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LIQUIDITY AND GOVERNANCE

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ABSTRACT

Liquidity and Governance*

Is greater trading liquidity good or bad for corporate governance? We address this question both theoretically and empirically. We solve a model consisting of an optimal IPO followed by a dynamic Kyle market in which the large investor's private information concerns her own plans for taking an active role in governance. We show that an increase in the liquidity of the firm's stock increases the likelihood of the large investor 'taking the Wall Street walk.' Thus, higher liquidity is harmful for governance. Empirical tests using three distinct sources of exogenous variation in liquidity confirm the negative relation between liquidity and blockholder activism.

JEL Classification: G23 and G34
Keywords: corporate governance, hedge funds, Kyle models, liquidity, shareholder activism, shareholder proposals and Wall Street walk

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1. Introduction

A liquid secondary market in shares facilitates capital formation but may be deleterious for corporate governance. Bhide (1993) argues that greater liquidity reduces the cost to a blockholder of selling her stake in response to managerial problems ('taking the Wall Street walk'), resulting in too little monitoring by large shareholders. Bhide's work has spawned an active literature on the effects of liquidity on governance. The present paper makes two contributions to that literature: (i) we solve a theoretical model consisting of an IPO followed by a dynamic Kyle (1985) market in which the large investor's private information concerns her own plans for taking an active role in governance and show that greater liquidity leads to lower blockholder activism, and (ii) we verify the negative theoretical relation between liquidity and activism using three distinct natural experiments.

Liquidity has opposing effects on governance because it facilitates both block acquisition and block disposition (Maug, 1998). We show that this is true in the dynamic Kyle model: the probability of blockholder activism increases (decreases) with the amount of liquidity trading if the blockholder's initial block is smaller (larger) than a certain critical value. We assume that the initial block is determined in an IPO. Following the analysis of IPO mechanisms in Stoughton and Zechner (1998), we show that optimal mechanisms lead to a block of sufficient size so that liquidity is harmful for governance (a conclusion opposite to that of Maug). A novel aspect of the dynamic Kyle model we study is that the realized sign and magnitude of liquidity trading affect the blockholder's choice about becoming active and so affect the ultimate value of the stock. If liquidity traders happen to sell shares, the blockholder is likely to buy shares and become active; conversely, if liquidity traders buy shares, the blockholder is likely to take the Wall Street walk.

Our empirical results support our theoretical results. Establishing the causal effect of liquidity on governance is empirically challenging because, as Edmans, Fang, and Zur (2013) note, liquidity and governance are likely jointly determined by a firm's unobserved characteristics. To address this challenge, we use three natural experiments: brokerage closures (Kelly and Ljungqvist, 2012), market maker closures (Balakrishnan et al., 2013), and mergers of retail with institutional brokerage firms (Kelly and Ljungqvist, 2012). Events of the first two types exogenously reduce liquidity and events of the third type exogenously increase liquidity. For two of them, we can even sign the direction of the resulting change in liquidity trading: as Kelly and Ljungqvist show, liquidity traders sell in response to brokerage-closure shocks and buy in response to retail brokerage-mergers.

In all three experiments, we find that blockholder activity, as measured by hedge fund activism and the number of shareholder proposals submitted in opposition to management, increases when liquidity decreases and vice versa. These findings suggest that for the average stock market-listed firm in the U.S., greater trading liquidity is harmful for governance. They stand in contrast to prior empirical work that treats the level of a firm's trading liquidity as exogenous (for example, Norli et al. (2010)) or that uses decimalization as a shock to liquidity. A potential explanation for the difference in results is that decimalization, which undoubtedly improved some aspects of liquidity, coincided with some other aggregate shock that independently improved governance (such as Regulation Fair Disclosure). The staggered nature of the 43 brokerage closures, the 50 market maker closures, and the six retail brokerage-mergers we use makes it highly unlikely that our results are confounded in a similar way.[1]

We are aware of only two other papers that study a dynamic market with a blockholder whose actions affect corporate value. One is Collin-Dufresne and Fos (2013), who in contemporaneous and independent work also solve a dynamic Kyle model with a blockholder who can expend costly effort to increase firm value. For the most part, they address different issues, though with a similar model.[2] The major difference between our theoretical model and theirs is that we determine the equilibrium initial block size in the Kyle market by analyzing optimal IPO mechanisms. This allows us to answer the question whether liquidity is harmful for governance. On the empirical side, they employ blockholder trade data to analyze predictions concerning the large trader's strategy, whereas we look at three distinct sources of exogenous variation in liquidity to confirm the negative relation between liquidity and blockholder activism that our theoretical model predicts.

DeMarzo and Urošević (2006) also analyze a dynamic market with a blockholder whose actions affect corporate value. A key distinction between their paper and ours is that they assume a fully revealing rational expectations equilibrium. In contrast, we follow Grossman and Stiglitz (1976,

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[1]We contrast our empirical approach to that used in decimalization studies in Section 5.2.

[2]Their version of the Kyle model differs from ours in some respects. For example, they assume continuous effort, whereas we assume effort is all-or-none. And unlike us, they assume the large trader has private information about the exogenous component of firm value.

1980) and Kyle (1985) by assuming there is some additional uncertainty in the market (namely, liquidity trading) that provides camouflage for the blockholder's trading. This allows the market's forecast of the blockholder's plans to sometimes deviate from what the blockholder herself regards as most likely, producing profitable trading opportunities.

There is a sizable literature on the importance of blocks (called toeholds) in overcoming the Grossman and Hart (1980) free-rider problem in corporate takeovers. A relatively small subset of that literature studies toehold acquisition. Without exception, the papers in that literature assume a single round of trading (see Shleifer and Vishny (1986), Kyle and Vila (1991), Ravid and Spiegel (1999), Bris (2002), and Goldman and Qian (2005)). Assuming a single period makes it impossible to study the decision of whether to unwind a toehold or to add to a toehold by trading in the open market. It also makes it difficult to examine the extent to which market activity affects the potential acquirer's decision to complete the acquisition.[3]

The literature on monitoring by blockholders also includes a small subset of papers that study trading by the blockholder, including Huddart (1993), Admati et al. (1994), Kahn and Winton (1998), Maug (1998), Stoughton and Zechner (1998), and Noe (2002). Again, each of these papers assumes a single round of trading, which makes it impossible to study any feedback from market prices to the trading and monitoring activities of blockholders. Within this literature, the paper most closely related to ours is Maug (1998), who solves a one-period Kyle model in which an investor can acquire a block of sufficient size to affect governance in the single round of trading.

We consider a set-up similar to that of Maug (1998) but allow trading to be continuous. Like Maug, we show that the probability of block acquisition and monitoring by the large investor increases with liquidity trading if the investor's initial stake is small and decreases with liquidity trading when the initial stake is large. However, unlike Maug, our analysis of IPO mechanisms suggests that the blockholder's initial stake will always be large in equilibrium.[4] Moreover, recalling a similar result in Kyle and Vila (1991), who study takeovers, we show that the probability of the blockholder becoming active depends on the sign of liquidity trading. In states of the world in

[3]Kyle and Vila (1991) tackle the latter issue by assuming that the blockholder can observe liquidity trades before submitting her own order. We derive some of the same results under the more plausible assumption that the blockholder can infer *past* liquidity trades from market prices, adapting to liquidity trading in a dynamic market.

[4]We discuss this difference further in Section 4.

which liquidity traders are net sellers, the blockholder is more likely to buy shares and become active. In states of the world in which liquidity traders are net buyers, the blockholder is more likely to exit by selling. Thus, whether or not the investor takes the Wall Street walk depends not only on the ex ante magnitude of liquidity trading and the size of the investor's initial stake, as in Maug, but also on the realized sign of the liquidity trading.

Another strand of the literature on the Wall Street walk that is tangentially related to our paper is the literature on "governance by exit," which includes the papers by Admati and Pfleiderer (2009), Edmans (2009), and Edmans and Manso (2011). The models in these papers all have a single round of trading, so they cannot analyze feedback from prices to blockholder actions. Moreover, to the extent that they allow blockholder actions to affect the value of the company, they assume the actions take place before trading. By implication, they do not study the accumulation of a block by an investor in anticipation of the investor becoming active. Their focus is on trading by an insider with information about a share value that is exogenous to their trading. The ability of blockholders to trade on negative information and the manager's concern with the short-term stock price cause the manager to be more concerned than he otherwise would be about the impact of his actions on firm value and thereby improves governance. In contrast, in our model, the blockholder has no private information about exogenous elements of corporate value. Instead, the private information is about the investor's own intentions, which in turn impact corporate value.

Our contribution is twofold. First, we derive the conditions under which liquidity is harmful for a firm's corporate governance. This will be the case if the blockholder holds a sufficiently large initial stake in the firm and if liquidity traders are net buyers (rather than net sellers) of the stock. Since, in equilibrium, the initial stake will always be large enough, our model supports Bhide's (1993) concern that greater liquidity need not be desirable. This result contrasts with the prevailing consensus in the literature, which views Bhide's concern as misplaced because it overlooks the beneficial effects of liquidity in enabling stakes to be assembled in the first place. Our model shows that the conditions under which these beneficial effects obtain are unlikely to met. Second, we use exogenous variation in liquidity (of a kind that maps closely into our model) to estimate the causal effect of liquidity on blockholder activism. We find this effect to be strongly negative, consistent with the model but, again, in contrast to the prevailing consensus.

2. The Kyle Market

In this section, we describe the Kyle model and its equilibrium, taking the initial block size as given. How the initial block size is determined is discussed in the next section.

2.1. Model

A corporate decision is to be made at date $1+\epsilon$, for $\epsilon > 0$. An investor owns a block $A \geq 0$ of shares at date 0. If the investor owns at least B shares and takes a costly action at date $1+\epsilon$, then she can influence the decision. If she does so, then the value of each share will be H. Otherwise, the value will be $L < H$. The parameters A, B, L, and H are common knowledge. This is a parsimonious way of modeling the fact that only blockholders can be effective in influencing corporate decisions. A more realistic model would allow the probability of effective intervention to increase continuously in the block size, rather than jumping from zero to one when the block size reaches a constant B. Obviously, the two-point distribution for the asset value is also an extreme simplifying assumption. Making these assumptions allows us to focus on how the market activity affects the blockholder's decision to become actively involved in the governance of the corporation.

We assume the shares are traded continuously during the time interval $[0,1]$. Let C denote the cost of intervention by the blockholder, and define

$$\xi = \frac{C}{H-L}\,. \tag{1}$$

The costly action is worthwhile for the blockholder if and only if she owns at least ξ shares at date 1. We assume that ξ is private information of the blockholder and is normally distributed with mean μ_ξ and standard deviation σ_ξ. Maug (1998) makes a similar assumption.[5] Define

$$V(x,\xi) = \begin{cases} pLx & \text{if } x < \max(B,\xi)\,, \\ Lx + (H-L)(x-\xi) & \text{otherwise}\,. \end{cases} \tag{2}$$

If the investor owns x shares before the costly action must be taken at date $1+\epsilon$, then they are

[5]Actually, Maug (1998) assumes the large investor plays a mixed strategy in the Kyle model in his main presentation and states that the outcome is equivalent to the large investor having private information about the cost of intervention. We do not investigate mixed strategies in the continuous-trading model.

worth $V(x,\xi)$ to her. The value of each share at date $1+\epsilon$ to any other investor is

$$\omega(x,\xi) = \begin{cases} L & \text{if } x < \max(B,\xi)\,, \\ H & \text{otherwise}\,, \end{cases} \tag{3}$$

where x again denotes the number of shares held by the blockholder.

We model the market for shares as a Kyle model, operating continuously during the time interval $[0,1]$. The blockholder's holding at any date t is X_t (with $X_0 = A$), and the liquidity trades are a Brownian motion Z with zero drift and volatility σ_z. We interpret Z as the cumulative number of shares purchased by liquidity traders, so $Z_0 = 0$. Aggregate purchases by the blockholder and liquidity traders are $Y = X + Z - A$. The process Y is observed by market makers.

We search for equilibria in which the price at date t is $P_t = \pi(t, Y_t)$ for some function π. Given π, the blockholder seeks to maximize

$$\mathsf{E}\left[V(X_1,\xi) - \int_0^1 P_{t-}\,\mathrm{d}X_t - \int_0^1 (\mathrm{d}P_t)(\mathrm{d}X_t) \;\middle|\; \xi\right]\,, \tag{4}$$

subject to the constraint that $P_t = \pi(t, Y_t)$, where we use the standard notation $a_{t-} = \lim_{s\uparrow t} a_s$. Formula (4) is based on the fact that each market order $\mathrm{d}X_t$ is executed at price $P_{t-} + \mathrm{d}P_t$. Back (1992) shows that trading strategies with nonzero quadratic variation are suboptimal. The same is true here, except possibly at date 1, when the investor may submit a discrete buy order in order to reach the threshold B required for intervention. Except for the possible discrete order at date 1, we expect an equilibrium strategy to be absolutely continuous, meaning that there is an order rate $\theta_t = \mathrm{d}X_t/\mathrm{d}t$. To simplify, we will only consider such strategies, so we take the investor's objective function to be

$$\mathsf{E}\left[V(X_1,\xi) - \int_0^1 P_t\theta_t\,\mathrm{d}t - P_1\Delta X_1 \;\middle|\; \xi\right]\,, \tag{5}$$

where $\Delta X_1 = X_1 - X_{1-}$. This objective function is the same as assumed by Kyle (1985), except that the value V is endogenous here and except that a discrete order ΔX_1 is allowed at date 1. In maximizing (5), the investor takes into account the dependence of P on her trades via the function π. Note that the price P_1 at which a discrete order trades at date 1 is $\pi(1, Y_1)$ and hence depends on the order size, just as in a single-period Kyle model.

An equilibrium is a triple $(\pi, \theta, \Delta X_1)$ such that the trading strategy $(\theta, \Delta X_1)$ maximizes (4) given π and such that

$$\pi(t, Y_t) = \mathsf{E}[\omega(X_1, \xi) \mid (Y_s)_{s \le t}] \tag{6}$$

for each t. This is the standard definition of equilibrium in a Kyle model.

To recap, the innovations here relative to the continuous-time model studied by Kyle (1985) are the endogenous values V and ω and the possibility of a discrete order at the last trading date. The endogenous values are the primary innovation. The values are endogenous because they depend on whether the large investor accumulates a block of sufficient size to make intervention worthwhile. The blockholder knows the value in advance only to the extent that she knows her own future trading plans. As we show in the next section, those plans can change based on market activity.

2.2. Equilibrium

This section describes an equilibrium and some of its properties. All proofs are in Appendix A. Let N denote the standard normal distribution function and n the standard normal density function.

The cost of intervention affects equilibrium outcomes to the extent that the cost deviates from its expected value. Define $\xi^* = \xi - \mu_\xi$. An important role is also played by the size of the initial stake A compared to the expected cost of intervention μ_ξ. When $A > \mu_\xi$, then the initial stake is large enough to make intervention worthwhile on average in the absence of trading (and ignoring the requirement that B shares are needed for intervention). The difference $A - \mu_\xi$ appears in the equilibrium price and trading strategy normalized for the amount of liquidity trading σ_z and the uncertainty about the cost of intervention σ_ξ. Define

$$\delta = \frac{\sigma_z}{\sqrt{\sigma_\xi^2 + \sigma_z^2}}\,, \tag{7}$$

and set

$$A^* = \frac{\delta(A - \mu_\xi)}{1 + \delta}\,. \tag{8}$$

Define the investor's value function as

$$J(t, x, y, \xi, A) = \sup_{\theta,\, \Delta X_1} \mathsf{E}\left[V(X_1, \xi) - \int_t^1 P_t \theta_t \, \mathrm{d}t - P_1 \Delta X_1 \mid X_t = x, Y_t = y, \xi\right]\,, \tag{9}$$

where the maximization is subject to the constraint that $P_u = \pi(u, Y_u)$ for all $u \ge t$. We include the initial stake A as an argument of the value function, because we consider endogenizing it in

Section 3.

Theorem 1. *Define*

$$\pi(1,y) = \begin{cases} L & \text{if } y + A^* < 0\,, \\ H & \text{otherwise}\,. \end{cases} \tag{10a}$$

and, for $t < 1$,

$$\pi(t,y) = L + (H-L)\,\mathrm{N}\left(\frac{y+A^*}{\sigma_z\sqrt{1-t}}\right)\,. \tag{10b}$$

Define

$$\theta_t = \frac{-\delta(\xi^* + Z_t) - Y_t}{(1-t)(1-\delta)}\,, \tag{11a}$$

$$\Delta X_1 = \begin{cases} (B - X_{1-})^+ & \text{if } \xi^* + Z_1 \le A^*/\delta\,, \\ 0 & \text{otherwise}\,. \end{cases} \tag{11b}$$

Then, $(\pi, \theta, \Delta X_1)$ is an equilibrium. In this equilibrium, the market converges to strong-form efficiency as $t \to 1$ in the sense that

$$P_{1-} = P_1 = \omega(X_1, \xi) \tag{12}$$

with probability one. Furthermore,

$$Y_{1-} = -\delta(\xi^* + Z_1) \tag{13}$$

with probability one. The value function of the blockholder is

$$J(t,x,y,\xi,A) = xL + (H-L)K(t,x,y,\xi,A)\,, \tag{14a}$$

where

$$K(t,x,y,\xi,A) = \sigma_z\sqrt{1-t}\big[d_1\,\mathrm{N}(d_1) - d_2\,\mathrm{N}(-d_2) + \mathrm{n}(d_1) + \mathrm{n}(-d_2)\big]$$

with

$$d_1 = \frac{y + A^*}{\sigma_z\sqrt{1-t}}\,, \tag{14b}$$

$$d_2 = \frac{y + A^* + \xi - x}{\sigma_z\sqrt{1-t}}\,. \tag{14c}$$

To interpret (10), recall that the equilibrium condition (6) is that the price equal the expected date–1 value $\omega(X_1, \xi)$. From (3), that value is

$$L + (H - L)1_{\{X_1 \geq \max(B,\xi)\}}\,,$$

where $1_{\{\cdot\}}$ denotes the zero-one indicator function. The blockholder becomes active if and only if $X_1 \geq \max(B, \xi)$. Conditions (10a) and (12) imply that $X_1 \geq \max(B, \xi)$ if and only if $Y_1 \geq -A^*$. The form (10b) of the equilibrium pricing rule implies that the market assigns probability

$$\mathrm{N}\left(\frac{Y_t + A^*}{\sigma_z\sqrt{1-t}}\right) \tag{15}$$

at each date $t < 1$ to the blockholder becoming active.

The definition (11a) implies that the trading rate θ_t blows up near $t = 1$ unless $\delta(\xi^* + Z_t) + Y_t \to 0$ as $t \to 1$. This is the reason that (13) holds. Condition (12) states that there is no jump in the price at date 1, even if there is a discrete order from the blockholder. This fact and (10a) imply that $Y_1 \geq A^*$ if and only if $Y_{1-} \geq A^*$. Thus, the blockholder becomes active if and only if $Y_{1-} \geq -A^*$. Combining this with (13) implies that the blockholder becomes active if and only if $Z_1 \leq -\xi^* + A^*/\delta$. Thus, the blockholder decides whether to become active based on the sign and magnitude of realized liquidity trades. This is because the price depends on liquidity trades. If liquidity traders buy shares, propping up the price, then the blockholder will surreptitiously sell shares (take the Wall Street walk). If liquidity traders sell shares, driving the price down, then the blockholder will surreptitiously buy shares and eventually make the costly intervention.

Condition (11b) states that the blockholder buys a discrete block at date 1 if and only if $X_{1-} < B$ and $Z_1 \leq -\xi^* + A^*/\delta$. When these conditions hold, the investor buys enough to raise her holding to the threshold B. It would also be an equilibrium for the blockholder to buy more than $(B - X_{1-})^+$ shares when $Z_1 \leq -\xi^* + A^*/\delta$, but buying the additional shares would be superfluous, because nothing is gained or lost from buying shares at price H when the blockholder plans to become active.

Condition (13) implies that the blockholder's cumulative purchases before the possible discrete trade at date 1 are

$$X_{1-} - X_0 = Y_{1-} - Z_1 = -\delta\xi^* - (1+\delta)Z_1\,. \tag{16}$$

Formula (16) shows that, as discussed above, the blockholder buys more when liquidity traders sell more. In fact, she buys $1+\delta$ shares for each share that liquidity traders sell and sells $1+\delta$ shares for each share that liquidity traders buy, other things equal. This "multiplier effect" is unusual in Kyle models and is a result of the blockholder adjusting her plans for intervention based on market activity.[6] If liquidity traders sell, then the blockholder finds it profitable to buy, as is customary in Kyle models, but here buying increases the expected value of intervention, raising the expected asset value and stimulating additional buying. This is a consequence of the fact that there is a fixed cost but no variable cost of intervention: by paying the cost C, the blockholder increases the value of all of the shares she owns from L to H.

The price $P_t = \pi(t, Y_t)$ evolves as

$$\mathrm{d}P_t = \lambda(Y_t)\,\mathrm{d}Y_t\,, \tag{17a}$$

where Kyle's lambda is given by

$$\lambda(y) = (H-L)\frac{\partial}{\partial y}\mathrm{N}\left(\frac{y+A^*}{\sigma_z\sqrt{1-t}}\right) = \frac{H-L}{\sigma_z\sqrt{1-t}}\,\mathrm{n}\left(\frac{y+A^*}{\sigma_z\sqrt{1-t}}\right)\,. \tag{17b}$$

Formula (17) follows from (10) by Itô's formula. To see that, note that $(\mathrm{d}Y)^2 = (\mathrm{d}Z)^2 = \sigma_z^2\,\mathrm{d}t$ and $\pi_t + (1/2)\sigma_z^2\pi_{yy} = 0$, where the subscripts denote partial derivatives. Thus, applying Itô's formula to $P_t = \pi(t, Y_t)$ yields $\mathrm{d}P = \pi_y\,\mathrm{d}Y$.

The equilibrium condition (6) implies that P must be a martingale relative to market makers' information (the history of Y). Because (17) implies $\mathrm{d}Y = (1/\lambda)\,\mathrm{d}P$, it follows that Y is at least a local martingale relative to market makers' information. This means that the expected insider trade is always zero, which is a standard feature of Kyle models. Because Y on the interval $[0,1)$ is a continuous local martingale with $(\mathrm{d}Y)^2 = \sigma_z^2\,\mathrm{d}t$, it must actually be a Brownian motion with

[6] In the basic continuous-time Kyle (1985) model, the equilibrium strategy of the informed trader has the property that $X_1 = f(v) - Z_1$ for some function f of the asset value v. Thus, except for buying $f(v)$ shares, the informed trader offsets the trades of the liquidity traders one-for-one.

volatility σ_z. This is Levy's theorem (Rogers and Williams, 2000, IV.33). Thus, excluding the possible discrete order at date 1, Y has the same distribution, given market makers' information, as does Z. This is again a standard feature of Kyle models (Back, 1992).

The fact that Y is a Brownian motion on $[0, 1)$ and formula (13) account for the value of the parameter δ in (7). Note that the unconditional variance of the right-hand side of (13) is $\delta^2(\sigma_\xi^2 + \sigma_z^2) = \sigma_z^2$. Thus, the unconditional variance of Y_{1-} is σ_z^2, as it must be in order for Y to have the same distribution as Z on $[0, 1)$.

A possible equilibrium path is shown in Figure 1. In this example, there is a single share outstanding and $\mu_\xi = 0.1$, which means that on average intervention is worthwhile if the blockholder owns 10% of the outstanding shares. We have set $\sigma_\xi = 0.02$, so the fraction of outstanding shares required to make intervention worthwhile is between 6% and 14% with 95% probability. We have also taken $\sigma_z = 0.05$, so that a 95% confidence interval for Z_1 is $\pm 10\%$ of the outstanding shares. With these parameter values, $\delta = 0.93$. It follows from (16) that the blockholder buys 1.93 shares for each share that liquidity traders sell, and sells 1.93 shares for each share that liquidity traders buy.

The conditional probability of the blockholder intervening, given the market's information, is shown in (15). From the blockholder's perspective, the conditional probability at date t is the probability that $Z_1 \leq -\xi^* + A^*/\delta$, conditional on Z_t and ξ^*. This probability is

$$\mathrm{N}\left(\frac{A^*/\delta - \xi^* - Z_t}{\sigma_z\sqrt{1-t}}\right). \tag{18}$$

In Figure 1, we have taken $A = \mu_\xi$, so the unconditional probability of intervention is 50%. We have also taken $\xi = \mu_\xi$, so the blockholder also views the probability of intervention as 50% at date 0, conditional on ξ.

A random path of liquidity trading is shown in Figure 1. All other values are calculated from the equilibrium, given the assumed parameter values. An uptick in liquidity buying between times $t = 0.10$ and $t = 0.18$ leads to a divergence between the market and the blockholder's conditional probabilities of intervention. The blockholder can infer from the price that liquidity traders have bought shares; consequently, her assessment of the probability of intervention declines. Accordingly, she sells shares. This selling lowers Y and eventually aligns the conditional probabilities of intervention. The opposite pattern – liquidity selling and blockholder buying – occurs around

$t = 0.40$. The magnitude of the selling by liquidity traders causes the blockholder's conditional probability to reach 90% or more. The magnitude of the buying by the blockholder leads to the same result for the market's conditional probability. However, a late flurry of buying by liquidity traders causes the blockholder to reverse course. The selling of shares between $t = 0.60$ and $t = 0.92$ by the blockholder is an example of the Wall Street walk. The selling causes the market to realize that intervention is unlikely, though, as always, the change in the market's conditional probability lags the blockholder's somewhat.

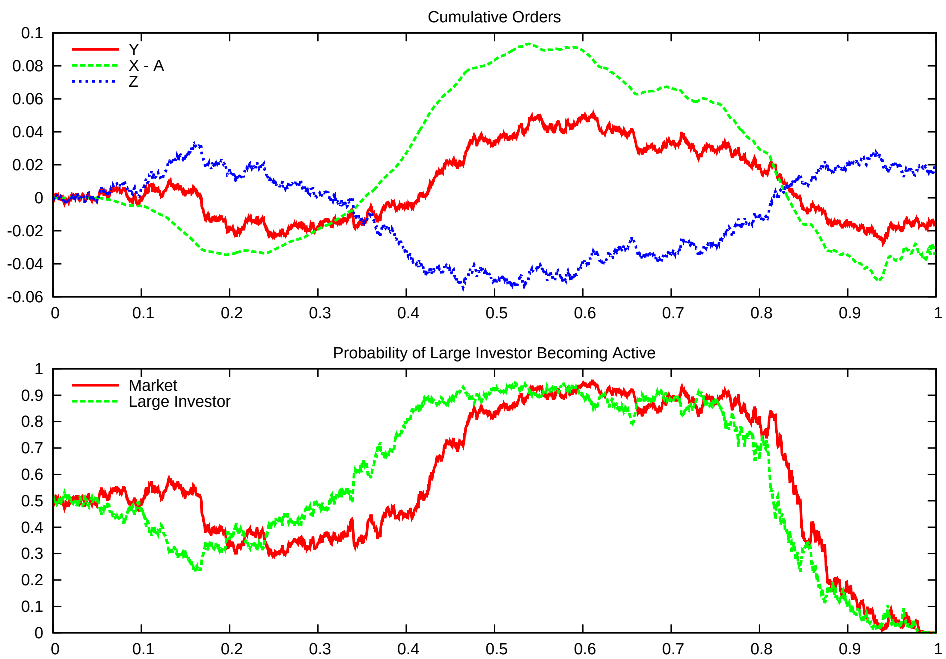

Figure 1: *A Simulation of the Equilibrium.* The top panel shows a possible path of liquidity trading Z and the corresponding paths of large investor cumulative purchases $X - A$ and aggregate purchases $Y = Z + X - A$, given the parameter values described in the text. The bottom panel shows the conditional probabilities of the large investor becoming active, given the market maker's information and the large investor's information, respectively.

2.3. Ex Ante Utility of the Blockholder

In this subsection, we calculate the blockholder's expected utility as a function of the initial block size prior to observing the cost of monitoring ξ. The result is used in the next section to determine the initial block size that would result from an optimal IPO. We consider the possibility that the market may anticipate a block size that is different from the actual block size. Let A denote the block size anticipated by the market (which determines the pricing rule in the Kyle market) and let x denote the actual block size. The blockholder's expected utility prior to observing ξ is

$$G(x,A) \stackrel{\text{def}}{=} \mathsf{E}[J(0,x,0,\xi,A)]\,. \tag{19}$$

Of course, in any equilibrium, we will have rational expectations, but distinguishing between the actual block and the anticipated block in this way is useful, because A being the argmax of $x \mapsto G(x,A)$ is potentially different from A being the argmax of $x \mapsto G(x,x)$, as Cournot is different from Stackelberg.

Theorem 2. *For any real a, define*

$$f(a) = \frac{\delta(a-\mu_\xi)}{1+\delta}\,. \tag{20}$$

The blockholder's ex ante expected utility function G is convex with derivatives

$$\frac{\partial G(x,A)}{\partial x} = L + (H-L)\,\mathrm{N}\left(\frac{(1+\delta)f(x)-\delta f(A)}{\sigma_z}\right)\,, \tag{21a}$$

$$\frac{\partial G(x,A)}{\partial A} = \frac{\delta}{1+\delta}(H-L)\left[\mathrm{N}\left(\frac{f(A)}{\sigma_z}\right) - \mathrm{N}\left(\frac{(1+\delta)f(x)-\delta f(A)}{\sigma_z}\right)\right]\,, \tag{21b}$$

$$\frac{\mathrm{d}G(x,x)}{\mathrm{d}x} = L + (H-L)\,\mathrm{N}\left(\frac{f(x)}{\sigma_z}\right)\,. \tag{21c}$$

The convexity has important consequences for the behavior of the large trader in any mechanism that might determine A – in particular, for the IPO mechanisms discussed in the next section. The convexity is a consequence of the cost of monitoring being a fixed cost, independent of the number of shares owned (i.e., increasing returns to scale). Another point worth noting is that the derivatives of the functions $x \mapsto G(x,A)$ and $x \mapsto G(x,x)$ each converge to H as $x \to \infty$. This is due to the fact that the blockholder is almost certain to intervene if her initial stake is very large, and the fixed cost of intervention is negligible when amortized over a very large number of shares, so the marginal value of an additional share is approximately H when x is large.

3. Initial Block Size

Stoughton and Zechner (1998) consider the problem of allocating shares in an IPO to maximize the value of a firm when there is a potential blockholder who can undertake costly but value enhancing monitoring.[7] They discuss five mechanisms, each of which we will consider here. Our

[7] Stoughton and Zechner (1998) also consider secondary market trading, as we do, but they assume a single round of trading with no liquidity shocks.

model is simpler than theirs in that our investors are risk neutral, so two of the mechanisms produce the same outcome. The mechanisms are:

1. Take-it-or-leave-it offers.
2. Walrasian.
3. Discriminatory pricing.
4. Discriminatory pricing with a take-it-or-leave-it offer to the large investor.
5. Non-discriminatory pricing with a take-it-or-leave-it offer to the large investor and rationing of small investors subject to a constraint that $A \leq \hat{A}$, where $\hat{A}$ is exogenously given.

In the context of our model, we will show that the second mechanism is infeasible, mechanisms #1 and #4 produce $A = 1$, mechanism #3 produces $A = 0$, and mechanism #5 produces $A = \hat{A}$. The worst mechanism from the firm's point of view is mechanism #3.

Normalize so there is a single share outstanding. To abstract from signaling issues, assume the IPO takes place before the large investor observes the cost of monitoring. In keeping with our previous notation, A denotes the allocation to the large investor in the IPO, so $1 - A$ is the allocation to small investors who do not monitor. Given an allocation A, the expected value of the ultimate share price $\omega(X_1, \xi)$ is the price $\pi(0, 0)$, where π is defined in (10). The expected share price is

$$P(A) \stackrel{\text{def}}{=} \pi(0,0) = L + (H - L)\,\mathrm{N}\left(\frac{f(A)}{\sigma_z}\right), \tag{22}$$

where f is defined in (20). Small investors in the IPO have zero demands if the price is $p > P(A)$, arbitrary demands if $p = P(A)$, and infinite demands if $p < P(A)$.[8]

The Walrasian mechanism does not have an equilibrium. An equilibrium outcome would be a pair (p, A) such that $1 - A$ is an optimal demand of small investors at price p and such that $x = A$ maximizes either $G(x, x) - px$ if we assume x is observed or maximizes $G(x, A) - px$ if x is not directly observed. Because of the convexity of G established in Theorem 2, the only possible maxima for the large investor are $A = 0$ and $A = \infty$, and, because the market must clear, the only possible equilibrium is $A = 0$. Consequently, we must have $p = P(0)$ to obtain a finite nonzero

[8]The small investors could be the liquidity traders in the Kyle market. They could also be the risk-neutral competitive market makers in the Kyle market. Because of the presence of such market makers in the Kyle market, we assume the marginal small investor in the IPO is a risk-neutral investor who does not require an illiquidity discount.

demand for the small investors. But, at price $p = P(0)$, the maxima of both $G(x, 0)$ and $G(x, x)$ occur at $x = \infty$. In fact, at any price less than H, the maxima occur at $x = \infty$. Thus, the Walrasian mechanism is infeasible.

In the price discrimination mechanism, the firm chooses (p, q, A) to maximize $pA + q(1 - A)$ subject to A being an optimal demand for the blockholder at price p and $1 - A$ being an optimal demand for small investors at price q. Again, we must have $A = 0$, which is optimal for the large investor at any price $p \geq H$. As in the Walrasian mechanism, the price for small investors must be $P(0)$. Thus, the mechanism produces $P(0)$ in revenue.

In the other mechanisms, it is natural to assume the allocation to the blockholder is observed. Mechanisms #1 and #4 have the same outcome. In mechanism #1, the firm chooses an allocation A and transfers R and S to maximize $R + S$ subject to the blockholder being willing to take A at cost R and small investors being willing to take $1 - A$ at cost S. Given A, the firm can charge the blockholder $G(A, A) - G(0, 0)$, and it can charge small investors $P(A)(1 - A)$, so the total revenue is $G(A, A) - G(0, 0) + P(A)(1 - A)$. The derivative of this is $P'(A)(1 - A) > 0$, so the optimum is $A = 1$, and the revenue achieved is $G(1, 1) - G(0, 0)$.

In mechanism #4, the firm chooses (p, q, A) to maximize $pA + q(1 - A)$ subject to $G(A, A) - pA \geq G(0, 0)$ (the blockholder agrees to take the take-it-or-leave-it offer) and subject to $1 - A$ being an optimal demand for small investors at price q. Given A, the firm sets $p = [G(A, A) - G(0, 0)]/A$ and $q = P(A)$, so the revenue is the same as in mechanism # 1, and the optimum is again $A = 1$, with revenue $G(1, 1) - G(0, 0)$.

In mechanism #5, the firm chooses (p, A) to maximize p subject to $G(A, A) - pA \geq G(0, 0)$ (the take-it-or-leave-it offer is acceptable to the blockholder) and subject to the optimal demand for small investors at price p being at least $1 - A$. In this mechanism, we assume the firm is constrained to choose $A \leq \hat{A}$ for some fixed $\hat{A} \leq 1$. This constraint reflects real-world listing standards that require the firm to have a minimum number of shareholders before it is allowed to list. For our purposes, this prevents small investors from being rationed to zero. Given A, the incentive compatibility conditions are that $p \leq [G(A, A) - G(0, 0)]/A$ and $p \leq P(A)$. Because G is convex, we always have $[G(A, A) - G(0, 0)]/A < P(A)$, so the optimal price, given A, is $p = [G(A, A) - G(0, 0)]/A$. Because of convexity again, this is an increasing function of A, so the optimal allocation is $A = \hat{A}$ with revenue $[G(\hat{A}, \hat{A}) - G(0, 0)]/\hat{A}$. In the absence of the constraint

$A \leq \hat{A}$, the outcome would be $A = 1$ and small investors would be rationed to zero, with the revenue being the same as in mechanisms #1 and #4.

As Stoughton and Zechner (1998) explain, the fifth mechanism can explain the puzzling coincidence of rationing and underpricing as an optimal outcome for the firm. This is true with or without the constraint $A \leq \hat{A}$. The rationing is simply more extreme without the constraint. In either case, there is underpricing in the sense that the initial price of the Kyle market $P(A)$ is larger than the issue price $[G(A,A) - G(0,0)]/A$. Note that the blockholder is also rationed, because his demand at price $[G(A,A) - G(0,0)]/A < H$ is infinite.

4. The Effect of Liquidity on Governance

From (15), the unconditional probability that the costly action is taken and the shares are worth H is

$$\mathrm{N}\left(\frac{A^*}{\sigma_z}\right) = \mathrm{N}\left(\frac{A - \mu_\xi}{\sigma_z + \sqrt{\sigma_\xi^2 + \sigma_z^2}}\right). \tag{23}$$

Hence, the costly action is more likely when the investor holds a larger initial position or when the expected cost of the action is lower. The probability is greater than 1/2 when $A > \mu_\xi$, which means that the expected net gain from the costly action is positive given the investor's initial position A. The probability (23) is increasing in σ_z if and only if $A < \mu_\xi$.

The expected number of shares required to make intervention worthwhile should be less than 100% of the outstanding shares, so assume $\mu_\xi < 1$. It also seems sensible to assume $\mu_\xi < \hat{A}$ in mechanism #5 from the previous section. Then we have $A > \mu_\xi$ in each of the feasible mechanisms discussed in the previous section except for price discrimination. If the firm can legally distinguish between the two investor classes in the offering terms, as price discrimination assumes, then surely it should be able to simply negotiate a separate arrangement with the blockholder before issuing shares to small investors. Since the other mechanisms all raise higher revenue, it seems very unlikely that the firm would choose the price discrimination mechanism. Our conclusion is that the initial allocation A should exceed μ_ξ. Consequently, an increase in liquidity will reduce the probability of blockholder activism.

Maug (1998) reaches the opposite conclusion because he has a different model of how the initial block is determined. He assumes that the large investor starts out with a block of zero shares and that the size of the block that she holds at the start of the Kyle model is determined in a market in which liquidity traders are price-taking marginal investors and in which the large investor behaves as a monopsonist. Thus, Maug's model is really a two-period model with a transparent market in the first period and a Kyle market in the second period. The initial block – meaning the block at the beginning of this two-period model – is assumed to be zero. Because the large trader prefers to trade in a Kyle market rather than in a transparent market, her trade in the transparent market is small; consequently, the block at the beginning of the Kyle market is small.[9] Rather than assuming a zero initial block, we have followed Stoughton and Zechner (1998) in assuming that the initial block is determined in an IPO.

5. Testing the Model

5.1. Empirical Implications and Strategy

The model has the following empirical implications.

Implication 1: When the blockholder's initial stake is sufficiently large, an increase in the amount of liquidity trading σ_z reduces the probability of intervention and vice versa.

This implication follows immediately from the analysis in the previous section. It is the central implication of our model: greater liquidity has the potential to be harmful for corporate governance.

Implication 2: When the blockholder's initial stake is sufficiently large, the blockholder's choice between intervening and taking the Wall Street walk depends on the direction of liquidity trading. The blockholder will sell (intervene) when liquidity traders buy (sell), which in turn increases the probability of walking (intervening).

This implication follows from Theorem 1. It adds nuance to Implication 1 by showing that an increase in liquidity trading is necessary but not sufficient to reduce the likelihood of intervention: the direction of the change in liquidity trading also matters. This nuance allows us to distinguish our model from that of Maug (1998) which generates a version of our Implication 1 as a special (and in his view, implausible) case.

[9] The large trader would actually choose to trade zero in the first period in Maug's model except that there is presumed to be an illiquidity discount in that period. The basis for the illiquidity discount is Maug's assumption that the market makers from the second-period Kyle market cannot participate in the first-period market. See footnote 8 for additional discussion.

Implication 3: The blockholder's buying amplifies the liquidity traders' selling, such that the blockholder buys $1 + \delta$ shares for each share the liquidity traders sell, with $\delta > 0$.

This implication follows immediately from formula (16).

Testing the model's empirical implications requires an exogenous shock to a stock's liquidity trading and knowledge of the resulting direction in liquidity trading. Given such an exogenous shock, we can test whether blockholders respond by becoming more or less prone to intervening when liquidity traders buy or sell (Implications 1 and 2).[10] To this end, we exploit three distinct natural experiments.

5.2. Experiment #1: Exogenous Brokerage Closures

We borrow our first experiment from Kelly and Ljungqvist (2012), who exploit closures of research departments at 43 securities brokerage firms in the U.S. over the period 2000 to 2008 to test asymmetric-information asset pricing models. The 43 closures led to 4,429 U.S. firms losing some or all analyst coverage and so represent shocks to the affected firms' information environment. Kelly and Ljungqvist demonstrate that the closures were unrelated to the affected firms' future prospects and so are plausibly exogenous at the level of the individual stocks.[11] Using this experiment, Balakrishnan et al. (2013) show that affected stocks lose a substantial amount of liquidity, so brokerage closures are a promising candidate for testing Implication 1. Moreover, Kelly and Ljungqvist find that when a stock loses analyst coverage in the wake of a closure, information asymmetry among investors increases and retail investors as a group sell while institutional investors as a group buy. To the extent that retail investors are liquidity traders, this finding implies that we know the resulting direction in liquidity trading as well, allowing us to test Implication 2.

5.2.1. Relation to Prior Literature

Using brokerage closures as a source of exogenous variation in liquidity is new in the literature on liquidity and governance. It departs from recent empirical work on blockholder activism such as Gerken (2009), Bharath et al. (2013), Fang et al. (2009), and Edmans et al. (2012), all of whom use decimalization as a shock to liquidity. While we agree that the move to quoting spreads in

[10] The difficulty of empirically distinguishing trades involving liquidity traders and blockholders from other trades precludes us from testing Implication 3.

[11] The closures were the result of adverse changes in the economics of sell-side research. See Kelly and Ljungqvist (2012) for further details.

1¢ increments likely improves some aspects of liquidity, we prefer the brokerage closures for three reasons:

- Unlike decimalization, which affects all traded firms without exception, only some stocks in the economy are shocked when a brokerage firm closes its research department. This fact yields a set of quasi-randomly selected firms that receive a shock to their liquidity when a brokerage firm closes down ('treated firms') and a set of quasi-randomly selected firms that do not ('control firms'). Armed with these, we can estimate a causal treatment effect using standard diff-in-diff estimators in a way that is not possible with the decimalization shock.

- Unlike decimalization, which affected all traded firms over a brief period of time between August 2000 and February 2001, the brokerage closures are staggered over many years. Given the way they cluster in time, the effects of decimalization-induced liquidity shocks on corporate governance are hard to disentangle from other shocks to corporate governance occurring at the same time (such as Regulation FD, which came into effect in late 2000). The staggered nature of the brokerage closures, on the other hand, minimizes the risk that the estimated treatment effect is confounded by unobserved contemporaneous events.

- Unlike brokerage closures, which represent a shock to the information environment that theory suggests hurts liquidity traders, inducing them to sell, it is unclear a priori whether decimalization should result in liquidity traders buying or selling a stock. So whether or not decimalization can help shed light on Implication 1, it can for sure not be used to test Implication 2.

5.2.2. Sample and Data

The test compares the evolution of liquidity and of activism among firms that suffer exogenous coverage terminations to a control sample composed of matched firms that do not suffer exogenous shocks to their analyst coverage. This difference-in-differences approach allows us to difference away secular trends and swings in liquidity and activism that occur for unrelated reasons.

The implementation of the test follows Balakrishnan et al. (2013) closely.[12] Balakrishnan et al.

[12]The only departure from Balakrishnan et al. is that we do not filter out firms without a history of providing earnings guidance. This filter is necessary in Balakrishnan et al.'s study given its focus on firms' guidance responses to coverage terminations. It is the reason why Balakrishnan et al. end up with fewer treated firms than we do.

construct panels of treated and control firms at the fiscal-quarterly level around brokerage closures. Because treated firms are larger, have more analysts, are more volatile, and enjoy greater liquidity than the average CRSP firm, Balakrishnan et al. use a nearest-neighbor propensity-score match to identify controls that match treated firms most closely on these four dimensions (each measured in the fiscal quarter before the treated firm's coverage termination). Following their approach results in a sample of 2,983 treated firms and the same number of matched controls. We observe each firm for (up to) four quarters before and (up to) four quarters after each of the 2,983 coverage terminations. In total, the estimation sample used in our tests consists of 24,653 firm-fiscal quarters for treated firms and 24,496 firm-fiscal quarters for their controls.

Columns 1 through 3 in Table 1 show that treated and control firms are matched quite tightly: there are no significant differences in liquidity, analyst coverage, market capitalization, or volatility in the quarter before a coverage termination. The same is true for the number of market-makers, even though this variable is not included in the propensity match.

We use two proxies for intervention. The first looks at hedge fund activism and is borrowed from Gantchev (2013). Gantchev uses data from 13D filings, proxies, and SharkRepellent.net to track the evolution of activist campaigns instigated by a large set of activist hedge funds between 2000 and 2008. We use his data to code, for each firm-fiscal quarter, whether a firm in our estimation sample was the subject of such a campaign. Our second proxy for intervention is the number of shareholder proposals. Activist investors use shareholder proposals to advocate that a company take a specific course of action or change a policy. Shareholder proposals can only be submitted by holders of at least 1% of a company's shares. We obtain data on all shareholder proposals submitted in the U.S. from RiskMetrics. The data cover both those proposals that came to a vote and those that were subsequently withdrawn by the proponent. Our variable of interest counts the number of proposals submitted in a given fiscal quarter.

5.2.3. Effect of Coverage Shocks on Liquidity Trading

For exogenous coverage terminations to be a useful experiment in our setting, they have to result in a reduction in liquidity. Column 4 of Table 1 shows that this is indeed the case. Losing an analyst results in a sizeable and significant increase in log AIM (which measures *il*liquidity), net of the contemporaneous change in log AIM among matched controls. The point estimate of 0.008

matches that of Balakrishnan et al. (2013) exactly. Column 5 provides further nuance by letting the effect of coverage shocks on liquidity depend on the number of analysts who continue to cover the company. The results show that AIM increases by significantly more, the fewer analysts the company is left with (p=0.029).

5.2.4. Reduced-form Effect of Coverage Shocks on the Likelihood of Intervention

Given that coverage terminations result in a sizeable reduction in liquidity, and given Kelly and Ljungqvist's (2012) finding that retail investors sell in response to an exogenous coverage termination, Implications 1 and 2 imply an increase in the likelihood of intervention as long as the blockholder's initial stake is sufficiently large. Because the model is necessarily silent on what constitutes a stake that is "sufficiently large", it is not possible to sort treated firms into those for which we expect a response and those for which we expect no change. Instead, we proceed by considering all treated firms. This will attenuate the estimated effect of reductions in liquidity on the likelihood of intervention and so bias us against finding support for the model.

We first present reduced-form estimates, relating our two proxies for shareholder intervention directly to the coverage shocks. Column 6 of Table 1 shows that the probability of a firm being subject to an activist campaign increases significantly when the firm exogenously loses analyst coverage (p=0.029). The point estimate suggests that the probability increases by 30 basis points (relative to untreated controls) from the unconditional probability of 1.4%, an increase of 21% (=0.3/1.4). Looking at the raw data, we see that the number of firms subject to an activist campaign increases from 34 to 49 following a brokerage closure, while control firms see little change (43 vs. 45). These magnitudes suggest that the regression estimates are economically meaningful.

We find similar patterns when we use shareholder proposals. Column 8 shows that the log number of proposals large shareholders submit to management increases (relative to untreated controls) when the firm loses coverage (p=0.002). The point estimate suggests that the number of proposals increases by 26.1% from the unconditional mean of 0.041 per firm-quarter.

5.2.5. Effect of Liquidity Trading on the Likelihood of Intervention

The reduced-form findings in columns 6 and 8 of Table 1 are consistent with Implication 2 (and hence Implication 1) of the model: exogenous brokerage closures—which we know lead to a reduction in liquidity and in liquidity trading—are followed by an increase in shareholder activism.

This is reassuring: as Angrist and Krueger (2001) note, if we do not see the proposed causal relation of interest in the reduced form, it is probably not there.

In the next step, we use the brokerage closures as an instrument for liquidity to estimate the causal effect of liquidity on shareholder activism. This involves using predicted values of AIM obtained from the first-stage regression of AIM on the instrument (and other firm characteristics) in place of actual liquidity in a second-stage regression of shareholder activism. The results are shown in columns 7 (for hedge fund activism) and 9 (for shareholder proposals). In both specifications, we find a negative and significant effect of liquidity (i.e., a positive effect of Amihud's illiquidity measure) on shareholder activism. This is consistent with our model. The effects are large economically. A one-standard-deviation reduction in liquidity leads to a 12.6 percentage-point increase in the likelihood that the firm becomes the target of an activist hedge fund campaign and a 60.1% increase in the number of proposals shareholders submit to management.

5.3. Experiment #2: Exogenous Reductions in Market Making

The identifying assumption central to a causal interpretation of the estimates in columns 7 and 9 is that brokerage closures only affect shareholder intervention through the liquidity channel and not directly (the exclusion restriction). While this assumption is inherently untestable, it would be violated if the adverse changes in the distribution of information brought about by brokerage closures directly induced blockholders to intervene. While it is not obvious why this might happen, we next consider a different exogenous source of variation in liquidity which, unlike brokerage closures, does not affect a firm's information environment: closures of market-making operations.

We use the 50 market-maker closures uncovered by Balakrishnan et al. (2013) for the period from 2000 to 2008, identify all affected firms using data from Nastraq and Thomson-Reuters, and screen out any firms that happened to suffer an exogenous analyst coverage termination in the same fiscal quarter. We then create a matched sample of 4,121 treated firms and the same number of controls, using the same approach as in the brokerage-closure experiment (except that we also match on the pre-shock number of market makers). Table 2 reports summary statistics. The match between treated and control firms is again very tight. Interestingly, firms that lose a market maker are considerably smaller, more volatile, less liquid, and covered by fewer analysts than are the firms in our first experiment (*cf.* column 1 in Tables 1 and 2). The reason for this is simple: as Kelly and Ljungqvist (2012) show, analysts are more likely to cover larger companies.

The first-stage results in column 4 of Table 2 confirm our expectation that liquidity suffers when a market maker ceases operations ($p < 0.001$). The point estimate is five times larger than in the brokerage-closure experiment, reflecting the fact that many more small (and hence already-illiquid) firms end up being treated in the market-maker experiment. Column 5 lets the effect of the shock depend on the number of firms that continue to make markets in the stock. The results show that liquidity falls by significantly more, the fewer market makers a stock is left with ($p < 0.001$)

The reduced-form results in columns 6 and 8 mirror those of our first experiment: shareholder activism increases after a firm exogenously loses a market maker.

The causal effects of liquidity on our two proxies for shareholder intervention, estimated this time using reductions in market making as an instrument, are reported in columns 7 and 9. As in the brokerage-closure experiment, the effects are negative: a reduction in liquidity leads to an increase both in hedge fund activism (p=0.023) and in the number of shareholder proposals (p=0.004). The effects are smaller economically than in the brokerage-closure experiment. A one-standard-deviation reduction in liquidity leads to a 1.8 percentage-point increase in the likelihood that the firm becomes the target of an activist hedge fund campaign and a 4.8% increase in the number of shareholder proposals. These smaller economic magnitudes reflect three differences between the two experiments:

1. As noted earlier, it is possible that the brokerage closures have a direct effect on shareholder activism. This would lead us to overestimate the causal effect of liquidity on activism in the brokerage-closure experiment.
2. Unlike in the brokerage-closure experiment, we cannot sign the effect of loss of market making on liquidity trading a priori: liquidity traders could reasonably respond to the liquidity shock by either buying or selling. This means that our set of treated firms likely consists of a mixture of the two cases, which leads us to underestimate the causal effect of liquidity on activism in the market-maker experiment. In this sense, we view the estimates in Tables 1 and 2 as upper and lower bounds on the causal relation between liquidity and activism, respectively.
3. The samples are not directly comparable, as firms that lose a market maker are systematically smaller and less liquid than firms that lose an analyst. This affects the economic magnitudes; for example, smaller companies attract far fewer shareholder proposals than larger compa-

nies. Heterogeneous treatment effects are therefore to be expected. More generally speaking, each set of estimates is sample-specific, so the external validity of the magnitudes cannot be guaranteed.

5.4. Experiment #3: Exogenous Reductions in Information Asymmetry

While brokerage and market-maker closures result in less liquidity trading, our final natural experiment achieves the opposite. Kelly and Ljungqvist (2012) identify a set of firms that experience an exogenous *reduction* in information asymmetry as a result of a particular type of brokerage merger: the acquisition by a brokerage firm that serves retail clients of a brokerage firm that exclusively caters to institutions. Before such a merger, the acquirer's retail clients would not have had access to the target's institutional research. After the merger, retail clients gain access to the research output of the acquired (institutional) research department. In other words, previously private signals (available only to institutional clients) now become public signals (available to all clients). As a result, information asymmetry is reduced, liquidity trading should increase, and liquidity traders should buy the stock.[13] This allows us to test Implication 2 from the other direction: as liquidity traders buy, blockholders should intervene less.

Using data from Kelly and Ljungqvist (2012), we identify 761 treated firms that experience an exogenous reduction in information asymmetry during our sample period. We match these to 761 controls using the same criteria as before. Table 3 describes the resulting sample. The match between treated and control firms is again tight, and firms subject to the merger treatment look similar to those subject to the brokerage-closure treatment and substantially larger, more liquid, and so on than those subject to the market-maker treatment.

Columns 4 and 5 of Table 3 show that liquidity increases significantly as a result of the merger treatment, the more so the fewer analysts covered the stock to begin with. Columns 6 and 8 show the reduced-form estimates, which (as expected) are opposite in sign to the other two treatments: reductions in information asymmetry lead to significant reductions in shareholder intervention. The causal effects of liquidity on intervention are shown in columns 7 and 9. Consistent with

[13] This natural experiment is quite distinct from Hong and Kacperczyk's (2010), who focus on cases where *both* brokers covered a stock before the merger, regardless of their client base. In other words, in their experiment, the total number of public signals in the economy falls as one of the analysts is made redundant. By contrast, Kelly and Ljungqvist's (2012) experiment keeps the number of analysts covering the stock (and hence the total number of signals) constant, by focusing on cases where only the institutional broker covered the stock before the merger.

the previous two experiments, we again find a negative relation between liquidity and both hedge fund activism (p=0.141) and the number of shareholder proposals (p=0.005). While only the latter is statistically significant, the implied economic magnitudes are similar to those we found in the brokerage-closure experiment: a one-standard-deviation reduction in liquidity leads to a 16.1 percentage-point increase in the likelihood that the firm becomes the target of an activist hedge fund campaign and a 61.3% increase in the number of shareholder proposals.[14]

6. Conclusion

We ask whether greater trading liquidity harms governance, by making it easier for a blockholder to vote with her feet and sell her stock when the firm's managers fail to maximize firm value (Bhide, 1993), or whether it improves governance, by reducing the cost of assembling large blocks in the first place (Maug, 1998).

We approach this question both theoretically and empirically. Theoretically, we solve a continuous-time Kyle model in which a large investor trades on private information about her own plans for taking an active role in corporate governance. Becoming active increases firm value to the benefit of all shareholders but is privately costly for the blockholder. The model shows that greater liquidity is harmful for governance when the blockholder holds a sufficiently large initial stake in the firm and when liquidity traders are net buyers of the stock. Based on analysis of optimal IPO mechanisms, we argue that the first condition is likely to hold in equilibrium.

We find strong empirical support for the model. We use three distinct exogenous shocks (two that reduce and one that increases liquidity and liquidity trading) to estimate the causal effects of liquidity on two measures of shareholder activism: the likelihood that a firm becomes the target of an activist hedge fund campaign and the number of shareholder proposals filed against the firm's management. We find strong causal effects consistent with the model: greater trading liquidity harms governance.

[14] At the same time, this treatment is subject to the same limitation as the brokerage-closure experiment: we cannot rule out that blockholders react to the shock to the information environment independently of the resulting shock to liquidity trading.

Appendix A. Proofs

We will establish a series of propositions, of which Theorem 1 is a corollary. Proposition 4 shows that the strategy (11) is optimal for the blockholder, given the pricing rule (10). Proposition 5 shows that the pricing rule (10) satisfies the equilibrium condition (6), given the trading strategy (11). Thus, collectively, Propositions 4 and 5 show that the trading strategy and pricing rule constitute an equilibrium. Part (c) of Proposition 1 establishes (13). Proposition 2 establishes (12). Proposition 3 shows that the function (14) satisfies the Hamilton-Jacobi-Bellman equation, and the proof of Proposition 4 verifies that it is indeed the value function. The last item in the appendix is the proof of Theorem 2.

Observe that the pricing rule (10) satisfies

$$\pi(t, y) = \mathsf{E}[\pi(1, Z_1) \mid Z_t = y] \,, \tag{A.1}$$

Also, by the continuity of π in t, $P_{1-} = \pi(1, Y_{1-})$. The Hamilton-Jacobi-Bellman (HJB) equation is

$$\sup_{\theta} \left\{ - P\theta + J_t + J_x\theta + J_y\theta + \frac{\sigma_z^2}{2} J_{yy} \right\} = 0 \,. \tag{A.2}$$

Because the maximand is linear in the control θ, the HJB equation is equivalent to the pair of equations:

$$J_x + J_y = P \,, \tag{A.3a}$$

$$J_t + \frac{\sigma_z^2}{2} J_{yy} = 0 \,. \tag{A.3b}$$

Set $\phi_t = -\delta(\xi^* + Z_t)$. The strategy (11a) implies that

$$\mathrm{d}Y_t = \frac{\phi_t - Y_t}{(1-t)(1-\delta)} \,\mathrm{d}t + \mathrm{d}Z_t$$

for $t < 1$. Let Σ_t denote the conditional variance of ϕ_t given the market makers' information at date t.

Proposition 1. *When the blockholder uses the trading strategy* (11a)*, then*

(a) $\Sigma_t = (1-t)(1-\delta^2)\sigma_z^2$ *for all* t.

(b) *The process* Y *is a Brownian motion with volatility* σ_z *on the time interval* $[0, 1)$*, given the* *market makers' information.*

(c) $Y_{1-} = -\delta(\xi^* + Z_1)$ *with probability one.*

(d) *If* $\xi^* + Z_1 \le A^*/\delta$, *then* $Y_1 \ge Y_{1-} \ge -A^*$.

(e) *If* $\xi^* + Z_1 > A^*/\delta$, *then* $Y_1 = Y_{1-} < -A^*$.

(f) *With probability one, either*

$$X_1 \ge B \quad \textit{and} \quad X_1 - \xi \ge Y_1 + A^* \ge 0\,, \tag{A.4}$$

or

$$0 > Y_1 + A^* > X_1 - \xi\,. \tag{A.5}$$

Proof. First, we want to compute $\hat{\phi}_t$, where, for any stochastic process U, $\hat{U}_t$ denotes the conditional expectation of U_t given the market makers' information at date t. The innovation process for the market makers' filtering is W defined by $W_0 = 0$ and

$$\mathrm{d}W = \mathrm{d}Y - \hat{\theta}_t\,\mathrm{d}t\,. \tag{A.6a}$$

It is a Brownian motion with volatility σ_z on the market makers' filtration (sometimes, the innovation process is scaled to have unit volatility, but we follow Kallianpur, 1980). The filtering equation for $\hat{\phi}$ is

$$\mathrm{d}\hat{\phi}_t = \left(\frac{\Sigma_t}{(1-t)(1-\delta)\sigma_z^2} - \delta\right)\mathrm{d}W\,. \tag{A.6b}$$

The conditional variance has initial value

$$\Sigma_0 = \delta^2\sigma_\xi^2 = (1-\delta^2)\sigma_z^2 \tag{A.6c}$$

and satisfies the differential equation

$$\frac{\mathrm{d}\Sigma_t}{\mathrm{d}t} = \delta^2\sigma_z^2 - \left(\frac{\Sigma_t}{(1-t)(1-\delta)\sigma_z} - \delta\sigma_z\right)^2\,. \tag{A.6d}$$

See Kallianpur (1980, p. 269).

It is straightforward to check that Σ defined in part (a) of the proposition satisfies the initial condition (A.6c) and differential equation (A.6d), so it is the conditional variance. Substituting it into (A.6b) reduces that equation to

$$\begin{aligned}
\mathrm{d}\hat{\phi}_t &= \mathrm{d}W = \mathrm{d}Y - \hat{\theta}\,\mathrm{d}t \\
&= \mathrm{d}Y - \frac{\hat{\phi}_t - Y_t}{(1-t)(1-\delta)}\,\mathrm{d}t\,.
\end{aligned} \tag{A.7}$$

We have $\hat{\phi}_0 = Y_0 = 0$. Therefore, (A.7) is solved by $\hat{\phi} = Y$. Hence, $\hat{\theta} = 0$, and $Y = W$. This verifies (b).

Because $Y_t = \hat{\phi}_t$,

$$\begin{aligned}
\mathsf{E}[(\phi_1 - Y_t)^2] &= \mathsf{E}[(\phi_1 - \hat{\phi}_t)^2] \\
&= \mathsf{E}[(\phi_1 - \phi_t + \phi_t - \hat{\phi}_t)^2] \\
&= \mathsf{E}[(\phi_1 - \phi_t)^2] + \mathsf{E}[(\phi_t - \hat{\phi}_t)^2] + 2\mathsf{E}[(\phi_t - \hat{\phi}_t)\mathsf{E}_t[(\phi_1 - \phi_t)]] \\
&= \mathsf{E}[(\phi_1 - \phi_t)^2] + \mathsf{E}[(\phi_t - \hat{\phi}_t)^2] \\
&= \delta^2\mathsf{E}[(Z_1 - Z_t)^2] + \mathsf{E}[\Sigma_t^2] \\
&= (1-t)\sigma_z^2\,,
\end{aligned}$$

where we used iterated expectations conditioning on the large investor's information for the third equality. Therefore, Y_t converges in the L^2 norm to ϕ_1 as $t \to 1$. However, it follows from part (b) that Y_t converges in the L^2 norm to Y_{1-}. Therefore, $Y_{1-} = \phi_1$. This verifies (c).

To verify (d), assume $\xi^* + Z_1 \leq A^*/\delta$. Then

$$Y_1 \geq Y_{1-} = -\delta(\xi^* + Z_1) \geq -A^*\,.$$

On the other hand, if $\xi^* + Z_1 > A^*/\delta$ as assumed in (e), then (11b) implies $\Delta Y_1 = 0$, and we have

$$Y_{1-} = -\delta(\xi^* + Z_1) < -A^*\,.$$

It remains to verify (f). Consider two cases. Suppose first that $\xi^* + Z_1 \leq A^*/\delta$. Because

$Y = X + Z - A$, we have

$$Y_1 \le X_1 + A^*/\delta - \xi^* - A = X_1 - A^* - \xi\,.$$

Therefore, (A.4) holds if $X_1 \ge B$ and $Y_1 \ge -A^*$. We have $X_1 \ge B$ from the fact that $\Delta X_1 = (B - X_{1-})^+$, and we have $Y_1 \ge -A^*$ from part (d). Now, assume that $\xi^* + Z_1 > A^*/\delta$. Then,

$$Y_1 > X_1 + A^*/\delta - \xi^* - A = X_1 - A^* - \xi\,.$$

Therefore, (A.5) holds if $Y_1 < -A^*$. This is part (e).

□

Proposition 2. *The pricing rule* (10) *and trading strategy* (11) *imply* (12).

Proof. Part (f) of Proposition 1 shows that

$$\omega(X_1, \xi) = \begin{cases} L & \text{if } Y_{1-} + A^* < 0\,, \\ H & \text{otherwise}\,. \end{cases} \tag{A.8}$$

Thus, $\omega(X_1, \xi) = \pi(1, Y_{1-}) = P_{1-}$. Parts (d) and (e) of Proposition 1 show that $Y_1 + A^* < 0 \Leftrightarrow Y_{1-} + A^* < 0$. Therefore, $P_1 = \pi(1, Y_1) = \pi(1, Y_{1-})$. □

Lemma 1. *The function J defined in* (14) *satisfies*

$$J(t, x, y, \xi, A) = \mathsf{E}[J(1, x, Z_1, \xi, A) \mid \xi, Z_t = y]\,, \tag{A.9a}$$

where

$$J(1, x, y, \xi, A) = Lx + (H - L) \max\big\{x - \xi, x - \xi - A^* - y, y + A^*, 0\big\}\,. \tag{A.9b}$$

Proof. Define $\varepsilon = Z_1 - Z_t$. We want to evaluate

$$\mathsf{E}\left[\max\big\{x - \xi, x - \xi - A^* - y - \varepsilon, y + A^* + \varepsilon, 0\big\}\right]\,. \tag{A.10}$$

We can write the maximum as

$$
\begin{aligned}
&(x-\xi)1_{\{x-\xi>y+A^*+\varepsilon>0\}} \\
&\qquad + (x-\xi-A^*-y-\varepsilon)1_{\{-A^*-y-\varepsilon>(\xi-x)^+\}} + (y+A^*+\varepsilon)1_{\{y+A^*+\varepsilon>(x-\xi)^+\}}\,.
\end{aligned}
$$

Notice that the first term is zero unless $x-\xi>0$, and we can write it as $(x-\xi)1_{\{0<y+A^*+\varepsilon<(x-\xi)^+\}}$. The maximum equals

$$
\begin{aligned}
&(x-\xi)\left[1_{\{-A^*-y<\varepsilon<-A^*-y+(x-\xi)^+\}} + 1_{\{-A^*-y-(\xi-x)^+>\varepsilon\}}\right] \\
&\qquad - (A^*+y)\left[1_{\{-A^*-y-(\xi-x)^+>\varepsilon\}} - 1_{\{\varepsilon>-A^*-y+(x-\xi)^+\}}\right] \\
&\qquad\qquad - \varepsilon\left[1_{\{-A^*-y-(\xi-x)^+>\varepsilon\}} - 1_{\{\varepsilon>-A^*-y+(x-\xi)^+\}}\right]
\end{aligned}
$$

Now, we use the facts that

$$
\begin{aligned}
\mathsf{E}\left[1_{\{\varepsilon<a\}}\right] &= \mathrm{N}\left(\frac{a}{\sigma_z\sqrt{1-t}}\right)\,, \\
\mathsf{E}\left[1_{\{\varepsilon>a\}}\right] &= \mathrm{N}\left(\frac{-a}{\sigma_z\sqrt{1-t}}\right)\,, \\
\mathsf{E}\left[\varepsilon 1_{\{\varepsilon<a\}}\right] &= -\sigma_z\sqrt{1-t}\,\mathrm{n}\left(\frac{a}{\sigma_z\sqrt{1-t}}\right)\,, \\
\mathsf{E}\left[\varepsilon 1_{\{\varepsilon>a\}}\right] &= \sigma_z\sqrt{1-t}\,\mathrm{n}\left(\frac{a}{\sigma_z\sqrt{1-t}}\right)\,.
\end{aligned}
$$

These imply that (A.10) equals

$$
\begin{aligned}
&(x-\xi)[\mathrm{N}(-d_3)+\mathrm{N}(-d_4)-\mathrm{N}(-d_1)] \\
&\qquad - (A^*+y)[\mathrm{N}(-d_4)-\mathrm{N}(d_3)] + \sigma_z\sqrt{1-t}\,[\mathrm{n}(-d_3)+\mathrm{n}(-d_4)]\,,
\end{aligned}
$$

where

$$
\begin{aligned}
d_3 &= \frac{y+A^*-(x-\xi)^+}{\sigma_z\sqrt{1-t}}\,, \\
d_4 &= \frac{y+A^*+(\xi-x)^+}{\sigma_z\sqrt{1-t}}\,.
\end{aligned}
$$

Now, by considering the separate cases $x > \xi$ and $\xi > x$, we see that $\mathrm{N}(-d_3) + \mathrm{N}(-d_4) - \mathrm{N}(-d_1) = \mathrm{N}(-d_2)$. Also, $\mathrm{N}(-d_4) - \mathrm{N}(d_3) = \mathrm{N}(-d_2) - \mathrm{N}(d_1)$. Finally, $\mathrm{n}(-d_3) + \mathrm{n}(-d_4) = \mathrm{n}(-d_1) + \mathrm{n}(-d_2) = \mathrm{n}(d_1) + \mathrm{n}(-d_2)$. □

Proposition 3. *Given the pricing rule* (10)*, the function J defined in* (14) *satisfies the HJB equation* (A.2)*.*

Proof. We will use the representation (A.9) of the function J. First, we observe that

$$J_x(1, x, y, \xi, A) + J_y(1, x, y, \xi, A) = \pi(1, y) \tag{A.11}$$

almost everywhere in (x, y), for each value of ξ. To see this, note that there are four possibilities for the maximum in (A.9b), excluding the set of zero measure on which J has a kink: (1) If the maximum is $x - \xi$, then $J_x + J_y = H$. (2) If the maximum is $x - \xi - A^* - y$, then $J_x + J_y = L$. (3) If the maximum is $y + A^*$, then $J_x + J_y = H$. (4) If the maximum is 0, then $J_x + J_y = L$. In cases (1) and (3), we must have $y + A^* \geq 0$, so $\pi(1, y) = H$. In cases (2) and (3), we must have $y + A^* < 0$, so $\pi(1, y) = L$.

J is sufficiently regular to allow the interchange of differentiation and expectation, so we have

$$\begin{aligned} J_x(t, x, y, \xi, A) + J_y(t, x, y, \xi, A) &= \mathsf{E}[J_x(1, x, Z_1, \xi, A) + J_y(1, x, Z_1, \xi, A) \mid \xi, Z_t = y] \\ &= \mathsf{E}[\pi(1, Z_1) \mid Z_t = y] \\ &= \pi(t, y)\,. \end{aligned}$$

Thus, (A.3a) is satisfied. The formula (A.9) implies that $J(t, x, Z_t, \xi)$ is a martingale for each fixed value of (x, ξ), so (A.3b) is also satisfied. □

Lemma 2. *$J(1, x, y, \xi) \geq V(x, \xi)$ for all (x, y, ξ). When the blockholder follows the trading strategy* (11)*, then $J(1, X_1, Y_1, \xi, A) = V(X_1, \xi)$ with probability one.*

Proof. The claim that $J \geq V$ is equivalent to

$$\max\left\{x-\xi, x-\xi-A^*-y, y+A^*, 0\right\} \geq \begin{cases} 0 & \text{if } x < \max(B,\xi)\,, \\ (x-\xi) & \text{otherwise}\,. \end{cases} \tag{A.12}$$

The left-hand side of (A.12) is at least as large as $(x-\xi)^+$, so the weak inequality always holds. Now, observe that there is equality in (A.12) if either

$$x \geq B \quad \text{and} \quad 0 \leq y + A^* \leq x - \xi\,, \tag{A.13a}$$

or

$$x - \xi < y + A^* < 0\,. \tag{A.13b}$$

If (A.13a) holds, then both sides of (A.12) equal $x-\xi$. If (A.13b) holds, then both sides of (A.12) equal 0. Part (f) of Lemma 1 shows that (X_1, Y_1) satisfies either (A.13a) or (A.13b) with probability one, so $J(1, X_1, Y_1, \xi, A) = V(X_1, \xi)$ with probability one. □

Proposition 4. *Given the pricing rule* (10)*, the trading strategy* (11) *is optimal for the blockholder.*

Proof. Consider an arbitrary strategy. For each value of ξ, we can substitute the HJB equation into Itô's formula for $\mathrm{d}J$ to obtain

$$\begin{aligned} J(1, X_1, Y_1, \xi, A) &= J(0, X_0, Y_0, \xi, A) + \int_0^1 \mathrm{d}J \\ &= J(0, X_0, Y_0, \xi) + \int_0^1 P\theta\,\mathrm{d}t + \int_0^1 J_y\,\mathrm{d}Z + \Delta J_1\,. \end{aligned}$$

Taking expectations, using the fact that $J(1, X_1, Y_1, \xi, A) \geq V(X_1, \xi)$, and substituting $X_0 = A$ and $Y_0 = 0$ yields

$$J(0, A, 0, \xi, A) \geq \mathsf{E}\left[V(X_1, \xi) - \int_0^1 P\theta\,\mathrm{d}t - \Delta J_1\right]\,.$$

By definition, $J(1, x, y, \xi)$ is the largest of four affine functions of (x, y). It is therefore convex in

(x, y). This implies

$$\begin{aligned}\Delta J_1 &\leq J_x(1, X_1, Y_1, \xi)\,\Delta X_1 + J_y(1, X_1, Y_1, \xi)\,\Delta Y_1 \\ &= P_1\,\Delta X_1\,,\end{aligned}$$

where we use (A.11) and $\Delta X_1 = \Delta Y_1$ to obtain the equality. It follows that

$$J(0, A, 0, \xi, A) \geq \mathsf{E}\left[V(X_1, \xi) - \int_0^1 P\theta\,\mathrm{d}t - P_1\,\Delta X_1\right].$$

This shows that $J(0, A, 0, \xi, A)$ is an upper bound on the investor's expected utility. The bound is achieved by a strategy if and only if the strategy implies $J(1, X_1, Y_1, \xi, A) = V(X_1, \xi)$ with probability one and $\Delta J_1 = P_1\,\Delta X_1$. Given the previous lemma, it remains only to show that $\Delta J_1 = P_1\,\Delta X_1$ when the large investor uses the strategy (11).

We can assume $Z_1 \leq A^*/\Delta - \xi^*$, because $\Delta X_1 = 0$ otherwise. From part (d) of Lemma 1, we have $Y_1 \geq Y_{1-} > -A^*$. Therefore, from the definition (A.9b), we have

$$J(1, X_{1-}, Y_{1-}, \xi, A) = LX_{1-} + (H - L)\max\{X_{1-} - \xi, Y_{1-} + A^*\}\,,$$

and

$$\begin{aligned}J(1, X_1, Y_1, \xi, A) &= LX_1 + (H - L)\max\{X_1 - \xi, Y_1 + A^*\} \\ &= L\big[X_{1-} + \Delta X_1\big] + (H - L)\Big[\Delta X_1 + \max\{X_{1-} - \xi, Y_{1-} + A^*\}\Big] \\ &= J(1, X_{1-}, Y_{1-}, \xi, A) + H\Delta X_1\,.\end{aligned}$$

Hence, $\Delta J_1 = H\Delta X_1$. Because $Y_1 \geq -A^*$, we have $P_1 = H$; consequently, $\Delta J_1 = P_1 \Delta X_1$. □

Proposition 5. *Given the trading strategy* (11) *and pricing rule* (10), *we have*

$$\pi(t, Y_t) = L\,\mathrm{prob}_t\big(X_1 < \max(B, \xi)\big) + H\,\mathrm{prob}_t\big(X_1 \geq \max(B, \xi)\big) \tag{A.14}$$

for all t with probability one, where the probability is conditional on the market makers' information *at date t.*

Proof. First, observe that

$$X_1 \geq \max(B, \xi) \quad \Rightarrow \quad \pi(1, Y_1) = H\,, \tag{A.15a}$$

$$X_1 < \max(B, \xi) \quad \Rightarrow \quad \pi(1, Y_1) = L\,. \tag{A.15b}$$

This is a consequence of the fact that either (A.4) or (A.5) holds when the investor uses the trading strategy (11). To derive (A.15), assume first that $X_1 \geq \max(B, \xi)$. Then (A.4) must hold, which implies $Y_1 + A^* \geq 0$. From the definition (10a), this implies $\pi(1, Y_1, A) = H$. Now, suppose that $X_1 < \max(B, \xi)$. If $X_1 < \xi$, then (A.5) must hold. On the other hand, if $X_1 < B$, then, given the definition (11b) of ΔX_1, we must have $Z_1 > A^*/\delta - \xi^*$. This implies

$$Y_1 = X_1 + Z_1 - A > X_1 + A^*/\delta - \xi^* - A = X_1 - A^* - \xi\,,$$

so (A.5) must hold in this case also. Thus, $X_1 < \max(B, \xi)$ implies (A.5), which implies $\pi(1, Y_1) = L$.

Part (b) of Proposition 1 states that Y_1 is a Brownian motion with volatility σ_z on the time interval $[0, 1)$, given the market makers' information. Therefore, Y_t is a sufficient statistic at date t for computing the conditional expectation of any function of Y_{1-}. Moreover, the distribution of Y_{1-} conditional on $Y_t = y$ is the same as the distribution of Z_1 conditional on $Z_t = y$. Therefore, (A.1) implies that

$$\pi(t, Y_t) = \mathsf{E}\left[\pi(1, Y_{1-}) \mid (Y_s)_{s \leq t}\right]\,.$$

Proposition 2 shows that $P_1 = P_{1-}$, so $\pi(1, Y_{1-}) = \pi(1, Y_1)$. Hence, we have

$$\pi(t, Y_t) = \mathsf{E}\left[\pi(1, Y_1) \mid (Y_s)_{s \leq t}\right]\,.$$

Now, the proposition follows from (A.15). □

Proof of Theorem 2. From the definition (14) of J, we can verify the formulas for the partial derivatives by showing that

$$\frac{\partial \mathsf{E}[K(0,x,0,\xi,A)]}{\partial x} = \mathrm{N}\left(\frac{(1+\delta)f(x)-\delta f(A)}{\sigma_z}\right), \tag{A.16a}$$

$$\frac{\partial \mathsf{E}[K(0,x,0,\xi,A)]}{\partial A} = \frac{\delta}{1+\delta}\left[\mathrm{N}\left(\frac{f(A)}{\sigma_z}\right) - \mathrm{N}\left(\frac{(1+\delta)f(x)-\delta f(A)}{\sigma_z}\right)\right]. \tag{A.16b}$$

where

$$K(0,x,0,\xi,A) = \sigma_z\left[d_1\,\mathrm{N}(d_1) - d_2\,\mathrm{N}(-d_2) + \mathrm{n}(d_1) + \mathrm{n}(-d_2)\right],$$

with

$$d_1 = \frac{f(A)}{\sigma_z}, \qquad d_2 = \frac{f(A)+\xi-x}{\sigma_z}.$$

Note that

$$\frac{\mathrm{d}}{\mathrm{d}y}[y\,\mathrm{N}(y) + \mathrm{n}(y)] = \mathrm{N}(y) + y\,\mathrm{n}(y) - y\,\mathrm{n}(y) = \mathrm{N}(y).$$

Applying this fact yields

$$\begin{aligned}\frac{\partial K(0,x,0,\xi,A)}{\partial x} &= -\sigma_z\,\mathrm{N}(-d_2)\frac{\partial d_2}{\partial x} \\ &= \mathrm{N}(-d_2), \\ \frac{\partial K(0,x,0,\xi,A)}{\partial A} &= \sigma_z\,\mathrm{N}(d_1)\frac{\partial d_1}{\partial A} - \sigma_z\,\mathrm{N}(-d_2)\frac{\partial d_2}{\partial A} \\ &= \frac{\delta}{1+\delta}[\mathrm{N}(d_1) - \mathrm{N}(-d_2)]\end{aligned}$$

To establish (A.16), it suffices to show that

$$\mathsf{E}[\mathrm{N}(-d_2)] = \mathrm{N}\left(\frac{(1+\delta)f(x)-\delta f(A)}{\sigma_z}\right) \tag{A.17}$$

Let z be a standard normal variable that is independent of ξ. Then,

$$\begin{aligned}\mathsf{E}\left[\mathrm{N}\left(-d_2\right)\right] &= \mathsf{E}\left[\mathrm{prob}\left(z \le -d_2 \mid \xi\right)\right] \\ &= \mathrm{prob}\left(z + d_2 \le 0\right).\end{aligned}$$

Because $z + d_2$ is normal with mean $(f(A) + \mu_\xi - x)/\sigma_z$ and variance $1 + \sigma_\xi^2/\sigma_z^2 = 1/\delta^2$, the probability $\text{prob}\,(z + d_2 \leq 0)$ equals

$$\text{prob}\left(\delta(z + d_2) - \frac{\delta(f(A) + \mu_\xi - x)}{\sigma_z} \leq -\frac{\delta(f(A) + \mu_\xi - x)}{\sigma_z}\right),$$

which is the same as the right-hand side of (A.17).

The formula for the total derivative follows immediately from the formulas for the partial derivatives. Furthermore, given the formulas for the partial derivatives, simple calculus shows that the matrix of second partials is positive definite, so G is convex.

□

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Table 1. The Effect of Exogenous Analyst Coverage Terminations on Liquidity and Shareholder Activism.
This table uses Kelly and Ljungqvist's (2012) exogenous analyst coverage terminations ('shock') to estimate the causal effect of liquidity on shareholder intervention. The terminations occurred as a result of 43 brokerage closures between 2000 and 2008. The sample consists of 2,983 treated firms and 2,983 control firms. Following Balakrishnan et al. (2013), treated and control firms are matched on market capitalization, volatility, the number of analysts providing coverage, and liquidity, all measured as of the fiscal quarter before the coverage termination. The unit of observation is a firm-fiscal-quarter. We observe each firm for (up to) four fiscal quarters before and after a termination quarter. All specifications are estimated using OLS with firm and year fixed effects. We measure liquidity using the log of one plus Amihud's Illiquidity Measure (AIM). We measure shareholder interventions using hedge fund activist campaigns (using data borrowed from Gantchev (2013)) and the log of one plus the number of shareholder proposals (using data obtained from RiskMetrics). Summary statistics (in the form of means and, in italics, standard deviations) are presented in columns 1-3. Note that the number of analysts, the number of market makers, and the firm's market capitalization enter the regressions in logs. Standard errors, clustered at the firm level, are shown in italics underneath the coefficient estimates in columns 4-9. ***, **, and * denote significance at the 1%, 5%, and 10% level (two-sided), respectively. The critical value for the weak-instruments test is 10.

	Summary statistics			log AIM		Prob. of activism		log no. of proposals	
	treated firms	matched controls	difference in means	first stage	first stage	reduced form	second stage	reduced form	second stage
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
shock				0.008***	0.026**	0.003**		0.011***	
				0.003	*0.010*	*0.001*		*0.003*	
log AIM	0.052	0.060	-0.008				0.377*		1.402**
	0.244	*0.341*					*0.211*		*0.598*
Firm characteristics at t = –1									
# analysts providing coverage	6.3	6.3	0	-0.004***	-0.003**	-0.001	0.000	-0.017***	-0.011***
	5.5	*5.8*		*0.001*	*0.001*	*0.001*	*0.001*	*0.002*	*0.003*
x shock					-0.010**				
					0.005				
# market makers	19.6	17.0	2.6	-0.022***	-0.022***	0.002	0.010*	-0.001	0.029*
	23.0	*20.6*		*0.007*	*0.007*	*0.003*	*0.006*	*0.002*	*0.015*
market capitalization ($m)	7,110	7,554	-444	-0.115***	-0.115***	-0.003**	0.040*	-0.001	0.160**
	19,700	*22,400*		*0.007*	*0.007*	*0.002*	*0.024*	*0.001*	*0.068*
monthly std. dev. of returns	0.033	0.034	-0.001	0.366**	0.366**	0.021	-0.117	-0.014	-0.527
	0.027	*0.034*		*0.153*	*0.153*	*0.028*	*0.107*	*0.015*	*0.333*
Diagnostics									
Within-firm R^2	n.a.	n.a.		10.1%	10.2%	50.0%	n.a.	11.7%	n.a.
Weak instrument test (F)	n.a.	n.a.		n.a.	n.a.	n.a.	10.0***	n.a.	10.0***
Number of firms (treated+controls)	n.a.	n.a.		5,966	5,966	5,966	5,966	5,966	5,966
Number of observations	2,983	2,983		49,149	49,149	49,149	49,149	49,149	49,149

Table 2. The Effect of Exogenous Reductions in Market Making on Liquidity and Shareholder Activism.

This table uses Balakrishnan et al.'s (2013) exogenous reductions in market making ('shock') to estimate the causal effect of liquidity on shareholder intervention. These reductions occurred as a result of 50 market makers closing down between 2000 and 2008. Firms that suffer simultaneous reductions in analyst coverage and market making are excluded. The sample consists of 4,121 treated firms and 4,121 control firms. Following Balakrishnan et al., treated and control firms are matched on market capitalization, volatility, the number of analysts providing coverage, the number of market makers, and liquidity, all measured as of the fiscal quarter before the coverage termination. The unit of observation is a firm-fiscal-quarter. We observe each firm for (up to) four fiscal quarters before and after a closure quarter. All specifications are estimated using OLS with firm and year fixed effects. We measure liquidity using the log of one plus Amihud's Illiquidity Measure (AIM). We measure shareholder interventions using hedge fund activist campaigns (using data borrowed from Gantchev (2013)) and the log of one plus the number of shareholder proposals (using data obtained from RiskMetrics). Summary statistics (in the form of means and, in italics, standard deviations) are presented in columns 1-3. Note that the number of analysts, the number of market makers, and the firm's market capitalization enter the regressions in logs. Standard errors, clustered at the firm level, are shown in italics underneath the coefficient estimates in columns 4-9. ***, **, and * denote significance at the 1%, 5%, and 10% level (two-sided), respectively. The critical value for the weak-instruments test is 10.

	Summary statistics			log AIM		Prob. of activism		log no. of proposals	
	treated firms	matched controls	difference in means	first stage	first stage	reduced form	second stage	reduced form	second stage
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
shock				0.042***	0.551***	0.003*		0.002***	
				0.006	*0.044*	*0.001*		*0.001*	
log AIM	0.668	0.739	-0.071				0.016**		0.040***
	1.040	*1.156*					*0.007*		*0.014*
Firm characteristics at *t* = –1									
# analysts providing coverage	1.6	1.6	0	0.006*	0.008**	-0.001	-0.001	-0.003***	-0.003***
	3.2	*3.3*		*0.004*	*0.004*	*0.001*	*0.001*	*0.001*	*0.001*
# market makers	21.2	21.3	-0.1	-0.174***	-0.168***	0.003	0.006**	0.000	0.007***
	12.5	*13.3*		*0.017*	*0.017*	*0.002*	*0.002*	*0.001*	*0.003*
x shock					-0.163***				
					0.013				
market capitalization ($m)	573	652	-79	-0.401***	-0.403***	-0.002	0.005	0.000	0.016***
	5,702	*3,272*		*0.011*	*0.011*	*0.002*	*0.004*	*0.000*	*0.006*
monthly std. dev. of returns	0.043	0.042	0.1	0.536***	0.547***	-0.044***	-0.055***	0.001	-0.021**
	0.039	*0.037*		*0.164*	*0.164*	*0.014*	*0.015*	*0.002*	*0.010*
Diagnostics									
Within-firm R^2	n.a.	n.a.		23.1%	23.3%	58.8%	n.a.	6.6%	n.a.
Weak instrument test (F)	n.a.	n.a.		n.a.	n.a.	n.a.	69.1***	n.a.	69.1***
Number of firms (treated+controls)	n.a.	n.a.		8,242	8,242	8,242	8,242	8,242	8,242
Number of observations	4,121	4,121		68,780	68,780	68,780	68,780	68,780	68,780

Table 3. The Effect of Exogenous Analyst Coverage Re-Initiations on Liquidity and Shareholder Activism.

This table uses Kelly and Ljungqvist's (2012) exogenous analyst coverage re-initiations ('shock') to estimate the causal effect of liquidity on shareholder intervention. The re-initiations occurred in the wake of mergers involving a retail broker with an institutional broker, as a result of which previously private analyst signals available only to institutional clients became available to the merged broker's retail clients, thereby reducing information asymmetry in the marketplace. The sample consists of 761 treated firms and 761 control firms. Following Balakrishnan et al. (2013), treated and control firms are matched on market capitalization, volatility, the number of analysts providing coverage, and liquidity, all measured as of the fiscal quarter before the coverage termination. The unit of observation is a firm-fiscal-quarter. We observe each firm for (up to) four fiscal quarters before and after a re-initiation quarter. All specifications are estimated using OLS with firm and year fixed effects. We measure liquidity using the log of one plus Amihud's Illiquidity Measure (AIM). We measure shareholder interventions using hedge fund activist campaigns (using data borrowed from Gantchev (2013)) and the log of one plus the number of shareholder proposals (using data obtained from RiskMetrics). Summary statistics (in the form of means and, in italics, standard deviations) are presented in columns 1-3. Note that the number of analysts, the number of market makers, and the firm's market capitalization enter the regressions in logs. Standard errors, clustered at the firm level, are shown in italics underneath the coefficient estimates in columns 4-9. ***, **, and * denote significance at the 1%, 5%, and 10% level (two-sided), respectively. The critical value for the weak-instruments test is 10.

	Summary statistics			log AIM		Prob. of activism		log no. of proposals	
	treated firms	matched controls	difference in means	first stage	first stage	reduced form	second stage	reduced form	second stage
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
shock				-0.012***	-0.047***	-0.006*		-0.027***	
				0.004	*0.013*	*0.003*		*0.005*	
log AIM	0.026	0.030	-0.004				0.729		2.157***
	0.111	*0.215*					*0.495*		*0.773*
Firm characteristics at *t* = –1									
# analysts providing coverage	6.8	6.7	0.1	-0.003	-0.005*	-0.001	0.001	-0.026***	-0.019***
	5.7	*6.0*		*0.002*	*0.003*	*0.002*	*0.003*	*0.004*	*0.006*
x shock					0.020***				
					0.006				
# market makers	26.1	27.2	-1.1	-0.002	-0.002	-0.002	-0.005	0.003	0.007
	23.4	*23.3*		*0.009*	*0.009*	*0.003*	*0.008*	*0.003*	*0.019*
market capitalization ($m)	6,675	5,745	930	-0.116***	-0.116***	0.012**	0.101*	0.003	0.255***
	20,400	*19,200*		*0.014*	*0.014*	*0.005*	*0.061*	*0.003*	*0.087*
monthly std. dev. of returns	0.028	0.026	0.002	0.026	0.027	-0.096*	-0.204	-0.037	-0.093
	0.033	*0.030*		*0.176*	*0.176*	*0.057*	*0.168*	*0.034*	*0.384*
Diagnostics									
Within-firm R^2	n.a.	n.a.		11.0%	11.1%	50.7%	n.a.	8.1%	n.a.
Weak instrument test (*F*)	n.a.	n.a.		n.a.	n.a.	n.a.	11.1***	n.a.	11.1***
Number of firms (treated+controls)	n.a.	n.a.		1,522	1,522	1,522	1,522	1,522	1,522
Number of observations	761	761		13,102	13,102	13,102	13,102	13,102	13,102