Liquidity and Governance

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Abstract

Is greater trading liquidity good or bad for corporate governance? We address this question both theoretically and empirically. We solve a model consisting of 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 once a block has been created, its continued existence is jeopardized by an increase in the liquidity of the firm's stock. Greater liquidity increases the likelihood of the large investor trading on her private information and selling her block instead of intervening. Thus, blocks are inherently fragile and higher liquidity can be harmful for governance. Empirical tests using three distinct sources of exogenous variation in liquidity confirm that greater liquidity reduces blockholder activism on average.

☆We are grateful to Jean-Noel Barrot, Alon Brav, Carole Comerton-Forde, David De Angelis, Alex Edmans, Vivian Fang, Dirk Hackbarth, Stacey Jacobsen, and Ernst Maug for helpful comments and to Nick Gantchev for sharing his hedge fund activism data.

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February 11, 2015

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. However, liquidity facilitates block formation in addition to block disposition, so there are countervailing effects (Maug, 1998). These observations have spawned an active literature on the effects of liquidity on governance, with the prevailing consensus being that liquidity is beneficial for governance. The present paper makes two contributions to this literature. First, we re-examine the theoretical foundation laid by Maug and show that the opposite conclusion (liquidity harms governance) is at least as tenable as is his conclusion that liquidity improves governance. To show this, we solve a model consisting of an optimal IPO mechanism 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 corporate governance. Second, we examine three distinct natural experiments and show that, in each case, there is a negative empirical relation between liquidity and blockholder activism.

Maug (1998) studies a two-period model. In his first period, the blockholder acts as a monopsonist whose trade is observable. Prices are set by small risk-neutral investors who require a liquidity discount. His second period is a Kyle (1985) model in which the blockholder's trade is anonymously batched with other trades and in which prices are set by risk-neutral competitive market makers who do not require a liquidity discount. By assumption, the blockholder owns zero shares at the beginning of the first period, so in order to build a stake, the investor has to trade. Maug's main result is that increased liquidity trading in the second-period Kyle market increases the likelihood of a blockholder emerging. This, in turn, means that liquidity is beneficial for governance.

While Maug's (1998) model has proved influential, we view its key assumptions as potentially problematic. First, it assumes that the market structure changes between the two periods: the blockholder's trade is transparently observable in the first period but anonymously batched with other trades in the second period, and the competitive market makers who set prices in the second period are not also present to set prices in the first period. Second, it assumes that the blockholder's initial stake is zero. This is an extreme assumption; it biases the conclusion towards finding that liquidity is beneficial for governance, because it implies that block formation in either the first or second period of the model is essential for blockholder activism. Furthermore, it is difficult to reconcile with the data, at least in the U.S. According to Edmans and Manso (2011), 88% of U.S. companies have at least one blockholder holding 5% or more of the company's stock. Thus, when an opportunity to create value by intervention is recognized, most companies should already have a blockholder in place.

To examine how these modeling choices affect Maug's (1998) conclusions, we replace his two-period first-transparent-then-opaque market with a dynamic Kyle model. This ensures consistency of market structure across periods. We show that increased liquidity in the dynamic Kyle model improves governance if and only if the blockholder's initial block is too small to make activism worthwhile on average (in the absence of additional trading). Thus, with a zero initial block, as assumed by Maug, liquidity improves governance, as concluded by Maug. On the other hand, whenever a block of sufficient size has been created, we show that liquidity harms governance going forward. Greater liquidity is harmful in this situation because it increases the risk that the blockholder will profit more from selling down his stake than from intervening in the company's running. This situation does not arise in Maug's model because he assumes that the initial block size is always zero.

There are many ways in which a large block could be created. As Maug (1998) emphasizes, greater liquidity aids block formation, and that remains true in our model. Our point is that once a block is in place, liquidity ceases to be beneficial and instead becomes harmful for governance. The simplest way to show this is to let the firm choose its ownership structure optimally before trading begins. Having no blockholders prior to the start of trading turns out not to be optimal. By examining the IPO mechanisms analyzed by Stoughton and Zechner (1998), we show that under a mild condition that accords well with real-life stock-market listing rules, the firm will create a block that is sufficiently large to make blockholder activism possible. Once such a block is in place, however, increased liquidity in the subsequent Kyle model harms governance. Empirically, virtually every company that goes public does so with one or more blockholders among its shareholders, consistent with this part of our model. Thus, with our two modifications to Maug's model—replacing the first-transparent-then-opaque market with a dynamic Kyle market and assuming the initial block is chosen optimally in an IPO rather than constraining it to be zero by assumption—we reach a conclusion opposite to his: greater liquidity reduces the likelihood of blockholder activism.

While we call the start of our model an IPO, this need not be taken literally: even after the firm's IPO, there are many ways for the firm's board of directors to create blockholders. Prominent mechanisms include seasoned equity offerings, private placements of either stock or convertible bonds, and PIPEs (private investments in public equity). Each of these gives the board an opportunity to create another block of sufficient size to encourage monitoring, should the initial blocks have been dissolved via the initial blockholder's optimal trading in the Kyle market. Similarly, we do not rule out that periods of high liquidity encourage the formation of blocks—but again: once a block is in place, subsequent increases in liquidity will tempt the blockholder to sell. In this sense, blocks are inherently fragile in our model.

Our empirical results support the conclusion that improving liquidity reduces the likelihood of blockholder activism. Establishing the causal effect of liquidity on governance is empirically challenging because, as Edmans, Fang, and Zur (2012) 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., 2014), 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.

In all three experiments, we find that blockholder activism, as measured by various forms of 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, in the sense of discouraging large shareholders from taking an active role in the governance of the firm. They stand in contrast to prior empirical work that treats the level of a firm's trading liquidity as exogenous (for example, Norli, Ostergaard, and Schindele, 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—a prime candidate being Regulation Fair Disclosure, which was adopted at the same time.[1] The narrow window over which decimalization

[1] See Cai et al. (2011) for evidence that Regulation FD had a positive effect on the intensity of board monitoring.

was phased in means that there are no control firms with which to establish a valid counterfactual. The staggered nature of the 43 brokerage closures, the 50 market maker closures, and the six retail brokerage-mergers we use allows us to establish a set of counterfactuals against which to measure the effect of liquidity on governance.[2]

To recap, 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 whenever a blockholder holds a sufficiently large stake in a firm. We also show that it is in the firm's interest to create such blocks. Thus, 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. 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.

1.1. Literature Review

There is a parallel between our result that liquidity improves governance if and only if the blockholder's stake is small and a result obtained by Maug (1998). Maug's Proposition 2 states that liquidity improves governance in his model if and only if the block at the start of his second-period Kyle model is small. The size of this block depends on trading in his first-period transparent market. Because the blockholder starts with a zero block prior to the transparent market and prefers to trade in the second-period opaque market rather than the first-period transparent market, the blockholder accumulates only a small position in Maug's first-period transparent market. This produces Maug's main result that higher liquidity in the second-period market improves governance, but this is an artifact of his assumption that the world ends after the second period: Maug does not allow for the block to be unwound again before intervention is to take place. Literally, Maug's model captures a situation in which an investor knows that intervention will be necessary "soon", in which case liquidity enables the investor to build a block in preparation for the intervention. Without liquidity, intervention would be impossible.

By contrast, we allow the investor to have built his block (or to have been allocated his block in the IPO) at some point before intervention is to take place. This opens up the interesting possibility

[2] We contrast our empirical approach to that used in decimalization studies in Section 4.2.1.

that from then on, increased liquidity will tempt the blockholder to trade on the difference between the market's belief about the likelihood of her intervening and her knowledge of her own evolving intentions. If the expected profit from selling down the block exceeds the expected profit from intervention, the block will be dissolved before the intervention point. As we show, increases in liquidity make this more likely. Establishing this result requires a continuous-time trading game, rather than the two-period setup Maug (1998) analyzes. An implication of our results is that the role of liquidity in governance is knife-edge: liquidity is good because it helps in the creation of blocks, as in Maug; but if the block has been created "too soon", liquidity is bad because it creates the temptation to sell profitably to uninformed liquidity traders instead of intervening.

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 (2015), who in contemporaneous and independent work also solve a dynamic Kyle model with a blockholder who can expend costly effort to increase firm value. 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. They obtain an ambiguous result regarding the effect of liquidity on governance: liquidity improves governance conditional on the large investor receiving a high signal about the asset value and harms governance when the large investor receives a low signal. They do not analyze how the initial block is determined. 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 establish the negative causal relation between liquidity and blockholder activism that our 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 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 are several papers that analyze single-period market microstructure models involving one or more large investors who may intervene in corporate governance. These include Kyle and Vila (1991), Kahn and Winton (1998), Ravid and Spiegel (1999), Bris (2002), and Noe (2002). The papers most closely related to ours are Kyle and Vila's and Kahn and Winton's. Kahn and Winton's model structure is quite similar to Maug's (1998). In their comparison of their work with Maug's, they state that they complement Maug by focusing on issues other than the effect of liquidity on governance. Kyle and Vila's conclusion regarding the effect of liquidity trading on blockholder activism (a value enhancing takeover in their case) is similar to Maug's Proposition 2. However, Kyle and Vila do not discuss the determination of the initial stake.

An interesting 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, then the blockholder is likely to buy shares and become active; conversely, if liquidity traders buy shares, then the blockholder is likely to take the Wall Street walk. Kyle and Vila (1991) obtain the same result in a single period model by assuming that the blockholder can observe contemporaneous liquidity trades before submitting her own order. We derive the feedback effect of the sign of liquidity trading on blockholder activism by assuming the blockholder can infer past liquidity trades from market prices, adapting to liquidity trading in a dynamic market.

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 instead on trading by an insider who has private information about firm value that is exogenous to her trading. The investor's ability 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.

In keeping with Bhide (1993) and Maug (1998), our focus is on shareholder activism. We do not address compensation, board structure, or other corporate governance mechanisms. A notable example of the literature that links such mechanisms to liquidity is Holmstrom and Tirole (1993). Their model shows that greater liquidity leads to more information collection by speculators, which makes prices more efficient and so increases the effectiveness of stock-based compensation as an incentive device.

Roosenboom et al. (2014) also find evidence in support of our conclusion that increased liquidity harms governance. They show that acquirer returns around merger announcements are higher for stocks with lower liquidity and infer that this reflects more effective monitoring by institutional shareholders when liquidity is low.

2. The Kyle Market

In this section, we describe the dynamic Kyle model and its equilibrium, taking as given that a block exists at the beginning of the trading game. As we discuss in the following section, the block can have been created in the firm's initial public offering, in the course of a capital raising exercise such as a PIPE, or indeed through open-market purchases in a prior round of trading.

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 this assumption allows us to focus on how the market activity affects the blockholder's decision to become actively involved in the governance of the corporation. This simple structure is also adopted by Maug (1998).

We assume the shares are traded continuously during the time interval $[0, 1]$. The empirical counterpart to this time interval could, for example, be the regulatory requirement in the U.S. that a shareholder must have held a block of sufficient size for at least one year before she is allowed to file a proposal with which to try and influence the running of the firm.[3] We are interested in the question how liquidity during the period since acquiring such a block affects the likelihood of shareholder intervention.

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.[4]

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 instantaneous standard deviation 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 $Y = X - A + Z$. The process Y is observed by market makers.

Define

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

If the blockholder owns x shares before the costly action is taken at date $1 + \epsilon$, then they are worth $V(x, \xi)$ to her. The value of each share at date $1 + \epsilon$ to any other investor is

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

We search for an equilibrium in which the price at date t is $P_t = \pi(t, Y_t)$ for some function π.

[3]Securities Exchange Act Rule 14a-8 sets out the conditions under which a shareholder can submit a proposal (possibly along with a supporting statement) for inclusion in (i) a firm's proxy statement and (ii) the firm's proxy card so that shareholders can vote on it at an annual or special meeting. Of relevance here, the Rule requires that to be eligible to submit a proposal, a shareholder must have held her shares continuously for at least one year.

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

This means that the price depends at each date only on aggregate net trades through that date rather than on the entire history of trades. 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 blockholder 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 blockholder'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 to the blockholder's actions and except that a discrete order ΔX_1 is allowed at date 1. In maximizing (5), the blockholder 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 ΔY_1 trades at date 1 is $\pi(1, Y_{1-} + \Delta Y_1)$ and hence depends on the order size, just as in a single-period Kyle model. Define the blockholder's value function as

$$J(t,x,y,\xi,A) = \sup_{\theta,\,\Delta X_1} \mathsf{E}\left[V(X_1,\xi) - \int_t^1 P_t\theta_t\,\mathrm{d}t - P_1\Delta X_1 \mid X_t = x, Y_t = y, \xi\right], \tag{6}$$

where the maximization is subject to the constraint that $P_u = \pi(u, Y_u)$ for all $u \geq t$. We include the initial stake A as an argument of the value function, because we endogenize it in Section 3.

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

$$\pi(t, Y_t) = \mathsf{E}[\omega(X_1,\xi) \mid (Y_s)_{s\leq t}] \tag{7}$$

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 blockholder 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 illustrate in Section 2.5, those plans can change based on market activity.

2.2. Equilibrium

An important role is played by the size of the initial stake A compared to the expected proportional cost of intervention μ_ξ. The condition $A > \mu_\xi$ means that $A(H - L) > \mathsf{E}[C]$; that is, 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

$$\delta = \frac{\sigma_z}{\sqrt{\sigma_\xi^2 + \sigma_z^2}}\,, \tag{8}$$

and set

$$A^* = \frac{\delta(A - \mu_\xi)}{1 + \delta}\,. \tag{9}$$

Let N denote the standard normal distribution function and n the standard normal density function. All proofs are in the appendices.

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

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

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

Then, $(\pi, \theta, \Delta X_1)$ is an equilibrium. In the equilibrium, the blockholder becomes active if and only if

$$\xi - \mu_\xi + Z_1 \le \frac{A - \mu_\xi}{1+\delta}\,. \tag{12}$$

The blockholder's value function is

$$J(t,x,y,\xi,A) = xL + (H-L)\sigma_z\sqrt{1-t}\Big[d_1\,\mathrm{N}(d_1) - d_2\,\mathrm{N}(-d_2) + \mathrm{n}(d_1) + \mathrm{n}(-d_2)\Big]\,, \tag{13a}$$

where

$$d_1 = \frac{y + A^*}{\sigma_z\sqrt{1-t}}\,, \tag{13b}$$

$$d_2 = \frac{y + A^* + \xi - x}{\sigma_z\sqrt{1-t}}\,. \tag{13c}$$

The probability of blockholder activism conditional on the market makers' information at any date t is

$$\mathrm{N}\left(\frac{Y_t + A^*}{\sigma_z\sqrt{1-t}}\right)\,. \tag{14}$$

The unconditional probability of blockholder activism is increasing in σ_z if and only $A(H-L) <$ $\mathsf{E}[C]$.

For our purposes, the main result is the last statement, which shows that higher liquidity improves governance only if the initial block is too small to make activism worthwhile on average in the absence of any additional purchases. We discuss the determination of the initial block in Section 3. The next subsection discusses some additional aspects of the equilibrium and the intuition for Theorem 1. We discuss Kyle's lambda in Section 2.4 and present a simulated path of the equilibrium in Section 2.5.

2.3. Discussion of the Equilibrium

The blockholder becomes active—that is, condition (12) holds—when the cost ξ is small and/or when Z_1 is small. If liquidity traders sell shares, driving the price down, then the blockholder will surreptitiously buy shares and become active. On the other hand, if liquidity traders buy shares, propping up the price, then the blockholder will surreptitiously sell shares (i.e., take the Wall Street walk). When condition (12) holds, the blockholder buys shares at time 1 if necessary to ensure she has the required number B in order to influence the corporate decision. This is the meaning of (11b).

The numerator in the trading strategy (11a) creates "mean reversion," pushing Y_t towards the moving target $-\delta(\xi - \mu_\xi + Z_t)$. The rate of mean reversion is determined by the denominator of (11a). It explodes as the end of the model is reached, ensuring that Y_{1-} (that is, Y without the possible discrete order of the blockholder at time 1) equals $-\delta(\xi - \mu_\xi + Z_1)$. Substituting this into (12), we see that the blockholder becomes active if and only if

$$\frac{Y_{1-}}{-\delta} \leq \frac{A - \mu_\xi}{1+\delta} \quad \Leftrightarrow \quad Y_{1-} \geq A^* \,. \tag{15}$$

Because Y is observable by market makers, this condition is useful to market makers for estimating the probability of activism.

The strategy (11a) also has the property that $\mathsf{E}_t[\theta_t] = 0$ for all t, where the conditional expectation is conditional on the market makers' information. This means that informed trades are unpredictable. It is a standard property of Kyle models. It implies that Y has no drift from the point of view of market makers. Because the stochastic part of Y is the same as that of Z, it follows that Y has the same law as Z; that is, it is a Brownian motion with standard deviation σ_z. Consequently, market makers compute the probability that $Y_{1-} \geq A^*$ by observing Y and forecasting it as a Brownian motion. This produces formula (14) for the conditional probability of activism.

Given that formula (14) is the conditional probability of activism, formula (10) for the equilibrium price follows immediately. Thus, to prove that $(\pi, \theta, \Delta X_1)$ is an equilibrium, it suffices to show that it is optimal for the blockholder to use strategy (11) and that θ has the properties that $\mathsf{E}_t[\theta_t] = 0$ and $Y_{1-} = -\delta(\xi - \mu_\xi + Z_1)$. These facts are established in the appendix.

Note that the condition $Y_{1-} = -\delta(\xi - \mu_\xi + Z_1)$ implies (by adding $A - Z_1$ to both sides) that

$$X_{1-} = A - \delta(\xi - \mu_\xi) - (1+\delta)Z_1 \,. \tag{16}$$

Thus, the blockholder buys shares when the realized cost of activism is small relative to its expected value and when liquidity traders sell shares. An unusual feature of this model is that the large trader "overcompensates" for liquidity trading in the sense that Z_1 is multiplied by $1+\delta$.[5] This is a result of the blockholder adjusting her plans for intervention based on market activity. 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 activism, 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 activism: by paying the cost C, the blockholder increases the value of all the shares she owns from L to H.

In this equilibrium, the market converges to strong-form efficiency as $t \to 1$ in the sense that

$$\lim_{t\to 1} \pi(t, Y_t) = \pi(1, Y_{1-}) = \pi(1, Y_1) = \omega(X_1, \xi) \tag{17}$$

with probability one. This follows from the pricing formula (10) and the fact that the conditional probability (14) converges to 1 when (12) or, equivalently, (15) holds with strict inequality (the blockholder becomes active) and converges to 0 when the opposite strict inequality holds (the blockholder takes the Wall Street walk). Also, because of the equivalence of (12) and (15), formula (11b) implies that the blockholder makes a discrete purchase at time 1 only when $Y_{1-} \geq A$. In this circumstance, $\pi(1, Y_{1-}) = \pi(1, Y_1) = H$, so the discrete purchase is made at price H. Because the price is already at H, there is no advantage to making the purchase in small pieces. This is the reason that the usual logic in Kyle models about breaking up trades into small pieces does not apply when a block purchase is made at time 1 in the equilibrium of our model. Note that, except for determining the size of any block purchase at time 1, the exact magnitude of B plays no role in the equilibrium.

[5] In the basic continuous-time Kyle (1985) model, the informed trader's equilibrium strategy 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.

2.4. Kyle's Lambda

Our empirical tests, discussed in Section 4, exploit three distinct natural experiments. Each experiment provides an exogenous shock to the amount of liquidity trading in a company's stock. Since liquidity trading is the quantity that according to the model affects intervention by the blockholder, the three experiments allow us to test whether a reduction in liquidity trading increases blockholder activism and vice versa, as predicted in Theorem 1.

In addition to testing whether the shocks to liquidity trading affect activism, we also test whether the effect on activism occurs through the channel of stock liquidity. In this section, we explain the theoretical relation between liquidity trading and stock liquidity.

Stock liquidity is measured by the reciprocal of Kyle's lambda, which is the price change caused by a unit buy order. We can compute Kyle's lambda in our model from formula (10) for the equilibrium price. We use Itô's lemma and the fact that $(\mathrm{d}Y)^2 = (\mathrm{d}Z)^2 = \sigma_z^2\,\mathrm{d}t$. This produces $\mathrm{d}P_t = \lambda(t, Y_t)\,\mathrm{d}Y_t$, where lambda is given by

$$\lambda(t, Y_t) = \frac{H - L}{\sigma_z\sqrt{1-t}}\,\mathrm{n}\left(\frac{Y_t + A^*}{\sigma_z\sqrt{1-t}}\right), \tag{18}$$

with n denoting the standard normal density function as before. To see the theoretical relation between liquidity trading and stock liquidity implied by (18), consider a cross-section of stocks that vary in σ_z and in $H - L$ but have the same ratio A^*/σ_z. For example, we could have $A^* = 0$ for all stocks. The distribution of Y_t is a Brownian motion with standard deviation σ_z given market makers' information, so the distribution of Y_t/σ_z is the same for all stocks. Under these assumptions, the distribution of $\mathrm{n}\left(\frac{y+A^*}{\sigma_z\sqrt{1-t}}\right)$ is the same for all stocks. It follows that the distribution of lambdas varies in the cross-section in proportion to $(H-L)/\sigma_z$. Lambdas are larger for stocks for which the value spread $H - L$ is larger and smaller for stocks with more liquidity trading.[6] This confirms that the usual property of Kyle models—higher liquidity trading implies higher liquidity—is present in our model also.

[6] We can reach the same general conclusion without the assumption that A^*/σ_z is constant in the cross-section, though the calculation is necessarily more complicated.

2.5. Simulation

Figure 1 shows a possible equilibrium path of the trading model. In this example, we have normalized so 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. We have taken $A = \mu_\xi$, so the unconditional probability of intervention is 50%. We have also taken the realized cost of activism to be the expected cost ($\xi = \mu_\xi$). This implies that 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. The bottom panel shows the conditional probability of activism given market makers' information, which is (14). It also shows the conditional probability of activism from the blockholder's perspective. This is the probability that (12) holds conditional on Z_t and ξ. It equals

$$\mathrm{N}\left(\frac{(A-\mu_\xi)/(1+\delta)-\xi+\mu_\xi-Z_t}{\sigma_z\sqrt{1-t}}\right). \tag{19}$$

An uptick in liquidity buying between times $t = 0.10$ and $t = 0.18$ leads to a divergence between the market's 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 blockholder activism is unlikely, though, as always, the change in the market's conditional probability lags the blockholder's somewhat. The figure thus illustrates that the possibility of trading profitably against uninformed liquidity traders can undermine the blockholder's incentive to keep her block intact for a possible future intervention.

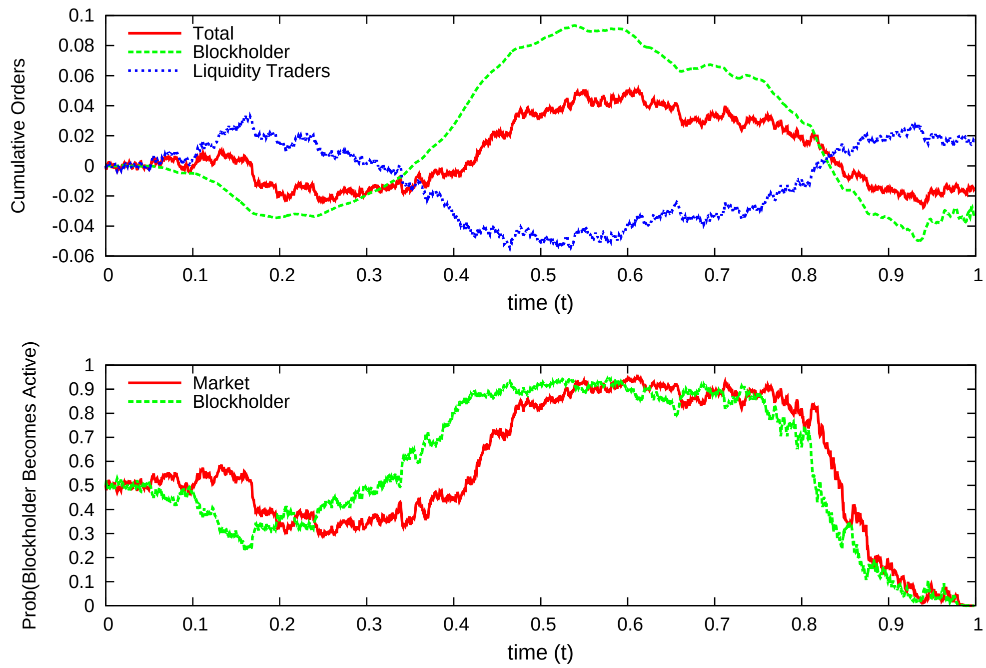

Figure 1: *A Simulation of the Equilibrium.* The top panel shows a possible path of liquidity trading Z and the corresponding paths of cumulative purchases $X - A$ by the blockholder and aggregate purchases $Y = Z + X - A$, given the parameter values described in the text. The bottom panel shows the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

3. Endogenizing The Initial Block Size

The results of Theorem 1 apply any time a block of size A has been created prior to the trading interval $[0, 1]$, regardless of how the block originally came into being. It can, for example, have been created in the firm's initial public offering, in the course of a capital raising exercise such as a PIPE, or through open-market purchases in a prior round of trading. In this section, we close the model by endogenizing the initial block size A as of the firm's IPO. Hence, we determine the optimal ownership structure that emerges when the company goes public. While focusing on the IPO keeps the algebra relatively simple, we stress that similar reasoning applies, and a similar conclusion obtains, after the IPO: if the firm does not currently have one, the board of directors has an incentive to create a blockholder (for example via a seasoned equity offering, a private placement, or a PIPE), and if the board doesn't but should have, there is an incentive for an activist investor to take advantage of periods of high liquidity to create a block herself. Once such a block exists, Securities Exchange Act Rule 14a-8 requires a waiting period of one year before the investor can submit a shareholder proposal, and it is during this period that increases in liquidity can cause the block to unravel again, as Theorem 1 shows.

As in the trading model that starts with the conclusion of the IPO, we assume that there is one large risk neutral investor and many small risk neutral investors (market makers and liquidity traders).[7] Normalize so that the firm has a single share of stock outstanding. We assume that the IPO is conducted before the potential blockholder observes the cost of activism C. This seems realistic, since the precise nature of any subsequent activism in which she might wish to engage is unlikely to be clear at the time of the IPO. It also simplifies our analysis, because it means that the IPO allocation and pricing cannot signal C to the rest of the market. Given a block size A, the value of a share to any investor other than the blockholder is $\pi(0,0)$ defined in (10), which is

$$P(A) \stackrel{\text{def}}{=} L + (H - L)\,\mathrm{N}\left(\frac{\delta(A - \mu_\xi)}{(1+\delta)\sigma_z}\right) . \tag{20}$$

Obviously, $L < P(A) < H$.

The blockholder's incentives to purchase shares in the IPO depend on her value function J in the subsequent Kyle market, which is defined in (13). More precisely, the incentives depend on the expectation of J taken over C (or equivalently ξ). If the blockholder's allocation A is observable by the market at the time she chooses it, then her utility for A is

$$\mathsf{E}[J(0, A, 0, \xi, A)]\,,$$

where the expectation is taken over ξ. On the other hand, if the allocation is unobservable, then her utility for A is

$$\mathsf{E}[J(0, A, 0, \xi, A')]\,,$$

where A' denotes the block the market anticipates. The anticipated block affects utility because it

[7] Because of the presence of market makers who do not require illiquidity discounts 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.

affects pricing in the subsequent Kyle market. For any A and A', set

$$G(A, A') = \mathsf{E}[J(0, A, 0, \xi, A')] \,. \tag{21}$$

Theorem 2. *The blockholder's utility function G is convex with total derivative*

$$\frac{\mathrm{d}G(A, A)}{\mathrm{d}A} = P(A) \,. \tag{22}$$

Furthermore,

$$\frac{\partial G(A, A')}{\partial A} = P(A) \tag{23}$$

when evaluated at $A' = A$.

The properties stated in Theorem 2 are the only properties of G that will be used in subsequent arguments. They are quite general properties and should hold for any dynamic market model, not just for the specific version of the Kyle model analyzed in the previous section. Convexity is a consequence of the cost of activism being fixed, independent of the number of shares owned—that is, increasing returns to scale. The derivative conditions are envelope properties. If the allocation to the blockholder is revised from A to $A + \Delta$, and the blockholder does not adapt her trading strategy in the Kyle market or change her plans for activism in response to the change in allocation, then the value of the additional Δ shares to her is the same as the value of the shares to a small investor, namely $P(A)\Delta$. For small Δ, the value of the Δ shares under the strategy that is optimal for $A + \Delta$ shares and the value under the strategy that is optimal for A shares are essentially the same, so the derivatives are equal to $P(A)$.

Our aim is to derive the value-maximizing allocation of shares between a large investor and a mass of small investors to incentivize costly but value-enhancing monitoring. How optimally to price and allocate a firm's shares when there is a potential blockholder who can monitor management is a problem studied in Stoughton and Zechner (1998).[8] Stoughton and Zechner discuss IPO mechanisms involving various combinations of fixed pricing (with demands optimally chosen by investors given prices) and take-it-or-leave-it offers (for which investors can choose either the allocation offered or zero). When the blockholder is made a take-it-or-leave-it offer, Stoughton and Zechner assume that the offer is visible to the market at large, so small investors observe the block-

[8]Stoughton and Zechner (1998) also consider secondary market trading, as we do, but they assume a single round of trading with no liquidity shocks and so do not consider the relation between trading liquidity and governance.

holder's allocation. When the blockholder chooses her quantity in a fixed price offering, investors have rational expectations regarding the quantity but do not observe it directly. The latter case corresponds to Mechanism I in the following theorem and the former case to Mechanisms II and III.[9]

Theorem 3 describes all feasible IPO mechanisms considered by Stoughton and Zechner (1998).[10] As Stoughton and Zechner note, real-world listing rules require firms to allocate a certain minimum number of shares to dispersed shareholders. This means that the blockholder cannot be sold the entire firm. The parameter γ captures the regulatory constraint on the size of the allocation to the blockholder and is given exogenously in their model.

Theorem 3. *Assume* $0 < \gamma < 1$*.*

I. *Discriminatory pricing. Assume the firm chooses a price* p_b *for the blockholder, a price* p_s *for small investors, and an allocation* $A \leq \gamma$ *such that*

   (a) *Optimal demand for the blockholder:* $G(A, A) - p_b A \geq G(x, A) - p_b x$ *for all* $x \geq 0$*,*

   (b) *Optimal demands for small investors:* $p_s = P(A)$*.*

   Then, the choices of p_b*,* p_s*, and* A *that maximize the value of the firm subject to these constraints are* $p_b = H$*,* $p_s = P(0)$*, and* $A = 0$*. The implied value of the firm is* $P(0)$*.*

II. *Uniform pricing with rationing. Assume the firm chooses a price* p *and an allocation* $A \leq \gamma$ *such that*

   (a) *Optimal demand for the blockholder:* $G(A, A) - pA \geq G(x, x) - px$ *for all* $0 \leq x \leq A$*,*

   (b) *Optimal demands for small investors:* $p \leq P(A)$ *.*

   Then, the choices of p *and* A *that maximize the value of the firm subject to these constraints are* $p = [G(\gamma, \gamma) - G(0, 0)]/\gamma$ *and* $A = \gamma$*. The implied value of the firm is* $[G(\gamma, \gamma) - G(0, 0)]/\gamma$*.*

III. *Discriminatory pricing with rationing. Assume the firm chooses a price* p_b *for the blockholder, a price* p_s *for small investors, and an allocation* $A \leq \gamma$ *such that*

[9] Take-it-or-leave-it offers are a natural outcome of bookbuilding. Stoughton and Zechner discuss discriminatory as well as uniform pricing. They also discuss rationing as well as market-clearing allocations. Take-it-or-leave-it offers are equivalent to rationing in our setting, due to risk neutrality of small investors and convexity of the blockholder's utility function (if she were to take an offer, she would also take any larger offer at the same price).

[10] Our model is somewhat simpler than the model of Stoughton and Zechner (1998), because we assume risk neutrality, to be consistent with our Kyle market. As a result of risk neutrality and the fact that the cost of intervention is fixed, the blockholder's utility function is convex, as shown in Theorem 2. Consequently, the Walrasian mechanism studied by Stoughton and Zechner (uniform pricing without rationing) is infeasible in our model.

(a) *Optimal demand for the blockholder:* $G(A, A) - p_b A \geq G(x, x) - p_b x$ *for all* $0 \leq x \leq A$,

(b) *Optimal demands for small investors:* $p_s \leq P(A)$.

Then, the choices of p_b, p_s, *and* A *that maximize the value of the firm subject to these constraints are* $p_b = [G(\gamma, \gamma) - G(0, 0)]/\gamma$, $p_s = P(\gamma)$, *and* $A = \gamma$. *The implied value of the firm is* $[G(\gamma, \gamma) - G(0, 0)] + (1 - \gamma)P(\gamma)$.

The implied value of the firm is higher for Mechanism III than for Mechanism II and higher for Mechanism II than for Mechanism I.

Theorem 3 implies that the firm will choose $A = \gamma$. This follows because both Mechanisms II and III give $A = \gamma$ and because Mechanism I, which does not, produces the lowest firm value and so is strictly dominated by the other mechanisms. Given an allocation $A = \gamma$, we conclude from Theorem 1 that liquidity reduces activism if $\gamma > \mathsf{E}[C]/(H - L)$, that is, if listing rules permit the firm to create blocks of sufficient size so that the blockholder's share of the value enhancement should she intervene covers her expected cost of intervening. In practice, activist investors typically own a few percent of a firm's outstanding shares (Gantchev and Jotikasthira, 2014), and certainly for the U.S., listing rules do not prevent firms from creating blocks of that size in their IPOs.

An important implication of Theorem 3 is that Maug's (1998) assumption that $A = 0$ cannot be optimal, as $A = 0$ fails to maximize firm value.

If at any point after the IPO, the firm found itself with $A = 0$ as a result of the initial blockholder's optimal trading, the board of directors could increase firm value by creating a new block of size $A > 0$ through an SEO, a PIPE, or a private placement. A board that failed to do so would run the risk of an activist investor taking advantage of periods of high liquidity to create a block herself—and eventually agitating to have the board replaced.

4. Testing the Model

4.1. Empirical Strategy

Our theoretical model shows that the conclusion of Maug (1998) that liquidity aids governance depends on his assumption that the block at the start of the dynamic model is small. Moreover, we have shown that if the block is chosen optimally in an IPO, then it will be sufficiently large that liquidity will harm governance. The same would be true if the block were created after the IPO, say through a PIPE or open-market trades.

To determine empirically whether liquidity aids or harms governance, we examine three natural experiments that involve exogenous shocks to liquidity and liquidity trading. The three experiments are:

1. Closures of brokerage research departments (Kelly and Ljungqvist, 2012)
2. Market maker closures (Balakrishnan et al., 2014)
3. Mergers of institutional with retail brokerages (Kelly and Ljungqvist, 2012)

The first and third experiments create shocks to retail trading, which we take as a proxy for liquidity trading. Experiment #1 reduces both retail ownership and retail trading while experiment #3 increases retail ownership and retail trading. Experiment #2 is a direct shock to stock liquidity. To measure liquidity, we use AIM, the illiquidity measure of Amihud (2002). We verify that all three experiments affect AIM in the predicted manner, and we verify that it is via these effects on AIM that the shocks affect blockholder intervention.

Our main proxy for intervention is the number of shareholder proposals submitted in opposition to management. Such proposals are an important weapon in activist investors' arsenals. Activist investors use shareholder proposals to advocate that a company take a specific course of action, such as removing obstacles to the influence of large shareholders (say, supermajority voting rules or staggered boards). Shareholder proposals are often accompanied by campaigns aimed at persuading other shareholders to back them, a process that is costly to the activist. Cuñat et al. (2012) show that shareholder proposals that pass increase shareholder value by 2.8%. Shareholder proposals are governed by Securities Exchange Act Rule 14a-8 which stipulates that they can only be submitted by shareholders who have held a minimum number of shares for at least one year. This waiting period opens the door to liquidity harming governance: while waiting to become eligible to submit a shareholder proposal, activist investors face the temptation that increases in liquidity trading make selling out more profitable than intervening. Their block may thus unravel. Overall, shareholder proposals map nicely into our notion of costly but value-increasing intervention by a blockholder whose decision to become engaged is influenced by shocks to the trading liquidity of the stock that occur between the time the block was formed and the time the intervention is to take place.

We obtain data on all governance-related shareholder proposals submitted in the U.S. from

RiskMetrics.[11] The data cover both those proposals that came to a vote and those that were subsequently withdrawn by the proponent. They are hence not selected ex post. Our variable of interest counts the number of proposals submitted in a given fiscal quarter.[12]

For each of our three experiments, we create a quarterly panel of treated and control firms centered on the fiscal quarter in which a firm receives treatment. To ensure parallel trends, we match treated and control firms on the basis of market capitalization, return volatility, AIM, the number of analysts providing coverage, and the number of market makers, each measured as of the quarter before the shock. We then estimate standard difference-in-difference regressions to estimate the effect of each of the three treatments on liquidity and on intervention. We also use the treatment shocks, one by one, as instruments to estimate the causal effect of liquidity on activism.

4.2. 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. Their aim is to test asymmetric-information asset pricing models. The 43 closures in their sample led to 4,429 U.S. listed firms losing some or all analyst coverage and so represent shocks to the affected firms' information environments. 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.[13] Using this experiment, Balakrishnan et al. (2014) show that affected stocks lose a substantial amount of liquidity, so brokerage closures are a promising candidate for testing the main prediction of our model: that activism should increase as a result.

4.2.1. 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

[11] We exclude social responsibility initiatives, tagged "SRI" in the RiskMetrics database. These tend to be proposed by unions or ethical investors such as churches. They are thus not aimed at increasing the value of the firm.

[12] As Cuñat et al. (2012) point out, RiskMetrics tracks 72 separate types of governance-related proposals (though many are quite rare). Following standard practice, we include all 72 types in our count. Our results are little changed if we instead focus only on proposals aimed at changing board structure, compensation arrangements, specific governance provisions in the corporate charter, or voting procedures, as decoded in Cunat et al.'s Data Appendix.

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

use decimalization as a shock to liquidity. While we agree that the move to quoting spreads in 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 house 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.

- Decimalization was phased in between August 2000 and February 2001. Given this clustering 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 brokerage closures, on the other hand, are staggered over a period of nine years. Staggering minimizes the risk that the estimated treatment effect is confounded by unobserved contemporaneous events.

- While decimalization undoubtedly led to a reduction in quoted spreads, it may not have improved the aspects of liquidity most important to blockholders or potential blockholders: market impact, depth, and trading costs. Specifically, Figure 1 in Balakrishnan et al. (2014) shows that there is no structural break in Amihud's illiquidity measure around the time of decimalization, suggesting that the market impact of trades remained largely unchanged. Figure 4 in Chordia et al. (2011) shows a dramatic decline in depth (the number of shares available for trade at the inside ask and bid), suggesting that market makers responded to the reduction in quoted spreads with a reduced willingness to trade large quantities at the inside quotes. The reduction in depth counteracts the reduction in quoted spreads. Finally, decimalization may not have reduced overall trading costs: Bessembinder (2003) finds that Nasdaq *effective* spreads were unchanged, while Figure 1 in Anand et al. (2013) shows that institutional trading costs (as measured using detailed proprietary data from Ancerno) were unaffected.[14]

4.2.2. Sample and Data

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

The implementation of the test follows Balakrishnan et al. (2014) closely.[15] Balakrishnan et al. 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, we obtain 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 brokerage closure. The same is true for the number of market-makers, even though this variable is not included in the propensity match.

4.2.3. Effect of Coverage Shocks on Liquidity

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

[14] An earlier reform of quoted spreads, the move from trading in eighths to trading in sixteenths in 1997, actually increased institutional trading costs (Jones and Lipson, 2001). Such negative effects on the costs of large traders are not unexpected, given that a reduction in tick size erodes the value of time priority (Harris, 1994).

[15] 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.

of the contemporaneous change in log AIM among matched controls. The point estimate of 0.008 matches that of Balakrishnan et al. (2014) 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 estimates show that AIM increases by significantly more, the fewer analysts the company is left with (p=0.029).

4.2.4. Reduced-form Effect of Coverage Shocks on Shareholder Intervention

Given that coverage terminations result in a sizeable reduction in liquidity, our model implies 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 the number of shareholder proposals directly to the coverage shocks. Column 6 shows that when the firm loses coverage, the log number of proposals submitted by large shareholders increases significantly (relative to untreated controls) ($p < 0.001$). The point estimate suggests that the number of proposals increases by 30.2% from the unconditional mean of 0.083 per firm-quarter. The magnitude of the effect suggests that the estimated impact of a reduction in liquidity is economically meaningful.

This reduced-form pattern is consistent with the model: exogenous brokerage closures—which we know from Kelly and Ljungqvist (2012) 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.

4.2.5. Causal Effect of Liquidity on Shareholder Intervention

In the next step, we use the brokerage closures as an instrument for liquidity to estimate the causal effect of reductions in liquidity on shareholder intervention. 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 the number of shareholder proposals. The results, shown in column 7, confirm that liquidity has a negative and significant effect on shareholder activism (i.e., a positive coefficient on Amihud's illiquidity measure). This is consistent with our model. The effect is large economically. A one-standard-deviation reduction in liquidity leads to a 200% increase in the number of shareholder proposals submitted in opposition to management.

4.3. Experiment #2: Exogenous Reductions in Market Making

The identifying assumption central to a causal interpretation of the estimates in column 7 of Table 1 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 file a larger number of shareholder proposals. For example, the reduction in analyst coverage may reduce the amount of external monitoring a firm is subject to, which may increase the returns to monitoring by blockholders. The outcome would be the same as in our model, but the channel would be variation in monitoring rather than variation in liquidity and liquidity trading.

We next consider a different exogenous source of variation in liquidity which, unlike brokerage closures, does not affect a firm's information environment and so leaves external monitoring unchanged: closures of market-making operations.

We use the 50 market-maker closures uncovered by Balakrishnan et al. (2014) for the period from 2000 to 2008 and identify all affected firms using data from Nastraq and Thomson-Reuters. To ensure this experiment is independent of experiment #1, we 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 described in the previous section 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. As a result, we expect the two experiments to yield treatment effects of different magnitudes.

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 estimates in column 6 mirror those of our first experiment: blockholder intervention increases significantly after a firm exogenously loses a market maker.

The causal effect of liquidity on the number of shareholder proposals, estimated this time using reductions in market making as an instrument, is reported in column 7. As in the brokerage-closure experiment, the effect is negative: a reduction in liquidity leads to a significant increase in the number of shareholder proposals (p=0.029), consistent with our model.

The effect is smaller economically than in the brokerage-closure experiment: a one-standard-deviation reduction in liquidity leads to a 4.3% increase in the number of shareholder proposals. This reflects an important difference between the two experiments. As noted earlier, 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 magnitude as smaller companies attract far fewer shareholder proposals than larger companies, all else equal. Heterogeneous treatment effects across the two experiments, such as those we find, are therefore not only to be expected but also consistent with the model.

4.4. Experiment #3: Exogenous Reductions in Information Asymmetry

While brokerage and market-maker closures result in lower liquidity and 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 and a corresponding increase in liquidity and liquidity trading. The trigger is 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 and liquidity trading should increase.[16]

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. Firms subject to the merger treatment look similar to those subject to the brokerage-closure treatment, and they are correspondingly 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. Column 6 shows the reduced-form estimates, which (as expected) are opposite in sign to the other two treatments: liquidity improvements that result from reductions in information asymmetry lead to a significant reduction in blockholder intervention.

The causal effect of liquidity on intervention is shown in column 7. Consistent with the previous two experiments, we again find a negative effect of liquidity on the number of shareholder proposals (p=0.005). The implied economic magnitude is similar to that in the brokerage-closure experiment, which hits firms with similar characteristics as those that are affected by a brokerage merger: a one-standard-deviation reduction in liquidity leads to a 63% increase in the number of proposals submitted by blockholders.[17]

4.5. Robustness: An Alternative Measure of Blockholder Intervention

To investigate the robustness of our empirical findings, we consider an alternative proxy for blockholder intervention, namely hedge fund activism. Gantchev (2013) uses data from 13D filings, proxies, and SharkRepellent.net to track the evolution of activist campaigns instigated by a large set

[16] This natural experiment is quite distinct from that of Hong and Kacperczyk (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.

[17] 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. Recall that this concern does not arise in the market-making treatment, which nonetheless yields the same results. This suggests that blockholders respond to the liquidity shock rather than to an information shock.

of hedge funds between 2000 and 2008. An activist campaign can involve demands that management negotiate strategic changes with the hedge fund, attempts by the hedge fund to install new directors on the firm's board, proxy contests, and other forms of intervention. We use Gantchev's data to code, for each firm-fiscal quarter, whether a firm in our estimation sample was the subject of such a campaign.

Hedge funds can become active in one of two ways. They can create a block ab initio through secondary-market purchases (triggering a 13D filing) or they can convert a pre-existing passive block into an active block by replacing their earlier Form 13G filing(s) with a Form 13D filing. [18] Hedge fund blockholders who emerge as a result of secondary market purchases just prior to starting a campaign are a good example of the kind of blockholder Maug (1998) models. Hedge funds who are already blockholders but later decide to become active are a good example of the kind of blockholder we model. Gantchev's (2013) data cover both scenarios but do not separately identify them. This means that we cannot separately test Maug's central prediction (that greater liquidity is beneficial for the emergence of new blockholders in the secondary market) against our central prediction (that greater liquidity is harmful for governance when a blockholder is already in place). But we can test which scenario, on net, is most empirically relevant: if the data supported a negative relation between liquidity and hedge fund activism, we would conclude that the predominant effect of lower liquidity is to induce pre-existing blockholders to become active rather than to discourage blocks from being created in the secondary market.

Table 4 uses the three exogenous shocks to liquidity from Tables 1 through 3 to estimate the effect of liquidity on the likelihood of a hedge fund launching an activist campaign against target management. Columns 1, 3, and 5 show the reduced-form estimates. Consistent with our model, we find the expected negative effect of liquidity on the likelihood of hedge fund activism. Column 1, for example, shows that the probability of a firm being targeted by an activist hedge fund 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

[18] Edmans et al. (2012) show that it is quite common for activist hedge funds to start as 13G filers and later switch to 13D status.

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). Similarly, the closure of a market maker leads to a significant increase in hedge fund activism (p=0.05), while the merger of a retail broker with an institutional broker reduces hedge fund activism as expected (p=0.058).

Columns 2, 4, and 6 show the second-stage estimates from 2SLS regressions that use the exogenous liquidity shocks as instruments for liquidity. The treatment effects are economically large in all three specifications and statistically significant in two of them. In column 2, for example, a one-standard-deviation reduction in liquidity following a brokerage firm closure leads to a 12.6 percentage-point increase in the likelihood that the company becomes the target of an activist hedge fund campaign (p=0.076). In column 4, a one-standard-deviation reduction in liquidity due to the closure of a market maker increases the likelihood that a firm becomes the target of an activist hedge fund campaign by 1.8 percentage points (p=0.023). (As before, the effect of market maker closures is smaller than that of brokerage firm closures for the simple reason that analysts have a tendency to cover larger companies which in turn attract more activist investors.) The corresponding effect in column 6, which uses the smaller sample of brokerage-firm mergers, is 16.1 percentage points, though this is not statistically significant at conventional levels (p=0.141).

Overall, these patterns echo those found for shareholder proposals in Tables 1 through 3. While Gantchev's (2013) data do not allow us to distinguish between pre-existing hedge fund blocks and those newly created through secondary market trading, the findings in Table 4 are more nearly consistent with the main prediction of our model—that lower liquidity induces blockholders to engage in corporate governance—than with Maug's (1998).

5. 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 once the blockholder holds a sufficiently large stake in the firm. It is irrelevant for our argument how this stake came into being. What matters is that from then on, greater liquidity increases the risk that the stake will unravel.

We use three distinct exogenous shocks (two that reduce and one that increases liquidity) to empirically estimate the effects of liquidity on a direct proxy for blockholder intervention: the number of proposals filed by shareholders in opposition to the target firm's management. We find strong effects consistent with the model: greater trading liquidity harms governance by reducing the likelihood that shareholders will submit proposals. We find similar patterns for an alternative proxy for blockholder intervention: activist hedge fund campaigns.

Our findings should not be interpreted as saying that liquidity cannot be beneficial for governance. As Maug (1998) notes, liquidity creates an opportunity for blocks to be formed. Our main insight is instead that the role of liquidity in governance is inherently knife-edge: liquidity aids the creation of blocks, but once a block has been created, its continued existence is at risk because liquidity creates the temptation to sell profitably to uninformed liquidity traders instead of intervening. Blocks created with a view to improving a firm's corporate governance and performance are hence intrinsically fragile.

Appendix A. Proof of Theorem 1

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 (7), given the trading strategy (11). Thus, collectively, Propositions 4 and 5 show that the trading strategy and pricing rule constitute an equilibrium. Proposition 3 shows that the function (13) satisfies the Hamilton-Jacobi-Bellman equation, and the proof of Proposition 4 verifies that it is indeed the value function.

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 $\xi^* = \xi - \mu$ and $\phi_t = -\delta(\xi^* + Z_t)$. 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.

Part (f) of Proposition 1 shows that activism occurs if and only if $Y_1 \geq A^*$. Part (e) of the proposition shows that $Y_1 \geq A^*$ if and only if $\xi^* + Z_1 \leq A^*/\delta$. This verifies that the blockholder becomes active if and only if (12) holds, as asserted in Theorem 1. Note that part (f) also shows that $Y_1 \geq A^*$ if and only if $Y_{1-} \geq A^*$. Thus, the blockholder becomes active if and only if $Y_{1-} \geq A^*$, as stated in (15). Combining this with part (b) of the proposition, we see that the conditional probability of activism is indeed given by the formula (14), as asserted in Theorem 1.

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 standard deviation* 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*

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

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 $\xi^* + Z_1 \le A^*/\delta$. 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).

□

The following proposition verifies the convergence to strong-form efficiency claimed in (17).

Proposition 2. *The pricing rule* (10) *and trading strategy* (11) *imply* (17).

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* (13) *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

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

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

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

We can write the maximum as

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

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

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

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

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

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* (13) *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). □

Proposition 6. *The unconditional probability of activism $N(A^*/\sigma_z)$ is an increasing function of σ_z if and only if $A < \mu_\xi$.*

Proof. The conditional probability $N(A^*/\sigma_z)$ is an increasing function of σ_z if and only if A^*/σ_z is an increasing function of σ_z. From the definitions of A^* and δ, we have

$$\frac{A^*}{\sigma_z} = \frac{\delta(A-\mu_\xi)}{\sigma_z(1+\delta)} = \frac{A-\mu_\xi}{\sigma_z + \sqrt{\sigma_z^2+\sigma_\xi^2}}\,.$$

This is increasing in σ_z if and only if $A < \mu_\xi$.

□

Appendix B. Proof of Theorem 2

Proof of Theorem 2. Define

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

where d_1 and d_2 are defined in (13). Then, we have

$$J(t,x,y,\xi,A) = xL + (H-L)K(t,x,y,\xi,A)\,. \tag{B.1}$$

For any real a, define

$$f(a) = \frac{\delta(a-\mu_\xi)}{1+\delta}\,. \tag{B.2}$$

We will first show that the partial derivatives of G are:

$$\frac{\partial G(x,A)}{\partial x} = L + (H-L)\,\mathrm{N}\left(\frac{(1+\delta)f(x)-\delta f(A)}{\sigma_z}\right), \tag{B.3a}$$

$$\frac{\partial G(x,A)}{\partial A} = \frac{\delta}{1+\delta}(H-L)\left[\mathrm{N}\left(\frac{f(A)}{\sigma_z}\right) - \mathrm{N}\left(\frac{(1+\delta)f(x)-\delta f(A)}{\sigma_z}\right)\right]. \tag{B.3b}$$

Given the formula (B.1), we can verify (B.3) by showing that

$$\frac{\partial \mathsf{E}[K(0,x,0,\xi,A)]}{\partial x} = \mathrm{N}\left(\frac{(1+\delta)f(x)-\delta f(A)}{\sigma_z}\right), \tag{B.4a}$$

$$\frac{\partial \mathsf{E}[K(0,x,0,\xi,A)]}{\partial A} = \frac{\delta}{1+\delta}\left[\mathrm{N}\left(\frac{f(A)}{\sigma_z}\right) - \mathrm{N}\left(\frac{(1+\delta)f(x)-\delta f(A)}{\sigma_z}\right)\right]. \tag{B.4b}$$

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

$$\begin{aligned} d_1 &= \frac{f(A)}{\sigma_z} , \\ d_2 &= \frac{f(A) + \xi - x}{\sigma_z} . \end{aligned}$$

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 (B.4), it suffices now to show that

$$\mathsf{E}[\mathrm{N}(-d_2)] = \mathrm{N}\left(\frac{(1+\delta) f(x) - \delta f(A)}{\sigma_z} \right) \tag{B.5}$$

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

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

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 $\mathrm{prob}\,(z + d_2 \leq 0)$ equals

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

which is the same as the right-hand side of (B.5), so we have verified (B.3).

The formulas (B.3) for the partial derivatives imply that the total derivative is

$$\frac{\mathrm{d}G(A,A)}{\mathrm{d}A} = L + (H-L)\,\mathrm{N}\left(\frac{f(A)}{\sigma_z}\right). \tag{B.6}$$

Note that the right-hand side of (B.6) is $P(A)$. Furthermore, the right-hand side of (B.3a) evaluated at $x = A$ is also $P(A)$. Finally, given the formulas for the partial derivatives, simple calculus shows that the matrix of second partials is positive definite, so G is convex.

□

Appendix C. Proof of Theorem 3

$$P(x) + (H-L)\left[\mathrm{N}\left(\frac{\delta(x-\mu_\xi)}{(1+\delta)\sigma_z} + \frac{\delta^2(A-x)}{(1+\delta)\sigma_z}\right) - \mathrm{N}\left(\frac{\delta(x-\mu_\xi)}{(1+\delta)\sigma_z}\right)\right].$$

Mechanism I. Because of the convexity of G, the blockholder has zero demand at any price $p_\ell \geq H$ and infinite demand at any price $p_\ell < H$. Thus, the only allocation consistent with (a) is $A = 0$. Consequently, (b) implies $p_s = P(0)$.

Mechanism II. First, suppose $A > 0$. For the optimum in condition (a) to occur at $x = A$, it is necessary and sufficient that $G(0,0) \leq G(A,A) - pA$. Thus, we must have $p \leq [G(A,A) - G(0,0)]/A$. Note that this bound on p is tighter than the bound in condition (b), because

$$P(A) > \frac{G(A,A) - G(0,0)}{A},$$

due to G being convex with derivative equal to P. Thus, the value maximizing price for $A > 0$ is $p = [G(A,A) - G(0,0)]/A$. This is an increasing function of A, again due to convexity. Therefore, the value maximizing allocation subject to $0 < A \leq \gamma$ is $A = \gamma$. Finally, $A = \gamma$ is superior to $A = 0$, because at $A = 0$, condition (b) implies $p = P(0)$, and we have

$$\frac{G(\gamma,\gamma) - G(0,0)}{\gamma} > P(0)$$

again because G is convex with derivative P.

Mechanism III. As with Mechanism II, if $A > 0$, then we must have $p_\ell \leq [G(A,A) - G(0,0)]/A$ in order for the maximum in condition (a) to occur at $x = A$, and the maximum price for small investors consistent with (b) is $p_s = P(A)$. Therefore, the maximum implied value of the firm consistent with given $A > 0$ is

$$Ap_\ell + (1-A)p_s = G(A,A) - G(0,0) + (1-A)P(A)\,.$$

The derivative of this is $(1-A)P'(A) > 0$, so the maximum subject to $0 < A \le \gamma$ is realized at $A = \gamma$. Furthermore, the formula $G(A,A) - G(0,0) + (1-A)P(A)$ also gives the implied value of the firm when $A = 0$, so $A = \gamma$ is in fact the maximum subject to $0 \le A \le \gamma$.

Revenue Rank. For any $A > 0$, we have

$$P(0) < \frac{G(A,A) - G(0,0)}{A} < P(A)\,.$$

The first inequality implies that Mechanism II produces a higher firm value than does Mechanism I. Furthermore, the second inequality implies

$$\begin{aligned} G(A,A) - G(0,0) + (1-A)P(A) &= A \cdot \frac{G(A,A) - G(0,0)}{A} + (1-A)P(A) \\ &> A \cdot \frac{G(A,A) - G(0,0)}{A} + (1-A)\frac{G(A,A) - G(0,0)}{A} \\ &= \frac{G(A,A) - G(0,0)}{A}\,. \end{aligned}$$

Thus, the value of the firm implied by Mechanism III is larger than that implied by Mechanism II.

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Table 1. The Effect of Exogenous Analyst Coverage Terminations on Liquidity and Shareholder Intervention.

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 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 4-7. ***, **, 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			Liquidity (log AIM)		Shareholder intervention (log no. of proposals)	
	treated firms (1)	matched controls (2)	difference in means (3)	first stage (4)	first stage (5)	reduced form (6)	second stage (7)
shock				0.008***	0.026**	0.025***	
				0.003	*0.010*	*0.005*	
log AIM	0.052	0.060	-0.008				3.275***
	0.244	*0.341*					*1.238*
Firm characteristics at t = –1							
# analysts providing coverage	6.3	6.3	0	-0.004***	-0.003**	-0.029***	-0.016**
	5.5	*5.8*		*0.001*	*0.001*	*0.002*	*0.007*
x shock					-0.010**		
					0.005		
# market makers	19.6	17.0	2.6	-0.022***	-0.022***	0.004	0.075**
	23.0	*20.6*		*0.007*	*0.007*	*0.002*	*0.032*
market capitalization ($m)	7,110	7,554	-444	-0.115***	-0.115***	0.002	0.378***
	19,700	*22,400*		*0.007*	*0.007*	*0.002*	*0.139*
monthly std. dev. of returns	0.033	0.034	-0.001	0.366**	0.366**	0.031	-1.168
	0.027	*0.034*		*0.153*	*0.153*	*0.035*	*0.737*
Diagnostics							
Within-firm R^2	n.a.	n.a.		10.1%	10.2%	11.2%	n.a.
Weak instrument test (F)	n.a.	n.a.		n.a.	n.a.	n.a.	10.0***
Number of firms (treated+controls)	n.a.	n.a.		5,966	5,966	5,966	5,966
Number of observations	2,983	2,983		49,149	49,149	49,149	49,149

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

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 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 4-7. ***, **, 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			Liquidity (log AIM)		Shareholder intervention (log no. of proposals)	
	treated firms	matched controls	difference in means	first stage	first stage	reduced form	second stage
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
shock				0.042^{***}	0.551^{***}	0.002^{**}	
				0.006	*0.044*	*0.001*	
log AIM	0.668	0.739	-0.071				0.036^{**}
	1.040	*1.156*					*0.016*
Firm characteristics at *t* = –1							
# analysts providing coverage	1.6	1.6	0	0.006^{*}	0.008^{**}	-0.005^{***}	-0.005^{***}
	3.2	*3.3*		*0.004*	*0.004*	*0.001*	*0.001*
# market makers	21.2	21.3	-0.1	-0.174^{***}	-0.168^{***}	0.000	0.006^{**}
	12.5	*13.3*		*0.017*	*0.017*	*0.001*	*0.003*
x shock					-0.163^{***}		
					0.013		
market capitalization ($m)	573	652	-79	-0.401^{***}	-0.403^{***}	0.000	0.015^{**}
	5,702	*3,272*		*0.011*	*0.011*	*0.000*	*0.007*
monthly std. dev. of returns	0.043	0.042	0.1	0.536^{***}	0.547^{***}	-0.002	-0.021^{*}
	0.039	*0.037*		*0.164*	*0.164*	*0.004*	*0.011*
Diagnostics							
Within-firm R^2	n.a.	n.a.		23.1%	23.3%	6.4%	n.a.
Weak instrument test (F)	n.a.	n.a.		n.a.	n.a.	n.a.	69.1^{***}
Number of firms (treated+controls)	n.a.	n.a.		8,242	8,242	8,242	8,242
Number of observations	4,121	4,121		68,780	68,780	68,780	68,780

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

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 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 4-7. ***, **, 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			Liquidity (log AIM)		Shareholder intervention (log no. of proposals)	
	treated firms (1)	matched controls (2)	difference in means (3)	first stage (4)	first stage (5)	reduced form (6)	second stage (7)
shock				-0.012***	-0.047***	-0.027***	
				0.004	*0.013*	*0.005*	
log AIM	0.026	0.030	-0.004				2.207***
	0.111	*0.215*					*0.787*
Firm characteristics at *t* = –1							
# analysts providing coverage	6.8	6.7	0.1	-0.003	-0.005*	-0.026***	-0.019***
	5.7	*6.0*		*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	0.003	0.008
	23.4	*23.3*		*0.009*	*0.009*	*0.003*	*0.019*
market capitalization ($m)	6,675	5,745	930	-0.116***	-0.116***	0.004	0.261***
	20,400	*19,200*		*0.014*	*0.014*	*0.003*	*0.089*
monthly std. dev. of returns	0.028	0.026	0.002	0.026	0.027	-0.024	-0.081
	0.033	*0.030*		*0.176*	*0.176*	*0.033*	*0.392*
Diagnostics							
Within-firm R^2	n.a.	n.a.		11.0%	11.1%	8.2%	n.a.
Weak instrument test (F)	n.a.	n.a.		n.a.	n.a.	n.a.	11.1***
Number of firms (treated+controls)	n.a.	n.a.		1,522	1,522	1,522	1,522
Number of observations	761	761		13,102	13,102	13,102	13,102

Table 4. The Effect of Exogenous Liquidity Shocks on Hedge Fund Activism.

This table uses the three exogenous shocks to liquidity from Tables 1 through 3 to estimate the effect of liquidity on an alternative proxy for shareholder intervention: the likelihood of a hedge fund launching an activist campaign against target management. The hedge fund activism data are borrowed from Gantchev (2013). Columns 1, 3, and 5 show reduced-form estimates, regressing an indicator that equals one if a hedge fund engages in activism on the shock indicator. Columns 2, 4, and 6 show the second-stage estimates from 2SLS regressions that use the exogenous liquidity shocks as instruments for liquidity as measured by Amihud's illiquidity measure. The unit of observation in each regression is a firm-fiscal-quarter. We observe each firm for (up to) four fiscal quarters before and after the quarter during which the exogenous liquidity shock occurs. All specifications are estimated using OLS with firm and year fixed effects. 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. ***, **, and * denote significance at the 1%, 5%, and 10% level (two-sided), respectively. The critical value for the weak-instruments test is 10.

	Dep. var.: Likelihood of hedge fund activism					
	Brokerage closures		Market maker closures		Brokerage mergers	
	reduced form	second stage	reduced form	second stage	reduced form	second stage
	(1)	(2)	(3)	(4)	(5)	(6)
shock	0.003**		0.003**		-0.006*	
	0.001		*0.001*		*0.003*	
log AIM		0.377*		0.016**		0.729
		0.211		*0.007*		*0.495*
Firm characteristics at *t* = –1						
# analysts providing coverage	-0.001	0.000	-0.001	-0.001	-0.001	0.001
	0.001	*0.001*	*0.001*	*0.001*	*0.002*	*0.003*
# market makers	0.002	0.010*	0.003	0.006**	-0.002	-0.005
	0.003	*0.006*	*0.002*	*0.002*	*0.003*	*0.008*
market capitalization ($m)	-0.003**	0.040*	-0.002	0.005	0.012**	0.101*
	0.002	*0.024*	*0.002*	*0.004*	*0.005*	*0.061*
monthly std. dev. of returns	0.021	-0.117	-0.044***	-0.055***	-0.096*	-0.204
	0.028	*0.107*	*0.014*	*0.015*	*0.057*	*0.168*
Diagnostics						
Within-firm R^2	50.0%	n.a.	58.8%	n.a.	50.7%	n.a.
Weak instrument test (F)	n.a.	10.0***	n.a.	69.1***	n.a.	11.1***
Number of firms (treated+controls)	5,966	5,966	8,242	8,242	1,522	1,522
Number of observations	49,149	49,149	68,780	68,780	13,102	13,102