Liquidity and Governance

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Abstract

We solve a dynamic Kyle model in which the large investor's private information concerns her 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 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 and four proxies for blockholder activism confirm that greater liquidity is harmful on average.

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1. Introduction

A liquid secondary market in shares facilitates capital formation but may be deleterious for corporate governance. Bhide (1993) argues that greater liquidity reduces the cost to a blockholder of selling her stake in response to managerial problems ("taking the Wall Street walk"), resulting in too little monitoring by large shareholders. However, liquidity facilitates block formation in addition to block disposition, so there are countervailing effects. 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 consensus is based largely on the seminal contribution of Maug (1998). We make 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 as tenable as is his conclusion that liquidity improves governance. Second, we examine three distinct natural experiments and show that, in each case, there is a negative empirical relation between liquidity and various measures of blockholder activism.

Maug (1998) studies a single-period Kyle model. Liquidity traders in his model only sell. The only possible buyer (other than market makers) is the blockholder. The amount of liquidity depends on the number of shares owned by liquidity traders at the start of the Kyle model and the frequency with which they incur a liquidity shock. Maug's Proposition 2 states that whether higher liquidity in the Kyle model leads to a higher or lower probability of activism depends on the number of shares initially owned by the blockholder: when the initial stake is small, liquidity is beneficial, and when it is large, liquidity is harmful. Nevertheless, Maug concludes that his paper "shows that the impact of liquidity on corporate control is unambiguously positive." We disagree with this conclusion, on both theoretical and empirical grounds.

1.1. Theoretical Contribution

Maug's (1998) definite conclusion is a consequence of his modeling choices and assumptions. Maug endogenizes the initial block in the Kyle model via a prior round of trading. The way he does so ensures that the initial stake will be small, which in turn ensures that liquidity, in his model, can only ever be beneficial. Specifically, Maug assumes that the prior round of trading takes place in a market with a very different—i.e., non-Kyle—structure. We argue that including this first round of trading is a misstep, for two reasons.

First, trying to endogenize the initial stake via a prior round of trading simply pushes the question of how the initial stake is determined to the prior date. With two rounds of trading, one still has to specify the blockholder's stake at the beginning of the first of the two rounds. Ideally, this stake should also be endogenized, but to do so requires that we introduce another prior round of trading, which just pushes the question of the initial stake further back. Maug (1998) arbitrarily assumes two rounds of trading and that the stake prior to the first round is zero. In our view, these assumptions do little to truly endogenize the initial stake. In fact, we show in Appendix A that if Maug had allowed his first round of trading to be repeated before the Kyle market took place, he would have reached the conclusion that liquidity has no effect on activism on average, rather than the conclusion that it is unambiguously beneficial.

Second, Maug (1998) makes the prior round so unattractive to the potential blockholder that she naturally acquires only a small stake. Maug's investors know, in both rounds, that there is a single potential blockholder who could become active; they also know the cost and benefit of activism and so can work out the value increase if a stake were created. In the first round, there are no market makers, prices are set by small investors who require a liquidity discount (because they may become liquidity traders in the second round), and—importantly—the blockholder's trade is transparent so that the equilibrium price is a function of her trade: seeing the blockholder coming, investors will only sell to her if offered a price that reflects the full value increase resulting from her future intervention less the liquidity discount.[1] In the second-round Kyle market, on the other hand, the blockholder's trade is opaque, in the sense that it is crossed with liquidity trades before market makers see the residual. Given the fact that all investors know everything there is to know before the start of the Kyle market, and given a choice between trading in a transparent market and trading in an opaque Kyle market, the blockholder will naturally delay trading until the start of the Kyle market.

There are two further modeling choices that contribute to Maug's (1998) "unambiguous" conclusion. The first is that he stops after one round of the Kyle market and so ends his model before the blockholder has an opportunity to be tempted to trade out of her position, rather than engaging

[1]Absent the liquidity discount, there would be no trade at all in the first round of Maug's model. This is a manifestation of the Grossman-Hart free rider problem (Grossman and Hart, 1980).

in corporate governance. The second is that Maug assumes that liquidity traders can only sell. By preventing them from buying, he ensures that the blockholder has no opportunity to take the "Wall Street walk" by selling to liquidity traders.

We build a dynamic Kyle model with a market structure that stays consistent over time. At each date t, the remaining time $T - t$ constitutes a self-contained model. The conditions of the model at date t can be regarded as initial conditions for the subsequent trading. Thus, the initial conditions are determined by prior trading, with all periods of trading being symmetric. In fact, there are an infinite number of periods, because we work in continuous time. From this exercise, we see that "initial" stakes (that is, date t stakes) are random, in the sense of depending on random events prior to t. Thus, only probabilistic statements can be made about the effect on activism of an unanticipated shock to liquidity at any date t.

In reality, blocks are created in various ways and for various purposes. Some arise through IPOs or through private placements of seasoned equity. Others arise from purchases by potential activists and still others by purchases from investors who simply regard the stock as a good value. It is probably impossible to build a model that adequately incorporates these various forces for block creation. However, our model illustrates the general phenomenon that the effect of shocks to liquidity on subsequent blockholder activism depends on the random prior circumstances that determine the block size at the time of the shock. In our model, the random circumstances include prior market conditions—in particular, the sign of prior liquidity trading. In more general models, other prior conditions would also matter. However, our model suffices to establish a contrast with Maug's (1998) definite statement that the effect of liquidity is "unambiguously positive."

In our model, every block, no matter what its size, is fragile in the sense that there is some probability that it will unravel in subsequent trading. Whether it unravels depends in our model on what liquidity traders do. If they happen to buy, supporting the price, then the blockholder will find it optimal to take the Wall Street walk, that is, to surreptitiously sell her shares rather than become active. This channel is closed off in Maug's (1998) model, both because he provides no opportunity for retrading after his single-period Kyle model and because liquidity traders in his model never buy shares.

Overall, the main contribution of our model is to show that blocks are inherently fragile: once created, they are at risk of unraveling if liquidity increases. This result supports Bhide's (1993) concern that greater liquidity need not be desirable. It contrasts with the prevailing consensus in the literature, which views Bhide's concern as misplaced.

1.2. Empirical Contribution

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 four alternative proxies, becomes more likely 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. This inference is supported by evidence from a recent large-scale survey of institutional investors conducted by McCahery, Sautner, and Starks (forthcoming), who report that institutions that hold more liquid stocks are more likely to take the Wall Street walk than to intervene.

Our empirical findings 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 as decimalization.[2] The narrow window over which decimalization 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

[2] See Cai et al. (2011) for evidence that Regulation FD had a positive effect on the intensity of board monitoring and so independently affected corporate governance.

against which to measure the effect of liquidity on governance in a cleaner way.[3]

Our main empirical contribution is to show that increases in liquidity, resulting from these plausibly exogenous shocks, have a detrimental effect on blockholder activism on average. This is not to say that liquidity has no beneficial aspects—without it, blocks could not easily be formed in the first place—but it contrasts with the prevailing consensus in the literature that liquidity is unambiguously good for corporate governance.

1.3. Literature Review

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 also obtain a probabilistic 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. Thus, higher liquidity improves governance half of the time and harms governance the other half. 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 identify the effect of liquidity on blockholder activism.

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

[3]We contrast our empirical approach to that used in decimalization studies in Section 3.6.

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.

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.

2. A Dynamic Kyle Model of an Activist Investor

2.1. Activism

A stock is traded continuously during a time interval $[0, T]$. A blockholder, who owns $X_0 \geq 0$ shares of the stock at date 0, can buy and sell shares during $[0, T]$. A corporate decision is to be made at date $T + \epsilon$, for $\epsilon > 0$. We are interested in the question of how liquidity—once a block has been assembled—affects the likelihood of shareholder activism at date $T + \epsilon$.

Activism takes the following form. If the blockholder owns at least μ shares and takes a costly action at date $T + \epsilon$, she can influence the corporate decision. If she does so, the value of each share is H. Otherwise, the value is $L < H$. The cost of influencing the decision is $C > 0$. The blockholder will choose to become active if $X_T \geq \mu$ and $(H - L)X_T \geq C$, where X_T denotes the number of shares owned by the blockholder after the close of trading at date T. The parameters μ, C, L, and H are common knowledge.

Define

$$V(x) = \begin{cases} Lx & \text{if } x < \max(\mu, C/(H-L))\,, \\ Hx - C & \text{otherwise}\,. \end{cases} \tag{1}$$

If the blockholder owns x shares at date T, then they are worth $V(x)$ to her. The value of each share at date T to any other investor is

$$\omega(x) = \begin{cases} L & \text{if } x < \max(\mu, C/(H-L))\,, \\ H & \text{otherwise}\,. \end{cases} \tag{2}$$

2.2. Kyle Market

We model the market for shares as a Kyle model, operating continuously during the time interval $[0, T]$. The blockholder's holding at any date t is denoted by X_t, 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 $Y_t = X_t - X_0 + Z_t$. We assume that the blockholding X_0 at the beginning of trading is private information of the blockholder. The empirical counterpart to this assumption is that investors in the U.S. do not have to publicly disclose the size of their stakes until the stake exceeds 5% of the company's outstanding shares.

Orders are submitted to risk-neutral competitive market makers. Competition among the market makers forces the price to the expected stock value conditional on the information in past orders, that is, conditional on the history of Y. What market makers are attempting to forecast is whether the blockholder will become active, because that determines the value of shares. So, what market makers are attempting to forecast is X_T. We assume market makers regard X_0 as having a normal distribution with mean $\hat{X}_0$ and standard deviation σ_x. For each t, let $\hat{X}_t$ denote the market makers' estimate of X_t; that is, $\hat{X}_t = \mathsf{E}[X_t \mid (Y_s)_{s \leq t}]$.

We search for an equilibrium in which the price at date t is $P_t = \pi(t, Y_t)$ for some function π. This means that the price at each date depends only on aggregate net trades through that date rather than on the entire history of trades.

2.3. Blockholder Trading

Given the pricing rule π, the blockholder seeks to maximize

$$\mathsf{E}\left[V(X_T) - \int_0^T P_{t-}\, \mathrm{d}X_t - \int_0^T (\mathrm{d}P_t)(\mathrm{d}X_t) \mid X_0 \right], \tag{3}$$

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 (3) 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 optimal trading strategies in Kyle models are of order $\mathrm{d}t$. The same is true here, except possibly at date T, when the blockholder may submit a discrete buy order in order to reach the threshold μ required for intervention. Except for the possible discrete order at date T, we expect an equilibrium strategy to be of order $\mathrm{d}t$, meaning that $\mathrm{d}X_t = \theta_t\, \mathrm{d}t$ for some stochastic process θ (the order rate). To simplify, we will only consider such strategies. For such strategies, the blockholder's objective function simplifies to

$$\mathsf{E}\left[V(X_T) - \int_0^T P_t \theta_t\, \mathrm{d}t - P_T \Delta X_T \mid X_0 \right], \tag{4}$$

where $\Delta X_T = X_T - X_{T-}$. 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_T is allowed at date T. In maximizing (4), the blockholder takes into account the dependence of P on her trades via the function π. Note that the price P_T at which a discrete order ΔX_T trades at date T is $\pi(1, Y_{1-} + \Delta X_T)$ and hence depends on the order size, just as in a single-period Kyle model.

2.4. Definition of Equilibrium

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

$$\pi(t, Y_t) = \mathsf{E}[\omega(X_T, \xi) \mid (Y_s)_{s \le t}] \tag{5}$$

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 T. 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 2.12, those plans can change based on market activity.

2.5. Equilibrium

In equilibrium, activism occurs if and only if cumulative purchases Y_T by the blockholder and liquidity traders exceed a certain threshold. The critical threshold and other aspects of the equilibrium depend on the amount of liquidity trading relative to the uncertainty about X_0. Define

$$\zeta = \frac{\sigma_z \sqrt{T}}{\sqrt{\sigma_x^2 + \sigma_z^2 T}}\,.$$

The critical threshold is

$$y^* = \frac{\zeta}{1+\zeta}\left(\frac{C}{H-L} - \hat{X}_0\right)\,. \tag{6}$$

This threshold is an increasing function of C, σ_z, and T. It is a decreasing function of $\hat{X}_0$, σ_x and $H - L$. Let N denote the standard normal distribution function. The equilibrium is described in the following theorem. All proofs are in Appendix B.

Theorem 1. *Define*

$$\pi(T, y) = \begin{cases} L & \textit{if } y < y^*\,, \\ H & \textit{otherwise}\,, \end{cases} \tag{7a}$$

and, for $t < T$, *set*

$$\pi(t, y) = L + (H - L)\,\mathrm{N}\left(\frac{y - y^*}{\sigma_z\sqrt{T - t}}\right)\,. \tag{7b}$$

Define

$$\theta_t = \frac{1}{1 - \zeta} \cdot \frac{\zeta(X_t - \hat{X}_0) - (1 + \zeta)Y_t}{T - t}\,, \tag{8a}$$

$$\Delta X_T = \begin{cases} (\mu - X_{T-})^+ & \textit{if } (H - L)X_{T-} \geq C\,, \\ 0 & \textit{otherwise}\,. \end{cases} \tag{8b}$$

Then, $(\pi, \theta, \Delta X_T)$ *is an equilibrium. In equilibrium, the conditional probability of blockholder activism at any date* t *is*

$$\mathrm{N}\left(\frac{Y_t - y^*}{\sigma_z\sqrt{T - t}}\right) = \mathrm{N}\left(\frac{1}{\sigma_z\sqrt{T} + \sqrt{\sigma_x^2 + \sigma_z^2 T}} \cdot \sqrt{\frac{T}{T - t}} \cdot \left(\hat{X}_t - \frac{C}{H - L}\right)\right)\,. \tag{9}$$

In equilibrium,

$$X_{T-} - \frac{C}{H - L} = \frac{1 + \zeta}{\zeta}(Y_{T-} - y^*) \tag{10}$$

with probability 1. The blockholder becomes active if and only if $(H - L)X_{T-} \geq C$*, and the following events*

$$(H - L)X_{T-} \geq C\,, \tag{11a}$$

$$Y_{T-} \geq y^*\,, \tag{11b}$$

$$Z_T \leq X_0 - \hat{X}_0 + \frac{1}{1 + \zeta}\left(\hat{X}_0 - \frac{C}{H - L}\right) \tag{11c}$$

are the same (up to a null set). The market makers' estimate of the blockholder's position at any date t *is*

$$\hat{X}_t = \hat{X}_0 + \frac{1 + \zeta}{\zeta}Y_t\,, \tag{12}$$

and the market makers' uncertainty about the blockholder's position is

$$\operatorname{var}\left(X_t \mid (Y_s)_{s\leq t}\right) = \frac{(T-t)\sigma_x^2}{T}\,. \tag{13}$$

The aggregate order process Y appears to market makers as a Brownian motion with zero drift and standard deviation σ_z on the time interval $[0,T)$.

2.6. Equivalent Conditions for Activism

The equivalence between condition (11c) and the conditions $Y_{T-} \geq y^*$ and $(H-L)X_{T-} \geq C$ is a consequence of the trading strategy (8a). The numerator of the trading strategy creates "mean reversion," pushing Y_t towards the moving target $\zeta(X_t - \hat{X}_0)/(1+\zeta)$. The rate of mean reversion is determined by the denominator of (8a). The rate of mean reversion explodes as the end of the model is reached, ensuring convergence of Y to $\zeta(X-\hat{X}_0)/(1+\zeta)$. This implies (10), which implies that the events (11a) and (11b) are the same. Substituting $Y_{T-} = X_{T-} - X_0 + Z_T$ in (10), we see the equivalence of (11a) and (11c).

2.7. Unpredictability of Blockholder Trades and Forecasting Activism

The strategy (8a) has the property that $\mathsf{E}_t[\theta_t] = 0$ for all t, where the 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 distribution as Z; that is, it is a Brownian motion with standard deviation σ_z, given market makers' information. Consequently, market makers compute the conditional probability of activism by computing the probability that $Y_{1-} \geq y^*$ and by forecasting Y as a Brownian motion. This produces the formula (9) for the conditional probability of activism, and, consequently, the formula (7b) for the equilibrium price.

2.8. Block Trade at T

The formula (8b) for the possible block trade at date T states that a block trade is made only if activism is already worthwhile for the blockholder, in the sense that the gain on the shares X_{T-} exceeds the cost of activism. When this is true, the blockholder submits a block order for just enough shares to reach the threshold μ required for activism.[4] Furthermore, when it is true, we also have $Y_{T-} \geq y^*$, so market makers know that the blockholder will become active, and they know it before observing any block order at date T. Thus, any block order at date T is priced at H. Consequently, there is no advantage in submitting the order in pieces and walking up the supply curve, as the large trader in a Kyle model ordinarily does. Note that, except for determining the size of any block purchase at date T, the exact magnitude of μ plays no role in the equilibrium.

2.9. Multiplier Effect of Liquidity Trading

An interesting feature of the equilibrium is that the large trader "overcompensates" for liquidity trading in the sense of buying more shares than liquidity traders sell or selling more shares than they buy. Substituting $Y_{T-} = X_{T-} - X_0 + Z_T$ in (10) yields

$$X_{T-} - X_0 = \zeta(X_0 - \hat{X}_0) - (1+\zeta)Z_T\,. \tag{14}$$

In the basic continuous-time Kyle (1985) model, the informed trader trades in such a way that $X_T = f(v) - Z_T$ 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. However, in our model, the offset is more than one-for-one. This is a consequence of the returns to scale of activism. There is a fixed cost but no variable cost. Paying the cost C increases the value of all shares owned by the amount $H - L$. Thus, the more shares the blockholder accumulates, the more desirable activism becomes, and the more valuable additional shares become.

2.10. Shocks to Liquidity and the Probability of Activism

There is nothing sacrosanct about date 0 in our model. At any date t, we can regard the remaining trading interval $[t, T]$ as a self-contained model. If convenient, we can just relabel date t as date 0 and redefine T as $T - t$ and study the remaining trading as another instance of the model with trading period $[0, T - t]$. At any date t, the initial conditions for this model are the estimate $\hat{X}_t$ of the block size and the uncertainty $(T - t)\sigma_x^2/T$ about the block size. Given these initial conditions, we can evaluate the effect of an unanticipated (out of equilibrium) shock to liquidity trading σ_z at any date t. This forms the basis of the empirical analysis in Section 3.

[4] It is also an equilibrium for the blockholder to buy more than $(\mu - X_{T-})^+$ shares when $(H - L)X_{T-} \geq C$; but, there is no value to doing so, since no gain is made on the additional shares.

Formula (9) gives the conditional probability of activism. From it, we can calculate that if the large investor is believed to have a block of such size that intervention is worthwhile (that is, if $(H - L)\hat{X}_t > C$), then an increase in σ_z that occurs at date t and is expected to persist throughout $[t, T]$ will reduce the probability of activism. Thus, once a large block has been formed, a subsequent increase in liquidity is harmful to activism. This is the main testable implication of our model.

Formula (9) follows from the fact that activism occurs if and only if $Y_{T-} \geq y^*$ and from the fact that Y is a Brownian motion with standard deviation σ_z given market makers' information. The equality in (9) is a consequence of (12). Formula (9) in turn implies the pricing rule (7b), which states that the price is a weighted average of L and H, with the weights determined by the conditional probability of activism. Note that the conditional probability of activism (9) is always less than 1. This means that blocks are always fragile—there is always some nonzero probability that a block will unravel.

Condition (11c) shows that whether a block actually unravels depends on whether it was large initially and whether liquidity traders buy or sell. Naturally, large initial blocks are less likely to unravel. Condition (11c) also yields the natural result that blocks will unravel if liquidity traders buy enough shares, propping up the price. When that happens, the blockholder will exit her position rather than becoming active.

2.11. Kyle's Lambda

Our empirical tests, discussed in Section 3, 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 blockholder activism, the three experiments allow us to estimate how changes in liquidity trading since block formation affect activism and 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 (7) 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

$$\lambda(t, Y_t) = \frac{H-L}{\sigma_z\sqrt{T-t}}\,\mathrm{n}\left(\frac{Y_t - y^*}{\sigma_z\sqrt{T-t}}\right), \tag{15}$$

with n denoting the standard normal density function. To see the theoretical relation between liquidity trading and stock liquidity implied by (15), consider a cross-section of stocks that vary in σ_z and in $H-L$ but have the same ratio y^*/σ_z. For example, we could have $y^* = 0$ 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 $\mathrm{n}\left(\frac{Y_t-y^*}{\sigma_z\sqrt{T-t}}\right)$ 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 $H-L$ of activism is larger and smaller for stocks with more liquidity trading.[5] This confirms that the usual property of Kyle models—higher liquidity trading implies higher liquidity—is present in our model also.

2.12. Simulation

Figure 1 shows a possible equilibrium path of the model. The top panel presents a random path of liquidity trading. Everything else in the figure is calculated from the path of liquidity trading and the assumed parameters. We set $T = 1$ and normalize so that there is a single share outstanding. We set $\sigma_x = 0.01$ and $\sigma_z = 0.02$. This implies $\zeta = 0.89$, so the blockholder buys 1.89 shares for each share that liquidity traders sell and sells 1.89 shares for each share that liquidity traders buy (see equation (14)). We assume the blockholder needs 2% of the outstanding shares in order for activism to be worthwhile ($C/(H-L) = 0.02$). We take $X_0 = \hat{X}_0 = C/(H-L)$, so both market makers and the blockholder begin with an assessment that the probability of activism is 50%.

The path of the blockholding X_t is shown in the middle panel of Figure 1. Aggregate shares purchased $Y_t = X_t - X_0 + Z_t$ are shown in the top panel of Figure 1. Market makers base their estimate of the large investor's block size X_t (shown in the middle panel) and their estimate of the likelihood of the blockholder becoming active (shown in the bottom panel) on the process Y. The bottom panel also shows the conditional probability of activism from the blockholder's perspective.

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

This is the probability that (11c) holds conditional on Z_t and X_0. It equals

$$\mathrm{N}\left(\frac{1}{\sigma_z\sqrt{T-t}}\left(X_0-\frac{\zeta\hat{X}_0}{1+\zeta}-\frac{C}{(1+\zeta)(H-L)}-Z_t\right)\right)\,. \tag{16}$$

In this simulation, purchases of shares by liquidity traders at the beginning of the trading period lead to a divergence between the assessments of market makers and the blockholder of the probability of activism. The blockholder can infer from the price (and knowledge of her own trading) that liquidity traders have purchased shares; consequently, her assessment of the probability of activism declines—she expects to exit rather than become active. However, market makers are unaware that the buying has come from liquidity traders. Consequently, their assessment of the likelihood of activism rises slightly. In response to the liquidity traders buying shares, the blockholder sells shares. This selling lowers Y and eventually aligns the conditional probabilities of activism around $t = 0.2$. However, liquidity traders, who begin to sell around $t = 0.18$, continue to sell, so the opposite pattern emerges: the blockholder plans to buy shares and become active, whereas market makers believe the blockholder has probably sold shares. This leads to another divergence between their respective assessments of the likelihood of activism. Again, beliefs later become aligned, with both market makers and the blockholder eventually believing that activism is highly likely. However, sustained buying of shares by liquidity traders beginning around $t = 0.6$ causes the blockholder to reverse course and to begin to sell shares. The selling of shares by the blockholder between $t = 0.6$ and $t = 0.95$ is an example of taking 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.

As discussed earlier, if there is an unanticipated shock to liquidity trading at any date t, and the shock is expected to persist, then its effect on the probability of activism depends on the expected block size, $\hat{X}_t$. If the block is expected to be sufficiently large to make intervention worthwhile ($\hat{X}_t > C/(H-L)$), then a subsequent increase in liquidity reduces the probability of activism. The middle panel plots $\hat{X}_t$ in the example. The threshold $C/(H-L)$ at which activism becomes worthwhile is indicated by the horizontal dotted line. When the expected block is above this threshold, an increase in liquidity would be harmful for activism. As an empirical matter, blocks above the threshold are common among both activist and institutional investors.

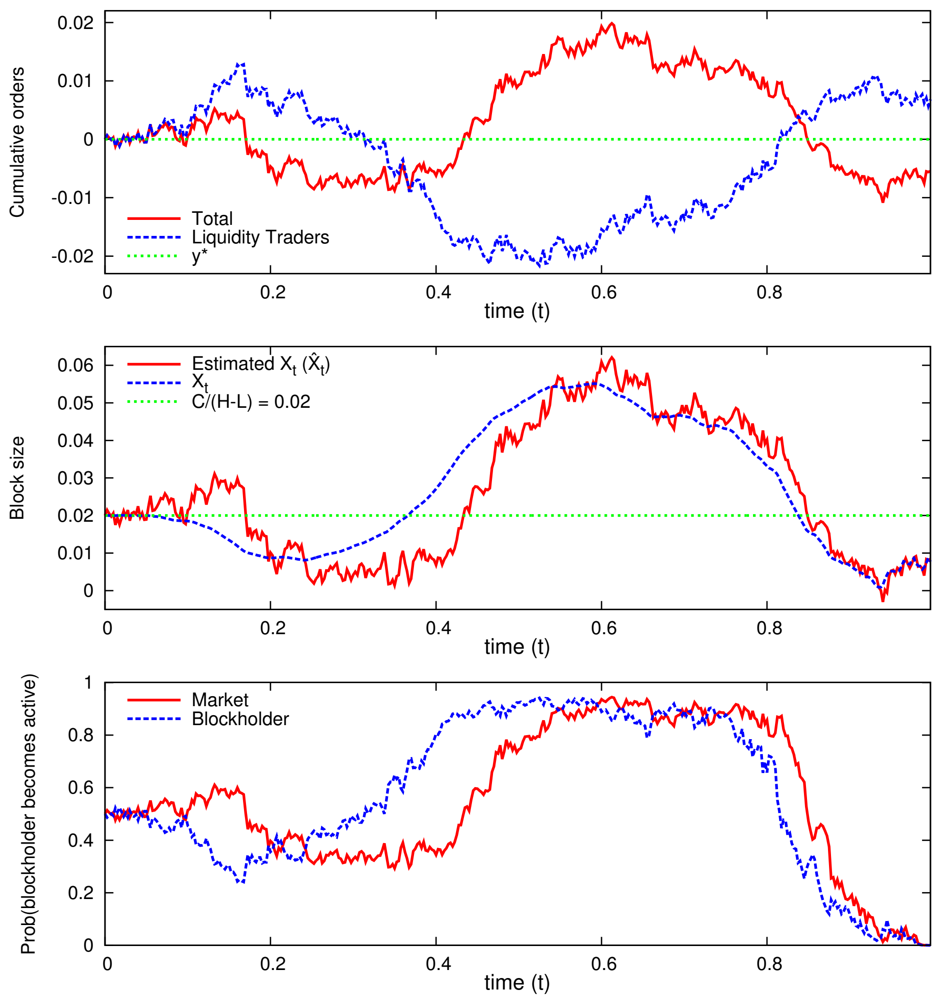

Figure 1: *A Simulated Path of the Equilibrium.* The top panel shows a possible path of liquidity trading Z_t. The path of liquidity trading determines the path of total purchases $Y_t = X_t - X_0 + Z_t$ that is also shown in the top panel. The second panel presents X_t and the estimate $\hat{X}_t$ of X_t made by market makers. The bottom panel shows the conditional probabilities of activism given the market's information and the blockholder's information, respectively. The parameters are $T = 1$, $\sigma_z = 0.02$, $\sigma_x = 0.01$, and $X_0 = \hat{X}_0 = C/(H - L) = 0.02$.

3. Testing the Model

3.1. Empirical Strategy

The main testable implication of Theorem 1 is that once a block has been created, a subsequent increase in liquidity reduces the probability of blockholder activism. This contrasts with Maug's (1998) conclusion that liquidity has an "unambiguously positive" effect on activism. To determine empirically whether liquidity aids or harms governance, we examine three natural experiments that involve exogenous shocks to stock liquidity and liquidity trading. The three experiments are:

1. Closures of brokerage research departments (Kelly and Ljungqvist, 2012)
2. Closures of market-making operations (Balakrishnan et al., 2014)
3. Mergers of institutional with retail brokerages (Kelly and Ljungqvist, 2012)

The first and third experiments have been shown to create shocks to retail trading, which we take as a proxy for liquidity trading. As we explain in greater detail below, 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 stock 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 activism, which we measure using four alternative proxies as outlined later in this section.

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 in the form of a shock to its stock liquidity. To ensure parallel trends, as required for identification, 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 (the "first stage") and on each of our four proxies for blockholder activism (the "reduced form"). We also use the treatment shocks, one by one, as instruments to estimate the causal effect of liquidity on activism in a two-stage least squares setting.

3.2. *Experiment #1: Exogenous Brokerage Closures*

We borrow our first natural 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.[6] 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 whether shocks to liquidity increase or decrease activism.

The brokerage-closure experiment compares the evolution of liquidity and various measures of blockholder activism 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 blockholder activism that occur for unrelated reasons (say, because governance or trading rules changed market-wide).

The implementation of the test follows Balakrishnan et al. (2014) closely.[7] 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 brokerage-closure tests consists of 24,653 firm-fiscal quarters for treated firms and 24,496 firm-fiscal quarters for their controls.

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

[7] 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.

Columns 1 through 3 of 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.

3.3. Experiment #2: Exogenous Reductions in Market Making

Our second natural experiment involves a different exogenous source of variation in liquidity which, unlike brokerage closures, does not work through changes in a firm's information environment: 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.

Columns 4 through 6 of Table 1 report 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.* columns 1 and 4 of Table 1). The reason for this is simple: as Kelly and Ljungqvist (2012) show, analysts are more likely to cover larger companies, while market makers tend to cover the whole spectrum of firms. The two experiments are thus complementary, in that they do not hit the same types of firms.

3.4. Experiment #3: Exogenous Brokerage Mergers

While brokerage and market-maker closures result in lower liquidity and less liquidity trading, our third 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.[8]

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. Columns 7 through 9 of Table 1 describe the resulting sample. The match between treated and control firms is again tight. Firms subject to the merger treatment are somewhat smaller and less volatile but much more liquid than those subject to the brokerage-closure treatment. Compared to firms subject to the market-maker treatment, they are substantially larger, less volatile, more liquid, and covered by more analysts.

3.5. Effect of Experiments on Liquidity

For our three sets of natural experiments to be useful in our setting, they have to result in significant variation in liquidity. Table 2 shows that this is indeed the case. Losing an analyst as a result of a brokerage closure, modeled in column 1, results in a sizable and significant increase in log AIM (which measures *il*liquidity), net of the contemporaneous change in log AIM among matched controls. The point estimate of 0.008 matches that of Balakrishnan et al. (2014) exactly. Column 2 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, which is intuitive (p=0.029).

We obtain similar results for the market maker closures. The estimates in column 3 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 4 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 ($p < 0.001$).

[8]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.

Brokerage mergers, in contrast to closures of brokerage firms or market makers, should lead to an improvement in liquidity. Columns 5 and 6 of Table 2 confirm this prediction. Liquidity increases significantly as a result of the merger treatment, the more so the fewer analysts covered the stock to begin with.

Economically, the results in Table 2 validate our use of brokerage and market maker closures and brokerage mergers as significant shocks to liquidity. Methodologically, we can use the estimates in Table 2 as the first stages of two-stage least-squares (2SLS) models, instrumenting the effect of liquidity on various measures of blockholder activism in the second stage using the predicted values from the regressions shown in Table 2.

Because we have three independent sets of natural experiments, which hit distinct subsets of firms, the treatment effects we estimate will likely vary across the three experiments. For example, Table 1 shows that market maker closures predominantly affect smaller, less liquid, and more volatile firms, while the brokerage closures and brokerage mergers tend to affect larger, more liquid, and less volatile firms. To the extent that these firm characteristics influence blockholder activism—say, because activists prefer targeting larger companies—we expect the treatment effects to be heterogeneous across the three experiments.

3.6. Relation to Prior Literature

Using brokerage closures, market maker closures, and brokerage mergers as sources of exogenous variation in liquidity is new in the literature on liquidity and governance. It departs from recent empirical work on blockholder activism such as Gerken (2009), Bharath et al. (2013), Fang et al. (2009), and Edmans et al. (2012), all of whom use decimalization as a shock to liquidity. While we agree that the move to quoting spreads in 1¢ increments likely improved liquidity, we prefer our three sets of natural experiments, for two reasons:

- Unlike decimalization, which affects all traded firms without exception, only some stocks in the economy are shocked in each of our experiments. This fact yields a set of quasi-randomly selected firms that receive a shock to their liquidity when, for example, a brokerage house closes down ('treated firms') and a set of quasi-randomly selected firms that do not ('control firms'). Armed with these pairs of treated and control firms, we can estimate the causal effect of liquidity on blockholder activism using standard diff-in-diff or 2SLS estimators. This is not possible with the decimalization shock, since it leaves no firm untreated, such that there are no controls with which to construct a plausible counterfactual.

- 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). In contrast, the brokerage closures are staggered over a period of nine years, as are the market maker closures and the brokerage mergers. Staggering minimizes the risk that the estimated treatment effects are confounded by unobserved contemporaneous events that affect blockholder activism independently.

3.7. Measuring Blockholder Activism

To estimate the effects of changes in liquidity on activism, we use four proxies for blockholder activism. Our first proxy—whether a shareholder proposal is submitted in opposition to management—is based on a suggestion by Maug (1998). While Maug does not attempt to test his model empirically, he notes that "large shareholders often choose proposals at annual general meetings to pursue their objectives." Prior work shows that such shareholder proposals are an important weapon in activist investors' arsenals. Activists typically use them 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. At the same time, they tend to be value-increasing if successful: 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 continuously 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 becoming active. As our model shows, their block may thus unravel as a result. This feature makes shareholder proposals a promising empirical counterpart to our notion of a costly but value-increasing intervention by a blockholder whose decision to become active is influenced by shocks to the trading liquidity of the stock that occur between the date the block was formed and the date the intervention is to take place.

We obtain data on all governance-related shareholder proposals submitted in the U.S. between 2000 and 2008 from RiskMetrics. (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 not typically aimed at increasing the value of the firm.) 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. We use these data to code an indicator set equal to one if a governance-related shareholder proposal is submitted in a given fiscal quarter.[9]

Our second proxy for activism captures a blockholder's decision to become active as opposed to staying passive or quietly trading out of her position. SEC rules require a blockholder to make a Schedule 13 filing within ten days of acquiring beneficial ownership of 5% or more of a public firm's shares. Depending on the blockholder's subsequent intentions, she must choose between a 13D and a 13G filing. A blockholder who intends to engage in activism must file Form 13D, which requires detailed disclosure of the nature of her intentions. Filing Form 13G is intended for passive investment only, involves less detailed disclosure, and precludes activism. If her intentions change, a 13G blockholder can convert a previous 13G filing to a 13D filing. A conversion to 13D is thus a prerequisite for a 13G filer to be able to intervene (other than by way of a shareholder proposal, which does not require a Form 13D filing). Following Edmans et al. (2012), we take 13G-to-13D conversions as a proxy for a blockholder's decision to become active. Note that a conversion involves a *pre-existing* block. It thus maps precisely into the condition in Theorem 1 that for liquidity to be harmful to activism, a block of sufficient size must already (be expected to) have been formed. The 13G conversion data are borrowed from Gantchev (2013).

While our second proxy allows us to estimate the effect of exogenous variation in liquidity on the likelihood that an existing blockholder chooses to intervene, our third proxy focuses on the

[9] 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.

likelihood that a blockholder chooses to build a stake of sufficient size to make activism worthwhile (quantity X_T in the model). Consider a blockholder who at time t holds X_t shares and experiences an exogenous reduction in liquidity. X_t is unobserved and could be large or small. If X_t is small, the liquidity reduction will make it hard to build a block of sufficient size to make intervention worthwhile. This will reduce the probability of intervention, for the same reason that Maug (1998) emphasizes. However, since small stakes do not have to be disclosed, we cannot measure this effect in the data. For blocks of size X_t that are already large, on the other hand, the liquidity reduction will make it hard for the blockholder to trade out of the position profitably, tilting the balance in favor of activism.

Our third proxy for activism attempts to capture this by focusing on a blockholder's first-ever 13D filing. If, following an exogenous reduction in liquidity, a blockholder files her first 13D, this reveals not only that she decided against quietly trading out of her stake and instead increased its size to exceed the 5% disclosure threshold, but also that she intends to use the stake to intervene in the way the target firm is run (since she filed a 13D and not a 13G). The identifying assumption for tests using this proxy is that reductions in liquidity make it costlier to trade. If so, only already-large stakes will result in a first 13D filing; small stakes will remain small or be sold. Under this assumption, we can test our main prediction that the likelihood of blockholder activism depends on what happens to liquidity between block creation and the intervention date. The 13D filings data are borrowed from Gantchev (2013) and Brav, Jiang, and Kim (2013).[10]

Our final proxy for blockholder intervention focuses on activist campaigns by hedge funds. We can think of such campaigns as the realization of the intention to intervene that is captured by 13G-to-13D conversions and by first-ever 13D filings. 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 such as demands for share buybacks, special dividends, or sales of non-core assets. Gantchev (2013) uses data from a range of sources (including 13D filings, proxies, and SharkRepellent.net) to track the evolution of activist campaigns instigated by a large set of hedge funds between 2000 and 2008.

[10] We focus on first 13D filings that are also the blockholder's first Schedule 13 filing. This ensures that our third proxy does not overlap with our second proxy.

We use Gantchev's data to code, for each firm-fiscal quarter and for each of our three estimation samples, whether a firm was the target of such a campaign.

4. Empirical Findings

4.1. Shareholder Proposals

Our model predicts that exogenous changes in liquidity in the period since block formation affect blockholder activism, with increases in liquidity being harmful to corporate governance and vice versa. Focusing on shareholder proposals, Table 3 uses our three sets of natural experiments to estimate the effects of changes in stock liquidity on activism. For each experiment, we present reduced-form difference-in-difference estimates, relating shareholder proposals directly to the shocks, and 2SLS estimates that use the shocks as instruments for liquidity. Each of these specifications is estimated as a linear probability model with year and firm fixed effects and so captures the determinants of the probability that one or more blockholders submit one or more shareholder proposals in opposition to management. The 2SLS specifications use predicted values of AIM obtained from the Table 2 first-stage regressions of AIM on the shocks (and other firm characteristics) in place of actual liquidity in the second-stage linear probability models.

Column 1 shows that when a firm suffers an exogenous reduction in analyst coverage, the likelihood of a shareholder proposal being submitted increases significantly, relative to untreated controls ($p < 0.001$). Looking at the raw data, we see that the average number of companies with shareholder proposals increases from 90.5 per quarter over the four quarters before a brokerage closure to an average of 125.8 per quarter in the four quarters after, while control firms see a much smaller increase (91 vs. 101).[11] The point estimate in column 1 implies that the quarterly probability of a shareholder proposal being filed increases from 2.01% before to 4.15% after, all else equal. The magnitude of the effect suggests that the estimated impact of losing an analyst is economically meaningful.

The 2SLS estimates, shown in column 2, confirm that variation in liquidity resulting from brokerage closures has a negative and significant effect on blockholder activism (i.e., the coefficient on Amihud's illiquidity measure is positive). This too is consistent with our model when blocks

[11] Since shareholder proposals are usually filed in connection with a firm's annual meeting, considering four-quarter periods rather than quarter-to-quarter changes makes most sense in the present context. The same is not true for our three other proxies.

are already large prior to the shock. The effect is large economically. To compute the economic magnitudes of our 2SLS estimates, we consider the change in liquidity experienced by the average treated firm. According to Table 2, the average treated firm's liquidity is reduced by 0.008 following a brokerage closure. Multiplying this point estimate by the 2SLS effect of liquidity on governance reported in Table 3, column 2 shows that a liquidity reduction of this magnitude increases the probability of a proposal being submitted in opposition to management by 111%, from 2.01% before to 4.26% after (p=0.009).[12]

The identifying assumption central to a causal interpretation of the 2SLS estimates in column 2 is that brokerage closures only affect blockholder activism 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 shareholder proposals more often. Though perhaps far-fetched, the reduction in analyst coverage may reduce the amount of external monitoring a firm is subject to, which could potentially increase the returns to effecting governance changes through shareholder proposals. 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. Our second experiment, closures of market-making operations, does not affect a firm's information environment and so leaves external monitoring unchanged. It thereby provides an important validation test of our brokerage-closure experiment: if we were to find no change in the likelihood of blockholder activism in response to variation in liquidity resulting from market maker closures, we would suspect that the brokerage closures identify a monitoring (rather than a liquidity) channel.

This appears not to be the case. The reduced-form estimates for the market maker closures, shown in column 3, mirror those for the brokerage closures in column 1: blockholder activism, as measured by the submission of a shareholder proposal in opposition to management, becomes significantly more likely after a firm exogenously loses a market maker, up from 0.1% before to 0.33% after (p=0.008). The effect of market maker closures is clearly smaller economically than

[12] These economic magnitudes are calculated as follows. The predicted post-shock probability of 4.26% is computed as 2.01% + 0.008 * 2.813, where 2.01% is the pre-shock probability, 0.008 is the average treated firm's increase in log AIM following a brokerage closure (see Table 2, column 1), and 2.813 is the estimated 2SLS coefficient (from Table 3, column 2). The percentage increase of 111% is computed as 4.26%/2.01% − 1.

that of brokerage closures, largely because firms that lose a market maker are systematically smaller than firms that lose an analyst. This is reflected in the lower pre-shock probability of a proposal being filed (0.1% vs. 2.01%). The 2SLS effect of liquidity, estimated this time using reductions in market making as an instrument, is reported in column 4. As in the brokerage-closure experiment, the effect is negative: a reduction in liquidity leads to a significant increase in the probability of shareholder proposals (p=0.013). To estimate the economic effect, note that the average treated firm's liquidity is reduced by 0.042 following a market maker closure (see Table 2). The resulting second-stage effect in Table 3, column 4 is to increase the probability of a shareholder proposal being filed from 0.1% before to 0.32% after for the average treated firm.

Our third experiment, the brokerage mergers, exogenously reduces information asymmetry and thereby, as Table 2 shows, improves liquidity, in contrast to our other two experiments. The reduced-form diff-in-diff estimates, shown in column 5, show that the improvement in liquidity causes shareholder proposals to become less common: brokerage mergers lead to a significant reduction in the probability of shareholder proposals ($p < 0.001$). The 2SLS effect of variation in liquidity induced by brokerage mergers is shown in column 6. Consistent with the previous two experiments, we again find a negative effect of liquidity on shareholder proposals (p=0.007).[13] The implied economic magnitude is fairly sizable. For the average treated firm, whose liquidity changes by 0.012 following a brokerage merger, the probability of a blockholder submitting a proposal increases from 0.92% before the shock to 3.14% after.

4.2. 13G Conversions

Table 4 considers the effects of the three exogenous liquidity shocks on our second proxy for blockholder activism: the likelihood that a blockholder intends to become active, as evidenced by filing a Form 13D for a block for which a Form 13G was previously filed. Recall that a 13G-to-13D conversion is a prerequisite for an existing 5%+ blockholder to be able to become active (other than to submit a shareholder proposal, for which no 13D filing is required). As noted earlier, our first two experiments exogenously reduce liquidity. According to our model, this should reduce the

[13]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 qualitatively similar results. This suggests that blockholders respond to the liquidity shock rather than to an information shock.

probability of an existing block unraveling and hence increase the probability of activism, all else equal. The opposite should occur in our third experiment, which exogenously increases liquidity.

The data strongly support these predictions. While 13G-to-13D conversions are fairly rare events, they become significantly more likely following a brokerage closure or a market maker closure, and significantly less likely following a brokerage merger. The diff-in-diff estimates in columns 1, 3, and 5 point to relatively large changes in probability. Compared to the quarter before the exogenous liquidity shock, the quarterly probability of converting to 13D increases by a factor of 3.875 (from 0.03% to 0.13%) following a brokerage closure (p=0.012) and doubles (from 0.1% to 0.2%) after a market maker closure (p=0.007); it declines by 31.6% (from 0.39% to 0.27%) following the merger of a retail broker with an institutional broker (p=0.085).

Columns 2, 4, and 6 show the second-stage estimates from 2SLS regressions that use the three sets of exogenous liquidity shocks as instruments for liquidity. The estimates confirm that a reduction in liquidity (i.e., an increase in Amihud's illiquidity measure) increases the probability of a 13G-to-13D conversion in each of the three experiments. This suggests that lower liquidity induces previously passive blockholders to become active, mirroring our results for shareholder proposals. The economic magnitudes are again large. In response to the mean liquidity reduction of 0.008 estimated in Table 2, the quarterly probability of a 13G conversion increases by 141%, from 0.03% in the quarter before a brokerage closure to 0.08% in the quarter after (p=0.023), all else equal. The corresponding effects of market maker closures and brokerage mergers are somewhat smaller but remain sizable, going from 0.1% to 0.13% (p=0.008) and from 0.39% to 0.58% (p=0.085), respectively.

4.3. First 13D Filings

Table 5 focuses on the likelihood that a blockholder increases the size of her block above 5%, as evidenced by filing a Schedule 13D notice for the target company for the first time. Crossing the 5% threshold reveals that the blockholder has decided to increase the size of the stake (possibly using a discrete order as in our model), rather than quietly trading out of the position. It also reveals her decision to become active, given the Form 13D filing. For blocks that are already large, Theorem 1 says that such activism should become more likely after exogenous reductions in liquidity and less likely when liquidity has exogenously increased.

In contrast to our tests using shareholder proposals and 13G conversions, for which we know that a block already exists, the tests using first 13D filings have to be interpreted with caution. The reason is that Theorem 1 requires a block of sufficient size to exist pre-shock for liquidity to be harmful. Filing a first 13D necessarily involves increasing the size of the block. After a reduction in liquidity, this should be more difficult to accomplish for small blocks than for already-large blocks. Our identifying assumption is hence that first 13D filings are likely to involve already-large blocks, in which case liquidity is harmful according to Theorem 1.

The data reveal that the probability of an activist-minded blockholder crossing the 5% reporting threshold increases significantly after liquidity-reducing events and vice versa, consistent with our prediction. In the raw data, the incidence among treated firms jumps from 8 in the quarter before a brokerage closure to 18 after, while control firms see little change (12 vs. 10). Results for the other two experiments are similar: up from 22 to 32 following a (liquidity-reducing) market maker closure and down from 10 to 1 after a (liquidity-improving) brokerage merger. In the three diff-in-diff specifications in columns 1, 3, and 5, we see that the quarterly probability of a first 13D filing increases by 68.3% (from 0.27% in the pre-shock quarter to 0.45%) after a brokerage closure (p=0.02) and by 44.7% (from 0.53% to 0.77%) after a market maker closure (p=0.012). It falls by 37.2% (from 1.31% to 0.82%) after a brokerage merger (p=0.002).

When we use the shocks as instruments for liquidity, we find that lower liquidity induces blockholders to choose to become active, consistent with the results for shareholder proposals and 13G-to-13D conversions. The effects, shown in columns 2, 4, and 6, are again sizable economically. An average-sized reduction in liquidity increases the quarterly probability of crossing the 5% threshold with activist intentions by 33.5%, from 0.27% in the quarter before a brokerage closure to 0.36% in the quarter after (p=0.033), all else equal. In the market maker experiment, the probability increases by 14.2%, from 0.53% to 0.61% (p=0.013). The effect is largest in the wake of brokerage mergers (up by 56.8%, from 1.31% to 2.06% per quarter), but it is more noisily estimated (p=0.064).

4.4. Activist Hedge Fund Campaigns

Table 6 uses the three exogenous shocks 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 for each of the three experiments. In each case, we find that liquidity-reducing shocks increase the likelihood of hedge fund activism and vice versa. 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=0.032). Looking at the raw data, we see that the number of firms subject to an activist campaign increases from 35 to 51 following a brokerage closure, while control firms see little change (43 vs. 45). The point estimate suggests that the probability increases by 29 basis points (relative to untreated controls) from the pre-shock probability of 1.17%, an increase of 24.8% (=0.29/1.17). Similarly, the closure of a market maker leads to a significant increase in the probability of hedge fund activism, up from 2.45% before the shock to 2.77% after (p=0.032). A brokerage merger reduces the likelihood of hedge fund activism as expected, from 3.02% to 2.42% (p=0.045).

Using the shocks as instruments for liquidity, we find that a reduction in liquidity (i.e., an increase in Amihud's illiquidity measure) increases the probability of hedge fund activism. The effects are economically large in all three specifications and statistically significant in two of them. In column 2, for example, an average-sized reduction in liquidity following a brokerage closure increases the quarterly probability that the company becomes the target of an activist hedge fund campaign by 26.1%, from 1.17% in the quarter before the shock to 1.48% in the quarter after (p=0.078). In column 4, the corresponding effect of a reduction in liquidity due to the closure of a market maker is to increase the probability by a more modest 2.8%, from 2.45% before to 2.52% after (p=0.017). The smaller estimated treatment effect presumably reflects the fact that hedge fund activists rarely target the smaller companies that predominate the treatment group in this experiment. Consistent with this conjecture, we find the largest treatment effect among firms shocked in connection with a brokerage-firm merger—which, according to Table 1, are among the largest treated firms in our three samples. An average-size change in liquidity (using the point estimate from Table 2) increases the probability of an activist hedge fund campaign by 30.4%, from 3.02% to 3.94% per quarter. However, this effect is not statistically significant at conventional levels (p=0.128), perhaps owing to the smaller sample size used in this experiment.

4.5. Discussion

Across all three natural experiments, and for each of our four measures of blockholder activism, we find consistent results: liquidity-reducing shocks increase the probability that a blockholder (i) files a shareholder proposal in opposition to management, (ii) changes her stance on the company from being a passive shareholder (Form 13G) to becoming activist (Form 13D), (iii) adds to her stake and does so with activist intentions, or (iv) launches an activist campaign against the company. Liquidity-increasing shocks have the opposite effect on these measures of activism. Using the shocks, one by one, as instruments for liquidity, we find that liquidity correlates negatively with blockholder activism as measured by shareholder proposals, 13G-to-13D conversions, crossing the 5% disclosure threshold, and activist campaigns. Each of these findings is consistent with the predictions of our model, to the extent that blocks are large prior to the shocks. Collectively, these findings suggest that liquidity is harmful to governance once a block has been created.

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.

Empirically, we use three distinct exogenous shocks (two that reduce and one that increases liquidity) to estimate the effects of liquidity on four proxies for blockholder activism: the filing of a shareholder proposal in opposition to the target firm's management, the likelihood that a previously passive blockholder turns activist, the emergence of a blockholder who has activist intentions, and the start of an activist hedge fund campaign against the target firm. We find strong effects consistent with the model: all else equal, and once a block has been created, greater trading liquidity harms governance by reducing the likelihood of activism for each of our four proxies.

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. The longer the wait between the block emerging and the time at which the blockholder can intervene, the greater this risk. Blocks created with a view to improving a firm's corporate governance and performance are hence intrinsically fragile. We thus disagree with Maug's contention that "the impact of liquidity on corporate control is unambiguously positive," on both theoretical and empirical grounds.

Appendix A. The Initial Condition in Maug's Model

In this section, we show that Maug's (1998) conclusion about the "unambiguously positive" effect of liquidity on activism is not robust to repeating the first-stage trading game that precedes Maug's Kyle market. In Maug's model, the value of the company's shares is L unless a blockholder exerts effort at cost C, in which case the value is increased to H. The equilibrium in the Kyle market is in mixed strategies, with the blockholder exerting effort with probability q. The total number of shares is normalized to 1, and the number of shares owned by the blockholder prior to the Kyle market is denoted by α. There is a market-wide liquidity shock with probability 1/2. The shock affects a fraction ϕ of the non-blockholder shareholders who own the asset prior to the Kyle market.

Maug shows that the expected value to the blockholder of owning α shares prior to the Kyle market, given the equilibrium of the Kyle market, is

$$(1-\alpha)G + [qH + (1-q)L]\alpha - qC\,, \tag{A.1}$$

where

$$G = \frac{\phi}{2}q(1-q)(H-L)\,, \tag{A.2}$$

and where the equilibrium q is given in Maug's equation (5) as

$$q = \frac{1}{2} - \frac{2[C-\alpha(H-L)]}{\phi(1-\alpha)(H-L)}\,. \tag{A.3}$$

Maug refers to the term $(1-\alpha)G$ in (A.1) as the expected profits from trading in the Kyle market. The term $[qH + (1-q)L]\alpha$ is the expected value of the α shares owned prior to the Kyle market, and qC is the expected cost of activism. The quantity α is determined in Maug's first-stage market. Maug assumes that the blockholder owns zero shares prior to the first-stage market, but we will generalize and suppose that the blockholder owns α_0 shares. The number of shares acquired in the first-stage market will be denoted by $\Delta = \alpha - \alpha_0$.

Maug's first-stage market is transparent in the sense that the equilibrium price depends on α. Moreover, the blockholder takes this dependence into account when trading in the first-stage market, so she acts as a monopsonist.[14] Maug's equation (11) states that the equilibrium price in the first-stage market is

$$P = qH + (1-q)L - G\,, \tag{A.4}$$

where q depends on α via (A.3). The blockholder chooses Δ to maximize the expected value (A.1) less the cost $P\Delta$. Of course, P depends on α, not just on Δ. Substituting for P from (A.4), we can write the blockholder's objective function in the first-stage market as

$$(1-\alpha_0)G + [qH + (1-q)L]\alpha_0 - qC\,. \tag{A.5}$$

This differs from the formula $G - qC$ in Maug's equation (13) only because we are allowing $\alpha_0 \neq 0$. We can substitute for q in (A.5) using (A.3) and then optimize in α, leading to

$$\alpha = \frac{C + (H-L-2C)\alpha_0}{2(H-L) - C - (H-L)\alpha_0}\,. \tag{A.6}$$

This is an increasing function of α_0, so the initial stake α_0 in the first-stage model affects the initial stake α in the Kyle market; hence, Maug's (1998) assumption that $\alpha_0 = 0$ is not innocuous. Equation (A.6) has two fixed points $\alpha = \alpha_0$, which occur at $\alpha = C/(H-L)$ and $\alpha = 1$. Only the former defines a stable equilibrium, in the sense that starting from any $\alpha_0 \neq 1$ and iterating on (A.6) produces $\alpha \to C/(H-L)$. This is exactly the value at which the blockholder "can recover the costs of monitoring through a capital gain on her initial stake α," and at this value of α, according to Maug's Proposition 2, liquidity in the Kyle market has *no* effect on the probability of activism ($q = 1/2$, independent of ϕ). Thus, repeating Maug's first-stage market prior to his second-stage Kyle market produces a very different conclusion about the effect of liquidity on activism than that reached by Maug.

The difference between running Maug's (1998) first-stage market a single time, as Maug does, and running it an infinite number of times is the same as the difference between a monopsonist and a perfectly discriminating monopsonist. A monopsonist facing a supply curve $P(x)$ and with a utility function $U(x)$ chooses x to equate marginal cost to marginal utility: $P(x) + xP'(x) = U'(x)$. However, if allowed to make many small purchases, the monopsonist will walk up the supply curve as

[14] There would not be an equilibrium if the blockholder acted as a price taker in the first-stage market, because at any price $P < H$ a price-taking blockholder would want to buy an infinite number of shares, pay the cost C, and earn infinite profit.

a perfectly discriminating monopsonist and arrive at the quantity x that equates price to marginal utility: $P(x) = U'(x)$. At this point, the monopsonist wishes to make no further purchases. The stable point at which the blockholder in Maug's first-stage market would wish to make no further purchases is the fixed point $\alpha = C/(H - L)$. At this value of α, the marginal value of shares—the derivative of (A.1) with respect to α, taking q to be the function of α given in (A.3)—equals the price of shares given in (A.4). As remarked before, at this value of α, liquidity in the Kyle market has no effect on activism, according to Maug's Proposition 2. Thus, Maug's rather arbitrary assumption that there is only a single round of trading before the Kyle market (and that the initial stake in this round is $\alpha_0 = 0$) determines his conclusion about the "unambiguously positive" effect of liquidity on activism.

Appendix B. Proof of Theorem 1

We first derive various implications of the blockholder trading strategy (8a). We start with the filtering problem of market makers, given the blockholder's strategy. Define

$$
\begin{aligned}
a(t) &= -\frac{1}{(1-\zeta)(T-t)}\,,\\
c(t) &= \frac{1+\zeta}{(1-\zeta)(T-t)}\,,\\
U_t &= \frac{\zeta(X_t-\hat{X}_0)-(1+\zeta)Y_t}{(1+\zeta)\sigma_z}\,.
\end{aligned}
$$

Substituting the equilibrium trading strategy for $\mathrm{d}X_t$, we obtain

$$\mathrm{d}U_t = a(t)U_t - \frac{1}{\sigma_z}\,\mathrm{d}Z_t\,.$$

Let $\hat{U}_t$ denote the conditional expectation of U_t and let $\Sigma(t)$ denote the conditional variance of U_t, given market makers' information at time t. Then, $\hat{U}_0 = 0$, and

$$\Sigma(0) = \frac{\zeta^2\sigma_x^2}{(1+\zeta)^2\sigma_z^2} = \frac{(1-\zeta)T}{1+\zeta}\,.$$

The observation process for the market makers' filtering problem, standardized to have unit volatility, is Y/σ_z, and

$$\frac{1}{\sigma_z}\mathrm{d}Y_t = c(t)U_t\,\mathrm{d}t + \frac{1}{\sigma_z}\mathrm{d}Z_t\,.$$

The innovation process is W defined by $W_0 = 0$ and

$$\mathrm{d}W = c(t)(U_t - \hat{U}_t) + \frac{1}{\sigma_z}\,\mathrm{d}Z_t\,.$$

Kallianpur (1980) shows that W is a standard Brownian motion on the filtration generated by Y. Moreover,

$$\frac{\mathrm{d}\Sigma(t)}{\mathrm{d}t} = 2a(t)\Sigma(t) + 1 - [c(t)\Sigma(t)-1]^2\,,$$

and

$$\mathrm{d}\hat{U}_t = a(t)\hat{U}_t\,\mathrm{d}t + \beta(t)\,\mathrm{d}W_t\,,$$

where

$$\beta(t) = c(t)\Sigma(t) - 1\,.$$

The differential equation and initial condition for Σ are satisfied by

$$\Sigma(t) = \frac{1}{c(t)} = \frac{(1-\zeta)(T-t)}{1+\zeta}\,.$$

Therefore, this is the conditional variance of U_t. It follows that $\beta(t) = 0$. Therefore, the differential equation and initial condition for $\hat{U}$ are satisfied by $\hat{U} = 0$. It follows that

$$\sigma_z\,\mathrm{d}W_t = \sigma_z c(t) U_t\,\mathrm{d}t + \mathrm{d}Z_t = \mathrm{d}Y_t\,,$$

so Y is a Brownian motion with standard deviation σ_z on its own filtration. Furthermore, the definition of U combined with $\hat{U} = 0$ gives us

$$0 = \zeta(\hat{X}_t - \hat{X}_0) - (1+\zeta)Y_t\,,$$

so (12) holds. Furthermore, the definition of U implies that

$$\operatorname{var}\left(X_t \mid (Y_s)_{s\le t}\right) = \frac{(1+\zeta)^2\sigma_z^2}{\zeta^2}\Sigma(t) = \frac{(1-\zeta^2)\sigma_z^2(T-t)}{\zeta^2} = \frac{(T-t)\sigma_x^2}{T}\,,$$

so (13) holds.

We have $Y_t \to Y_{T-}$ and $Z_t \to Z_T$ in L^2, because each is a Brownian motion on its own filtration. Hence,

$$U_t = \frac{\zeta(X_0 - \hat{X}_0 - Z_t) - Y_t}{(1+\zeta)\sigma_z} \to \frac{\zeta(X_0 - \hat{X}_0 - Z_T) - Y_{T-}}{(1+\zeta)\sigma_z}\,.$$

On the other hand,

$$\mathsf{E}[U_t^2] = \mathsf{E}\left[\mathsf{E}[U_t^2 \mid \mathcal{F}_t^Y]\right] = \Sigma(t) \to 0\,.$$

Therefore, $U_t \to 0$ in L^2. Hence,

$$0 = \frac{\zeta(X_0 - \hat{X}_0 - Z_T) - Y_{T-}}{(1+\zeta)\sigma_z}\,,$$

which implies

$$Y_{T-} = \zeta(X_0 - \hat{X}_0 - Z_T)\,.$$

It follows that $Y_{T-} \ge y^*$ if and only if

$$X_0 - \hat{X}_0 - Z_T \ge \frac{y^*}{\zeta} = \frac{1}{1+\zeta}\left(\frac{C}{H-L} - \hat{X}_0\right)\,,$$

which is the same as (11c). Also, we have

$$X_{T-} - X_0 + Z_T = Y_{T-} = \zeta(X_0 - \hat{X}_0 - Z_T)\,,$$

so

$$Z_T = X_0 - \frac{1}{1+\zeta}X_{T-} - \frac{\zeta}{1+\zeta}\hat{X}_0\,.$$

Substituting this expression for Z_T in (11c), we see that (11c) is the same as $X_{T-} \geq C/(H-L)$.

The blockholder becomes active if and only if $(H-L)X_T \geq C$, and the blockholder's strategy is such that $(H-L)X_T \geq C$ if and only if $(H-L)X_{T-} \geq C$. We have just shown that the latter condition is equivalent to $Y_{T-} \geq y^*$, so the conditional probability of activism, given the market makers' information, is the probability that $Y_{T-} \geq y^*$, conditional on the history of Y and regarding Y as a Brownian motion. Thus, the formula (9) is the correct formula for the conditional probability of activism, and this also implies that the pricing formula (7b) satisfies the equilibrium condition (5).

It remains to show that the blockholder strategy (8) is optimal. We will construct the value function of the blockholder. First, define

$$g(x,y) = Lx + (H-L)\begin{cases} (y-y^*)^+ & \text{if } x + y^* - y < C/(H-L)\,, \\ x + (y^*-y)^+ - C/(H-L) & \text{if } x + y^* - y \geq C/(H-L)\,. \end{cases} \tag{B.1}$$

Note that if $x + y^* - y < C/(H-L)$, then

$$\begin{aligned} y < y^* \quad &\Rightarrow \quad (y-y^*)^+ = 0 > x + y^* - y - C/(H-L) = x + (y^*-y)^+ - C/(H-L) \\ y \geq y^* \quad &\Rightarrow \quad (y-y^*)^+ = y - y^* > x - C/(H-L) = x + (y^*-y)^+ - C/(H-L)\,. \end{aligned}$$

On the other hand, if $x + y^* - y \geq C/(H-L)$, then

$$\begin{aligned} y < y^* \quad &\Rightarrow \quad (y-y^*)^+ = 0 \leq x + y^* - y - C/(H-L) = x + (y^*-y)^+ - C/(H-L) \\ y \geq y^* \quad &\Rightarrow \quad (y-y^*)^+ = y - y^* \leq x - C/(H-L) = x + (y^*-y)^+ - C/(H-L)\,. \end{aligned}$$

Consequently, we can also represent g as

$$g(x,y) = Lx + (H-L)\max\left((y-y^*)^+, x + (y^*-y)^+ - \frac{C}{H-L}\right)\,. \tag{B.2}$$

Noting that $a^+ = \max(0, a)$ for any a, we see that g is the maximum of four affine functions of (x, y). This implies that g is convex.

Define

$$\hat{V}(x) = Lx + (H - L)\left(x - \frac{C}{H-L}\right)^+$$
$$= \begin{cases} Lx & \text{if } x < C/(H-L)\,, \\ Hx - C & \text{if } x \geq C/(H-L)\,. \end{cases}$$

The difference between $\hat{V}$ and V is the consideration of the minimum block μ required for intervention in the definition of V. We have $g(x, y) \geq Lx$ and

$$g(x, y) \geq Lx + (H - L)x - C = Hx - C\,.$$

Therefore $g(x, y) \geq \hat{V}(x)$. Now, we show that $g(X_{T-}, Y_{T-}) = \hat{V}(X_{T-})$ with probability 1 when the blockholder follows the strategy (8). This follows from (10). If $Y_{T-} \geq y^*$, then (10) implies

$$X_T + (y^* - Y_T)^+ - \frac{C}{H-L} = X_T - \frac{C}{H-L} = \frac{1+\zeta}{\zeta}(Y_{T-} - y^*) \geq Y_{T-} - y^* = (Y_{T-} - y^*)^+\,,$$

so

$$g(X_{T-}, Y_{T-}) = LX_{T-} + (H - L)\left(X_{T-} + (y^* - Y_{T-})^+ - \frac{C}{H-L}\right)$$
$$= HX_{T-} - C = \hat{V}(X_{T-})\,. \tag{B.3}$$

On the other hand, if $Y_{T-} < y^*$, then (10) implies

$$X_T + (y^* - Y_T)^+ - \frac{C}{H-L} = X_T + y^* - Y_T - \frac{C}{H-L} = \frac{1}{\zeta}(Y_{T-} - y^*) < 0 = (Y_{T-} - y^*)^+\,,$$

so

$$g(X_{T-}, Y_{T-}) = LX_{T-} + (H - L)(Y_{T-} - y^*)^+$$
$$= LX_{T-} = \hat{V}(X_{T-})\,. \tag{B.4}$$

This completes the proof that $g(X_{T-}, Y_{T-}) = \hat{V}(X_{T-})$.

Set $J(T,x,y) = g(x,y)$ and, for $t < T$, define

$$J(t,x,y) = \mathsf{E}[g(x, y + Z_T - Z_t) \mid Z_t]\,,$$

We will show that J is the value function of the blockholder, meaning that

$$J(t,x,y) = \sup_{\theta,\,\Delta X_T} \mathsf{E}\left[V(X_T,\xi) - \int_t^T P_t\theta_t\,\mathrm{d}t - P_T\Delta X_T \mid X_t = x, Y_t = y\right]\,,$$

where the maximization is subject to the constraint that $P_u = \pi(u, Y_u)$ for all $u \geq t$. More importantly, we will use J to show that the blockholder strategy is optimal.

We can interchange differentiation and expectation to calculate derivatives of J as

$$J_x(t,x,y) + J_y(t,x,y) = \mathsf{E}[g_x(x, y + Z_T - Z_t) + g_y(x, y + Z_T - z_t) \mid Z_t]$$

It is easy to see from the definition (B.1) that

$$g_x(x,y) + g_y(x,y) = \begin{cases} L & \text{if } y < y^*\,, \\ H & \text{if } y > y^*\,. \end{cases}$$

Therefore, except at $y = y^*$, which has zero probability relative to the distribution of $Z_T - Z_t$, we have

$$g_x(x,y) + g_y(x,y) = h(y) = \pi(T,y)\,. \tag{B.5}$$

It follows that

$$J_x(t,x,y) + J_y(t,x,y) = \mathsf{E}[\pi(T, y + Z_T - Z_t) \mid Z_t] = \pi(t,y)\,. \tag{B.6}$$

Also, note that

$$J(t,x,Z_t) = \mathsf{E}[g(x, Z_T) \mid Z_t]\,,$$

which is a martingale on $\mathbb{F}^Z$. Using Itô's formula to calculate the drift of $J(t,x,Z_t)$ and equating it to zero, we obtain a standard partial differential equation for J:

$$J_t(t,x,y) + \frac{1}{2}\sigma_z^2 J_{yy}(t,x,y) = 0\,. \tag{B.7}$$

Consider an arbitrary trading strategy for the blockholder. Using Itô's formula and substituting

(B.6) and (B.7), we obtain

$$
\begin{aligned}
J(T, X_{T-}, Y_{T-}) &= J(0, X_0, Y_0) + \int_0^{T-} \mathrm{d}J \\
&= J(0, X_0, Y_0) + \int_0^{T} P\theta \,\mathrm{d}t + \int_0^{T} J_y \,\mathrm{d}Z \,.
\end{aligned}
$$

Taking expectations and substituting $Y_0 = 0$ yields

$$
J(0, X_0, 0) = \mathsf{E}\left[J(T, X_{T-}, Y_{T-}) - \int_0^T P\theta \,\mathrm{d}t \right] \,.
$$

The convexity of $(x, y) \mapsto g(x, y) = J(T, x, y)$ implies that

$$
\begin{aligned}
\Delta J_T &\le J_x(T, X_T, Y_T)\,\Delta X_T + J_y(T, X_T, Y_T)\,\Delta Y_T \\
&= P_T\,\Delta X_T \,,
\end{aligned}
$$

where we use (B.5) and $\Delta X_T = \Delta Y_T$ to obtain the equality. It follows that

$$
J(0, X_0, 0) \ge \mathsf{E}\left[J(T, X_T, Y_T) - \int_0^T P\theta \,\mathrm{d}t - P_T\,\Delta X_T \right] \,.
$$

Now, we use the fact that $J(T, X_T, Y_T) = g(X_T, Y_T) \ge \hat{V}(X_T) \ge V(X_T)$ to obtain

$$
J(0, X_0, 0) \ge \mathsf{E}\left[V(X_T) - \int_0^T P\theta \,\mathrm{d}t - P_T\,\Delta X_T \right] \,. \tag{B.8}
$$

This shows that $J(0, X_0, 0)$ is an upper bound on the blockholder's expected value. The bound is achieved by a strategy if and only if the weak inequalities in the derivation of (B.8) are actually equalities. Thus, the bound is achieved if and only $\Delta J_T = P_T \Delta X_T$ and $J(T, X_T, Y_T) = V(X_T)$.

The trading strategy (8) implies that, if there is a discrete trade at time T, then $Y_T \ge Y_{T-} \ge y^*$, so $P_T = H$. Furthermore, when there is a discrete trade at time T, then (B.3) holds at both $T-$ and T, so

$$
\Delta J_T = g(X_T, Y_T) - g(X_{T-}, Y_{T-}) = \hat{V}(X_T) - \hat{V}(X_{T-}) = H\Delta X_T \,.
$$

This confirms that $\Delta J_T = P_T \Delta X_T$ for the trading strategy (8). Finally, we have

$$
J(T, X_T, Y_T) = g(X_T, Y_T) = \hat{V}(X_T) = V(X_T) \,,
$$

the last equality following from the fact that, due to (8b), $X_T \ge C/(H - L)$ if and only if $X_T \ge \mu$. Thus, the trading strategy (8) is optimal.

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Table 1. Summary Statistics.

This table reports summary statistics for the estimation samples created for our three empirical experiments. Each experiment uses a set of exogenous shocks that are staggered across time and firms to estimate the causal effect of variation in liquidity on blockholder activism. The first experiment uses Kelly and Ljungqvist's (2012) exogenous analyst coverage terminations as a shock. The terminations occurred as a result of 43 brokerage closures between 2000 and 2008. The associated sample consists of 2,983 treated firms and 2,983 control firms. Following Balakrishnan et al. (2014), treated and control firms are matched on market capitalization, volatility, the number of analysts providing coverage, and liquidity, all measured as of quarter t = –1, the fiscal quarter before the brokerage closure. The second experiment uses Balakrishnan et al.'s (2014) exogenous reductions in market making as a shock. 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 associated sample consists of 4,121 treated firms and 4,121 control firms, matched on market capitalization, volatility, the number of analysts providing coverage, the number of market makers, and liquidity, measured as of quarter t = –1. The third experiment uses Kelly and Ljungqvist's (2012) exogenous analyst coverage re-initiations as a shock. 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 associated sample consists of 761 treated firms and 761 control firms, matched on market capitalization, volatility, the number of analysts providing coverage, and liquidity, measured as of quarter t = –1. The table reports means and, in italics, standard deviations, along with differences in means between treated and control firms (none of which is statistically significant).

	Brokerage closures			Market maker closures			Brokerage mergers		
	treated firms (1)	matched controls (2)	difference in means (3)	treated firms (4)	matched controls (5)	difference in means (6)	treated firms (7)	matched controls (8)	difference in means (9)
Firm characteristics at *t* = –1									
log Amihud illiquidity measure	0.052	0.060	-0.008	0.668	0.739	-0.071	0.026	0.030	-0.004
	0.244	*0.341*		*1.040*	*1.156*		*0.111*	*0.215*	
# analysts providing coverage	6.3	6.3	0	1.6	1.6	0	6.8	6.7	0.1
	5.5	*5.8*		*3.2*	*3.3*		*5.7*	*6.0*	
# market makers	19.6	17.0	2.6	21.2	21.3	-0.1	26.1	27.2	-1.1
	23.0	*20.6*		*12.5*	*13.3*		*23.4*	*23.3*	
market capitalization ($m)	7,110	7,554	-444	573	652	-79	6,675	5,745	930
	19,700	*22,400*		*5,702*	*3,272*		*20,400*	*19,200*	
monthly std. dev. of returns	0.033	0.034	-0.001	0.043	0.042	0.1	0.028	0.026	0.002
	0.027	*0.034*		*0.039*	*0.037*		*0.033*	*0.030*	
Number of observations	2,983	2,983		4,121	4,121		761	761	

Table 2. First-stage Estimates of the Effect of Exogenous Shocks on Liquidity.

This table estimates the effects of the three sets of exogenous shocks introduced in Table 1 on liquidity, measured using the log of one plus Amihud's Illiquidity Measure (AIM). The resulting three models constitute the first stage of the 2SLS regressions reported in subsequent tables. The unit of observation is a firm-fiscal-quarter. In each of the three experiments, we observe each firm for (up to) four fiscal quarters before and (up to) four fiscal quarters after the fiscal quarter in which the shock occurs. All specifications are estimated using OLS with firm and year fixed effects. 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.

	Dep. var.: Liquidity (log AIM)					
	Brokerage closures		Market maker closures		Brokerage mergers	
	(1)	(2)	(3)	(4)	(5)	(6)
shock	0.008***	0.026**	0.042***	0.551***	-0.012***	-0.047***
	0.003	*0.010*	*0.006*	*0.044*	*0.004*	*0.013*
Firm characteristics at $t = -1$						
log # analysts providing coverage	-0.004***	-0.003**	0.006*	0.008**	-0.003	-0.005*
	0.001	*0.001*	*0.004*	*0.004*	*0.002*	*0.003*
x shock		-0.010**				0.020***
		0.005				*0.006*
log # market makers	-0.022***	-0.022***	-0.174***	-0.168***	-0.002	-0.002
	0.007	*0.007*	*0.017*	*0.017*	*0.009*	*0.009*
x shock				-0.163***		
				0.013		
log market capitalization ($m)	-0.115***	-0.115***	-0.401***	-0.403***	-0.116***	-0.116***
	0.007	*0.007*	*0.011*	*0.011*	*0.014*	*0.014*
monthly std. dev. of returns	0.366**	0.366**	0.536***	0.547***	0.026	0.027
	0.153	*0.153*	*0.164*	*0.164*	*0.176*	*0.176*
Diagnostics						
Within-firm R^2	10.1%	10.2%	23.1%	23.3%	11.0%	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

Table 3. The Effect of Exogenous Liquidity Shocks on Blockholder Activism: Shareholder Proposals.

This table uses the three exogenous shocks to liquidity from Tables 1 and 2 to estimate the effect of liquidity on our first proxy for blockholder activism: the likelihood of a shareholder proposal being submitted in opposition to management (using data obtained from RiskMetrics). The dependent variable equals 1 if one or more shareholders file one or more proposals in quarter *t*, and zero otherwise. The variable of interest ('shock') equals 1 for treated firms beginning in the quarter of treatment. Columns 1, 3, and 5 show reduced-form difference-in-difference estimates, regressing the log number of shareholder proposals 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 (log AIM). (The first stages for the three experiments are shown in Table 2, columns 1, 3, and 5, respectively.) 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 as linear probability models using OLS with firm and year fixed effects. 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.

	Likelihood of a shareholder proposal being filed					
	Brokerage closures		Market maker closures		Brokerage Mergers	
	reduced form diff-in-diff	2SLS (second stage)	reduced form diff-in-diff	2SLS (second stage)	reduced form diff-in-diff	2SLS (second stage)
	(1)	(2)	(3)	(4)	(5)	(6)
shock	0.025***		0.002**		-0.027***	
	0.005		*0.001*		*0.005*	
log AIM		3.275***		0.036**		2.207***
		1.238		*0.016*		*0.787*
Firm characteristics at $t = -1$						
log # analysts providing coverage	-0.029***	-0.016**	-0.005***	-0.005***	-0.026***	-0.019***
	0.002	*0.007*	*0.001*	*0.001*	*0.004*	*0.006*
log # market makers	0.004	0.075**	0.000	0.006**	0.003	0.008
	0.002	*0.032*	*0.001*	*0.003*	*0.003*	*0.019*
log market capitalization ($m)	0.002	0.378***	0.000	0.015**	0.004	0.261***
	0.002	*0.139*	*0.000*	*0.007*	*0.003*	*0.089*
monthly std. dev. of returns	0.031	-1.168	-0.002	-0.021*	-0.024	-0.081
	0.035	*0.737*	*0.004*	*0.011*	*0.033*	*0.392*
Diagnostics						
Within-firm R^2	11.2%	n.a.	6.4%	n.a.	8.2%	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

Table 4. The Effect of Exogenous Liquidity Shocks on Blockholder Activism: 13G-to-13D Conversions.

This table uses the three exogenous shocks to liquidity from Tables 1 and 2 to estimate the effect of liquidity on our second proxy for blockholder activism: the likelihood that a blockholder intends to become active, as evidenced by filing a Schedule 13D for a block for which a 13G has previously been filed. The 13G conversion data are borrowed from Gantchev (2013). The dependent variable equals 1 if one or more blockholders convert from 13G to 13D status in quarter *t*, and zero otherwise. The variable of interest ('shock') equals 1 for treated firms beginning in the quarter of treatment. Columns 1, 3, and 5 show reduced-form difference-in-difference estimates, regressing an indicator that equals one when a 13G is converted to a 13D for the company 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 (log AIM). (The first stages for the three experiments are shown in Table 2, columns 1, 3, and 5, respectively.) 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 as linear probability models using OLS with firm and year fixed effects. 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.

	Likelihood of 13G to 13D conversion					
	Brokerage closures		Market maker closures		Brokerage mergers	
	reduced form diff-in-diff (1)	2SLS (second stage) (2)	reduced form diff-in-diff (3)	2SLS (second stage) (4)	reduced form diff-in-diff (5)	2SLS (second stage) (6)
shock	0.001**		0.001***		-0.001**	
	0.0004		*0.0004*		*0.0005*	
log AIM		0.059**		0.008***		0.159*
		0.026		*0.003*		*0.092*
Firm characteristics at *t* = –1						
log # analysts providing coverage	0.000	0.000	0.001***	0.001***	0.000	0.001
	0.000	*0.000*	*0.000*	*0.000*	*0.001*	*0.001*
log # market makers	0.000	0.001**	0.000	0.001***	0.001*	0.000
	0.000	*0.001*	*0.000*	*0.000*	*0.000*	*0.001*
log market capitalization ($m)	0.000	0.006**	-0.001**	0.003**	-0.001	0.019*
	0.000	*0.003*	*0.000*	*0.001*	*0.001*	*0.011*
monthly std. dev. of returns	-0.003	-0.026*	0.003	-0.003	-0.021**	-0.044
	0.007	*0.016*	*0.005*	*0.005*	*0.010*	*0.034*
Diagnostics						
Within-firm R^2	0.1%	n.a.	0.3%	n.a.	0.5%	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

Table 5. The Effect of Exogenous Liquidity Shocks on Blockholder Activism: First 13D Filings.

This table uses the three exogenous shocks to liquidity from Tables 1 and 2 to estimate the effect of liquidity on our third proxy for blockholder activism: the likelihood that a blockholder increases the size of her block above 5%, as evidenced by filing a Schedule 13D notice for the company for the first time. The 13D data are borrowed from Gantchev (2013) and Brav, Jiang, and Kim (2013). The dependent variable equals 1 if one or more shareholders file a 13D in quarter *t*, and zero otherwise. The variable of interest ('shock') equals 1 for treated firms beginning in the quarter of treatment. Columns 1, 3, and 5 show reduced-form difference-in-difference estimates, regressing an indicator that equals one when a 13D has been filed for the company 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 (log AIM). (The first stages for the three experiments are shown in Table 2, columns 1, 3, and 5, respectively.) 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 as linear probability models using OLS with firm and year fixed effects. 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.

	Likelihood of crossing 5% threshold					
	Brokerage closures		Market maker closures		Brokerage mergers	
	reduced form diff-in-diff	2SLS (second stage)	reduced form diff-in-diff	2SLS (second stage)	reduced form diff-in-diff	2SLS (second stage)
	(1)	(2)	(3)	(4)	(5)	(6)
shock	0.002**		0.002**		-0.005***	
	0.001		*0.001*		*0.0016*	
log AIM		0.112**		0.018**		0.622*
		0.053		*0.007*		*0.336*
Firm characteristics at *t* = –1						
log # analysts providing coverage	0.000	0.000	0.001	0.001	0.000	0.002
	0.001	*0.001*	*0.001*	*0.001*	*0.001*	*0.002*
log # market makers	0.002**	0.004***	0.002*	0.004***	0.001	-0.001
	0.001	*0.002*	*0.001*	*0.001*	*0.001*	*0.006*
log market capitalization ($m)	-0.002**	0.011*	-0.002***	0.006*	0.000	0.076*
	0.001	*0.006*	*0.001*	*0.003*	*0.002*	*0.041*
monthly std. dev. of returns	0.015	-0.029	0.008	-0.005	-0.030	-0.122
	0.022	*0.035*	*0.010*	*0.011*	*0.034*	*0.126*
Diagnostics						
Within-firm R^2	1.2%	n.a.	1.5%	n.a.	1.6%	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

Table 6. The Effect of Exogenous Liquidity Shocks on Blockholder Activism: Activist Campaigns.

This table uses the three exogenous shocks to liquidity from Tables 1 through 3 to estimate the effect of liquidity on our fourth proxy for blockholder activism: the likelihood of a shareholder launching an activist campaign against target management. The activism data are borrowed from Gantchev (2013). The dependent variable equals 1 if the firm is subject to an activist campaign in quarter *t*, and zero otherwise. The variable of interest ('shock') equals 1 for treated firms beginning in the quarter of treatment. Columns 1, 3, and 5 show reduced-form difference-in-difference estimates, regressing an indicator that equals one if a firm is subject to an activist campaign 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 (log AIM). (The first stages for the three experiments are shown in Tables 1-3, column 4.) 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 as linear probability models using OLS with firm and year fixed effects. 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.

	Likelihood of an activist campaign					
	Brokerage closures		Market maker closures		Brokerage mergers	
	reduced form diff-in-diff (1)	2SLS (second stage) (2)	reduced form diff-in-diff (3)	2SLS (second stage) (4)	reduced form diff-in-diff (5)	2SLS (second stage) (6)
shock	0.003**		0.003**		-0.006**	
	0.001		*0.001*		*0.003*	
log AIM		0.383*		0.017**		0.766
		0.217		*0.007*		*0.503*
Firm characteristics at $t = -1$						
log # 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*
log # market makers	0.002	0.010*	0.003	0.006**	-0.002	-0.005
	0.003	*0.006*	*0.002*	*0.003*	*0.003*	*0.008*
log market capitalization ($m)	-0.003**	0.041*	-0.001	0.006	0.012**	0.105*
	0.002	*0.025*	*0.002*	*0.004*	*0.005*	*0.062*
monthly std. dev. of returns	0.019	-0.121	-0.043***	-0.055***	-0.094*	-0.207
	0.028	*0.109*	*0.015*	*0.016*	*0.057*	*0.173*
Diagnostics						
Within-firm R^2	50.2%	n.a.	58.3%	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