysis on an alternative matched sample. This table examines the relationship between trading with multiple brokers and price impacts, using a matched sample of trades in the same stock and trading day but executed by different DMA firms. Panel A compares the trade attributes of multi-broker trades and those of one-broker trades for the matched sample. Panel B presents the results of the multivariate regressions. The dependent variables include the dollar-weighted price impacts at 5 minutes (Impact5), 15 minutes (Impact15), and at 30 minutes (Impact30) frequency. In columns (1) – (3), 𝟙(Multi-broker Trades) is the measure of multi-broker trading, and in columns (4) – (6), #Brokers is the measure of multi-broker trading. The variables are defined in Appendix 2. T-statistics, based on standard errors clustered by stock and day, are in parentheses. *i* denotes stocks, *j* denotes DMA firms, and *t* denotes days. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels.

Panel A: Summary statistics of trade characteristics

	Multi-broker Trades (N=15,422)		One-broker Trades (N=32,288)		Multi-broker Trades - One-broker Trades	
	Mean	STD	Mean	STD	Diff	t-stat
Number of Trades	673.22	1327.46	704.00	1309.80	-30.78	-2.27
Share Volume (1,000)	25.60	75.42	27.29	83.52	-1.68	-2.12
DollarVol ($1,000)	963.77	2351.37	1041.86	2434.59	-78.09	-3.31
Vol Imbalance (1,000)	0.73	63.60	0.78	72.88	-0.05	-0.07
Dollar Imbalance ($1,000)	-10.94	1074.13	-10.47	1194.88	-0.47	-0.04
Price Impact 5 min (bps)	6.18	27.78	7.06	33.63	-0.88	-3.01
Price Impact 15 min (bps)	6.60	39.94	8.43	47.14	-1.83	-4.41
Price Impact 30 min (bps)	7.43	51.52	9.36	60.84	-1.93	-3.61

Table A7 Continued

Panel B: Regression results

	Price Impact 5 min $_{i,j,t}$	Price Impact 15 min$_{i,j,t}$	Price Impact 30 min $_{i,j,t}$	Price Impact 5 min $_{i,j,t}$	Price Impact 15 min $_{i,j,t}$	Price Impact 30 min $_{i,j,t}$
	(1)	(2)	(3)	(4)	(5)	(6)
Trading characteristics:						
𝟙(Multi-broker Trades) $_{i,j,t}$	-1.163***	-2.007***	-1.997***			
	(-2.87)	(-3.60)	(-3.33)			
#Brokers $_{i,j,t}$				-0.733**	-1.333***	-1.359***
				(-2.39)	(-3.41)	(-2.98)
Log(DollarImbalance) $_{i,j,t}$	0.391***	0.368**	0.278	0.401***	0.388**	0.298
	(3.17)	(2.36)	(1.26)	(3.28)	(2.48)	(1.35)
Stock characteristics:						
Log(Market Cap) $_{i,t}$	-4.948	-5.778	-10.480**	-4.952	-5.785	-10.487**
	(-1.59)	(-1.35)	(-2.16)	(-1.59)	(-1.36)	(-2.16)
Price $^{-1}{}_{i,t}$	-3.154	-14.349	-14.556	-3.079	-14.199	-14.396
	(-0.11)	(-0.37)	(-0.35)	(-0.11)	(-0.36)	(-0.35)
Quoted Spread $_{i,t}$	0.181*	0.227	0.183	0.181*	0.226	0.182
	(1.94)	(1.44)	(0.94)	(1.94)	(1.43)	(0.94)
Turnover $_{i,t}$	3.169***	3.703***	5.578***	3.175***	3.711***	5.586***
	(2.91)	(3.31)	(3.28)	(2.92)	(3.32)	(3.29)
Return $_{i,t}$	-0.167	-0.185	-0.272	-0.167	-0.184	-0.271
	(-0.96)	(-0.69)	(-0.73)	(-0.96)	(-0.69)	(-0.72)
Volatility $_{i,t}$	30.924	48.490	80.849	30.875	48.395	80.750
	(1.02)	(0.96)	(1.20)	(1.02)	(0.96)	(1.20)
𝟙(Pre News) $_{i,t}$	-0.388	0.188	0.210	-0.393	0.179	0.201
	(-0.75)	(0.24)	(0.20)	(-0.76)	(0.23)	(0.19)
𝟙(News) $_{i,t}$	0.049	0.582	0.680	0.050	0.583	0.681
	(0.11)	(0.86)	(0.85)	(0.11)	(0.86)	(0.85)
𝟙(Pre EA) $_{i,t}$	-0.346	-1.130*	-2.377**	-0.343	-1.125*	-2.372**
	(-0.53)	(-1.69)	(-2.52)	(-0.52)	(-1.68)	(-2.51)
𝟙(EA) $_{i,t}$	-0.707	-1.491	-1.860	-0.711	-1.498	-1.867
	(-0.91)	(-1.38)	(-1.32)	(-0.92)	(-1.39)	(-1.33)
Day FEs	Y	Y	Y	Y	Y	Y
Stock FEs	Y	Y	Y	Y	Y	Y
DMA FEs	Y	Y	Y	Y	Y	Y
Observations	47,710	47,710	47,710	47,710	47,710	47,710
Adjusted R-squared	0.059	0.035	0.026	0.059	0.035	0.026

Table A8: Trading with multiple brokers and followers' trading volume, regression analysis on an alternative matched sample. This table provides the results for the multivariate regressions examining the relationship between trading with multiple brokers and subsequent follower trading activity, using a matched sample of trades in the same stock but executed on different trading days by different DMA firms. The unit of observation is at the DMA firm-broker-stock-day level. Followers are DMA firms, excluding the one initiating trade, who trade the stock with the same broker who handles the initiating trade. In columns (1) and (3) the dependent variable is the log of the net dollar volume of followers on the following day after the DMA firm's trades. In columns (2) and (4) the dependent variable is the log of the net dollar volume of followers on the second following trading day after the DMA firm's trades. In columns (1) and (2), $\mathbb{1}$(Multi-broker Trades) is the measure of multi-broker trading, and in columns (3) and (4), #Brokers is the measure of multi-broker trading. The remaining variables are defined in Appendix 2. T-statistics, based on standard errors clustered by stock and day, are in parentheses. *i* denotes stocks, *j* denotes DMA firms, *k* denotes brokers, and *t* denotes days. ***, **, and * denote significance at the 0.01, 0.05, and 0.10 levels.

Table A8 Continued

	Log(Follower Volume) $_{i,j,k,t}$			
	Day 1	Day 2	Day 1	Day 2
	(1)	(2)	(3)	(4)
Trading characteristics:				
𝟙(Multi-broker Trades) $_{i,j,t}$	-0.577**	-0.715***		
	(-2.51)	(-3.85)		
#Brokers $_{i,j,t}$			-0.307***	-0.126*
			(-3.60)	(-1.69)
Log(Dollar Imbalance) $_{i,j,t}$	0.004	0.005	0.009	0.005
	(0.27)	(0.42)	(0.61)	(0.41)
Broker characteristics:				
Log(Broker Dollar Volume) $_{j,k,t}$	0.268***	0.181***	0.265***	0.180***
	(11.56)	(9.20)	(11.53)	(9.25)
Stock characteristics:				
Log(Market Cap) $_{i,t}$	0.314	0.549***	0.306	0.538***
	(1.57)	(3.92)	(1.55)	(3.92)
Price $^{-1}_{i,t}$	1.900	3.349*	1.889	3.273*
	(1.11)	(1.87)	(1.10)	(1.83)
Quoted Spread $_{i,t}$	0.137	0.443*	0.124	0.435
	(0.38)	(1.65)	(0.34)	(1.61)
Turnover $_{i,t}$	0.098*	0.028	0.104**	0.031
	(1.89)	(0.70)	(2.01)	(0.79)
Return $_{i,t}$	0.004	-0.015*	0.005	-0.015*
	(0.42)	(-1.91)	(0.44)	(-1.91)
Volatility $_{i,t}$	0.014	0.011	0.013	0.010
	(1.22)	(1.10)	(1.15)	(1.01)
𝟙(Pre News) $_{i,t}$	0.077*	0.032	0.073*	0.031
	(1.74)	(0.67)	(1.67)	(0.64)
𝟙(News) $_{i,t}$	-0.009	0.026	-0.008	0.026
	(-0.19)	(0.62)	(-0.17)	(0.63)
𝟙(Pre EA) $_{i,t}$	0.113***	0.060	0.116***	0.062
	(2.60)	(1.07)	(2.65)	(1.10)
𝟙(EA) $_{i,t}$	-0.090	-0.021	-0.091	-0.022
	(-0.93)	(-0.21)	(-0.92)	(-0.21)
Day FEs	Y	Y	Y	Y
Stock FEs	Y	Y	Y	Y
DMA FEs	Y	Y	Y	Y
Observations	75,639	75,639	75,639	75,639
Adjusted R-squared	0.561	0.562	0.562	0.562

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