Activism, Strategic Trading, and Liquidity[☆]

Kerry Back

Jones Graduate School of Business and Department of Economics, Rice University

Pierre Collin-Dufresne

École Polytechnique Fédérale de Lausanne and Swiss Finance Institute

Vyacheslav Fos

Carroll School of Management, Boston College

Tao Li

Department of Economics and Finance, City University of Hong Kong

Alexander Ljungqvist

Stern School of Business New York University, and NBER

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Email addresses: `Kerry.E.Back@rice.edu` (Kerry Back), `pierre.collin-dufresne@epfl.ch` (Pierre Collin-Dufresne), `fos@bc.edu` (Vyacheslav Fos), `TaoLi3@cityu.edu.hk` (Tao Li), `aljungqv@stern.nyu.edu` (Alexander Ljungqvist)

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Abstract

We analyze dynamic trading in an anonymous market by an investor who can expend costly effort to affect the firm value. We obtain the equilibrium in closed form for a general cost-of-effort function, including both binary and continuous outcomes. The optimal trading strategy is independent of the cost function, but equilibrium trades do depend on the investor's position in the stock. We verify the dependence on the investor's position by analyzing trades of investors who file 13Ds. The relationships between liquidity trading, activist productivity, market liquidity, and economic efficiency depend on the cost function and are elaborated in a series of examples.

1. Introduction

Activist shareholders play an important role in modern corporate governance.[1] Some activist investors follow a strategy of accumulating stakes in firms in which they feel they can create value by influencing management.[2] Other activists are traditional investors who recognize an opportunity for enhancing the value of an existing stake via activism.[3] The empirical literature suggests that activists are often successful in increasing the values of targeted companies (e.g., Brav, Jiang, Partnoy and Thomas, 2008). There are also examples of investors taking actions so as to decrease the values of firms, presumably benefitting their short positions.[4] The profitability of activism for investors who have no existing stakes hinges on their ability to purchase (or short) shares in the open market before stock prices reflect their intention to become active. On the other hand, investors with existing stakes who see an opportunity for value enhancing activism may find it profitable to sell their shares in the market rather than to incur the cost of activism (Bhide, 1993). Thus, there is a fundamental link between market conditions, activism, and firm value.

[1] A recent issue of *The Economist* describes them as "capitalism's unlikely heroes." It reports that "Last year activists launched 344 campaigns against public companies, large and small. In the past five years one company in two in the S&P 500 index of America's most valuable listed firms has had a big activist fund on its share register, and one in seven has been on the receiving end of an activist attack." It also reports that assets under management in activist hedge funds reached $120 billion in 2014.

[2] Activist hedge funds constitute the core of this group. Icahn, Ackman, Peltz, and Loeb are some of the better known examples of such activist shareholders.

[3] Pension funds, mutual funds, and insurance companies are prominent representatives of this group. CALPERS and the Norwegian Sovereign Wealth Fund are well known examples.

[4] See Bloomberg Business on how "Hedge funds found a new way to attack drug companies and short their stock," describing how some activist hedge funds challenge pharmaceutical patents in court to destroy the value of the firms owning these patents, presumably benefitting from their previously established short positions in these companies.

In his seminal contribution, Kyle (1985) derives equilibrium price dynamics when a large trader possesses long-lived private information about the value of a stock that will be revealed at some known date and that is independent of the large trader's actions. This paper extends the dynamic version of Kyle's model to a large trader who can affect the liquidation value of the firm by expending costly effort. We obtain the equilibrium in closed form for a general cost function. The model accommodates both binary effort and outcomes and continuous effort and outcomes.[5] We analyze several specific examples to illustrate properties of the model.

A surprising feature of the model is that the equilibrium trading strategy of the large trader does not depend on the cost-of-effort function. Unlike the standard Kyle model, the equilibrium trade size depends on the number of shares currently owned as well as on aggregate orders. Purchases are higher when the number of shares already owned is higher. This reflects the increasing returns to scale inherent in activism—the aggregate benefit depends on the number of shares owned but the cost does not. Hence, the value of a share to the large trader is higher the more shares she already owns. We examine a sample of 13D filers (who must report their trades within the prior 60 days) and verify this property of the trading strategy.

We revisit the classic question of how market liquidity affects economic effi-

[5] Many activist campaigns have a specific objective, and the outcome can be expressed as success or failure. For example, activists may attempt to block a merger, to force a company to be put up for sale, to oust a CEO, to remove anti-takeover provisions, to initiate a dividend, etc. In our binary model, the amount of effort required to achieve success is known. However, it is often reasonable to regard success as a random event, the probability of which depends on the effort expended. This fits within our continuous model with a bounded value distribution. Furthermore, other examples are naturally continuous: how much of a dividend the firm pays, how good the terms are in the sale of a firm, etc.

ciency. Coffee (1991) and Bhide (1993) argue that higher liquidity should be associated with lower economic efficiency, because illiquid markets lock in large shareholders who cannot easily sell their shares and thus commit them to exert effort in monitoring the firm and improving its value. However, Maug (1998) points out that liquidity enables potential activists who do not already own stakes to accumulate blocks and become active. Thus, liquidity has both beneficial and harmful effects.[6] Maug studies a single-period Kyle model in which effort and outcomes are binary. We consider other cost functions and a dynamic model so we can provide a broader perspective on the link between liquidity and activism. We obtain the following results:

- If effort and outcomes are binary, then an increase in liquidity trading increases expected activism if and only if the initial stake of the activist is on average too small to justify the cost of activism on its own. This is the same result as Maug's.

- If effort and outcomes are continuous, then the relationship between liquidity trading and expected activism depends on the function V that relates the number of shares x owned by the activist at the end of trading to the share value $V(x)$ implied by the activist's optimal effort.

[6] Maug concludes that liquidity is unambiguously beneficial for corporate governance. The conclusion is based on a Kyle model in which the blockholding at the beginning of the Kyle model is obtained in a prior round of trading in a non-anonymous market. A difficulty with the model is that the outcome of the prior round of trading is not stable—the large trader would prefer to trade a second time in the non-anonymous market before the Kyle market commences. At the only stable point of the non-anonymous market, the large trader has a stake that makes expected activism independent of liquidity in the Kyle market (Back, Li and Ljungqvist, 2015).

  - If V is linear (which corresponds to a quadratic cost function) then there is no relation between liquidity trading and activism, because higher liquidity trading makes it easier to short shares and destroy value just as it makes it easier to accumulate shares and create value.
  - If V is concave with $V'(x) \to 0$ as $x \to \infty$, then the relationship is as in the binary case: There exists a number x^* such that higher liquidity trading implies greater (less) expected activism if the expected initial stake of the large trader is less (greater) than x^*.
  - There are examples with V concave such that higher liquidity trading always implies lower expected activism and examples with V convex such that higher liquidity trading always implies greater expected activism.

- The realized amount of activism depends on realized liquidity trading. If liquidity traders sell shares, then the large trader will buy more shares and exert more effort.

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 two natural experiments that constitute shocks to retail trading, which we take as a proxy for liquidity trading. The two experiments are brokerage closures (Kelly and Ljungqvist, 2012) and mergers of retail with institutional brokerage firms (Kelly and Ljungqvist, 2012). Events of the first type exogenously reduce retail trading and events of the second type exogenously increase retail trading. Moreover, events of the first type reduce the liquidity of the stock based on the illiquidity measure of Amihud (2002a), and events of the second type increase liquidity.

In both experiments, we find that blockholder activism, as measured by four alternative proxies, becomes more likely when liquidity trading 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 exit their positions rather than to intervene.

The relation of liquidity trading to economic efficiency is related to the debate about the optimal duration of the pre-disclosure period (e.g., Bebchuk, Brav, Jackson and Jiang, 2013) for 13D filers. Specifically, shortening the period in which an activist can trade anonymously has the effect of reducing cumulative liquidity trading during the period in which the activist can trade anonymously. Other parameters of the model also affect economic efficiency and market liquidity. We explore these relationships in a series of examples in Section 6.

2. Related Literature

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, in addition to Maug (1998), that analyze single-period market microstructure models involving one or more large investors who may intervene in corporate governance. These include Kyle and Vila (1991), Kahn and Winton (1998), Ravid and Spiegel (1999), Bris (2002), and Noe (2002). The papers most closely related to ours are Kyle and Vila's and Kahn and Winton's. Kahn and Winton's model structure is quite similar to Maug's (1998). In their comparison of their work with Maug's, they state that they complement Maug by focusing on issues other than the effect of liquidity on governance. Kyle and Vila's conclusion regarding the effect of liquidity trading on blockholder activism (a value enhancing takeover in their case) is similar to the result we obtain with a binary value distribution (and similar to Maug's result).

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 exit rather than intervene. 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.

Our empirical findings on liquidity trading and activism 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.[7] 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 against which to measure the effect of liquidity on governance in a cleaner way.[8]

Another strand of the literature on trading and activism 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

[7]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.

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

they allow blockholder actions to affect the value of the company, they assume the actions take place before trading. They do not study strategic trading by an investor who can become 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.

3. Model

We analyze a Kyle model in which the large trader can undertake costly effort to influence the management of the firm and hence influence the value of the stock. The large trader has no private information about the exogenous value of the stock but has private information about his own position in the stock and thus is better informed about the value he will create. Trading is continuous during a time interval $[0, T]$. Denote the number of shares owned by the large trader at each date t by X_t. We assume that X_0 is known only to the large trader. Immediately after T, the large trader can expend effort to affect the value of the stock. Afterwards, positions can be liquidated frictionlessly at some common value v.

Denote the cost to the large trader of achieving a common value of v by $C(v)$. Given $X_T = x$, the large trader chooses effort to maximize $vx - C(v)$. The optimal value to the large trader is

$$G(x) \stackrel{\text{def}}{=} \sup_v \{vx - C(v)\}\,.$$

Let $V(x)$ denote the value of v at which the supremum is attained. This is the common value of shares to all traders after the large trader's expenditure of effort. By the envelope theorem, $\partial G(x)/\partial x = V(x)$. Thus,

$$G(x) = G(0) + \int_0^x V(a)\,\mathrm{d}a\,. \tag{1}$$

Assume G is a convex function, so V is increasing. A sufficient condition for G to be convex is that C be convex (G is the Fenchel conjugate of C).

In addition to the large trader, there are liquidity traders in the market. Let Z_t denote the cumulative number of shares purchased by liquidity traders through date t, with $Z_0 = 0$. Assume Z is a Brownian motion with zero drift and instantaneous standard deviation σ. Aggregate purchases by the large trader and liquidity traders are $Y_t = X_t - X_0 + Z_t$.

All orders are submitted to risk-neutral competitive market makers. The market makers therefore observe Y. They compete to fill orders, pushing the price to the expected value of $V(X_T)$ conditional on the history of orders. Let $\mathcal{F}_t^Y$ denote the information conveyed by the history of orders through date t. We assume market makers are uncertain about the number of shares X_0 that the large trader initially owns and view it as normally distributed with mean μ_x and standard deviation σ_x.

We search for an equilibrium in which the price at date t is $P(t, Y_t)$ for some function P. This means that the price depends at each date only on aggregate net orders through that date rather than on the entire history of orders. The argument[9] in Back (1992) shows that the equilibrium X will be of order $\mathrm{d}t$, so $\mathrm{d}X_t = \theta_t\,\mathrm{d}t$ for some stochastic process θ. Given $P(\cdot)$, the large trader seeks to maximize

$$\mathsf{E}\left[G(X_T) - \int_0^T P(t,Y_t)\theta_t\,\mathrm{d}t \mid X_0\right] \\ = G(X_0) + \mathsf{E}\left[\int_0^T \left(V(X_t) - P(t,Y_t)\right)\theta_t\,\mathrm{d}t \mid X_0\right], \quad (2)$$

where we have used the envelope condition to rewrite the objective function. This form of the objective function shows that, in the full information case, both the market makers and the large trader would agree on the marginal value of every additional share accumulated despite the fact that the large trader bears the entire cost of effort. This condition seems intuitively very important for an equilibrium to exist, since both the market maker and the large trader are risk-neutral.

4. Equilibrium

An equilibrium is a pair (P,θ) such that the trading strategy θ maximizes (2) given P and such that

$$P(t,Y_t) = \mathsf{E}\left[V(X_T) \mid \mathcal{F}_t^Y\right] \quad (3)$$

for each t, given θ. This is the standard definition of equilibrium in a Kyle model, except for the fact that the value V depends on X_T in our model.

[9] The argument is that if there are jumps or nonzero quadratic variation in the large trader's holdings X, then bid-ask spread costs are paid by the informed investor on these components of the order flow, that are similar to those paid by liquidity traders in the model. The informed investor can avoid paying these costs by using orders of infinitesimal size; that is, by taking $\mathrm{d}X$ to be of order $\mathrm{d}t$.

There are two standard features of continuous-time Kyle models that we use to guess the form of an equilibrium. The first feature is that the large trader trades in such a way as to ensure that at the terminal date the price of shares equals the marginal value. Otherwise, he is clearly leaving money on the table. In our model, this means that $P(T, Y_T) = V(X_T)$ with probability one. The other feature is that informed orders are unpredictable to market makers, meaning that the drift of Y is zero on its own filtration; that is, Y is a martingale on its own filtration.[10] Because Y has the same quadratic variation as Z, this martingale property implies that Y must actually be a Brownian motion with the same standard deviation as Z. These two features (and a new Brownian bridge result that we prove as a lemma) allow us to guess the equilibrium. We provide additional detail in the next section about how the equilibrium is derived.

Set

$$\Lambda = 1 + \sqrt{1 + \frac{\sigma_x^2}{\sigma^2 T}}. \tag{4}$$

Define

$$P(t, y) = \mathsf{E}\left[V(\mu_x + \Lambda\, Z_T) \mid Z_t = y\right], \tag{5}$$

$$\theta_t = \frac{\frac{1}{\Lambda-2}(X_t - \mu_x) - \frac{\Lambda}{\Lambda-2} Y_t}{T - t}. \tag{6}$$

Finally, define the value function of the large trader as

$$J(t, x, y) = \sup_\theta \mathsf{E}\left[G(X_T) - \int_t^T P(u, Y_u)\theta_u \, \mathrm{d}u \,\middle|\, X_t = x, Y_t = y\right]. \tag{7}$$

[10] Cho (2003) calls this 'inconspicuous insider trading.' It is a consequence of the Hamilton-Jacobi-Bellman equation and is therefore a necessary condition for equilibrium. See Back (1992).

Theorem 1. *The pricing rule* (5) *and the trading strategy* (6) *constitute an equilibrium. In this equilibrium, the distribution of* Y *given market makers' information is that of a Brownian motion with zero drift and standard deviation* σ*. Moreover,* $P(T, Y_T) = V(X_T)$ *with probability 1. The value function is*

$$J(t,x,y) = \frac{\Lambda - 1}{\Lambda} \mathsf{E}\left[G\left(\frac{\Lambda(x - Z_T) - \mu_x}{\Lambda - 1}\right) \,\middle|\, Z_t = y \right] + \frac{1}{\Lambda} \mathsf{E}\left[G(\mu_x + \Lambda Z_T) \mid Z_t = y \right]. \quad (8)$$

The equilibrium price evolves as $\mathrm{d}P(t, Y_t) = \lambda(t, Y_t)\,\mathrm{d}Y_t$*, where Kyle's lambda is*

$$\lambda(t,y) = \frac{\partial P(t,y)}{\partial y}. \quad (9)$$

Furthermore, $\lambda(t, Y_t)$ *is a martingale on* $[0, T - \delta]$ *for every* $\delta > 0$*, relative to the market makers' information.*

We note the surprising finding that the trading strategy of the large investor is independent of the effort cost function, at least as expressed as a function of the cumulative noise trading and the investor's accumulated shares. Instead, the cost function determines the equilibrium price process and market liquidity. Thus, expressed as a function of the price process, which may seem more natural, the trading strategy will look different. We summarize some of the properties of the holdings of the insider in the following corollary, which is proven in the appendix.

Corollary. *The equilibrium position of the insider at time T is*

$$X_T = \mu_x + \frac{\Lambda}{\Lambda - 1}(X_0 - \mu_x - Z_T)\,. \tag{10}$$

It follows that X_T is normally distributed with unconditional mean $\mathsf{E}[X_T] = \mu_x$ and unconditional variance $\mathsf{V}[X_T] = (\sigma\sqrt{T} + \sqrt{\sigma^2 T + \sigma_x^2})^2$.

As in a standard Kyle model, the trades of the large trader are not forecastable. On average the market maker does not expect the large trader to trade in one direction or the other. Consequently, $\mathsf{E}[X_T] = \mu_x$ as stated in the corollary. However, the variance of the terminal position of the insider is different than in the standard Kyle model, because liquidity shocks have an amplifying effect. The variance of the accumulated position increases more than linearly in noise trading. The foundation for this amplifying or multiplier effect is the increasing returns to scale inherent in activism. The cost of activism is a fixed cost in the sense that it does not depend directly on the number of shares owned by the activist. The more shares that are owned the more valuable activism is. This induces the activist to buy more shares than the liquidity traders sell, in constrast to the standard Kyle model.[11]

Our model has predictions for how variations in the parameters affect economic efficiency and market liquidity. We measure economic efficiency by the initial price $P(0,0)$, which incorporates the value expected to be created by activism. We measure

[11] In the standard Kyle model, $X_T = X_0 + h^{-1}(v) - Z_T$ for some function h of the exogenous asset value v. Thus, the large trader buys (or sells if negative) the quantity $h^{-1}(v)$ and offsets liquidity trades one-for-one. This is discussed further in the next section.

liquidity by the expected average lambda:

$$\frac{1}{T}\,\mathsf{E}\int_0^T \lambda(t, Y_t)\,\mathrm{d}t\,.$$

The theorem shows that λ is a martingale, so the expected average lambda is equal to the initial lambda $\lambda(0,0)$. Let $\overline{P}(\mu_x, \sigma_x, \sigma)$ denote $P(0,0)$ as a function of the model parameters. Likewise, let $\overline{\lambda}(\mu_x, \sigma_x, \sigma)$ denote $\lambda(0,0)$ as a function of the parameters. We calculate the functions $\overline{P}$ and $\overline{\lambda}$ in a series of examples (for different V functions) in Section 6.[12] Theorem 2 below is a general result about economic efficiency. The hypothesis regarding the derivative of V must be satisfied if V is bounded above (see footnote 5 for a discussion of when V would be bounded). The theorem shows that, if the large trader has a large initial position, then an increase in liquidity trading harms economic efficiency, because it makes it easier for the large trader to exit his position.

Theorem 2. *Suppose V is concave and satisfies $\lim_{x\to\infty} V'(x) = 0$. Then, for each (σ_x, σ), there exists μ_x^* such that*

$$\frac{\partial \overline{P}(\mu_x, \sigma_x, \sigma)}{\partial \sigma} < 0$$

if $\mu_x > \mu_x^*$.

[12] We may also regard $\overline{P}$ and $\overline{\lambda}$ as depending on parameters of V, which will be different in different cases.

5. Sketch of the Proof of Theorem 1

In this section, we explain how the two basic principles of continuous-time Kyle models (price equals marginal value at the end of trading, and strategic trades are inconspicuous) lead to the equilibrium stated in Theorem 1. For convenience, let $h(y)$ denote $P(T, y)$. This is a function we need to find. The property of inconspicuous strategic trading and the risk neutrality of market makers imply that the price at all dates $t < T$ is the expectation of $P(T, Y_T)$ treating Y as a Brownian motion with standard deviation σ. Therefore, we know the equilibrium pricing rule if we know h.

In the standard Kyle model, $h(Y_T) = v$ in equilibrium, where v is the exogenous value of the asset. This equality occurs because the large trader trades in such a way that $Y_T = h^{-1}(v)$, equivalently, $X_T = X_0 + h^{-1}(v) - Z_T$. The large trader achieves the equality $Y_T = h^{-1}(v)$ by causing Y to be a Brownian bridge terminating at $h^{-1}(v)$. In our model, the asset value depends on X_T, because the large trader's incentives to be active depend on X_T, and the equality $h(Y_T) = V(X_T)$ should hold in equilibrium (price equals marginal value). This implies a relationship between X_T and Y_T that is inconsistent with the large trader offsetting liquidity trades one-for-one. In fact, there is a multiplier effect in our model: The large trader chooses to more than offset liquidity trades. We discuss this further below. The equality $h(Y_T) = V(X_T)$ implies a link between Y_T and Z_T that does not occur in a Brownian bridge. The following lemma generalizes the concept of a Brownian bridge and is key to our equilibrium construction. The first term on the right-hand side of (11) is the large trader's equilibrium order $\mathrm{d}X_t = \theta_t \,\mathrm{d}t$.

Lemma. *Let ε be a standard normal random variable that is independent of Z. Let* *b be a nonnegative constant, and set* $a = \sigma\sqrt{(2b+1)T}$*. Then, the solution* Y *of the stochastic differential equation*

$$\mathrm{d}Y_t = \frac{a\varepsilon - bZ_t - (b+1)Y_t}{T-t}\,\mathrm{d}t + \mathrm{d}Z_t \tag{11}$$

on the time interval $[0,T)$ *has the following properties:* $Y_T \stackrel{def}{=} \lim_{t\to T} Y_t$ *exists a.s.,* Y *is a Brownian motion with zero drift and standard deviation* σ *on its own filtration on* $[0,T]$*, and, with probability 1,*

$$Y_T = \frac{a\varepsilon - bZ_T}{b+1}\,. \tag{12}$$

The proof is provided in the appendix. The stochastic differential equation of a Brownian bridge is (11) with $b = 0$, so the process Y defined by (11) is a generalization of a Brownian bridge. The distribution of a Brownian bridge, conditional on ε, is the distribution of Z conditioned to end at $a\varepsilon$, and the unconditional distribution of the Brownian bridge is the same as that of Z. As stated in the lemma, the unconditional distribution of the generalized Brownian bridge is also the same as that of Z. Thus, the property of inconspicuous insider trading (the second standard feature of continuous-time Kyle models) holds. Note that for the unconditional distribution to be the same as that of Z, the right-hand side of (12) must have variance equal to $\sigma^2 T$. This is equivalent to the condition $a = \sigma\sqrt{(2b+1)T}$ specified in the lemma.

In the standard Kyle model, the standard normal random variable ε in (11) is a transformation of the exogenous asset value v—assuming v is continuously distributed, $\varepsilon = \mathrm{N}^{-1}(F(v))$, where N is the standard normal distribution function and

F is the distribution function of v. In our model, the private information of the large trader is about his initial position X_0. Set $\varepsilon = (X_0 - \mu_x)/\sigma_x$, which is a standard normal random variable. Substitute $Z_T = Y_T - (X_T - X_0)$ and the definition of ε into (12) and rearrange to obtain

$$Y_T = \frac{a(X_0 - \mu_x)/\sigma_x + b(X_T - X_0)}{2b+1}\,. \tag{13}$$

The random variable Y_T cannot depend directly on X_0, because X_0 is not observed by market makers. In order to cancel the X_0 terms in (15), we need $a = b\sigma_x$. Combining the two conditions on a we find that b must satisfy the equation:

$$\sigma\sqrt{(2b+1)T} = b\sigma_x\,. \tag{14}$$

This has a unique positive solution $b = 1/(\Lambda - 2)$. With this formula for b, we have

$$Y_T = \frac{b(X_T - \mu_x)}{2b+1} \qquad \Longleftrightarrow \qquad X_T = \mu_x + \Lambda\, Y_T\,, \tag{15}$$

Therefore, $V(X_T) = V(\mu_x + \Lambda\, Y_T)$. This equals $h(Y_T)$—and hence price equals marginal value at the end of trading—if we define $h(y) = V(\mu_x + \Lambda\, y)$ as in (5). To prove the equilibrium result, all that remains is to verify that (6) is an optimal strategy for the large trader. We do that in the appendix. It is straightforward to verify optimality because every strategy is optimal that implies that price equals marginal value at the end of trading.

As in Back (1992), the value function of the large trader can be interpreted as the expected profit achieved by not trading until maturity T at which time he trades along the residual supply curve of the asset, buying or selling shares until price equals marginal value. We use that characterization in the proof of the theorem to derive the formula (8) for the value function.

6. Examples

Example 1 (Binary V)**.** This example is from Back, Liu, and Ljungqvist (2015). The effort decision is binary (all or none). The cost of effort is a constant $c > 0$. The value of the stock is a constant v_0 in the absence of effort and equal to $v_0 + \Delta$ for a constant $\Delta > 0$ if effort is exerted. It is optimal to exert effort if $X_T \Delta \geq c$. We have

$$G(x) = \begin{cases} v_0 x & \text{if } x \leq c/\Delta\,, \\ (v_0 + \Delta)x - c & \text{if } x \geq c/\Delta\,, \end{cases}$$

and $V(x) = v_0 + \Delta \mathbf{1}_{[c/\Delta,\infty)}(x)$. Therefore,

$$\begin{aligned} h(y) &= v_0 + \Delta \mathbf{1}_{[c/\Delta,\infty)}\left(\mu_x + \Lambda y\right) \\ &= \begin{cases} v_0 & \text{if } y < \frac{c/\Delta - \mu_x}{\Lambda}\,, \\ v_0 + \Delta & \text{otherwise}\,. \end{cases} \end{aligned}$$

It follows that the price function is

$$P(t, y) = v_0 + \Delta \cdot \mathsf{N}\left[\frac{\mu_x + \Lambda y - c/\Delta}{\Lambda \sigma \sqrt{T - t}}\right]\,. \tag{16}$$

Kyle's lambda is

$$\lambda(t, y) = \Delta \frac{\mathsf{n}\left[\frac{\mu_x + \Lambda y - c/\Delta}{\Lambda \sigma \sqrt{T-t}}\right]}{\sigma \sqrt{T - t}}\,. \tag{17}$$

The comparative statics are as follows:

(a) With respect to liquidity trading:

$$\frac{\partial \overline{P}}{\partial \sigma} > 0 \iff \mu_x - c/\Delta < 0 \tag{18}$$

$$\frac{\partial \overline{\lambda}}{\partial \sigma} < 0 \iff (\mu_x - c/\Delta)^2 < T\sigma^2\Lambda^2(\Lambda - 1) \tag{19}$$

(b) With respect to uncertainty about the activist's initial position:

$$\frac{\partial \overline{P}}{\partial \sigma_x} > 0 \iff \mu_x - c/\Delta < 0$$

$$\frac{\partial \overline{\lambda}}{\partial \sigma_x} > 0$$

(c) With respect to the activist's productivity:

$$\frac{\partial \overline{P}}{\partial \Delta} > 0$$

$$\frac{\partial \overline{\lambda}}{\partial \Delta} > 0 \iff \mu_x - \frac{c}{\Delta} < \frac{\Delta\Lambda^2\sigma^2 T}{c}$$

$$\frac{\partial \overline{P}}{\partial c} < 0$$

$$\frac{\partial \overline{\lambda}}{\partial c} < 0 \iff \mu_x - \frac{c}{\Delta} < 0$$

Discussion. The equilibrium price in this example is the base value v_0 plus the value Δ of activism multiplied by the conditional probability that activism will occur. Activism occurs if and only if

$$Y_T \geq \frac{c/\Delta - \mu_x}{\Lambda}\,.$$

Market makers compute the probability of activism at each date t based on Y_T being normally distributed with mean Y_t and standard deviation $\sigma\sqrt{T-t}$. From (15) and (10), we have

$$
\begin{aligned}
Y_T \geq \frac{c/\Delta - \mu_x}{\Lambda} \quad &\iff \quad X_T \geq \frac{c}{\Delta} \\
&\iff \quad Z_T \leq X_0 - \mu_x + \frac{\Lambda - 1}{\Lambda}\left(\mu_x - \frac{c}{\Delta}\right).
\end{aligned}
$$

Of course, the condition $X_T \geq c/\Delta$ is necessary and sufficient for exerting effort to be optimal for the large trader. The last condition shows that the large trader exerts effort if and only if liquidity traders sell enough shares (or do not buy too many shares). Selling by liquidity traders makes the asset cheaper for the large trader and hence induces him to buy shares and become active.

Example 2 (Concave Bounded V)**.** The domain of the value is $[v_0, v_0 + \Delta)$ for constants v_0 and Δ. On this domain, the cost function is

$$
C(v) = (v - v_0)c + (v_0 + \Delta - v)c \cdot \log\left(\frac{v_0 + \Delta - v}{\Delta}\right)
$$

for a constant c. This implies that the value of shares x to the large trader at date T is

$$
G(x) = \begin{cases} v_0 x & \text{if } x \leq 0 \\ (v_0 + \Delta)x - c\Delta\left(1 - \mathrm{e}^{-x/c}\right) & \text{if } x > 0 \end{cases}
$$

and the marginal value is

$$V(x) = \begin{cases} v_0 & \text{if } x \leq 0 \\ v_0 + \Delta\left(1 - \mathrm{e}^{-x/c}\right) & \text{if } x > 0 \end{cases}$$

We can interpret this as a binary outcome (success or failure) with the probability of success depending on the effort of the activist. The value is higher by Δ when the activist is successful. The activist chooses 0 effort and is successful with probability 0 when $x \leq 0$. Given the optimal effort when holding $x > 0$ shares, the probability of success is $1 - \mathrm{e}^{-x/c}$. The equilibrium price rule is

$$P(t, y) = v_0 + \Delta\,\mathrm{N}(d_1) - \Delta\,\mathrm{N}(d_2)\exp\left(-\frac{\mu_x + \Lambda y}{c} + \frac{\Lambda^2\sigma^2(T-t)}{2c^2}\right)$$

where

$$d_1 = \frac{\mu_x + \Lambda y}{\Lambda\sigma\sqrt{T-t}}$$

$$d_2 = d_1 + \frac{\Lambda\sigma\sqrt{T-t}}{c}\,.$$

Kyle's lambda is

$$\lambda(t, y) = \frac{\Delta\,\mathrm{n}(d_1)}{\sigma\sqrt{T-t}} + \left[\frac{\Delta\Lambda\,\mathrm{N}(d_2)}{c} - \frac{\Delta\,\mathrm{n}(d_2)}{\sigma\sqrt{T-t}}\right]\exp\left(-\frac{\mu_x + \Lambda y}{c} + \frac{\Lambda^2\sigma^2(T-t)}{2c^2}\right)\,.$$

$$P(t, y) = v_0 + \Delta\left[1 - \exp\left(-\frac{\mu_x + \Lambda y}{c} + \frac{1}{2}\cdot\frac{\Lambda^2\sigma^2(T-t)}{c^2}\right)\right]\,.$$

Kyle's lambda is

$$\lambda(t,y) = \frac{\Delta\Lambda}{c} \cdot \exp\left(-\frac{\mu_x + \Lambda y}{c} + \frac{1}{2} \cdot \frac{\Lambda^2\sigma^2(T-t)}{c^2}\right).$$

In this example,

$$\frac{\partial \overline{P}}{\partial \sigma} < 0\,.$$

Example 3 (Linear V)**.** This example is from Collin-Dufresne and Fos (2015). Effort is continuous and cost is quadratic. The cost function is $C(v) = (v - v_0)^2/(2\psi)$ for constants v_0 and $\psi > 0$. The problem $\sup_v\{vx - C(v)\}$ is solved at $v = V(x) = v_0 + \psi x$, so $G(x) = v_0 x + \psi x^2/2$, and $h(y) = v_0 + \psi\mu_x + \psi\Lambda y$. Therefore, the price function is

$$P(t,y) = v_0 + \psi\mu_x + \psi\Lambda y\,. \tag{20}$$

Kyle's lambda is

$$\lambda(t,y) = \psi\Lambda\,. \tag{21}$$

Comparative statics are as follows.

(a) With respect to liquidity trading:

$$\frac{\partial \overline{P}}{\partial \sigma} = 0 \quad \text{and} \quad \frac{\partial \overline{\lambda}}{\partial \sigma} < 0$$

(b) With respect to uncertainty about the activist's initial position:

$$\frac{\partial \overline{P}}{\partial \sigma_x} = 0 \quad \text{and} \quad \frac{\partial \overline{\lambda}}{\partial \sigma_x} > 0$$

(c) With respect to the activist's productivity:

$$\frac{\partial \overline{P}}{\partial \psi} > 0 \quad \text{and} \quad \frac{\partial \overline{\lambda}}{\partial \psi} > 0$$

Discussion. This symmetric quadratic example closely resembles the classic Kyle model in which the terminal value is normally distributed. As in that model, Kyle's lambda is constant and increasing in the signal-to-noise ratio σ_x/σ. Kyle's lambda is also increasing in the productivity ψ of the insider. In fact, and unlike in the Kyle model, the limit of lambda when the signal-to-noise ratio goes to zero is strictly positive: $\lim_{\hat{\lambda}\to 0} \lambda = \psi$. This illustrates the difference between the two models. Even if there is very little private information at the start of our model, there is private information later in the model because only the large trader knows his own trades, which determine his incentives for activism and so ultimately determine the asset value. The importance of this private information depends on the activist's productivity ψ, which is the lower bound on lambda.

Example 4 (Convex Piecewise Linear V)**.** Effort is continuous and nonnegative and cost is quadratic. The cost function is

$$C(v) = \begin{cases} (v - v_0)^2/(2\psi) & \text{if } v \geq v_0\,, \\ \infty & \text{otherwise}\,. \end{cases}$$

for constants v_0 and $\psi > 0$. The problem $\sup_v\{vx - C(v)\}$ is solved at $v = V(x) = v_0 + \psi x^+$, so $G(x) = v_0 x + \psi(x^+)^2/2$, and $h(y) = v_0 + \psi\,(\mu_x + \Lambda y)^+$. Therefore, the price function is

$$P(t,y) = v_0 + \psi(\mu_x + \Lambda y)\mathsf{N}\left[\frac{\mu_x + \Lambda y}{\Lambda\sigma\sqrt{T-t}}\right] + \psi\Lambda\sigma\sqrt{T-t}\,\mathsf{n}\left[\frac{\mu_x + \Lambda y}{\Lambda\sigma\sqrt{T-t}}\right] \qquad (22)$$

Kyle's lambda is

$$\lambda(t,y) = \psi\Lambda\mathsf{N}\left[\frac{\mu_x + \Lambda y}{\Lambda\sigma\sqrt{T-t}}\right] \qquad (23)$$

Comparative statics are as follows.

(a) With respect to liquidity trading:

$$\frac{\partial\overline{P}}{\partial\sigma} > 0 \quad \text{and} \quad \frac{\partial\overline{\lambda}}{\partial\sigma} < 0$$

(b) With respect to uncertainty about the activist's initial position:

$$\frac{\partial\overline{P}}{\partial\sigma_x} > 0 \quad \text{and} \quad \frac{\partial\overline{\lambda}}{\partial\sigma_x} > 0$$

(c) With respect to the activist's productivity:

$$\frac{\partial\overline{P}}{\partial\psi} > 0 \quad \text{and} \quad \frac{\partial\overline{\lambda}}{\partial\psi} > 0$$

Discussion. In this example, unlike Example 2, the activist can only create and cannot destroy value. This may perhaps be seen as a more realistic scenario. It is remarkable that the trading strategy (expressed as a function of cumulative order flow and position of the insider) is identical in this case to that in Example 2 (and in fact is the same in all examples). The price and Kyle's lambda do, however, depend on the cost function. To illustrate the differences between Examples 2 and 3, we plot two (randomly generated) paths of uninformed order flow and the corresponding informed orders, the resulting equilibrium price, and Kyle's lambda in Figures 1 and 2 below. Figure 1 shows a case where the uninformed noise traders are net cumulative buyers of the stock, whereas Figure 2 shows a path where cumulative trades by noise traders are sales. Independent of the (symmetric or asymmetric) cost function, the informed trader trades in the opposite direction of the noise traders with an amplification as discussed before. The figures illustrates the amplification. When the informed investor accumulates a positive number of shares (Figure 2), prices ultimately reflect the positive value creation; thus, the prices with symmetric and asymmetric cost function converge to the same value. Also, in that case, Kyle's lambda in the asymmetric model converges to the constant price impact that prevails throughout in the symmetric cost function model. However, when the insider accumulates a large short position, the price and price impact processes look very different in the two models. In the asymmetric model, the market infers the short position of the insider from the net short order flow, and price converges to v_0 as the market correctly expects the insider to not expend any effort. Correspondingly, Kyle's lambda converges to zero, because, given the large negative position anticipated to be held by the insider, a marginal increase in his position would not be expected to lead to significant positive value creation. However, in the symmetric model, the market infers from the net cumulative short position that the activist will destroy value at maturity, and the market impounds this negative value in the price. Kyle's lambda remains always constant and strictly positive in the symmetric model.

Example 5 (Convex V)**.** Effort is continuous. For parameters $v_0 > 0$ and $\psi > 0$ and for $v > 0$, the cost of effort is

$$C(v) = \frac{1}{\psi} v \log\left(\frac{v}{v_0}\right) - \frac{1}{\psi} v \,.$$

The problem $\sup_v\{vx - C(v)\}$ is solved at $v = V(x) = v_0 e^{\psi x}$, so $G(x) = v_0(e^{\psi x} - 1)/\psi$, and $h(y) = v_0 e^{\psi(\mu_x + \Lambda y)}$. Therefore, the price function is

$$P(t, y) = v_0 e^{\psi\left(\mu_x + \Lambda y + \frac{1}{2}\Lambda^2 \sigma^2 (T-t)\right)} \tag{24}$$

Kyle's lambda is

$$\lambda(t, y) = \psi \Lambda \, P(y, t) \tag{25}$$

Comparative statics are as follows.

(a) With respect to liquidity trading:

$$\frac{\partial \overline{P}}{\partial \sigma} > 0 \quad \text{and} \quad \frac{\partial (\overline{\lambda}/\overline{P})}{\partial \sigma} < 0$$

(b) With respect to uncertainty about the activist's initial position:

$$\frac{\partial \overline{P}}{\partial \sigma_x} > 0 \;\text{ and }\; \frac{\partial \overline{\lambda}}{\partial \sigma_x} > 0 \;\text{ and }\; \frac{\partial \overline{\lambda}/\overline{P}}{\partial \sigma_x} > 0$$

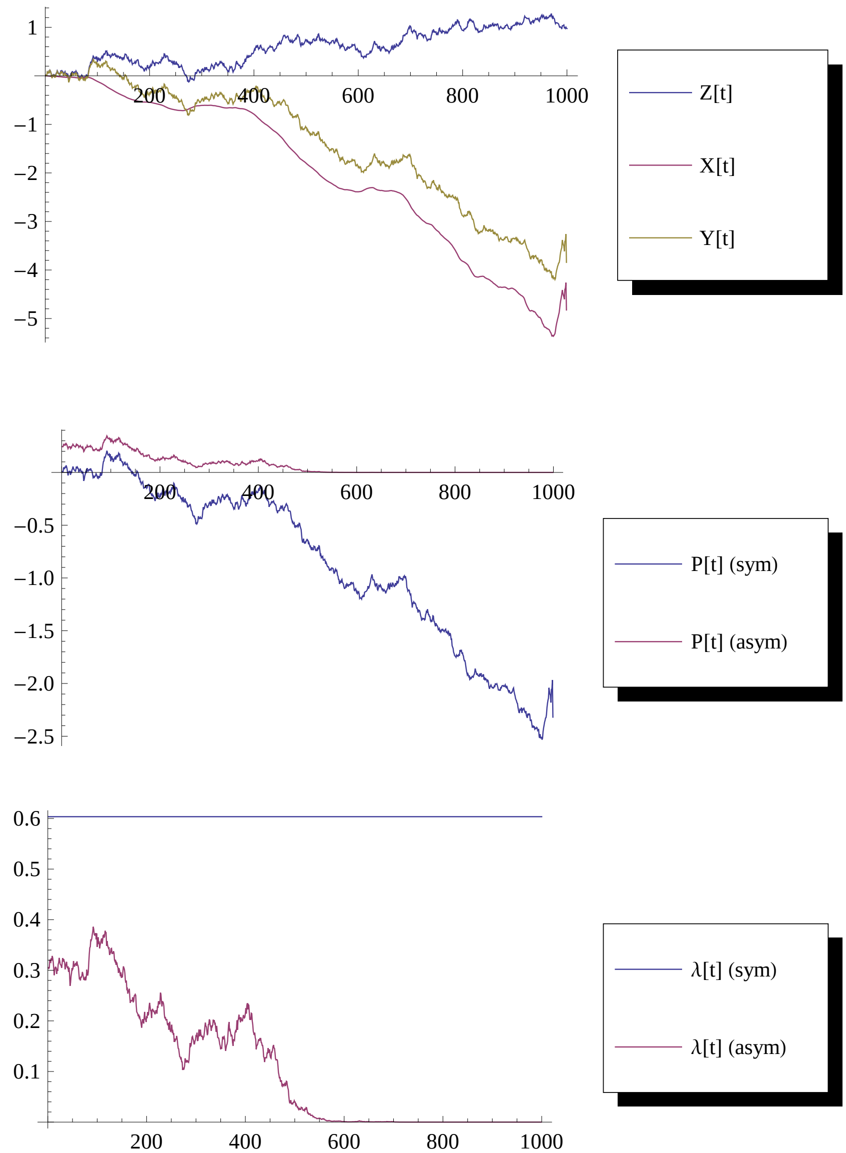

Figure 1: **Informed, uninformed and total order flow, prices and Kyle's lambda in the symmetric and asymmetric quadratic cost function examples: liquidity traders are net buyers**

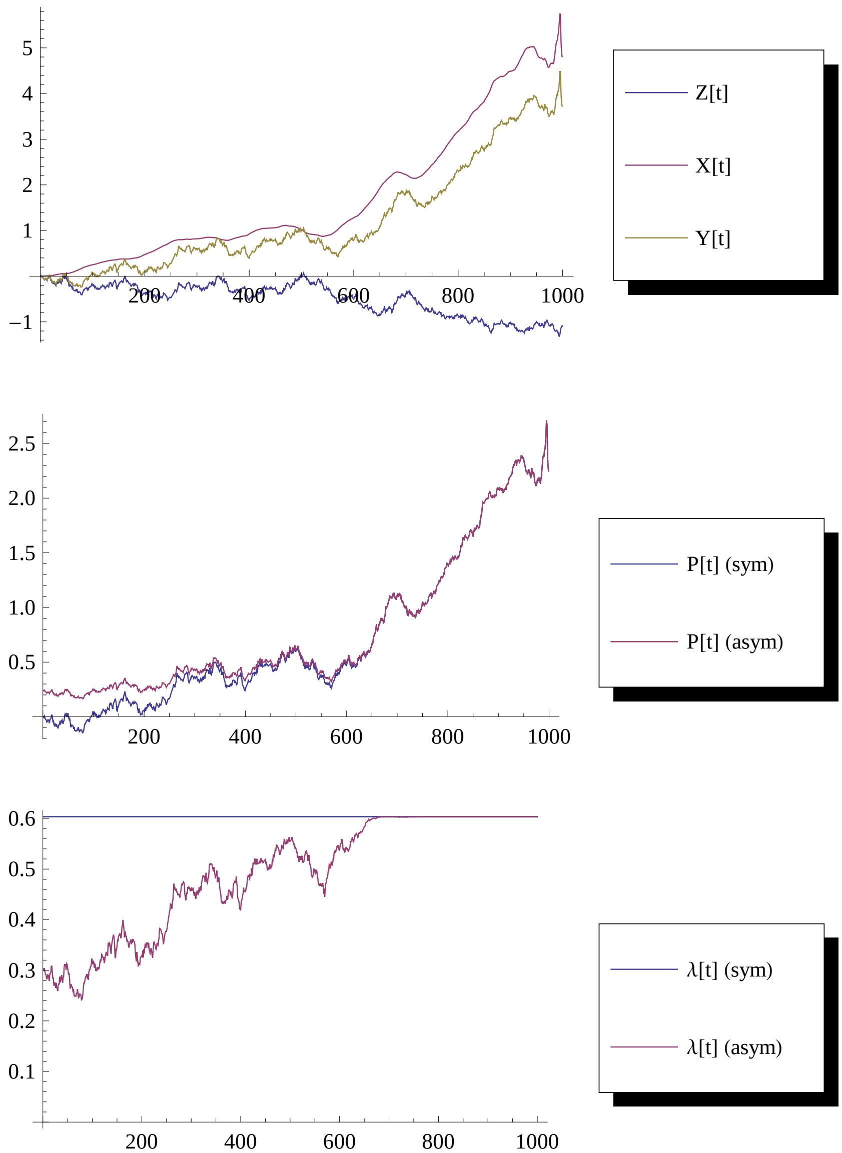

Figure 2: **Informed, uninformed and total order flow, prices and Kyle's lambda in the symmetric and asymmetric quadratic cost function examples: liquidity traders are net sellers**

(c) With respect to the activist's productivity:

$$\frac{\partial \overline{P}}{\partial \psi} > 0 \text{ and } \frac{\partial \overline{\lambda}}{\partial \psi} > 0 \text{ and } \frac{\partial \overline{\lambda}/\overline{P}}{\partial \psi} > 0$$

Discussion. In this example, the activist can both create and destroy value, but there is limited liability, so the value of the stock cannot fall below 0. However, the possible value creation is unbounded. This asymmetry causes the example to have similar comparative statics to the asymmetric quadratic example. In this example, even though the prior uncertainty is normal and thus the cumulative holdings of the informed investor are normally distributed, the endogenous terminal value of the stock is lognormally distributed. The stock price follows a geometric Brownian motion process as in the Black-Scholes (1973) model. The parameters of the process are endogenously determined by the primitives of the model (the signal-to-noise ratio σ_x/σ, the noise trader volatility, and the productivity parameter). This model is similar to the Kyle model with an exogenous lognormally distributed terminal value presented in Back (1992). As with an exogenous lognormal value, the percentage price impact is constant. However the constant 'return impact' is not the same as when the value is exogenous. Indeed, in our model, price impact depends not only on the signal-to-noise ratio but also on the productivity of the insider. As in the Gaussian case discussed above, when the signal-to-noise ratio goes to zero, the return price impact remains strictly greater than zero.

7. Liquidity, Activism, and Public Policy

Regulatory policies can affect the parameters of the model. For example, a Tobin tax on stock transactions might reduce liquidity trading. A change in the number of days after crossing the 5% threshold before a 13D must be filed can also be viewed as a change in liquidity trading.[13] A change in disclosure rules more generally could change the uncertainty about the large trader's initial position. Also, regulatory changes that would affect the marginal productivity of activists (e.g., any new regulation that makes it more or less costly to take over firms or to challenge patents) can be interpreted as changes in ψ, Δ, or c. The model has predictions for the effects of such policies on economic efficiency and market liquidity. We first consider the effect of changes in liquidity trading.

In the binary example, there are four possible outcomes of a change in liquidity trading, depending on the inequalities on the right-hand sides of (18) and (19). The four possibilities are illustrated in Figure 3. An increase in the standard deviation σ of liquidity trading increases economic efficiency if the expected initial stake of the activist is low (that is, if $\mu_x < c/\Delta$). In that case, the large trader must on average acquire shares in the market to make activism worthwhile. An increase in liquidity trading makes it easier to acquire the needed shares. On the other hand, if the expected initial stake of the large trader is high, then additional liquidity trading makes it easier for the large trader to unwind his stake and exit rather than incurring the

[13] This is because in the model, what matters is $\sigma^2 T$—the cumulative amount of noise trading over the entire trading period. So from the perspective of the large trader, reducing the trading horizon T is isomorphic to reducing the noise trading volatility and keeping T fixed.

cost to become active, so an increase in liquidity trading reduces economic efficiency. These are the effects described by Maug (1998).

In the binary example, the effect of liquidity trading on market liquidity (that is, on the reciprocal of Kyle's lambda) depends on the absolute size of the expected initial stake of the activist relative to a threshold that depends on σ, σ_x, and T. The threshold is specified on the right-hand side of (19). When the absolute expected initial stake of the activist is large, then it is unlikely that he will trade enough to change the profitability of activism—if $\mu_x - c/\Delta$ is positive and large, then it is unlikely that he will sell enough shares so that $X_T < c/\Delta$ and if $\mu_x - c/\Delta$ is negative and large in absolute value, then it is unlikely that he will buy enough shares so that $X_T > c/\Delta$. Thus, Kyle's lambda is low—the market is highly liquid. In this circumstance, if liquidity trading increases, then the probability that the activist will trade out of an existing position or into a new position increases, and it increases so much that market liquidity actually falls.

The effect of liquidity trading on market liquidity is simpler in the three continuous examples. In all cases, an increase in liquidity trading increases market liquidity—price impact falls in the quadratic examples and the percent price impact falls in the logarithmic (geometric Brownian motion) example. However, the effect of liquidity trading on economic efficiency is not the same in all of the examples. In the symmetric quadratic example, a change in liquidity trading has no effect on economic efficiency. In that example, an increase in liquidity trading makes it easier for the large trader to acquire a long position and increase value, but symmetrically it also makes it easier for the large trader to acquire a short position and destroy

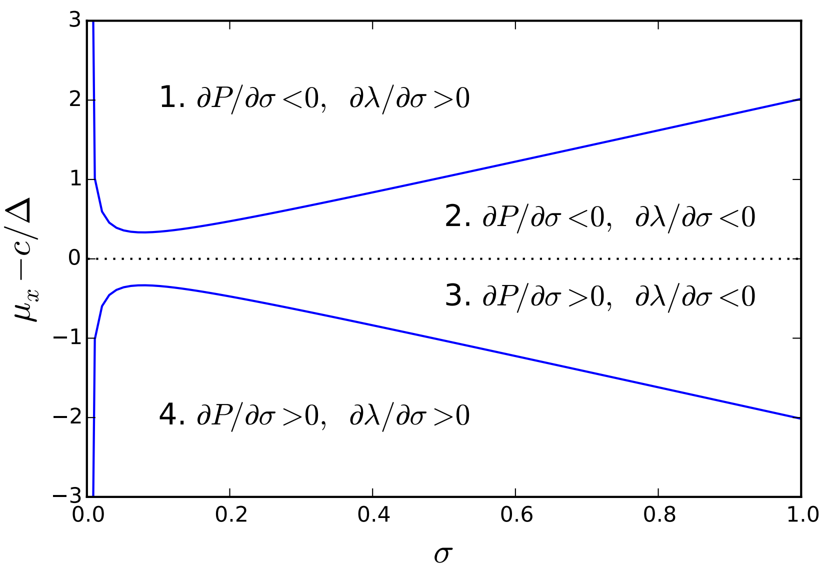

Figure 3: **Effect of Changing Liquidity Trading in the Binary Example.** Increasing liquidity trading increases economic efficiency ($\partial\overline{P}/\partial\sigma > 0$) when $\mu_x > c/\Delta$ and decreases economic efficiency when $\mu_x < c/\Delta$. Increasing liquidity trading increases market liquidity ($\partial\overline{\lambda}/\partial\sigma < 0$) when $|\mu_x - c/\Delta|$ is below a threshold depending on σ that is specified in (19) and decreases market liquidity when $|\mu_x - c/\Delta|$ is above the threshold. In this example, $\sigma_x = 0.1$ and $T = 1$.

value. In the two continuous asymmetric examples, an increase in liquidity trading increases economic efficiency.

Now, consider a change in uncertainty about the large trader's initial position. An increase in uncertainty about the initial position represents an increase in the private information of the large trader, and it reduces market liquidity in all of the examples. This is consistent with the classic Kyle model. The effects on economic efficiency vary across the examples. In the binary example, an increase in uncertainty about the initial position increases economic efficiency when the mean of the initial position is low (less than c/Δ). This is because the probability of activism is the probability that the normally distributed random variable X_T with mean μ_x has a realized value above c/Δ. When $\mu_x < c/\Delta$, this probability is higher when the variance of X_T is higher. An increase in uncertainty about the initial position has no effect on economic efficiency in the symmetric quadratic model and increases economic efficiency in the other two continuous examples.

Finally, consider changing the productivity of the activist. When the activist is more productive (that is, ψ is larger in the continuous examples, and either Δ is larger or c is smaller in the binary example), then economic efficiency is higher. In the continuous examples and in certain circumstances in the binary example, an increase in the productivity of the analyst also makes the market less liquid. This is intuitive. When the activist is more productive, the asset value becomes more sensitive to the number of shares he accumulates. This makes his private information about his holdings more valuable, reducing market liquidity. However, an increase in productivity increases market liquidity in the binary example when μ_x is large.

In that case, an increase in Δ or a decrease in c reduces uncertainty about whether activism will occur, because it makes it less likely that the activist will sell enough shares to make activism not worthwhile (because an increase in Δ or a decrease in c reduces the number of shares needed to cover the cost of effort). The reduction in uncertainty about activism can reduce uncertainty about the asset value even when Δ rises, provided μ_x is sufficiently large.

8. Evidence on Activists' Trading Strategies

The model predicts that the large trader's strategy should depend not only on the stock price (via its dependence on aggregate orders), but also on the trader's position in the stock. Specifically, Theorem 1 shows that the trading rate is increasing in the size of the trader's position even after controlling for the cumulative order flow (see equation (6)). This differs from the trading strategy in the standard Kyle model. In that model, the trading strategy only depends on cumulative order flow. This then suggests an interesting test of our model, namely regress trades of potential activist traders on market prices and the traders' positions. If the endogenous liquidation value is realistic, then there should be a positive coefficient on traders' positions.

We test this hypothesis using the novel data-set built by Collin-Dufresne and Fos (2015a) on individual trades by activist shareholders as identified from Schedule 13D filings. Schedule 13D filings reveal the date and price at which all trades by the Schedule 13D filer were executed during the 60 days that precede the filing date.[14] For each event, we extract the following information from the Schedule 13D

[14] Rule 13d-1(a) of the 1934 Securities Exchange Act requires investors to file with the SEC within 10 days of acquiring more than 5% of any class of securities of a publicly traded company if they

filings: CUSIP of the underlying security, date of every transaction, transaction type (purchase or sell), transaction size, transaction price, filing date, and the beneficial ownership of the Schedule 13D filer at the filing date. The final sample consists of 3,126 Schedule 13D filings from 1994 to 2010. The average (median) stock ownership of a Schedule 13D filer on the filing date is 7.51% (6.11%). The average (median) filer purchases 3.8% (2.8%) of outstanding shares during the sixty-day period prior to the filing date. This corresponds to an average (median) purchase of 899,692 (298,807) shares at an average (median) cost of $16.4 ($2.5) million.

We merge the data on trades by 13D filers with stock-level and firm-level data. Stock returns, volume, and prices come from the Center for Research in Security Prices (CRSP). Firm-level accounting information comes from Compustat. We estimate the following time-series regression for each 13D filer:

$$\theta_{it} = a_{0i} + a_{1i} X_{it-1} + a_{2i} P_{it} + \varepsilon_{it}, \tag{26}$$

where θ_{it} is the number shares purchased by a Schedule 13D filer in company i on date t, X_{it-1} is the number shares owned by the Schedule 13D filer on date $t-1$, and P_{it} is the closing price of the stock i on date t. The analysis is based on daily observations from 60 days before the filing date to the filing date.

Consistent with the model (and the endogenous liquidation value), we find that the 13D filer's trading strategy is positively associated with the trader's position in

have an interest in influencing the management of the company. In particular, Item 5(c) of Schedule 13D requires the filer to "... describe any transactions in the class of securities reported on that were effected during the past sixty days or since the most recent filing of Schedule 13D, whichever is less."

97% of the cases. It is negatively associated with the stock price in 91% of the cases. The cross-sectional mean of a_1 is 4.5 with a t-stat of 41.05. The cross-sectional mean of a_2 is -18.4 with a t-stat of -14.66. Thus, there is strong support for the model's prediction that activist trades are increasing in the activist's position.

9. Evidence on Liquidity Trading and Activism

The effect of liquidity trading on shareholder activism depends on the cost-of-effort function in our model. In our various examples, there is either no effect (Example 3), an unambiguously positive effect (Examples 4 and 5) or an effect that depends on the expected initial stake of the potential activist (Examples 1 and 2). In the latter examples, an increase in liquidity trading reduces expected activism if the initial stake is large, because higher liquidity makes it easier for the potential activist to exit. In this section, we report empirical evidence on the effects of shocks to liquidity trading on activism. This evidence is not a test of the model's predictions, which are ambiguous as noted.

We examine two natural experiments, each of which is studied in Kelly and Ljungqvist (2012): closures of brokerage research departments, and mergers of institutional with retail brokerages. Both 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, the first experiment reduces both retail ownership and retail trading while the second experiment increases retail ownership and retail trading. In most of our examples—and for some parameter values in all of our examples—greater liquidity trading implies higher stock liquidity. We verify this prediction of our model in both experiments. To measure stock liquidity, we use AIM, the illiquidity measure of Amihud (2002b). The channel through which the magnitude σ of liquidity trading affects activism in our model is via stock liquidity—the large trader cares about σ only to the extent that it affects Kyle's lambda. Hence, we run two-stage regressions to see how shocks to liquidity trading affect activism via the channel of shocks to AIM. We find in both experiments that the shocks to AIM created by the experiments affect activism, with activism being lower when liquidity is higher. This inverse relation between liquidity trading and activism also holds in a reduced form regression of activism on the shocks. We find the same result for each of four alternative proxies for activism, which are outlined later in this section.

For each of our 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, and the number of analysts providing coverage, each measured as of the quarter before the shock. We then estimate standard difference-in-difference regressions.

9.1. 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.[15] 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 trading 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.[16] 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

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

[16] 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.

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.

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.

9.2. Experiment #2: 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.[17]

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.

9.3. Effect of Experiments on Liquidity

Table 2 shows that both experiments produce significant variation in liquidity. 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).

[17]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 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.

9.4. Relation to Prior Literature

Using brokerage 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 penny 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.

9.5. 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.[18]

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

[18]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.

third proxy focuses on the 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).[19]

[19]We focus on first 13D filings that are also the blockholder's first Schedule 13 filing. This ensures

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. 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.

9.6. Effects on Shareholder Proposals

Table 3 presents reduced-form difference-in-difference estimates for each of our experiments, 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.

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that our third proxy does not overlap with our second proxy.

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).[20] 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 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

[20]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.

management by 111%, from 2.01% before to 4.26% after (p=0.009).[21]

Our second experiment, the brokerage mergers improves liquidity. The reduced-form diff-in-diff estimates for the second experiment, 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).[22] 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.

9.7. 13G Conversions

Table 4 considers the effects of the two 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

[21]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 $4.26\%/2.01\% - 1$.

[22]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.

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 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 and significantly less likely following a brokerage merger. The diff-in-diff estimates in columns 1 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 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 and 6 show the second-stage estimates from 2SLS regressions that use the two 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 experiment. 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 effect of brokerage mergers is somewhat smaller but remain sizable, going from 0.39% to 0.58% (p=0.085).

9.8. 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.

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). The results for the other experiment are similar: down from 10 to 1 after a (liquidity-improving) brokerage merger. In the two diff-in-diff specifications in columns 1 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 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 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. The effect is larger 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).

9.9. Activist Hedge Fund Campaigns

Table 6 uses the two exogenous shocks to estimate the effect of liquidity on the likelihood of a hedge fund launching an activist campaign against target management. Columns 1 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). 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. Column 2 shows that 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). We find a larger 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 two 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.

10. Conclusion

Appendix A. Proof of the Lemma

Define $U_t = a\varepsilon - bZ_t$. We use filtering to establish the proposition. As is customary, we use the symbol $\hat{}$ to denote conditional expectations given $\mathcal{F}_t^Y$. We want to compute $\hat{U}_t$. Let $\Sigma(t)$ denote the conditional variance of U_t given $\mathcal{F}_t^Y$. We have $U_0 = a\varepsilon$, $\hat{U}_0 = 0$, and $\Sigma(0) = a^2$. The stochastic process U evolves as

$$\mathrm{d}U_t = -b\,\mathrm{d}Z_t\,.$$

The observation process is Y, and

$$\mathrm{d}Y_t = \frac{1}{T-t}U_t\,\mathrm{d}t - \frac{b+1}{T-t}Y_t\,\mathrm{d}t + \mathrm{d}Z_t\,.$$

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

$$\mathrm{d}W_t = \frac{1}{\sigma}\left(\mathrm{d}Y_t - \frac{1}{T-t}\hat{U}_t\,\mathrm{d}t + \frac{b+1}{T-t}Y_t\,\mathrm{d}t\right) = \frac{1}{\sigma}\left(\frac{1}{T-t}(U_t - \hat{U}_t)\,\mathrm{d}t + \mathrm{d}Z_t\right)\,. \tag{A.1}$$

From Kallianpur (1980, Equation 10.5.9), the filtering equation is

$$\mathrm{d}\hat{U}_t = \frac{1}{\sigma}\left(\frac{\Sigma(t)}{T-t} - b\sigma^2\right)\mathrm{d}W_t\,. \tag{A.2}$$

From Kallianpur (1980, Equation 10.5.10), the conditional variance evolves as

$$\frac{\mathrm{d}\Sigma(t)}{\mathrm{d}t} = -\frac{\Sigma(t)^2}{(T-t)^2\sigma^2} + \frac{2b\Sigma(t)}{T-t}\,. \tag{A.3}$$

The ODE (A.3) with initial condition $\Sigma(0) = a^2$ is satisfied by $\Sigma(t) = (T-t)a^2/T$. For this function $\Sigma(\cdot)$, the left-hand side of (A.3) is $-a^2/T$, and the right-hand side is

$$-\frac{a^4}{\sigma^2 T^2} + \frac{2ba^2}{T} = -\frac{a^2}{T}\left(\frac{a^2}{\sigma^2 T} - 2b\right) = -\frac{a^2}{T}\,,$$

using the definition $a = \sigma\sqrt{(2b+1)T}$ for the last equality. Thus, the conditional variance of U_t is $(T-t)a^2/T$. Consequently, the filtering equation (A.2) simplifies to

$$\mathrm{d}\hat{U}_t = \frac{1}{\sigma}\left(\frac{a^2}{T} - b\sigma^2\right)\mathrm{d}W = (b+1)\sigma\mathrm{d}W\,,$$

using the definition $a = \sigma\sqrt{(2b+1)T}$ again for the last equality. Because $\hat{U}_0 = W_0 = 0$, this equation implies that $\hat{U} = (b+1)\sigma W$. Equation (A.1) for the innovation process now becomes

$$\mathrm{d}W_t = \frac{1}{\sigma}\left(\mathrm{d}Y_t + \frac{b+1}{T-t}(Y_t - \sigma W_t)\,\mathrm{d}t\right)$$

This equation is satisfied by $W = Y/\sigma$. Thus, Y/σ is the innovation process. The innovation process is a standard Brownian motion on $\mathbb{F}^Y$, so Y is a Brownian motion with standard deviation σ on $\mathbb{F}^Y$. Moreover, we have

$$\mathrm{d}\hat{U}_t = (b+1)\sigma\mathrm{d}W_t = (b+1)\mathrm{d}Y_t\,,$$

so $\hat{U}_t = (b+1)Y_t$. Because Y is a Brownian motion on $\mathbb{F}^Y$, the limit $Y_T = \lim_{t\to T} Y_t$ exists almost surely, and we have $U_T = (b+1)Y_T$, which is the same as (12).

Appendix B. Proof of Theorem 1

We need to verify the optimality of the trading strategy (6). Define

$$g(x,y) = \sup_{\overline{y}} \int_y^{\overline{y}} \left(V(x-y+z) - h(z)\right)\,\mathrm{d}z \equiv \int_y^{\overline{y}^*(x-y)} \left(V(x-y+z) - h(z)\right)\,\mathrm{d}z\,. \tag{B.1}$$

where the function $\overline{y}^*(u)$ satisfies the first order condition $V(u + \overline{y}^*(u)) = h(\overline{y}^*(u))$ and is given by:

$$\overline{y}^*(u) = \frac{u - \mu_x}{\Lambda - 1} \tag{B.2}$$

It is straightforward to verify that

$$g_x(x, y) + g_y(x, y) = h(y) - V(x)\,.$$

Define $J(T, x, y) = g(x, y)$ and, for $t < T$, set

$$J(t, x, y) = \mathsf{E}[g(x, y + Z_T - Z_t) \mid \mathcal{F}_t^Z]\,. \tag{B.3}$$

Note that

$$J(t, x, Z_t) = \mathsf{E}[g(x, Z_T) \mid \mathcal{F}_t^Z]\,,$$

which is an $\mathbb{F}^Z$ martingale. Applying Itô's formula and equating the drift to zero gives

$$J_t(t, x, y) + \frac{1}{2}\sigma^2 J_{yy}(t, x, y) = 0\,. \tag{B.4}$$

Also, we can interchange differentiation and expectation (should we check this? easy to put conditions on $V()$ via$C()$ for that to be ok) to obtain

$$\begin{aligned} J_x(t, x, y) + J_y(t, x, y) &= \mathsf{E}[g_x(x, y + Z_T - Z_t) + g_y(x, y + Z_T - Z_t) \mid \mathcal{F}_t^Z] \\ &= \mathsf{E}[h(y + Z_T - Z_t) - V(x) \mid \mathcal{F}_t^Z] \\ &= P(t, y) - V(x)\,. \end{aligned} \tag{B.5}$$

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

(B.4) and (B.5), we obtain

$$\begin{aligned} J(T, X_T, Y_T) &= J(0, X_0, Y_0) + \int_0^T dJ \\ &= J(0, X_0, Y_0) + \int_0^T (P(t, Y_t) - V(X_t))\theta_t \, \mathrm{d}t + \int_0^T J_y(t, X_t, Y_t) \, \mathrm{d}Z_t \,. \end{aligned}$$

Rearranging and taking expectations (do we need to check this? idem) yields

$$J(0, X_0, 0) = \mathsf{E}\left[J(T, X_T, Y_T) - \int_0^T (P(t, Y_t) - V(X_t))\theta_t \, \mathrm{d}t \right] .$$

Also,

$$J(T, X_T, Y_T) = g(X_T, Y_T) \geq 0 \,,$$

since $\overline{y} = 0$ is clearly feasible in equation (B.1). so we have

$$J(0, X_0, 0) \geq \mathsf{E}\left[\int_0^T (V(X_t) - P(t, Y_t))\theta_t \, \mathrm{d}t \right] . \tag{B.6}$$

This shows that $J(0, X_0, 0)$ is an upper bound on the large trader's expected value. The bound is achieved by a strategy if and only if $g(X_T, Y_T) = 0$.

Now, consider the strategy (6). For this strategy, $V(X_T) = h(Y_T)$ which implies (from the definition of $\overline{y}^*$ in equation (B.2)) $\overline{y}^*(X_T - Y_T) = Y_T$ and $g(X_T, Y_T) = 0$. Thus, the strategy is optimal.

Appendix C. Proof of the Corollary

From (15), we have $X_T - \mu_x = \Lambda Y_T$. Substitute the definition $Y_T = X_T - X_0 + Z_T$ and rearrange to obtain (10).

Appendix D. Proof of Theorem 2

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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 (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	0.025***		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 (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	0.002**		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