The Value of Control and the Costs of Illiquidity

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ABSTRACT

We develop a search model of block trades that values the illiquidity of controlling stakes. The model considers several dimensions of illiquidity. First, following a liquidity shock, the controlling blockholder is forced to sell, possibly to a less efficient acquirer. Second, this sale may occur at a fire sale price. Third, absent a liquidity shock, a trade occurs only if a potential buyer arrives. Using a structural estimation approach and U.S. data on trades of controlling blocks of public corporations, we estimate the value of control, the blockholders' marketability discount and the dispersed shareholders' illiquidity-spillover discount.

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High ownership concentration is a predominant phenomenon in the corporate world. In many countries, including the United States, evidence suggests that high ownership concentration is pervasive in public corporations.[1] By definition, ownership concentration is also an integral part of privately held corporations.[2] In this paper, we study the value of controlling blocks of shares in public corporations, contributing to the understanding of the costs and benefits of concentrated ownership. An inherent difficulty in valuing controlling blocks of shares is the illiquidity of the market. Theoretically, illiquidity in the market for controlling blocks is a cost that affects the block value, possibly in a nonlinear way. Empirically, illiquidity reduces the number of observations available to the econometrician and constrains the empirical strategy of estimating the block value. We provide a model of the trading and pricing of controlling blocks in an illiquid market with search frictions. We argue that block-trading events convey information that identifies the model parameters and allows the estimation of the value of control.

The model's main premise is that a controlling blockholder of a public corporation affects the value of the firm's assets (Holderness and Sheehan (1988); Barclay and Holderness (1989); and more recently Pérez-González (2004)). Therefore, given the choice, the controlling blockholder will only sell to a bidder who can increase asset value. In addition, we assume that the controlling blockholder is forced to sell if hit by a liquidity shock, in which case he may sell to a party that creates less asset value and be paid a fire sale price. The potential absence of a bidder at any given time further increases the illiquidity of the block. These frictions give rise to a *marketability discount* on the value of the block. Additionally, the possibility that the new blockholder may decrease asset value introduces a discount on the dispersed shares traded in the stock market. We name this novel effect the *illiquidity-spillover discount*.

The estimation of the marketability and the illiquidity-spillover discounts is notoriously difficult because they require a counter-factual analysis: what should the price be absent search frictions? The structural estimation adopted in the paper uses the model's pricing equations to evaluate this counter-factual price. To meet that goal, the structural estimation must successfully identify the parameters of these pricing equations. In particular, since the pricing will differ depending on whether or not the trade was caused by liquidity shocks, the model must identify ex post the reasons for trading. These reasons are unobservable to the econometrician. One contribution of this paper is to show that it is possible to identify the model's parameters by using the valuations of two different types of shareholders during a block trade: the blockholders' valuation implicit in the negotiated block price and the dispersed shareholders' valuation revealed in the exchange share price.

In the model, a liquidity shock is the realization of a random variable with a Bernoulli distribution that forces blockholder turnover. Following a liquidity shock, the block is sold at a fire sale price equal to a fraction of the buyer's valuation. In contrast, the dispersed shareholders only care about the discounted value of future cash flows under the new blockholder and not the fire sale price. This price difference allows us to identify fire sale discounts.

In the absence of a liquidity shock, the block changes hands only if a potential new blockholder arrives and can generate more cash flow. In this case, block and share prices differ partly because liquidity shocks penalize blockholders more than dispersed shareholders, who are unaffected by the lower expected fire sale price in a future sale. In short, our model is able to fully exploit the data by identifying liquidity shock probabilities not only out of the frequency of trades with negative price reactions, but also the block vs. share price differences that exist whether or not liquidity shocks have occurred.

We estimate an average probability of getting a liquidity shock within one year of 20%, and, conditional on a liquidity shock, an average fire sale discount of 8% of the block value.[3] The estimated probability of meeting a potential buyer within one year is 43%. We find that the marketability discount, which is a non-linear function of these three estimates, is on average 13% of the block value, with a standard deviation of 22%. The spillover effect of the block's illiquidity on the dispersed shares is on average 2.1% of the share price.[4]

A selection bias in our estimates may arise if not all liquidity shocks lead to a fire sale. That is, blockholders may have a reservation value that is determined by the actions taken to avoid a fire sale, for example, using the block as collateral for a loan. We argue that this selection bias leads to downward-biased estimates of the probability of a liquidity shock. In addition, our reduced form approach to fire sale prices may lead to upward-biased estimates of the fire sale price. That is, what we call a fire sale price is likely to be the maximum payout among many alternative ways of reacting to the liquidity shock, which include, for example, the arrival of a private equity firm supplying liquidity. Because the marketability and the illiquidity-spillover discounts are decreasing in the fire sale price and increasing in the probability of a liquidity shock, these biases lead to the underestimation of the discounts. Our approach, therefore, gives a conservative estimate of the discounts we study.

We allow the probability of a liquidity shock and the fire sale price to vary across deals as a function of economy-wide and deal-specific determinants of liquidity in order to match the observed variation in the block and exchange share prices. Economy-wide determinants of liquidity appear to capture unobserved variation in the probability of a liquidity shock, whereas firm and industry characteristics appear to capture unobserved variation in fire sale values. We find that the probability of a liquidity shock is increasing in the Fontaine and Garcia (2012) measure of aggregate funding illiquidity, and decreasing in GDP growth and the stock market return. However, the probability of a liquidity shock is high when GDP growth and market returns are high and the yield curve is steep. Our interpretation is that macroeconomic expansions increase block holder liquidity via their balance sheet effects but may also trigger a preference for cash if they bring good investment opportunities when outside funding is costly. The block's fire sale value decreases with the degree of asset specificity of the target firm's industry and with the target firm's leverage relative to that of its industry. The evidence that the state of the aggregate economy determines firm-specific liquidity complements the work of Chordia, Roll, and Subrahmanyam (2000) and Bao, Pan, and Wang (2011), who find commonalities in asset-specific liquidity measures.

We discuss the robustness of our results to other possible motives for trading. Trading could arise if the block buyer derives more private benefits than the seller. If the buyer is also unable to increase share value, the resulting drop in the dispersed shareholders' valuation could be misinterpreted as a the consequence of a liquidity trade. We show that the use of data on the blockholders' valuation, together with data on the dispersed shareholders' valuation, allows us to distinguish these two types of trades. Intuitively, liquidity trades are bad events for the block sellers whereas private benefits trades are good events. Therefore, the two trading reasons have opposite effects on the blockholder's valuation.

The literature has considered alternative ways of measuring the value of control. One approach is to look at the voting premium, measured directly as the price difference of shares with different voting rights (e.g., Masulis, Wang, and Xie (2009)), or indirectly as deviations from put-call parity (Kalay, Karakas, and Pant (2012)) and equity-loan values (Christoffersen et al. (2007)). By studying per share prices, these approaches measure the marginal value of control. Because in our data we have the total price of a block, we are able to comment on the total value of control. Moreover, our structural approach allows us to isolate the cost of illiquidity from the total effect of control, which also includes the increase in security benefits.

The paper that is closest to ours is Albuquerque and Schroth (2010). They estimate private benefits of control that result from diverting cash flow, whereas we are the first to estimate the costs of illiquidity embedded in the value of control. Albuquerque and Schroth (2010) focus on smaller controlling blocks as they expect that private benefits of control are more likely to have a first order effect on valuations and trading decisions in these blocks. Illiquidity has no role in their model. In contrast, our main premise is the opposite: for larger blocks, illiquidity is more likely to have a first order effect whereas incentive alignment between controlling and dispersed shareholders should imply zero private benefits of control derived from the firm's cash flows. The literature started by Barclay and Holderness (1989) also looks at the total value of control. These papers do not consider the costs of illiquidity associated with large blocks.

There is a vast literature on the pricing of illiquid assets (see Amihud, Mendelson, and Pedersen (2005) for a comprehensive survey). Longstaff (1995) measures the marketability discount associated with stocks with trading restrictions. Our paper considers search frictions as opposed to trading restrictions and allows the owner of the shares to have an influence over the cash flows of the firm. Duffie, Garleanu, and Pedersen (2005, 2007) present search models of over-the-counter markets with atomistic investors. In these papers there is no controlling shareholder that can affect the value of assets and discounts result from a pure search cost. In our paper, liquidity costs also arise from the possibility of having to sell the block at fire sale prices and to a less efficient buyer.

Related theoretical work shows that concentrated ownership induces illiquidity in the firm's exchange traded shares (see Demsetz (1968), Holmstrom and Tirole (1993), and Bolton and von Thadden (1998)).[5] This literature focuses on the price implications of a reduced float. Instead, by studying block-trading events where the float is unchanged, we are able to focus on the pricing implications of liquidity shocks to large blockholders. Kahn and Winton (1998) and Maug (1998) argue that, if blockholders obtain value-relevant information from their monitoring, then the resulting adverse selection problem when blockholders trade their shares lowers liquidity (see also Edmans and Manso (2011)). We believe that the size of the controlling blocks studied in this paper and the fact that blocks are not partitioned suggest that this cause for illiquidity is of second order in our exercise and should not affect our results.

Vayanos and Wang (2007) and Weill (2008) study illiquidity spillovers in search models with multiple securities. They find that search frictions can lead to higher prices in more liquid assets (i.e., with lower search times) despite the fact that the assets have identical cash flows. Chordia, Sarkar, and Subrahmanyam (2011) find evidence of liquidity spillovers across size portfolios by inspecting lead-lag cross-correlation patterns. Aragon and Strahan (2009) use the Lehman Brothers bankruptcy to show that stocks traded by hedge funds connected to Lehman experienced greater declines in market liquidity. The illiquidity spillover studied in this paper instead looks at how the liquidity shocks to the controlling blockholder spill over to the value of the shares held by dispersed investors of the same firm.

The paper proceeds as follows. Section I presents preliminary evidence on controlling block trades, motivating some of our modeling assumptions and our identification strategy. Section

II presents the search model that we use to price controlling blocks and dispersed shares. Section III describes the empirical strategy. Section IV summarizes the data used and Section V presents the main results. Section VI discusses additional tests and Section VII concludes.

I. Preliminary Evidence on Controlling Block Trades

In a block trade, the incumbent holder of a block of shares on a target firm sells the entire block to a rival blockholder. Simultaneously, dispersed shareholders of the same target firm react to the news of the trade leading to a change in the price of the exchange-traded shares. This information is summarized respectively in the block premium (BP) paid by the acquirer of the block and in the cumulative abnormal (announcement) return (CAR) on the exchange-traded shares.

Our data comprise 114 U.S. disclosed-value acquisitions of blocks of more than 35% but less than 90% of the shares of a company between January 1, 1990, and December 31, 2010. These data are described in detail in Section IV. We measure BP as the ratio of the unit block price to the exchange-traded share price 21 trading days before the block trade announcement. We measure CAR as the ratio of the exchange-traded share price 2 trading days after the block trade announcement to the exchange-traded share price 21 trading days before the announcement. This choice of event window follows Barclay and Holderness (1989) and others, and is meant to capture the full effect of market expectations about the unfolding block trade and the corresponding effect of the change of control on security benefits.

Figure 1 shows the scatter plot of BP and CAR in our sample. There are several noteworthy features. First, the average BP in our sample is 6.8% and the average CAR is 9.6%. Despite these positive means, 47% of deals have negative BP and 42% of deals have negative CAR. Second, BP and CAR are positively correlated, with a correlation coefficient of 0.37. This strong association captures the fact that most trades are concentrated in two regions of the scatter plot, with 74% of the trades with positive CAR exhibiting a block premium and 75% of the trades with a negative CAR exhibiting a block discount. Therefore, this evidence suggests that, for most majority-block trades, dispersed shareholders and blockholders either gain or lose simultaneously.

<INSERT FIGURE 1 ABOUT HERE>

How are these data informative of liquidity shock probabilities? Consider the subsample of trades where dispersed shareholders respond negatively to the announcement (i.e., $CAR < 0$). For these deals, a decline in the shared security benefits may have been caused by either a liquidity shock that forced the incumbent blockholder to sell, implying also losses to the blockholder (i.e., $BP < 0$) or a gain in private benefits at the expense of the dispersed shareholders, so that $BP > 0$.

Based on this distinction, one approach to identify the probability of liquidity shocks would be to treat all deals with $CAR < 0$ and $BP < 0$ as having been caused by such shocks and then specify a reduced-form probabilistic regression model to explain the event that $CAR < 0$ and $BP < 0$. However, this approach introduces biases by neglecting the fact that deals with $CAR > 0$ can also be informative of liquidity shocks. First, the incumbent blockholder may have been hit by a liquidity shock but found a white knight that provided liquidity while increasing shared security benefits. Second, forward-looking block and share prices must incorporate the possibility of liquidity shocks in the future, even for deals that were not caused by liquidity shocks. Indeed, 30% of our sample contains deals where blockholders gain more than shareholders ($BP > CAR > 0$). While these deals were most likely caused by an increase in security benefits, the transaction prices embedded in BP and CAR are likely to also reflect information about liquidity shocks.

We extract two conclusions from this discussion. First, because block trades by and large imply either simultaneous gains or losses to blockholders and dispersed shareholders, the main reasons for trading in our data must be increase in security benefits or sales forced by liquidity shocks. Second, a successful approach to identify the probability of liquidity shocks must recognize the different pricing scenarios that generate block premia or discounts, and positive or negative CAR. Moreover, due to their forward-looking nature, the prices in different scenarios will incorporate information about the same parameters. Essentially, any deal in the data can potentially be informative of liquidity shocks if structurally modeled.

The difficulties in identifying illiquidity-driven trades carry over to estimating the value of control. Because the block premium in deals with positive CAR incorporates both shared security benefits and illiquidity costs, estimation of illiquidity costs requires a way to disentangle these two opposing effects. The model developed in this paper proposes an economic mechanism whereby illiquidity costs have different effects on blockholder valuations and dispersed shareholder valuations. The structural estimation infers these illiquidity costs by matching the data on BP and CAR to the model's predictions of these prices.

II. A search theory of block trades

This section presents an estimable model of the valuation of a controlling block that includes a proportion $\alpha < 1$ of the shares of a firm, and the valuation of the $1 - \alpha$ remaining shares held by dispersed shareholders. Time is discrete and investors have discount factor $\delta < 1$.

A. Blockholder's value

The current block owner is called the incumbent and is denoted by I. The firm's cash flow is a discrete random variable that takes values on a grid $\{\pi_1, ..., \pi_N\}$. Without loss of generality, we assume that $\pi_m > \pi_l$ for any $m > l$. Let π_l^I denote the firm's cash flow in state π_l when I is in control. It evolves stochastically according to the conditional probability distribution $\Pr[\pi' = \pi_m | \pi = \pi_l] = q_{lm}$ with $q_{lm} > 0$ and $\sum_{m=1}^{N} q_{lm} = 1$ for every $l = 1..., N$, where the prime denotes next period values. We assume that the transition matrix induced by the conditional probabilities q_{lm} is monotone.

Denote by $v\left(\pi_l^I\right)$ the incumbent's per share value of the block at π_l^I. This value includes the shared security benefits and illiquidity costs to the blockholder. The blockholder also obtains private benefits. We assume that these private benefits do not come from the firm's cash flows, but rather from social prestige and network building in the case of an individual blockholder or from valuable synergies in the case of a corporate blockholder. We assume per share private benefits are constant across incumbent and rival and equal to B.

At the beginning of every period, I may face a liquidity shock with probability θ. If a liquidity shock occurs, then I is forced to sell at a fire sale price to a rival blockholder denoted by R. The firm's cash flow under the rival is denoted by π_m^R and is drawn from the same transition matrix induced by q_{lm} given the current state π_l. We do not model how the block trades following a liquidity shock. Instead, we specify the fire sale price in reduced form as $\phi v\left(\pi_m^R\right)$. The parameter θ summarizes the owner's liquidity and the parameter ϕ summarizes the asset's liquidity. Therefore, the ex ante block price upon a liquidity shock is

$$L_l^v = \phi \sum_{k=1}^{N} q_{lk} v\left(\pi_k\right). \tag{1}$$

If a liquidity shock does not occur, the incumbent is matched with a potential buyer with probability η. The parameter η is a measure of market thinness. We assume trading is the result of Nash bargaining, where the seller's relative bargaining power is $\psi \in [0,1]$. If bargaining is successful, R pays the price $s\left(\pi_k^I, \pi_m^R\right)$ and gets $v\left(\pi_m^R\right)$ plus the private benefits.

The value of the block to the incumbent, v, is the sum of the current cash flow, π_l^I, the continuation value in the absence of a liquidity shock, $\tilde{v}$, and the liquidation value, L_l^v, that is,

$$v\left(\pi_l^I\right) = \pi_l^I + \delta\left[(1-\theta)\sum_{k=1}^{N} q_{lk}\tilde{v}_l\left(\pi_k^I\right) + \theta L_l^v\right]. \tag{2}$$

The continuation value absent a liquidity shock plus private benefits equal

$$\tilde{v}_l\left(\pi_k^I\right) + B = \eta\sum_{m=1}^{N} q_{lm} \max\left[s\left(\pi_k^I, \pi_m^R\right), v\left(\pi_k^I\right) + B\right] + (1-\eta)\left[v\left(\pi_k^I\right) + B\right]. \tag{3}$$

The incumbent has an option to sell the block for $s\left(\pi_k^I, \pi_m^R\right)$ to a higher valued blockholder. Under Nash bargaining, $s\left(\pi_k^I, \pi_m^R\right)$ solves

$$\max_s \left[s - \left(v\left(\pi_k^I\right) + B\right)\right]^{\psi}\left[\left(v\left(\pi_m^R\right) + B\right) - s\right]^{1-\psi}.$$

When a there are gains from trade $\left(v\left(\pi_k^I\right) < v\left(\pi_m^R\right)\right)$, the solution is

$$s\left(\pi_k^I, \pi_m^R\right) = B + v\left(\pi_k^I\right) + \psi\left[v\left(\pi_m^R\right) - v\left(\pi_k^I\right)\right]. \tag{4}$$

Otherwise, no trade occurs and I remains the blockholder with valuation $v\left(\pi_k^I\right)+B$. From (4), the block price must compensate I for the value attained by not selling plus I's fraction of the added surplus that results from R taking over.

The next proposition characterizes the function $v\left(\pi\right)$. The proof is provided in the appendix.

Proposition 1 *The value function v exists, is unique, and is strictly increasing in π.*

The property that v is strictly increasing implies that it is optimal to sell the block if and only if $\pi_k^I < \pi_m^R$. Therefore, we can simplify $\tilde{v}$ as

$$\tilde{v}_l\left(\pi_k^I\right) = v\left(\pi_k^I\right) + \eta\psi \sum_{m>k} q_{lm}\left[v\left(\pi_m^R\right) - v\left(\pi_k^I\right)\right]. \tag{5}$$

The last term on the right hand side of equation (5) is the value of the option to sell. The fraction ψ of the option to sell accrues to I but can only be captured if a rival appears, which occurs with probability η. Note that it is worth selling to an incrementally better rival because all future increases in value that result from a sale by the rival are already properly valued in v and there are no fixed costs of selling.

The model's property that the block is sold if and only if $\pi_k^I < \pi_m^R$ (rather than if and only if $v\left(\pi_k^I\right) < v\left(\pi_m^R\right)$) is extremely useful. As we show in Appendix B, this property implies that we can solve the fixed point problem defining v (equations (2) and (5)) via a perfectly identified system of linear equations that only requires inverting a matrix. Proposition 1 guarantees that this matrix inverse exists. This property follows from the assumption that R and I are heterogeneous only with respect to the cash flow they generate. Any two blockholders generating the same cash flow have equal security benefits, $v\left(\pi\right)$. Without this property, we would have to solve the value function fixed point problem simultaneously with the decision rule that $v\left(\pi_k^I\right) < v\left(\pi_m^R\right)$ (see Afonso and Lagos (2012) for a similar result).

B. Dispersed shareholders' value

The model assumes complete information by all investors. Therefore, dispersed shareholders know the cash flow under current and rival management and trade the stock in a competitive stock market at the share price p such that

$$p\left(\pi_l^I\right) = \pi_l^I + \delta\left[(1-\theta)\sum_{k=1}^{N} q_{lk}\tilde{p}_l\left(\pi_k^I\right) + \theta L_l^p\right]. \tag{6}$$

Dispersed shareholders know that with probability $1-\theta$ there is no liquidity shock and the block is sold if and only if a rival is present and generates higher cash flows. The share price absent a liquidity shock, $\tilde{p}$, is given by

$$\tilde{p}_l\left(\pi_k^I\right) = p\left(\pi_k^I\right) + \eta\sum_{m=1}^{N} q_{lm}\max\left[p\left(\pi_m^R\right) - p\left(\pi_k^I\right), 0\right]. \tag{7}$$

Dispersed shareholders also benefit from I's option to sell. Further, we will show that $p(\pi)$ is increasing in π, which implies that I's decision rule to sell is efficient. This result is appealing because it is consistent with the correlation between the block premium and announcement return documented in Section I. The last component of the share price is the expected share price if a liquidity shock occurs,

$$L_l^p = \sum_{k=1}^{N} q_{lk}p\left(\pi_k\right). \tag{8}$$

Dispersed shareholders differ from blockholders in three ways. First, they do not receive any private benefits from holding the stock. Second, dispersed shareholders are able to extract all the value from the option to sell because they act in a competitive market. Indeed, they do not bargain over the gains from trade. Third, dispersed shareholders are not hit with liquidity shocks and are not forced to sell at a fire sale price. However, they lose if, upon a liquidity shock, the incumbent sells to a rival that generates lower cash flows. These differences are critical for the model to identify the illiquidity cost parameters.

The next proposition characterizes the function $p(\pi)$.

Proposition 2 *The value function p exists, is unique, and is strictly increasing in π. Also, $p(\pi) > v(\pi)$ for any π whenever $\theta > 0$ and $\phi < 1$, or $\eta > 0$ and $\psi < 1$.*

As in Bolton and von Thadden (1998), dispersed shareholders value security benefits more than the blockholder. This discrepancy arises because the model imposes search frictions to blockholders that have less impact on dispersed shareholders. Specifically, when the probability of a liquidity shock is strictly positive, fire sale discounts affect blockholders more than they do dispersed shareholders if $\phi < 1$. Likewise, when $\eta > 0$, selling to a more efficient rival benefits the dispersed shareholders more because $\psi < 1$. The model therefore relies on private benefits to explain why blockholders may value shares of the target firm more than dispersed shareholders.

C. The block premium and the price reaction to the trade

Conditional on a trade, the block price is $\phi v\left(\pi_m^R\right)$ if a liquidity shock occurs, and $s\left(\pi_k^I, \pi_m^R\right)$ otherwise. The block premium is defined as the ratio of the per-share block price to the per-share pre-trade price:

$$BP\left(\pi_k^I, \pi_m^R\right) \equiv \begin{cases} \frac{\phi v\left(\pi_m^R\right)}{p\left(\pi_k^I\right)} - 1, & \text{if a liquidity shock occurs,} \\ \frac{s\left(\pi_k^I, \pi_m^R\right)}{p\left(\pi_k^I\right)} - 1, & \text{else.} \end{cases} \tag{9}$$

The price reaction to the block trade announcement is defined by:

$$CAR\left(\pi_k^I, \pi_m^R\right) \equiv \frac{p\left(\pi_m^R\right)}{p\left(\pi_k^I\right)} - 1. \tag{10}$$

Note that $CAR < 0$ signals liquidity shocks: it only occurs if the block is traded after a liquidity shock and the new block owner generates lower cash flow. However, the converse is not true: $CAR > 0$ occurs following a liquidity shock if the randomly matched rival produces a higher cash flow. The next section discusses how the probability of a liquidity shock is identified despite this difficulty.

III. Empirical strategy

The unit of observation in our data is a block trade indexed by i. The dependent variables are CAR_i and BP_i. Our model allows us to construct theoretical counterparts to these for each deal as a function of the parameters of interest: the owner's liquidity shock probability, θ, the asset's liquidity parameter, ϕ, market thinness, η, the blockholder's private benefits, B, and the seller's bargaining power, ψ. This section starts by providing an intuitive description of how the model identifies these parameters from the data. These parameters are constant in the model for each trade and we will treat them as such in the empirical estimation. However, there is no model-imposed restriction on how these parameters vary across trades. We then discuss how we specify variation across trades for some of these parameters. Finally, the section describes the estimation method.

A. *Identification*

We develop a novel identification strategy to estimate a search model that uses the differences in the valuation of blockholders, BP, and of dispersed shareholders, CAR, at the time of the block trade. Traditional identification strategies in search models require either information on the time between two trades of the same block or contemporaneous trades of different blocks on the same stock (Feldhütter (2012)). Neither alternative is feasible to us.

A.1. Identification of θ

The model defines three main regions in the (CAR, BP) space that can be used to identify liquidity shocks. First, the model infers that trades exhibiting a negative price reaction $(CAR < 0)$ must have been caused by a liquidity shock.

Second, the model infers that a liquidity shock cannot have occurred if the trade resulted in a block premium that surpassed the increase in dispersed shareholders's valuation, $BP \geq CAR > 0$. To see this note that $\phi v\left(\pi^R\right) \leq v\left(\pi^R\right) < p\left(\pi^R\right)$, for any π^R, so that any trade caused by a liquidity shock must have

$$BP = \frac{\phi v\left(\pi^R\right)}{p\left(\pi^I\right)} - 1 < \frac{p\left(\pi^R\right)}{p\left(\pi^I\right)} - 1 = CAR.$$

Hence, deals in Figure 1 with $BP \geq CAR > 0$ are voluntary trades where shared benefits increased.

Third, for the remaining deals in the sample with $CAR > 0$ and $CAR > BP$, the model assigns an ex-post probability that a liquidity shock occurred that is equal to

$$\frac{\theta \times \Pr\left[\pi' > \pi_l | \pi = \pi_l\right]}{\theta \times \Pr\left[\pi' > \pi_l | \pi = \pi_l\right] + (1-\theta)\,\eta}. \tag{11}$$

The numerator describes the probability that a trade results from a liquidity shock to the incumbent that nonetheless yields an increase in shared benefits. The denominator describes the probability that a trade occurs and there is an increase in shared benefits.

Interestingly, the model allows us to extract information about θ even for those deals that it predicts were not caused by a liquidity shock, that is, in the region where $BP \geq CAR > 0$. To see this, consider panel (a) of Figure 2, which plots the simulated mean valuation spread $BP - CAR$ conditional on $BP \geq CAR > 0$, against θ. The parameter values are close to the actual estimates given below, but the plot has an identical shape for a wide range of values. The valuation spread is decreasing in θ. Intuitively, this spread reflects the fact that these shocks penalize blockholders more than dispersed shareholders because blockholders have a lower expected fire sale price. Interestingly, the valuation spread is informative (i.e., steeper) when liquidity shocks did not occur ex post (i.e., $BP > CAR > 0$) and were unlikely ex ante (i.e., low θ).

<INSERT FIGURE 2 HERE>

A.2. Identification of ϕ and η

Estimation of ϕ relies on the fact that fire sale prices affect only the blockholders' value, v, but not the share price, p. Therefore, when a liquidity shock has occurred, the model primarily assigns the variation in block prices that is not associated with variation in the price reaction to variation in ϕ. In addition, it is possible to infer variation in ϕ even in deals that the model predicts that there was no liquidity shock. Panel (b) of Figure 2 indicates that the valuation spread increases with ϕ conditional on $BP \geq CAR > 0$. The intuition is that, in this region, the block premium incorporates the likelihood of a future fire sale and therefore is increasing in ϕ, whereas the announcement return is unaffected by ϕ.

Market thinness, η, affects directly the value of the option to sell to a high-valued rival. Like θ, BP and CAR increase with η. However, as depicted in panel (c) of Figure 2, $BP - CAR$ shows little sensitivity to η whereas it shows great sensitivity to θ and ϕ. The identification of

η relies on the fact that, unlike θ, it cannot explain the occurrence of negative price reactions.

A.3. Identification of B and ψ

The size of private benefits B has an important role in capturing variation in the data where $CAR > 0$. The choice of B faces the following trade-off: too low and the estimation may fail to match the average block premium in deals where $BP \geq CAR > 0$; too high and it may misclassify trades with low BP and $CAR > 0$ as due to liquidity shocks. For this reason, we add some flexibility to the functional form of B, allowing private benefits to vary across deals but, to remain consistent with the model, not across blockholders in the same deal.

To identify the bargaining parameter, ψ, the model relies on the fact that ψ affects the block price but not CAR. While these facts are also true for the asset liquidity parameter, ϕ, there is one important difference between ψ and ϕ: ψ has a first order effect on the block price absent a liquidity shock through the value of the option to sell, whereas ϕ has a first order effect on the block price in the presence of a liquidity shock.

B. Modeling liquidity

In our estimation, as well as in the model, θ and ϕ are constant for each deal but allowed to vary across deals. We model the cross-sectional variation in θ and ϕ using parametric logistic functions:

$$\theta\left(\mathbf{x}_i, \boldsymbol{\beta}\right) = \frac{\exp\left(\mathbf{x}_i' \boldsymbol{\beta}\right)}{1 + \exp\left(\mathbf{x}_i' \boldsymbol{\beta}\right)}, \tag{12}$$

$$\phi\left(\mathbf{z}_i, \boldsymbol{\gamma}\right) = \frac{\exp\left(\mathbf{z}_i' \boldsymbol{\gamma}\right)}{1 + \exp\left(\mathbf{z}_i' \boldsymbol{\gamma}\right)}. \tag{13}$$

By construction, the logistic function guarantees that θ and ϕ are bounded between 0 and 1. In these functions, $\mathbf{x}_i$ and $\mathbf{z}_i$ are vectors of exogenous determinants of liquidity shocks and fire sale prices, respectively, whereas $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$ are vectors of fixed sensitivities to be estimated. As we describe in detail in Section IV, $\mathbf{x}_i$ includes variables that describe the state of liquidity, such as aggregate indices of funding costs and investment opportunities. The variables included in $\mathbf{z}_i$ capture variation in the traded blocks' fire sale value, including proxies for industry redeployability and asset specificity. Variation in $\mathbf{x}_i$ and $\mathbf{z}_i$ across deals allows us to estimate $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$ through the variation they produce on BP and CAR.

While θ varies with $\mathbf{x}_i$ and ϕ varies with $\mathbf{z}_i$, the model and the estimation constrain θ and ϕ to be constant over time for each deal i. This assumption is equivalent to assuming that blockholders and dispersed shareholders display a myopic attitude towards changes in these quantities. The ability of the model to reasonably fit the data suggests that our assumption may not be too restrictive and the reason may be that the variables we include in $\mathbf{x}_i$ and $\mathbf{z}_i$ are quite persistent. Ideally, the model and estimation would allow for $\mathbf{x}_i$ and $\mathbf{z}_i$ to be state variables in the investors' problems and for investors to change their valuations as their forecasts of θ and ϕ changed. We do not pursue this approach because it is highly computationally demanding, but allowing for time variation in θ and ϕ is a goal for future research.

C. Estimation

C.1. Algorithm

For each deal, we estimate the conditional probabilities q_{lm} using annual cash flow data at the target firm's 3-digit SIC level. We obtain an industry cash flow grid and its associated Markov transition matrix from the discretization of the estimated AR(1) process of the log-detrended cash flow time series. We construct a firm-level grid from the industry grid assuming constant price to cash flow ratios. The use of industry data for the regressions guarantees, with its longer time series, more precise estimates. More details can be found in Appendix C.

We set the discount factor δ to 1/1.1. This choice of a 10% discount rate includes a risk-free rate, a market premium and an additional premium for the lack of diversification. Lower discount factors tend to generate higher variation in CAR because the changes in CAR approach the changes in one-period cash flows when the future matters less. Section VI shows that this additional variation in CAR comes at the cost of limiting the effect of the liquidity frictions on prices because these frictions impact prices through future cash flow variation.

Private benefits are identical across incumbent and rival for each deal, but as with the liquidity parameters, we allow private benefits to vary across deals. We specify B_i as

$$B_i = b_0 + b_1 E\left(v\left(\pi_i\right)\right) + b_2 E\left(p\left(\pi_i\right)\right)\left(1-\alpha_i\right)/\alpha_i,$$

which allows for a higher utility from running a more valuable block, through $E(v)$, and a "glow" effect, through $E\left(p\right)\left(1-\alpha\right)$, that the blockholder gets from running a firm with a large capitalization of the dispersed shares. The parameters to estimate, b_0, b_1, and b_2, are constant across deals.

We estimate the model's parameters, $\mathbf{\Gamma} = \{\psi, \eta, b_0, b_1, b_2, \boldsymbol{\beta}, \boldsymbol{\gamma}\}$, using the simulated method of moments (SMM). This estimator minimizes the norm function,

$$\mathcal{J} = \left[\mathbf{m}\left(\{BP_i, CAR_i\}_i; \mathbf{\Gamma}\right) - \mathbf{M}\right]' \times \mathbf{W} \times \left[\mathbf{m}\left(\{BP_i, CAR_i\}_i; \mathbf{\Gamma}\right) - \mathbf{M}\right],$$

where $\mathbf{m}\left(\{BP_i, CAR_i\}_i; \mathbf{\Gamma}\right)$ is a vector of model-predicted moments of the joint distribution of the two observed endogenous variables, the block premium and the price reaction to the announcement, and $\mathbf{M}$ is the vector of the same moments in the sample. $\mathbf{W}$ is a matrix of weights. The procedure to search for the SMM estimator is explained in Appendix C, including the care we take in the choice of initial conditions.

C.2. Moment conditions

The number of parameters to estimate is equal to the number of parameters in $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$ plus 5. We identify these parameters through an over-identifying set of $3 \times \left(\#\left(\boldsymbol{\beta}\right) + \#\left(\boldsymbol{\gamma}\right)\right) + 7$ moment conditions. First, $\mathbf{m}$ includes moments that condition on deals the model predicts were caused by liquidity shocks, that is, where $CAR < 0$ and $BP < 0$. We include the first and second moments of BP and CAR: $E(BP|CAR < 0, BP < 0)$, $Var(BP|CAR < 0, BP < 0)$, $Var(CAR|CAR < 0, BP < 0)$, and $E(BP \times CAR|CAR < 0, BP < 0)$. In this subsample, BP is directly related to ϕ via the fire sale price equation. Therefore, we impose the restriction that the model match the co-movement between the estimated ϕ and the determinants of the asset's liquidity, $\mathbf{z}$. Hence, we include the moments $E(BP \times \mathbf{z}|CAR < 0, BP < 0)$.

Second, and also motivated by the identification arguments above, $\mathbf{m}$ includes moments that the model predicts were not caused by liquidity shocks, where we have $BP \geq CAR > 0$. In this region, the value spread is highly informative of θ. Hence, we include the first and second order conditional moments of $BP - CAR$: $E[BP - CAR|BP \geq CAR > 0]$, $Var\,(BP|BP \geq CAR > 0)$, $Var\,(CAR|BP \geq CAR > 0)$, $Var\,(BP - CAR|BP \geq CAR > 0)$, and $E[BP \times CAR|BP \geq CAR > 0]$. Similarly, we include the moments $E\,[(BP - CAR) \times \mathbf{x}|BP \geq CAR > 0]$ to constrain that our estimates of θ match the co-movement between the valuation spread and the determinants of the owner's liquidity, $\mathbf{x}$.

Third, $\mathbf{m}$ includes the first-order unconditional moments $E\,(BP \times \mathbf{x})$, $E(CAR \times \mathbf{x})$, $E\,(BP \times \mathbf{z})$, and $E(CAR \times \mathbf{z})$.[6] These moments provide additional information on all parameters, because they are weighted averages of the conditional moments above (and of moments not included) where the weights are the corresponding conditional probabilities, which are themselves informative about θ, η and ϕ.

IV. Data

Our data set combines Thomson One Banker's Mergers and Acquisitions data, CRSP and Compustat. We complement these with characteristics of the aggregate economy, which are obtained from the Board of Governors of the U.S. Federal Reserve. Table I describes in detail the variables constructed from these sources.

<INSERT TABLE I ABOUT HERE>

A. *Sample selection*

We consider all U.S. disclosed-value acquisitions of a block of more than 35% but less than 90% of the stock between January 1, 1990, and December 31, 2010 in Thomson One Banker's M&A. The lower bound on block size is imposed so that the blockholder has effective control over the firm. Arguably, control can be effectively achieved with less than 35% of the stock (e.g., Barclay and Holderness (1991) and Agrawal and Nasser (2012) argue that 5% may be enough).

We use the conservative value of 35% because smaller blocks are subject to different economics: (i) with smaller blocks, a raider may acquire control without buying the existing block (see Burkart, Gromb, and Panunzi (2000)), complicating the pricing mechanism with the effect of alternative buying strategies; (ii) the incentive alignment effect strengthens with block size, minimizing the chances that a trade for larger controlling blocks is motivated by heterogeneity in private benefits; and (iii) larger blocks are more likely to be subject to liquidity shocks as they represent a larger fraction of the owner's wealth, all else equal. The Internet Appendix presents results of estimating the model using a lower bound of 10%. This larger sample appears to have more trades due to private benefits, producing weaker estimation results.

We exclude deals such as block trades between parent companies and subsidiaries, spin-offs, equity carve-outs, recapitalizations, repurchases and others that either fail to have a price for the target before the trade or do not otherwise fit the structure of the model of two independent blockholders trading an existing block. Our sample starts with 1,751 deals. Of these, only 395 deals involve publicly traded targets. From these 395 deals, we drop 146 deals because the deal synopses or one of at least two news articles about each deal report either (i) a different deal type than in the Thomson One Banker data (e.g., spin-offs or parent-subsidiary deals that should have been eliminated previously), or (ii) changes in the block size simultaneous or subsequent to the trade (in 51 deals the block is made of newly issued shares, in 22 deals the trade was shortly followed by an acquisition of the remaining interest and in 14 deals it was followed by a tender offer). Indeed, the latter events are inconsistent with the model, where the block size remains constant after the trade. We match each deal to the target firm's Compustat record on the last December preceding the trade announcement. The final sample of 114 deals (45.7% of 249) excludes deals where the target is not covered by CRSP or Compustat after the trade. Details of the sample selection are included in Appendix D.

Table II summarizes the main characteristics of the block trades: the mean block size is 59.7% with a standard deviation of 15.1%, and the average deal value is \$193 million with a standard deviation of \$720 million. To measure CAR and BP, we compute each stock's market beta and liquidity beta from a regression of daily returns on the contemporaneous value-weighted CRSP portfolio return and the innovations in the Pástor-Stambaugh (2003) market liquidity index using all available prices from 252 days to 21 days before the announcement. The estimated parameters are used to adjust CAR and BP for changes in systematic risk and liquidity risk in line with the assumption of risk-neutral shareholders in the model.

<INSERT TABLE II ABOUT HERE>

B. Determinants of the owner's liquidity

We interpret θ as shock to the blockholder's preference for, or access to cash, which forces the sale of the block. We expect this shock to occur in times of tighter aggregate funding liquidity. Our proxy for funding liquidity is the bond liquidity premium index in Fontaine and Garcia (2012) (*Fontaine-Garcia*). Fontaine and Garcia (2012) identify a monthly latent liquidity factor from the yield spread between US Treasury bills with the same cash flows but different ages. They interpret the higher yields on otherwise identical older Treasury bills as a premium on the liquidity of on-the-run bonds. We hypothesize that their index is positively associated with θ. We discuss other measures of liquidity in Section VI.

We include also the growth of U.S. GDP per capita (*GDP growth*). The inclusion of a business cycle variable is meant to capture two opposing effects: during expansions, (i) investors have stronger balance sheets and are less likely to face liquidity shocks, and, (ii) better alternative investment opportunities may generate a preference for cash. We try to separate these hypotheses by interacting the business cycle variable with variables that describe aggregate funding costs. We argue that having a better alternative investment opportunity would only force the blockholder to sell if at the same time the cost of borrowing is high. The proxy for the cost of funding used is the slope of the yield curve, measured by the difference in interest rates on the 10-year and the 3-month Treasury bills (*Yield curve slope*). We expect high GDP growth to have a negative direct effect on θ, but a positive effect via its interaction with the yield curve slope.

We also include in the determinants of θ the average daily return on the equally-weighted portfolio of all NYSE, AMEX, and NASDAQ stocks (*Market Return*) and the standard deviation of the returns on the same portfolio (*Market Volatility*). Gromb and Vayanos (2002) and Brunnermeier and Pedersen (2009) show that liquidity providers face tighter funding constraints when market returns are low and volatility is high and thereby diminish their role as liquidity providers (see also Chordia, Roll, and Subrahmanyam (2002)). We therefore predict θ to decrease with *Market Return* and to increase with *Market Volatility.* Because stock returns may also capture investment opportunities, we also include the interaction between the *Yield curve slope* and *Market Return.*

C. Determinants of the asset's liquidity

We think of ϕ as describing the liquidity of controlling blocks. The empirical literature on the liquidity of productive assets largely follows Williamson (1988) and specifies liquidation values as a function of the asset's physical redeployability.[7] We adopt this idea and specify the block's liquidity as a function of its *financial redeployability.* Given that measuring the block's financial redeployability requires unavailable data on incumbent and potential blockholders, we borrow proxies for the asset's redeployability. Indeed, we expect the physical capital to be correlated with the human capital needed to make good use of it (e.g., the more 'specific' the asset, the more scarce the required human capital). The cost of this choice is the risk of introducing noise in the estimation. Only more data in the future can help capture these effects better.

The industry's asset specificity captures the human capital needed to make good use of the assets. Therefore, we view it as a proxy for the amount of industry-specific knowledge required by the controlling blockholder, and expect more potential buyers of controlling stakes in firms that use generic productive assets. We hypothesize that higher specificity causes a steeper fire sale discount of the block. We follow Stromberg (2000) and measure *Industry Specificity* with the median proportion of machinery and equipment to total assets of all firms in the industry (non-industry specific assets include land, commercial real estate and cash). Shleifer and Vishny (1992) add that, because assets of distressed firms tend to be best sold within the same industry, redeployability is a function of the industry's capacity to absorb them. As an additional measure of the block's redeployability, we use the ratio of the block value to the total market capitalization of all firms in the same 2-digit SIC group (*Block-to-Industry Size*). Table II shows that, while the trades in our sample are small relative to their industries' total equity (mean of 0.008), there is large variation in this measure. Based on this interpretation, we expect the liquidation parameter, ϕ, to decrease with the relative size of the block. However, if blockholders have a preference for relatively larger blocks in order to, say, exert control over industry policies, then ϕ would vary positively with *Block-to-Industry Size*.

We let the block's fire sale parameter vary with the target's leverage relative to its industry's median leverage. We define *Target minus Industry Leverage* as the difference between the target's proportion of long-term debt to assets and the median proportion of long-term debt to assets of all firms in the same 3-digit SIC code. We expect blockholders to price a bigger discount for firms with more long term debt as they are more constrained in borrowing to fund any restructuring activities.

We include the total dollar volume of M&A activity involving targets in the same 2-digit SIC group during the last quarter before the deal. High *Industry's M&A Activity* could be the result of an increased supply of industry-specific assets, which would depress the liquidation value of the block. High *Industry's M&A Activity* could also reflect high liquidity for industry-specific assets as in Schlingemann, Stulz, and Walkling (2002) and Ortiz-Molina and Phillips (2012) and, therefore, increase the block's liquidation value. To control for the time-series variation in investment opportunities in the same industry, we include the median ratio of the market-to-book value of assets of all firms in the same 3-digit SIC code. Finally, we control for the possibility that fire sale prices are affected by the target firm's return volatility.

V. Results

We present results for a baseline specification and for an extension of the baseline specification that tries to distinguish between liquidity shocks due to an increase in investment opportunities or a shortage of funding.

A. *Model fit*

Panel A of Table III evaluates the quality of the model's fit to the data. In the baseline specification (specification (1)), the model estimates the average block premium to be 9.6%, which is larger than the sample mean of 6.7%. In the extended specification (specification (2)), the model gets closer, predicting an average block premium of 6.2%. Specification (2) is better at matching the fraction of discounts, but it underestimates the standard deviation of the block premium. The model produces a correlation between actual and predicted block premiums of about 0.11.

The two specifications predict similar CAR moments. Under both specifications, the model underpredicts the mean and standard deviation of CAR, but gets close to matching the fraction of negative CAR in the data. Despite underpredicting CAR, the model generates a correlation between actual and predicted CAR of almost 0.4. The model can fit BP better than CAR because: (i) unlike share prices, block prices are also directly affected by private benefits of control, fire sale discounts and the bargaining power parameter; and, (ii) the variation in the cash flow distribution, which we estimate to be quite high, is smoothed out significantly in p by the fact that share prices are forward looking, therefore constraining the maximum possible predicted CAR. A detailed discussion of point (ii) is provided in the Internet Appendix.

Recall from Section I that 74% of the trades with positive CAR exhibit a block premium and that 75% of the trades with a negative CAR exhibit a block discount. In the baseline specification the corresponding numbers are 61% and 55% whereas in the extended specification the corresponding numbers are 77% and 67%. Note that specification (2) performs well in capturing these moments despite the fact that they were not targeted by the SMM estimation.

For both specifications, we reject the hypothesis that all of the model's parameters are zero (p-value of 0.00). Further, with 95% confidence, we cannot reject the joint hypotheses that the model is correctly specified and that the moment conditions over-identify the model's parameters. We investigate the model fit also by inspecting the model's ability to match the moment conditions in the SMM estimation. Table IV reports a moment-by-moment match for both specifications.

The model does a good job matching the moments that are most informative of θ and ϕ: the unconditional mean of BP; the mean of $BP - CAR$ conditional on $BP > CAR > 0$; the correlation of the valuation spread $BP - CAR$ with some of the proposed determinants of liquidity conditional on $BP > CAR > 0$; and, many of the correlations of BP and CAR with some of the proposed determinants of liquidity shocks (the yield curve slope and its interactions with GDP growth or market returns) and of fire sale values (target leverage relative to its industry median, target industry's asset specificity). The ability to match the correlations of BP and CAR with determinants of liquidity is consistent with the relatively low standard errors for the associated coefficients.

The model does poorly in matching the second order moments and specifically moments that are related to CAR. One possible reason for this failure is the risk neutrality assumption that eliminates all variation in risk premia. Future models should consider risk aversion and variation in risk premia to better match the moments associated with CAR. Another possibility for this failure is that that SMM gives these moments smaller optimal weights, as the estimation procedure trades off the matching error with the precision of the moments' measurement.

As an additional test to the fit of the model, we count the number of trades that satisfy the condition that trading following a liquidity shock is inefficient, that is, $v(\pi_I) + B > \phi v(\pi_R)$. This condition is verified in each specification for all trades in the sample.

<INSERT TABLE III ABOUT HERE>

<INSERT TABLE IV HERE>

B. Parameter estimates

Panel B of Table III presents the parameter estimates. We estimate the parameter associated with market thinness, η, to be 0.59 in specification (1) and 0.43 in specification (2). These estimates are statistically significant at the 1% level. Their magnitude suggests that a seller is expected to meet a potential buyer absent a liquidity shock roughly once every two years.

In both specifications, the estimated incumbent's bargaining power *in the absence of a liquidity shock* is close 0.5. These point estimates are statistically significantly different from 0, but not from 0.5. We take this result as additional empirical support for our model given that there is no reason to expect buyers to have a bargaining advantage over sellers in times of normal liquidity.

At the bottom of panel B of Table III, we present the estimates of the private benefits function parameters. The estimated average private benefits per share in the block are 17.6% in specification (1) and 7.9% in specification (2). Neither is statistically significant at normal significance levels.

B.1. Cross-sectional determinants of owner's liquidity

GDP growth has a negative and significant effect on θ. In terms of economic significance, and in both specifications, a one standard deviation increase in *GDP growth* is associated with a decrease in θ of 0.03. The sign of the point estimate supports the hypothesis that in expansions agents have stronger balance sheets and are less likely to face liquidity shocks.

The coefficient on *Market Return* is negative and has the strongest effect on θ in terms of economic significance: one sample standard deviation increase in *Market Return* is associated with a large decrease in θ of 0.11 in specification (1) and of 0.31 in specification (2). This result is in line with that of *GDP growth* and suggests that periods of high market returns in the sample are periods of increased liquidity. The effect of *Market Volatility* is unexpectedly negative, although not always significant at the 5% level.

Tighter funding liquidity in the bond market, as measured by the *Fontaine-Garcia* index, has a statistically and economically significant positive effect on θ. The cost of funding as proxied by the *Yield curve slope* has positive effect on θ, which is especially strong in specification (2).

Specification (2) adds the interactions between *GDP growth* and *Market Return* with the *Yield curve slope*. The estimated coefficients of these variables are positive and strongly statistically and economically significant. These results support the hypothesis that blockholder liquidity shocks are more likely to occur with the arrival of better alternative investment opportunities in expansions, together with high cost of borrowing.

B.2. Cross-sectional determinants of asset's liquidity

The effects of *Target minus Industry Leverage* and of *Industry Specificity* on ϕ are negative as expected, statistically significant in both specifications in Table III, and in further tests discussed later. In specification (2), a one sample standard deviation increase in *Target minus Industry Leverage* leads to a reduction in the fire sale parameter of 4 percentage points, and one sample standard deviation increase in the specificity of the industry's assets is associated with a decrease in the fire sale parameter of 2 percentage points.

While not statistically significant, the *Industry's M&A Activity* has a strong positive effect on fire sale prices. The sign of this estimate is consistent with the interpretation that a large volume of M&A activity within an industry reflects enhanced liquidity for acquisitions (Schlingemann, Stulz, and Walkling (2002)), although its lack of precision suggests the proxy may be contaminated by supply effects, which have the opposite sign.

Industry Market-to-Book has a positive effect on fire sale prices, if not always statistically significant, implying that a given controlling block is worth more when there are more growth options available in the industry. Finally, beyond these controls, we find insignificant effects of the *Target Volatility*, or of the size of the block relative to its industry, *Block-to-Industry Size*.

C. In-sample distributions of θ and ϕ

Table V and Figure 3 show the estimated distribution of θ under specification (2). The estimated average θ is 0.2, with a standard deviation of 0.3. This estimate suggests that on average a blockholder is hit by a liquidity shock that forces a sale once every five years.[8] The table also shows that approximately 25% of the trades have an estimated θ of at least 24%. The frequency of deals with extremely large θ may appear low relative to the 42% of deals in the data with negative CAR. This discrepancy is explained by the following reasons. First, θ is an ex ante measure of liquidity shocks computed using ex post data from each deal. A liquidity shock may have occurred despite the low ex ante probability. Second, and more mechanically, the estimate of θ is not equal to the proportion of deals with negative CAR but is a nonlinear function of this statistic and also deal dependent. We further discuss in Section V.E the interpretation of the size of the estimates of θ and of ϕ in the context of our model.

<INSERT TABLE V ABOUT HERE>

<INSERT FIGURE 3 ABOUT HERE>

Table V shows that, conditional on a liquidity shock, the estimated block's fire sale price is on average 92% of the buyer's block valuation, with 25% of the targets with an estimated ϕ of less than 89%. The implied fire sale discounts are similar to estimates for other markets, that is, to the aircraft liquidation values reported in Pulvino (1998) and to the gains from trading on price pressure sales reported in Coval and Stafford (2007). Panel (b) of Figure 3 shows the predicted histogram of ϕ.

D. Illiquidity discounts

D.1. Marketability discount

We define the *marketability discount* of a controlling block with respect to security benefits, d^M, as

$$d^M(\theta) \equiv 1 - \frac{v(\theta, \phi, \eta, .)}{v(0, 1, 1, .)}.$$

The formula makes explicit the dependence of v on θ, η, and ϕ. It is easy to show that $d^M(\theta)$ is positive, and that $v(0, 1, 1, .) > v(\theta, \phi, \eta, .)$ for any ϕ, provided $\theta > 0$ or $\eta < 1$. The function

$d^M(\theta)$ quantifies the value of the shares *in the block* relative to the counterfactual scenario where it is possible to trade at any time ($\eta = 1$) and voluntarily ($\theta = 0$). This measure of the marketability discount differs from the one in Longstaff (1995) because in d^M it is presumed that the blockholder remains in control, whereas in Longstaff's measure there is no presumption of control.

Table V shows that the estimated average marketability discount is 13%, reaching a maximum of 89%. The predicted marketability discount varies with the predicted θ. Panel (a) of Figure 4 plots the marketability discount function for every $\theta \in [0, 1]$. We see that, for the firms in the lower quartile of ϕ, the marketability discount increases quickly, reaching 40% for θ just below 20%. The estimated marketability discount is also large for blocks with intermediate fire sale prices. However, for blocks with the highest fire sale parameter estimates, the marketability discount is under 5% for any θ. Panel (b) plots the predicted distribution of the marketability discount.

<INSERT FIGURE 4 ABOUT HERE>

D.2. Illiquidity-spillover discount

We define the *illiquidity-spillover discount*, d^{IS}, as

$$d^{IS}(\theta) \equiv 1 - \frac{p(\theta, \eta, .)}{p(0, 1, .)}.$$

We have that $p(0, .) > p(\theta, .)$ for any $\theta > 0$ and that $d^{IS} > 0$. The illiquidity-spillover discount quantifies the price of dispersed shares that would prevail in the absence of search costs. It is a spillover effect in that the dispersed shareholders are not hit by a liquidity shock nor experience market thinness directly but rather through the blockholder. However, p incorporates the possibility that control may change hands and that the value of assets will change as a result.

Table V shows that the cost of forced block turnover is important to dispersed shareholders: we estimate an average illiquidity-spillover discount of 2.1% on dispersed shares (maximum close to 10%). This effect is five times as large as the average quoted bid-ask spread (Bollen, Smith, and Whaley (2004)).

Panel (a) of Figure 5 plots the illiquidity-spillover discount against θ, conditional on the firm's cash flow state before the trade. As the figure shows, this discount is higher for firms with high cash flow because these firms have more to lose if, due to a liquidity shock, the incumbent blockholder is forced to sell to a less efficient rival. Panel (b) plots the predicted distribution of the illiquidity-spillover discount.

<INSERT FIGURE 5 ABOUT HERE>

D.3. Control discount

We define the control discount from security benefits, d^C, as

$$d^C(\theta) \equiv 1 - \frac{v(\theta, \phi, \eta, .)}{p(\theta, \eta, .)}.$$

Given that $v < p$ for any $\theta > 0$, then $d^C > 0$. The control discount measures the difference in valuations of security benefits between the controlling blockholder and the dispersed shareholders. This estimate of the control discount ignores the private benefits afforded to the controlling shareholder. Given that d^{IS} is much smaller than d^M, the estimated control discount shares similar properties with the marketability discount, as displayed in Table V. As with the marketability discount, Panel (a) of Figure 6 shows that the control discount displays high sensitivity to the probability of a liquidity shock when the fire sale parameter is lowest (solid line). Panel (b) of Figure 6 shows that the sample distribution of control discount is highly skewed with many trades displaying negligible discounts.

<INSERT FIGURE 6 ABOUT HERE>

The estimates of the control discount on blocks of shares in public corporations can be applied to block valuations in the case of privately held corporations. Valuing blocks of shares in privately held corporations is difficult, as illustrated in Mandelbaum et al. v. Commissioner of Internal Revenue (1995). As the court indicated, these difficulties arise from the limited evidence on the proper size of the discount relative to the value of exchange traded shares. Our estimates of the control discount can be applied to a paired sample of comparable publicly traded firms with controlling blockholders to determine the block value. Using firms with controlling blockholders guarantees that the pricing by dispersed shareholders already incorporates the added value of the blockholder and the illiquidity-spillover costs.

E. Interpreting discount estimates

Our modeling of search frictions has potential biases in the estimation of the parameters θ and ϕ and hence potential biases in the measurement of the various discounts. Consider the following two possible extreme alternatives. First, suppose that θ is a pure liquidity shock, that is, one that does not necessarily force a sale. Then ϕ does not represent a pure fire sale price but rather represents the blockholder's reservation value. This reservation value is the best outcome out of all possible ways of dealing with the liquidity shock, including when the incumbent keeps the block but borrows against it as collateral; sells to a white knight, such as a private-equity firm supplying the needed liquidity; sells only a fraction of the block while retaining control (though this is rare according to Barclay and Holderness, 1989); or, sells at a fire sale price. While these possibilities are out of the model, we note that, since the fire sale is the chosen alternative in our sample, then ϕ is an upper bound to the fire sale price.

Second, suppose that θ captures a more restrictive event: the event of a liquidity shock and having failed to deal with it in any other way other than selling. By definition, this more restrictive type of shock leads to a fire sale and ϕ then represents a pure fire sale price. In this case, θ is a lower bound on a pure liquidity shock.

Consider now the impact of these two alternative interpretations of θ and ϕ on the marketability discount, d^M. Because d^M is decreasing in ϕ, an upper bound on the fire sale price as implied by the first scenario leads to a lower bound on d^M. As for the second alternative, a lower bound on θ also leads to a lower bound on the marketability discount because d^M is increasing in θ. In conclusion, while we may not be measuring θ and ϕ exactly as pure search costs, the implications for mismeasurement of d^M are consistent and lead to an estimated marketability discount that is always a lower bound to the true marketability discount.

The illiquidity-spillover discount, d^{IS}, is invariant to ϕ and increasing in θ. Hence the estimation also produces a lower bound for the illiquidity-spillover discount. Finally, the control discount d^C is decreasing in ϕ, but monotonicity with respect to θ cannot be determined analytically. Numerically, we showed above that d^C is increasing in θ, so that the estimated d^C is also a lower bound to the true control discount.

F. Illiquidity discounts by industry

To illustrate the cross-sectional differences in the illiquidity discounts, Table VI presents the highest and lowest values of the discounts by 2-digit SIC code group of the target firm. The analysis excludes the 2-digit SIC groups with fewer than 3 observations.

Firms in the Air Transportation industry (code 45) have the highest average marketability and control discounts. This result may be surprising given that aircraft would appear to be assets of very low specificity. However, Pulvino (1998) and Benmelech and Bergman (2008) provide strong evidence that aircraft fire sales do exist, and that their liquidation values can vary significantly across airlines. The high discount estimates for this industry, which are the result of a combination of relatively high estimates of θ (0.46) and relatively low estimates of ϕ (0.81), are largely explained by high values of the high yield curve slope contemporaneous to these trades, and the fact that the traded firms were highly levered with respect to their industry.

Firms in Business Services (code 73) and Electronic and Other Electrical Equipment (code 36) rank among the industries with the lowest for marketability discount. Their ranking is explained by the fact that these industries have relatively high estimates of average θ, but also high estimates of average ϕ. For Business Services, θ is relatively high due to a combination of a steep yield curve and high values of the *Fontaine-Garcia* index contemporaneous to the trades, while ϕ is high due to low target leverage and low asset specificity. In the case of Electronic and Other Electrical Equipment, the high value of ϕ appears to come from a high volume of industry-specific M&A.

Industries 73 and 36 are interesting because, despite having some of the lowest marketability discounts, they have the fourth and fifth highest illiquidity-spillover discounts, respectively. The reason for their high illiquidity-spillover discount is the high variance of cash flows in the industry: they rank second and fifth in terms of cash flow volatility, respectively. The high cash flow volatility yields a high option value associated with finding a better blockholder to run the firm, but market thinness reduces the contribution of this option to share prices. For the same reason, the firms in Engineering, Accounting and Management Services (code 87) and Building Contractors (code 15) rank first and second in terms of illiquidity-spillover discounts. These industries have the highest and third highest estimated cash flow volatilities, respectively, among the industries in the sample.

<INSERT TABLE VI ABOUT HERE>

VI. Additional Tests

This section considers several extensions to our model. Unless noted, the results are tabulated in an Internet Appendix.

A. *Trading due to private benefits*

In our model, blocks are traded due to liquidity shocks or efficiency gains. In practice, block trades may also occur due to differences in private benefits of control, as in Burkart, Gromb, and Panunzi (2000) or Dyck and Zingales (2004). Therefore, one important question is whether our identification of the modelled motives for trading is affected by the omission of the private benefits motive. For example, trades in our sample may have occurred because the new blockholders enjoyed significantly more private benefits than the incumbent while being detrimental to dispersed shareholders, that is, $\pi^R < \pi^I$. Given that those trades would also result in $CAR < 0$, we could potentially identify them incorrectly as liquidity shock-driven, biasing the estimate of θ upwards.

The crucial feature of our identification strategy that distinguishes the effects of liquidity from the private benefits motive is that we use the *joint distribution* of BP and CAR. To see how the distinction is made, consider the possible outcomes of liquidity and private benefits trades. The former causes either that (L1) the block is bought by a white knight who can also run the firm more efficiently, and $CAR > 0$; or that (L2) the block buyer is less efficient at running the firm, and $CAR < 0$. The latter will have seemingly similar effects: either (B1) the buyer, who values private benefits more than the seller, is also able to run the firm more efficiently, and $CAR > 0$; or (B2) the buyer is less efficient at managing the firm and $CAR < 0$. Clearly, from CAR data alone the two types of trades are observationally equivalent and we cannot distinguish neither (L1) from (B1) nor (L2) from (B2).

But in addition to CAR, BP is informative because it captures the fact that liquidity shocks are a bad event for the block holder (because the block holder is forced to sell, likely resulting in $BP < 0$), whereas private benefits trades are good events for the block seller (they can only create gains from trade and must result in $BP > 0$). Formally, in our model liquidity trades exhibit a negative block premium if and only if

$$CAR < \left[p\left(\pi^R\right) - \phi v\left(\pi^R\right)\right]/p\left(\pi^I\right),$$

that is, if the trade is sufficiently inefficient. Since $p\left(\pi^R\right) - \phi v\left(\pi^R\right) > 0$ (Proposition 2), then the upper bound on CAR is positive. Therefore, if a liquidity trade causes $CAR < 0$, then it also causes $BP < 0$. The reason why private benefits trades cause $BP > 0$ is straightforward: the seller is not forced to sell unless there are gains from trade with the high private benefits bidder. As we show in Appendix E, this intuition holds in a standard negotiated block pricing framework (Dyck and Zingalesn (2004)) and extends also to a version of our model without liquidity shocks.

Finally, note too that liquidity trades may exhibit $BP > 0$ if CAR is larger than

$$\left[p\left(\pi^R\right) - \phi v\left(\pi^R\right)\right]/p\left(\pi^I\right).$$

Table VII summarizes the discussion above by illustrating the map of the possible types of trades L1,L2, B1 and B2 into joint outcomes of BP and CAR. The table shows that liquidity trades and private benefits trades are in general not observationally equivalent, mainly because the latter cannot generate $BP < 0$. The only case where both motives have similar implications are where $BP > 0$ and $CAR > 0$.

<INSERT TABLE VII ABOUT HERE>

We conduct several tests to guarantee that our estimates are not influenced by the possibility of private benefits motives. First, we verify that our estimates are largely unaffected if we exclude from the sample the deals where $CAR < 0$ and $BP > 0$ (i.e., B2 type trades). After excluding these 12 deals, we find slightly lower average estimates of $\theta\,(0.16)$ and ϕ (0.9) but almost identical estimates of the marketability and liquidity discounts, while still matching the main conditional and unconditional moments as well as with the full sample. This robustness is due to the fact that identification of θ does not rely solely on occurrences of $CAR \leq 0$ but also on the model-imposed constraints that, conditional on $BP > CAR > 0$, the spread $BP - CAR$ is monotone in θ and must therefore covary with determinants of funding illiquidity. The risk of overestimating θ would be present only in the unlikely case that buyers with relatively large private benefits valuation were more likely to be drawn in times of low aggregate liquidity.

Second, we reestimate the model by additionally excluding deals with $BP > 0$ and low but positive CAR. This procedure is meant to ensure that we eliminate all B1 type trades, as these would exhibit the lowest CAR among those where $BP > 0$ and $CAR > 0$, and all B2 type trades, as these could also exhibit positive but low CAR due to measurement error in CAR. After excluding the 12 deals with $BP > 0$ and $CAR < 0$, we re-estimate the model on progressively smaller subsamples, removing each time the deals with the five lowest CAR values among the surviving deals where $BP > 0$ and $CAR > 0$. We find that the estimates of θ do not change significantly after dropping the first 10 deals. This result is remarkable given that this exclusion already drops deals with CAR up to 8.25%. This result confirms our previous findings and makes a stronger case that the model is able to identify liquidity trades from private benefits trades.[9]

B. Trading due to asymmetric information

Trading may also occur if I privately learns bad news about the firm. Such a trade could be disguised as a liquidity-driven sale provided adverse selection is not too severe in the market. We believe these trades are rare or non-existent in our data because (i) they fall under the Securities and Exchange Commission's insider trading laws (Rule 10b-5); (ii) unlike other settings where insider trading exists, in block trades the identities of both the seller and the buyer are known, which significantly increases the risk of subsequent litigation due to insider trading; (iii) no deal in our sample was followed by insider trading litigation; and, (iv) buyers and sellers in this market are sophisticated investors, including financial and non-financial corporations, private equity firms, and wealthy individuals that are advised by financial corporations in these deals.

C. Random effects in θ and ϕ

Unobservable shocks to the blockholder's personal wealth may be the cause of forced sales (de Jong et al. (2012)). To explore this possibility, we introduce unobservable, deal-specific effects on the probability of a liquidity shock and on the fire sale parameter. We estimate a specification that keeps ϕ_i as before but adds a random effect in θ_i, that is,

$$\theta_i = \frac{\exp\left(\mathbf{x}_i'\boldsymbol{\beta}+\xi_i\right)}{1+\exp\left(\mathbf{x}_i'\boldsymbol{\beta}+\xi_i\right)},$$

where ξ_i is drawn from a normal distribution with mean zero and variance σ_ξ^2. We estimate an alternative where we add a random effect to ϕ_i but not to θ_i. For each specification, we estimate the volatility of the random effect as an additional parameter, by randomly drawing 1000 values for ξ_i for each deal and averaging them at each of the moment conditions specified above. The models are unable to produce statistically significant estimates of the volatilities of the random effects, despite predicting large point estimates. The presence of the random effects, however, does not significantly affect the estimates reported in Table III. We conclude that there may be important unobservable determinants of illiquidity costs associated with blockholders that the model is unable to identify, but their exclusion does not affect our estimates.

D. Other aspects of investor heterogeneity

Blockholders may not be as diversified as dispersed shareholders. As in Acharya and Pedersen (2005), blockholders may still use a higher discount rate despite the adjustment of prices for market and for liquidity factors. To test this possibility, we decrease the discount factor to 1/1.15 for blocks larger than 65%. This specification produces similar results to those in Table III, with the main differences being a slight increase in the predicted CAR variation (estimated standard deviation equal to 0.85%) and a worsening in matching the average BP (estimated average equal to 8.9%). The ability to generate more CAR variation is due to the fact that when the future matters less to the investor, the maximum value for CAR approaches the maximum value of the change in cash flows, which tends to be large. We find also that an alternative specification where the blockholder's discount factor decreases by 1 percentage point for every 10 percentage points increase in block size fits the data poorly. Our conclusion is that blockholders may use different discount rates than dispersed shareholders, but that the difference appears to be relatively small for most deals.

E. Other drivers of owner's liquidity and asset's liquidity

In addition to the *Fontaine-Garcia* index of funding liquidity, we also considered as candidate proxies of illiquidity the spread between the 3-month dollar LIBOR rate and the 3-month Treasury bill (TED spread), and the Pástor and Stambaugh (2003) stock market liquidity factor. The TED spread has the expected sign on θ but is not statistically significant, whether we include it as an additional driver of θ in specification (2) or in substitution of the *Fontaine-Garcia* index. Our interpretation of these results is that the TED spread is a noisier proxy because it also captures bank-credit risk. The Pástor-Stambaugh liquidity factor has the expected sign but an insignificant effect on θ. Our interpretation is that the illiquidity costs associated with over the counter trades of large blocks of shares differ from the costs associated with trades in the more liquid market of dispersed shares. We have also considered the corporate assets liquidity measure of Schlingemann, Stulz and Walkling (2002) as an additional determinant of ϕ. This variable has an insignificant effect on ϕ as does the total M&A activity amount, a similar variable which we already include.

Shleifer and Vishny (1992) argue that, in equilibrium, determinants of liquidity shocks may affect fire sale prices and vice-versa. To accommodate this possibility, we add the most important industry-specific determinants of ϕ to the specification of θ and the most important determinants of θ to the specification of ϕ. Neither specification passes the test of over-identifying restrictions. Moreover, in both cases the model severely underpredicts the block premia. Except for *Target minus Industry Leverage* and *Yield curve slope*, none of the added variables has a significant effect on either θ or ϕ, respectively. The weakness of these models suggest that common effects may not be a first order force in explaining liquidity shocks and fire sale prices. Of course, these tests may be inconclusive if over-specification compromises the identification of the main parameters. To mitigate this concern, we have estimated the model specifying only industry and firm-specific variables in θ and aggregate liquidity variables in ϕ, finding also a poor fit.

VII. Conclusion

One of the main challenges in estimating the value of control is the illiquidity of the market for controlling blocks. This paper uses data on controlling block trades and the theoretical restrictions imposed by a search model to identify and estimate the effect of liquidity shocks on controlling blockholders' valuations. Unobservable to the econometrician, the probability that a block is traded because the blockholder has a sudden preference for liquidity and sells at a fire sale price, can be estimated from the observed block premium and share price reaction to the trade announcement. We find that the estimated liquidity shock probabilities are correlated with measures of aggregate liquidity, whereas the fire sale discount on blocks traded following liquidity shocks is correlated with industry and target-firm-specific variables.

The estimates of the average marketability discount are large, but they also vary considerably across deals, time and market conditions. Moreover, liquidity shocks that force the trade of controlling blocks impose non-negligible costs on the same firm's dispersed shareholders. The paper also shows how to estimate the control discount, that is the private value to the blockholder with respect to the exchange traded stock price. The determinants discussed here can be applied to valuation exercises in a straightforward way.

Appendix A: Proofs

Proof of Proposition 1. Define the support of π as $X = \{\pi_0, ..., \pi_N\}$ and let $\mathcal{X}$ be the σ-algebra containing all the subsets of the countable and bounded X. $(X, \mathcal{X})$ defines a measurable space. Let $C(X)$ be the space of bounded, continuous functions $f : X \to \mathbf{R}$ with the sup norm. Let $T_v : C(X) \to C(X)$ be an operator defined by

$$\begin{aligned} & T_v(f)(\pi_l) \\ = \;& \pi_l + \delta \left\{ (1-\theta) \left[\sum_{m=1}^{N} q_{lm} \left(\eta \sum_{k=1}^{N} q_{lk} \max\left[s(f)(\pi_m, \pi_k) - B, f(\pi_m) \right] + (1-\eta) f(\pi_m) \right) \right] + \theta L_l^v \right\}, \end{aligned}$$

where

$$s(f)(\pi_m, \pi_k) = B + \psi f(\pi_k) + (1-\psi) f(\pi_m),$$

if $f(\pi_m) < f(\pi_k)$ and 0 otherwise. It is straightforward to show that the operator T_v satisfies Blackwell's sufficient conditions of monotonicity and discounting. Theorem 9.6 in Stokey and Lucas (1989) shows that T_v is a contraction mapping and therefore has a unique fixed point v. Under the assumption that the transition matrix induced by the conditional probabilities q_{lm} is monotone, Theorem 9.11 in Stokey and Lucas (1989) can then be used to show that v is a strictly increasing function in π. ■

Proof of Proposition 2. Let $T_p : C(X) \to C(X)$ be the operator defined by

$$T_p(f)(\pi_l) = \pi_l + \delta \left\{ (1-\theta) \left[\sum_{m=1}^{N} q_{lm} \left(\eta \sum_{k=1}^{N} q_{lk} \max\left[f(\pi_k), f(\pi_m) \right] + (1-\eta) f(\pi_m) \right) \right] + \theta L_l^p \right\}.$$

The first part of the proof follows the proof of Proposition 1. It remains to show that $p(\pi) > v(\pi)$. Take two functions $f_p, f_v \in C(X)$ and assume that $f_p \geq f_v$. Then, we show that $T_p(f_p)(\pi) > T_v(f_v)(\pi)$. Since f_p and f_v were arbitrary, we have that the fixed points must also have the property that $p(\pi) > v(\pi)$. Using $f_p \geq f_v$ note that $L^p \geq L^v$, with strict inequality if $\phi < 1$. Also, $f_p(\pi_k) > \iota f_v(\pi_k) + (1-\iota) f_v(\pi_m)$ for any $\iota < 1$ and $\pi_k \geq \pi_m$. Therefore, $T_p(f)(\pi) > T_v(f_v)(\pi)$, for any $\theta > 1$. The same reasoning applies alternatively for $\eta > 0$ and $\psi < 1$. ■

Appendix B. Model solution

Cash flow π lies on a discrete grid $\{\pi_1, ..., \pi_N\}$ and evolves stochastically according to the conditional probability distribution $\Pr[\pi' = \pi_k | \pi = \pi_l] = q_{lk}$ with $q_{lk} > 0$ and $\sum_{k=1}^{N} q_{lk} = 1$. The transition matrix is $\mathbf{Q} = \left[\mathbf{q}_1^\intercal, ..., \mathbf{q}_N^\intercal\right]^\intercal$, where $\intercal$ is for the transpose. The l-th row of $\mathbf{Q}$ is $\mathbf{q}_l = [q_{l1}, ..., q_{lN}]$ and adds to one.

Define $v_k \equiv v(\pi_k)$ and $\tilde{v}_{lk} \equiv \tilde{v}_l(\pi_k)$. We may now rewrite (5) as

$$\tilde{v}_{lk} = v_k + \eta\psi \sum_{m>k} q_{lm}(v_m - v_k).$$

Define $\mathbf{I}_k$ as a diagonal matrix with ones only on the diagonal elements $k+1$ through N (e.g., $\mathbf{I}_N$ is the null matrix). Let $\mathbf{1}$ be a column vector of ones. Also define the row vector $\mathbf{v} = [v_1, ..., v_N]$, of size N. We then rewrite the previous expression in vector notation as

$$\tilde{v}_{lk} = v_k + \eta\psi \mathbf{q}_l \mathbf{I}_k (\mathbf{v}^\intercal - \mathbf{1} v_k).$$

Let $\tilde{\mathbf{v}}_l$ be the $1 \times N$ vector collecting all terms $\tilde{v}_{lk}$. We have

$$\begin{aligned} \tilde{\mathbf{v}}_l &= \mathbf{v} + \eta\psi \left(\left(\mathbf{M}_l^0 - \mathbf{M}_l^1\right)\mathbf{v}^\intercal\right)^\intercal \\ &= \mathbf{v} + \eta\psi \mathbf{v}\left(\mathbf{M}_l^0 - \mathbf{M}_l^1\right)^\intercal, \end{aligned}$$

where

$$\mathbf{M}_l^0 \equiv \begin{bmatrix} \mathbf{q}_l \mathbf{I}_1 \\ ... \\ \mathbf{q}_l \mathbf{I}_N \end{bmatrix}, \qquad \mathbf{M}_l^1 \equiv \operatorname{diag}\left(\begin{bmatrix} \mathbf{q}_l \mathbf{c}_1 \\ ... \\ \mathbf{q}_l \mathbf{c}_N \end{bmatrix}\right),$$

and $\mathbf{c}_l = [0, ..., 0, 1, ..., 1]^\intercal = \mathbf{I}_l \mathbf{1}$ with the first 1 in row $l+1$.

Define the scalar $\tilde{v}_l \equiv \sum_{m=1}^{N} q_{lm} \tilde{v}_{lm} = \tilde{\mathbf{v}}_l \mathbf{q}_l^\intercal$. Integrating $\tilde{\mathbf{v}}_l$ over possible future states by post-multiplying $\tilde{\mathbf{v}}_l$ by $\mathbf{q}_l^\intercal$ gives:

$$\tilde{v}_l = \mathbf{v}\mathbf{q}_l^\intercal + \eta\psi \mathbf{v}\left(\mathbf{M}_l^0 - \mathbf{M}_l^1\right)^\intercal \mathbf{q}_l^\intercal.$$

The vector $\tilde{\mathbf{v}}$, composed of the elements $\tilde{v}_l$, can be written as

$$\tilde{\mathbf{v}} = \mathbf{v}\mathbf{Q}^\intercal + \eta\psi \mathbf{v}\mathbf{M}^2, \tag{A1}$$

where

$$\mathbf{M}^2_{(N\times N)} = \left[\ \left(\mathbf{M}_1^0 - \mathbf{M}_1^1\right)^\intercal \mathbf{q}_1^\intercal, ..., \left(\mathbf{M}_N^0 - \mathbf{M}_N^1\right)^\intercal \mathbf{q}_N^\intercal\ \right].$$

Denote the column vector $\boldsymbol{\pi} = [\pi_1, ..., \pi_N]^\intercal$ and rewrite (2) as

$$v_l = \pi_l + \delta\left[(1-\theta)\,\tilde{v}_l + \theta\phi\sum_{k=1}^{N} q_{lk}v_k\right],$$

or in vector notation

$$\mathbf{v} = \boldsymbol{\pi}^\intercal + \delta\left[(1-\theta)\,\tilde{\mathbf{v}} + \theta\phi\mathbf{v}\mathbf{Q}^\intercal\right].$$

Substituting equation (A1) into this last expression gives the solution for $\mathbf{v}$:

$$\mathbf{v} = \boldsymbol{\pi}^\intercal\left\{\mathbf{I} - \delta\left[(1-\theta)\left(\mathbf{Q}^\intercal + \eta\psi\mathbf{M}^2\right) + \theta\phi\mathbf{Q}^\intercal\right]\right\}^{-1}. \tag{A2}$$

This inverse matrix exists as a consequence of Proposition 1.

For the valuation of dispersed shareholders, define the row vector $\mathbf{p} = [p_1, ..., p_N]$, of size N, where $p_l \equiv p(\pi_l)$. To solve for $\tilde{p}_{lk} \equiv \tilde{p}_l(\pi_k)$ in (7), we first write equation (7) in vector notation:

$$\tilde{p}_{lk} = p_k + \eta\mathbf{q}_l\mathbf{I}_k\left(\mathbf{p} - \mathbf{1}p_k\right).$$

As with $\tilde{\mathbf{v}}_l$, the vector $\tilde{\mathbf{p}}_l$ of size $(1\times N)$ that collects all $\tilde{p}_{lk}$ can be written as

$$\tilde{\mathbf{p}}_l = \mathbf{p} + \eta\mathbf{p}\left(\mathbf{M}_l^0 - \mathbf{M}_l^1\right)^\intercal.$$

Define the scalar $\tilde{p}_l \equiv \sum_{m=1}^{N} q_{lm}\tilde{p}_{lm} = \tilde{\mathbf{p}}_l\mathbf{q}_l^\intercal$. Integrating $\tilde{\mathbf{p}}_l$ over possible future states by post-multiplying $\tilde{\mathbf{p}}_l$ by $\mathbf{q}_l^\intercal$ gives:

$$\tilde{p}_l = \mathbf{p}\mathbf{q}_l^\intercal + \eta\mathbf{p}\left(\mathbf{M}_l^0 - \mathbf{M}_l^1\right)^\intercal\mathbf{q}_l^\intercal.$$

The row vector $\tilde{\mathbf{p}}$, composed of the elements $\tilde{p}_l$, can be written as

$$\tilde{\mathbf{p}} = \mathbf{p}\mathbf{Q}^\intercal + \eta\mathbf{p}\mathbf{M}^2.$$

Now, write equation (6),

$$p_l = \pi_l + \delta\left[(1-\theta)\,\tilde{p}_l + \theta\sum_{k=1}^{N} q_{lk}p_k\right],$$

or in vector notation:

$$\mathbf{p} = \boldsymbol{\pi}^{\intercal} + \delta\left[(1-\theta)\,\tilde{\mathbf{p}} + \theta\mathbf{p}\mathbf{Q}^{\intercal}\right].$$

Substituting in for the value of $\tilde{\mathbf{p}}$ and solving for $\mathbf{p}$ yields,

$$\mathbf{p} = \boldsymbol{\pi}^{\intercal}\left\{\mathbf{I} - \delta\left[\mathbf{Q}^{\intercal} + (1-\theta)\,\eta\mathbf{M}^{2}\right]\right\}^{-1}. \tag{A3}$$

This inverse matrix exists as a consequence of Proposition 2.

Appendix C. Details of the estimation procedure

This appendix describes the procedure to estimate the model in Section II. We start by estimating the Markov transition matrix, $\mathbf{Q}$, with conditional probabilities q_{lm}. For each trade we estimate an AR(1) process of the detrended logarithm of the average yearly cash flows of all firms in the same 3-digit SIC as the target, using at least the last fifteen years of data preceding the trade. We feed the estimated AR(1) process to the Tauchen and Hussey (1991) quadrature method to compute the industry's discrete cash flow grid, $\{\pi_1, \pi_2, ..., \pi_N\}$, and the Markov transition matrix, $\mathbf{Q}$, for the same year as the trade. We set N to 15. We then recover the target's cash flow grid by assuming that, in each state, the target's cash flow is proportional to the industry cash flow, where the constant of proportionality is the ratio of the observed target share price to the equal-weighted 3-digit SIC average share price.

We estimate the parameters, $\boldsymbol{\Gamma} = \{\psi, \eta, b_0, b_1, b_2, \boldsymbol{\beta}, \boldsymbol{\gamma}\}$ using SMM. That is, $\widehat{\boldsymbol{\Gamma}}$ minimizes

$$\mathcal{J}(\boldsymbol{\Gamma}) = (\mathbf{m}(.,\boldsymbol{\Gamma}) - \mathbf{M})' \, \mathbf{W} \, (\mathbf{m}(.,\boldsymbol{\Gamma}) - \mathbf{M}),$$

where $\mathbf{m}(\{BP_i, CAR_i, \mathbf{x}_i, \mathbf{z}_i\}; \boldsymbol{\Gamma})$ is a vector of moments derived from the joint distribution of BP and CAR simulated by the model; $\mathbf{M}$ is the vector of the same moments from actual data; $\{BP_i, CAR_i\}_i$ are the block premium and cumulative abnormal returns data, for each deal, i; $\{\mathbf{x}_i, \mathbf{z}_i\}_i$ are the data on the determinants of θ_i and ϕ_i; and, $\mathbf{W}$ is a weighting matrix.

To evaluate $\mathcal{J}$, we proceed iteratively. Let $\boldsymbol{\Gamma}^{(n)}$ be the candidate parameter vector at each iteration $n \geq 0$, with $\boldsymbol{\Gamma}^{(0)}$ being the initial candidate minimizer:

1. Evaluate $\theta_i = \Lambda\left(\mathbf{x}_i'\boldsymbol{\beta}^{(n)}\right)$ and $\phi_i = \Lambda\left(\mathbf{z}_i'\boldsymbol{\gamma}^{(n)}\right)$ for each deal i;
2. Evaluate $\mathbf{m}\left(\{BP_i, CAR_i, \mathbf{x}_i, \mathbf{z}_i\}; \boldsymbol{\Gamma}^{(n)}\right)$ by numerical simulation, following the next steps:

   (a) solve for the functions $v(\pi)$ and $p(\pi)$ from the system of equations (A2) and (A3), for each i, given $\boldsymbol{\Gamma}^{(n)}$;

   (b) compute the model's CAR for all possible states before and after the trade, lm, and choose the grid values $\pi_i^I = \pi_l$ and $\pi_i^R = \pi_m$ that minimize the distance between the actual CAR and $\frac{p(\pi_m)}{p(\pi_l)} - 1$;

(c) compute the model's block premium using

$$\begin{cases} \phi_i v\left(\pi_i^R\right)/p\left(\pi_i^I\right) - 1, & \text{if } CAR_i < 0, \\ s\left(\pi_i^I, \pi_i^R\right)/p\left(\pi_i^I\right) - 1, & \text{if } BP_i \geq CAR_i \geq 0, \\ \begin{array}{c} q_{liq} \times \left(\phi_i v\left(\pi_i^R\right)/p\left(\pi_i^I\right) - 1\right) + \\ \left(1 - q_{liq}\right)\left(s\left(\pi_i^I, \pi_i^R\right)/p\left(\pi_i^I\right) - 1\right) \end{array}, & \text{if } CAR_i > BP_i \text{ and } CAR_i > 0; \end{cases}$$

where q_{liq} is defined in (11).

(d) compute the relevant conditional and unconditional moments of the simulated $\{\widehat{BP}_i, \widehat{CAR}_i\}$ distribution;

(e) Evaluate $\mathcal{J}\left(\mathbf{\Gamma}^{(n)}\right)$. If $\mathcal{J}$ is not minimized, proceed with new $\mathbf{\Gamma}^{(n+1)}$.

We estimate the optimal weight matrix $\widehat{\mathbf{W}}$ in two stages: we run through steps 1 and 2 with $\mathbf{W}$ set to the identity matrix, and then compute $\widehat{\mathbf{W}} = \frac{1}{N}\left(\mathbf{m}\left(.,\widehat{\Gamma}_{Stage1}\right) \times \mathbf{m}\left(.,\widehat{\Gamma}_{Stage1}\right)'\right)$. We obtain the final parameter estimates after minimizing $\left(\mathbf{m}\left(.,\mathbf{\Gamma}\right) - \mathbf{M}\right)' \widehat{\mathbf{W}} \left(\mathbf{m}\left(.,\mathbf{\Gamma}\right) - \mathbf{M}\right)$.

In our search for the global maximizer, we repeat the maximization from each of 16 possible vectors of initial conditions for $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$. This set is fairly exhaustive, in that each initial condition corresponds to a unique combination of mean and variance of the the logistic distributions of ϕ and θ. For example, one particular initial condition generates a distribution of ϕ with low mean and high variance, and a distribution of θ with high mean and low variance. Hence, we have 2^4 possible combinations of mean and variance for the two distributions. The possible values for the mean are -0.5 (low) and 0.5 (high), and for the variance are 2 (low) and 3 (high), which are chosen so as to get a wide range of implied skewness and kurtosis. Each initial condition is therefore the GMM estimate of $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$ that most closely matches up to the fourth order moments of the joint distribution of θ and ϕ. In short, this procedure guarantees that we start our search for the SMM estimator of $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$ from different points that exhaust the possibilities of the shape of the joint distribution of θ and ϕ. For b_0, b_1, b_2, η and ψ we search in the range of values [0,1].

We estimate the covariance matrix of the estimator, $var\left(\widehat{\mathbf{\Gamma}}\right)$, with $(\mathbf{G}'\widehat{\mathbf{W}}^{-1}\mathbf{G})^{-1}$, where $\mathbf{G}$ is the gradient matrix of vector $\mathbf{m}$ with respect to $\mathbf{\Gamma}^{-1}$. Finally, we verify that our solution is locally identified by checking that the Hessian $\mathbf{H}\left(\widehat{\mathbf{\Gamma}}\right)$ is nonsingular.

Appendix D. Data

Our data consists of acquisitions of blocks between 35% and 90% of the common shares of a company. Our sample selection proceeds in the following manner. From Thomson One Banker Acquisitions, we select from all U.S. disclosed-value acquisitions of 35% up to 90% between January 1, 1990 and December 31, 2010. We use the "Type of Acquisition" field in the Thomson One banker database to exclude: privatizations, tender offers, exchange offers, spin-offs, recapitalizations and repurchases, equity carve-outs, joint ventures, going private deals, debt restructurings, and bankruptcies. There are several reasons behind these exclusions. First, the identification approach requires the existence of a share price for the target before and after the deal (which excludes such deals as equity carve-outs and going private deals). Second, some of these deals possibly involve the creation of a new block of shares (such as a tender offer, and exchange offer, or a joint venture). Third, some of these deals involve possibly a disappearing block (such as a bankruptcy of the target where the debtholders take over control).

We use the "Consideration Sought" field to exclude deals where the exchange involves instruments that could lead to predictable future changes in block size. For example, we exclude deals where payment was made using warrants, convertible bonds, debt-equity swaps, or any form of options. The reason for these exclusions is that the price reaction in the stock market would be responding to a changing block size as well.

We use the "Target Public Status" field to exclude deals where the target firm is private. These target firms have no share price before the deal.

There are 1,751 deals in Thomson One Banker satisfying the first two criteria above, of which only 395 satisfy the third criterion. From our starting sample of 395 deals, we drop the deals where we find additional evidence that deals do not conform with our criteria above (using either the "Deal Synopsis" field from Thomson One Banker or at least two news articles reporting on the deal). We find 146 such violations, where the most common ones are trades where the block is made of newly issued shares (51), or where the acquisition was shortly followed by a pre-announced acquisition for the remaining interest (22) or a tender offer (14). In this sample of 146 deals, the transfer price is observable and confirmed by reading the deal synopsis.

We merge the remaining 249 deals to Compustat and CRSP. We impose the additional restrictions that: (i) the target's traded share price is observable for at least 20 trading days after the announcement, to verify that the share price does not exhibit a trend beyond the window where the cumulative abnormal returns are estimated; (ii) the target's traded share price is observable for at least 51 trading days before the announcement, where the 21 days prior are used to compute pre-announcement price and the previous 30 (or up to 50 if available) are used to estimate the market model. The final sample contains 114 deals. We obtain the 13F filings from Thomson-Reuter's Institutional Holdings data for each target firm in our final sample and verify that no other block larger than 5% exists. This guarantees that some float remains in the stock market, but also that no significant other blockholder exists in conformity with the model.

Appendix E. Private benefits

Consider a version of our model where blocks are priced following Nash-bargaining and trades are due to either higher buyer security benefits or higher buyer private benefits, but not liquidity shocks. Let B_i be the private benefits of agent $i = R, I$. The per share block price s equals:

$$s = \frac{(1-\psi)\left[B_I + \alpha p\left(\pi^I\right)\right] + \psi\left[B_R + \alpha p\left(\pi^R\right)\right]}{\alpha}, \tag{14}$$

which equals the price in equation (4) when $B_I = B_R$ and when there are no liquidity shocks (so $v = p$). It also equals the block price in Dyck and Zingales (2004). The block premium, defined relative to the pre-announcement price $p\left(\pi^I\right)$ (this normalization is different from Dyck and Zingales, 2004), is

$$\begin{aligned} \frac{s}{p\left(\pi^I\right)} - 1 &= \frac{(1-\psi)\left[B_I + \alpha p\left(\pi^I\right)\right] + \psi\left[B_R + \alpha p\left(\pi^R\right)\right] - \alpha p\left(\pi^I\right)}{\alpha p\left(\pi^I\right)} \\ &= \frac{(1-\psi) B_I + \psi B_R}{\alpha p\left(\pi^I\right)} + \psi \frac{p\left(\pi^R\right) - p\left(\pi^I\right)}{p\left(\pi^I\right)}, \end{aligned}$$

or,

$$BP = \frac{(1-\psi) B_I + \psi B_R}{\alpha p\left(\pi^I\right)} + \psi CAR. \tag{15}$$

The gains from trade condition, which states that the block buyer must value the block more than the buyer, including private and shared benefits, is

$$B_R + \alpha p\left(\pi^R\right) > B_I + \alpha p\left(\pi^I\right).$$

Rearranging this condition we obtain a lower bound for CAR, i.e.,

$$CAR > \frac{B_I - B_R}{\alpha p\left(\pi^I\right)}.$$

Together with the block premium in equation (15), this condition implies that

$$\begin{aligned} BP &= \frac{(1-\psi) B_I + \psi B_R}{\alpha p\left(\pi^I\right)} + \psi CAR > \frac{(1-\psi) B_I + \psi B_R}{\alpha p\left(\pi^I\right)} + \psi \frac{B_I - B_R}{\alpha p\left(\pi^I\right)} \\ &\Leftrightarrow \quad BP > \frac{B_I}{\alpha p\left(\pi^I\right)} > 0. \end{aligned} \tag{16}$$

This result says that the block premium in a model where trades may be driven by private benefits but not by liquidity shocks is always positive.

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Table I: Description of variables used and their sources

Type	Variable name	Variable description	Source
Outcome variables	p^0, p^1	Target share prices, adjusted using the market and liquidity factors' model, 21 trading days before (p^0) and 2 trading days after (p^1) the trade announcement ($).	CRSP
	P	Price per share in the block ($), adjusted using the market and liquidity factors' model.	Thomson One Banker
	α	Block size (%).	Thomson One Banker
	Block value	Dollar value of the trade, equal to $\alpha \times P \times$ number of outstanding shares ($ Millions).	Thomson One Banker
	BP	Block premium, defined as $\frac{P-p^0}{p^0}$ (%).	Constructed
	CAR	Market response to the block trade annoucement, defined as $\frac{p^1-p^0}{p^0}$ (%).	Constructed
Determinants of aggregate liquidity ($\mathbf{x}$)	*GDP growth*	Average annual US GDP per capita growth rate in the last quarter prior to the trade (%).	FED Board of Governors
	Market Return	Annualized average daily returns on the equally-weighted portfolio of all NYSE, AMEX and NASDAQ stocks for the last month before the deal (%).	CRSP
	Market Volatility	Standard deviation of the annualized daily returns on the equally-weighted portfolio of all NYSE, AMEX and NASDAQ stocks for the 12 month-period before the deal (%).	CRSP
	Fontaine-Garcia	Fontaine and Garcia's (2011) monthly index of the value of funding liquidity: the higher the index, the lower the bond market liquidity.	Fontaine and Garcia (2011)
	Yield curve slope	Difference between the yield on the 10-year and the 3-month Treasury bill (%).	FED Board of Governors

(continues)

Table I: continued

Type	Variable name	Variable description	Source
Determinants of liquidation values (**z**)	*Block-to-Industry Size*	Ratio of the total *Block value* to the total market capitalization of all NYSE and AMEX firms in the same 2-digit SIC Code as the target.	Thomson One Banker, CRSP
	Industry's M&A Activity	Total M&A activity during the last quarter before the deal, where the target is in the same 2-digit SIC Code as the deal's target ($ Billions).	Thomson One Banker
	Industry Leverage	Median long-term debt to total assets of all the firms in the same 3-digit SIC code of the target firm.	Compustat
	Industry Specificity	Median proportion of machinery and equipment to total assets of all firms in the same 3-digit SIC code as the target firm, as defined by Stromberg (2001).	Compustat
	Industry Market-to-Book	Median ratio of the market value of the firm (book value of debt + market value of equity) to the book value of total assets of all firms in the same 3-digit SIC code as the target firm.	Compustat
	Target Leverage	Proportion of long-term target debt to total assets on the last fiscal year before the trade announcement.	Compustat
	Target minus Industry Leverage	The difference between *Target Leverage* and *Industry Leverage*.	Compustat
	Target Volatility	Standard deviation of the target's annualized average daily return for the 12 month-period ending two months before the trade announcement (%).	Compustat

Table II: Sample summary statistics

This table summarizes the characteristics of the 114 blocks traded in our sample, as well as all the potential determinants of aggregate illiquidity and liquidation costs. The sample consists of all US privately negotiated block trades in the Thomson One Banker's Acquisitions data (formerly SDC) between 1/1/1990 and 31/12/2010, where the block represents between 35% and 90% of the target's outstanding stock.

Variable	Mean	Standard deviation	5th percentile	First quartile	Median	Third quartile	95th percentile
α	59.74%	15.15%	38.55%	49.32%	54.61%	72.33%	87.00%
Block value	192.92	719.23	0.80	7.14	23.02	100.00	774.23
BP	6.79%	58.83%	−89.16%	−18.20%	3.45%	27.80%	121.42%
CAR	9.64%	31.93%	−25.88%	−10.11%	4.96%	23.04%	78.06%
GDP growth	3.23%	3.11%	−3.69%	1.92%	3.10%	5.78%	6.96%
Market Return	12.74%	15.78%	−19.95%	8.89%	14.92%	23.58%	30.69%
Market Volatility	14.03%	5.25%	8.28%	10.10%	11.66%	17.80%	24.06%
Fontaine-Garcia	0.812	0.508	−0.154	0.459	0.914	1.110	1.396
Yield curve slope	1.69%	1.17%	−0.19%	0.69%	1.51%	2.82%	3.45%
Block-to-Industry Size	0.008	0.033	0.000	0.000	0.000	0.001	0.027
Industry's M&A Activity	3.879	3.682	0.173	1.095	2.761	6.084	11.667
Industry Leverage	0.564	0.191	0.377	0.437	0.546	0.629	0.820
Industry Specificity	0.271	0.189	0.015	0.162	0.221	0.336	0.697
Industry Market-to-Book	1.238	0.475	1.000	1.000	1.000	1.249	2.444
Target Leverage	0.600	0.280	0.144	0.376	0.595	0.831	1.000
Target minus Industry Leverage	0.045	0.280	−0.382	−0.158	0.041	0.226	0.566
Target Volatility	39.83%	40.13%	5.51%	10.77%	23.80%	59.08%	110.07%

Table III: Model fit and SMM parameter estimates

This table shows the estimates of the matching probability, η, the block seller's bargaining power, ψ, the controlling shareholder's private benefits of control per share, B_i, and the sensitivities, $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$, of the liquidity shock probability, θ, and the block's liquidation value, ϕ, to $\mathbf{x}$ and $\mathbf{z}$, respectively. For each deal i, θ_i, ϕ_i and B_i are given by

$$\theta_i = \frac{\exp(\mathbf{x}_i'\boldsymbol{\beta} + \beta_0)}{1 + \exp(\mathbf{x}_i'\boldsymbol{\beta} + \beta_0)}, \quad \phi_i = \frac{\exp(\mathbf{z}_i'\boldsymbol{\gamma} + \gamma_0)}{1 + \exp(\mathbf{z}_i'\boldsymbol{\gamma} + \gamma_0)},$$
$$\text{and} \quad B_i = b_0 + b_1 \times E(v_i) + b_2 \times E(p_i) \times \frac{1-\alpha_i}{\alpha_i},$$

where $E(v_i)$ is the expected private value of the block, $E(p_i)$ is the expected dispersed shareholders valuation of the shares and α_i is the block size. The parameters are estimated using the Simulated Method of Moments, matching the actual moments, $\mathbf{M}$, of the joint distribution of the percentage block premium, BP, and the cumulative abnormal returns, CAR, to those simulated by the theoretical search model, $\mathbf{m}(\psi, \eta, b_0, b_1, b_2, \boldsymbol{\beta}, \boldsymbol{\gamma})$. The data is for a sample of 114 US negotiated block trades in the Thomson One Banker's Acquisitions data between 1/1/1990 and 31/12/2010. Blocks are larger than 35% and smaller than 90% of the outstanding stock. Standard errors are shown in parenthesis next to the coefficient estimates.[a] The economic significance of each coefficient is the change in θ_i or ϕ_i associated with a one sample standard deviation change in each variable in $\mathbf{x}$ and $\mathbf{z}$, respectively.

Panel A: Model fit

	(1)				(2)			
	BP		**CAR**		**BP**		**CAR**	
	Actual	*Predicted*	*Actual*	*Predicted*	*Actual*	*Predicted*	*Actual*	*Predicted*
Mean	0.067	0.101	0.096	0.022	0.067	0.062	0.096	0.023
Std. deviation	0.584	0.468	0.319	0.078	0.584	0.269	0.319	0.078
Median	0.035	0.058	0.050	0.016	0.035	0.043	0.050	0.017
Proportion of negatives	0.465	0.412	0.421	0.421	0.465	0.404	0.421	0.412
corr(*Actual*, *Predicted*)		0.121		0.393		0.111		0.396
	Over-identifying restrictions test[b]		Joint significance test[c]		Over-identifying restrictions test[b]		Joint significance test[c]	
	χ^2	p value	χ^2	p value	χ^2	p value	χ^2	p value
	28.28	0.34	1,587.60	0.00	41.93	0.07	1,953.21	0.00

(continues)

Table III: continued

Panel B: Parameter estimates

	(1)				(2)			
	Coefficient				Coefficient			
η	0.59***	(0.17)			0.43***	(0.10)		
ψ	0.48***	(0.15)			0.54***	(0.14)		
Liquidity shock determinants (x)								
	Coefficient		Economic significance		Coefficient		Economic significance	
GDP growth	−36.46***	(11.18)	−0.03***	(0.01)	−12.00**	(6.02)	−0.03**	(0.01)
Market Return	−28.47***	(10.36)	−0.11***	(0.04)	−27.31*	(15.31)	−0.31*	(0.17)
Market Volatility	−26.34*	(14.21)	−0.03*	(0.02)	−14.30**	(6.33)	−0.05**	(0.02)
Fontaine-Garcia	0.60***	(0.19)	0.07***	(0.02)	0.96**	(0.47)	0.03**	(0.02)
Yield curve slope	0.21*	(0.12)	0.06*	(0.03)	1.44***	(0.49)	0.12***	(0.04)
× *GDP growth*					50.68***	(10.86)	0.24***	(0.05)
× *Market Return*					5.62***	(1.80)	0.13***	(0.04)
Constant (β_0)	2.17	(12.66)			1.37	(2.41)		
Liquidation value determinants (z)								
	Coefficient		Economic significance		Coefficient		Economic significance	
Block-to-Industry Size	0.09	(4.31)	0.00	(0.02)	−0.17	(0.67)	0.00	(0.00)
Industry's M&A Activity	0.43	(0.29)	0.17	(0.11)	0.51	(0.40)	0.12	(0.09)
Target - Industry Leverage	−0.98***	(0.35)	−0.03***	(0.01)	−2.40***	(0.64)	−0.04***	(0.01)
Industry Specificity	−0.24***	(0.04)	0.00***	(0.00)	−1.83***	(0.45)	−0.02***	(0.01)
Industry Market-to-Book	1.02***	(0.29)	0.05***	(0.01)	3.85	(2.36)	0.12	(0.07)
Target Volatility	0.87***	(0.29)	0.04***	(0.01)	1.08	(0.91)	0.03	(0.02)
Constant (γ_0)	−0.81**	(0.32)			−2.53**	(1.09)		
Private benefits of control								
	Coefficient		Sample mean (Std. deviation)		Coefficient		Sample mean (Std. deviation)	
b_0	0.09***	(0.01)	0.176	(0.120)	0.05**	(0.03)	0.079	(0.097)
b_1	0.14***	(0.04)			0.04	(0.04)		
b_2	0.10**	(0.04)			0.05	(0.05)		

[a] Estimates followed by ***, ** and * are statistically different from zero with 0.01, 0.05 and 0.1 significance levels, respectively.
[b] The null hypothesis is that the optimally weighted distance between the actual and simulated moments vector is zero.
[c] The null hypothesis is that all model parameters are zero.

Table IV: Actual and simulated moments

This table shows the moments used in the SMM estimation. The moments are simulated from the theoretical search model using the parameter estimates for specifications (1) and (2) in Table III. The moment condition t-statistic is for the test that the simulated moment equals the actual data moment. The data used are for a sample of 114 US negotiated block trades in the Thomson One Banker's Acquisitions data between 1/1/1990 and 31/12/2010. Blocks are larger than 35% and smaller than 90% of the outstanding stock.

Conditional moments

	Actual	Std. Error	(1) Simulated	(1) t-statistic	(2) Simulated	(2) t-statistic
$E[BP - CAR \mid BP > CAR > 0]$	0.271	0.110	0.197	0.669	0.132	1.268
$E[(BP - CAR) \times x \mid$						
$BP > CAR > 0]$						
GDP growth	0.008	0.003	0.005	0.846	−0.005	3.589
Market Return	0.022	0.021	0.006	0.738	−0.022	2.076
Market Volatility	0.038	0.018	0.031	0.394	0.008	1.681
Fontaine-Garcia	−0.149	0.066	−0.094	−0.840	−0.100	−0.753
Yield curve slope	−0.503	0.288	−0.379	−0.427	−0.140	−1.259
× *GDP growth*	−0.012	0.005			−0.010	−0.355
× *Market Return*	−0.013	0.045			−0.056	0.952
$E[BP \mid CAR < 0, BP < 0]$	−0.368	0.077	−0.143	−2.909	−0.317	−0.660
$E[BP \times z \mid CAR < 0, BP < 0]$						
Block-to-Industry Size	−0.004	0.004	−0.002	−0.574	−0.004	−0.026
Industry's M&A Activity	−1.593	0.401	−0.304	−3.216	−0.217	−3.434
Target - Industry Leverage	−0.039	0.027	−0.067	1.029	−0.018	−0.776
Industry Specificity	−0.115	0.030	−0.139	0.794	−0.096	−0.624
Industry Market-to-Book	−0.483	0.112	−0.450	−0.301	−0.338	−1.294
Target Volatility	−0.148	0.040	−0.150	0.060	−0.061	−2.167

Second order moments

	Actual	Std. Error	(1) Simulated	(1) t-statistic	(2) Simulated	(2) t-statistic
$Var[BP \mid BP > CAR > 0]$	0.417	0.368	0.213	0.553	0.142	0.745
$Var[CAR \mid BP > CAR > 0]$	0.126	0.046	0.005	2.649	0.005	2.654
$E[BP \times CAR \mid BP > CAR > 0]$	0.227	0.070	0.159	0.967	0.147	1.142
$Var[(BP - CAR) \mid BP > CAR > 0]$	0.181	0.343	0.188	−0.022	0.140	0.119
$Var[BP \mid CAR < 0, BP < 0]$	0.196	0.050	0.029	3.336	0.102	1.881
$Var[CAR \mid CAR < 0, BP < 0]$	0.040	0.012	0.003	3.060	0.003	3.059
$E[BP \times CAR \mid CAR < 0, BP < 0]$	0.080	0.022	0.019	2.756	0.003	3.464

(continues)

Table IV: continued

Unconditional moments

	Actual	Std. Error	(1) Simulated	(1) t-statistic	(2) Simulated	(2) t-statistic
$E(BP)$	0.067	0.077	0.102	−0.461	0.062	0.059
$E[BP \times z]$						
Block-to-Industry Size	−0.001	0.002	0.001	−0.630	−0.001	0.523
Industry's M&A Activity	0.183	0.337	0.519	−0.997	0.102	0.240
Target - Industry Leverage	0.002	0.028	0.016	−0.483	0.015	−0.452
Industry Specificity	0.000	0.019	0.016	−0.843	−0.030	1.612
Industry Market-to-Book	0.094	0.102	0.137	−0.427	−0.039	1.295
Target Volatility	−0.013	0.054	0.051	−1.198	−0.017	0.074
$E[BP \times x]$						
GDP growth	0.001	0.004	0.006	−1.153	−0.003	0.798
Market Return	−0.009	0.015	0.016	−1.615	−0.009	0.036
Market Volatility	0.013	0.012	0.016	−0.239	−0.001	1.108
Fontaine-Garcia	−0.003	0.061	0.060	−1.033	−0.075	1.195
Yield curve slope	−0.132	0.149	0.139	−1.816	−0.179	0.315
× *GDP growth*	−0.002	0.006			−0.010	1.393
× *Market Return*	−0.026	0.022			−0.032	0.251
$E(CAR)$	0.096	0.029	0.022	2.543	0.023	2.515
$E[CAR \times z]$						
Block-to-Industry Size	0.000	0.000	0.000	−0.655	0.000	−0.653
Industry's M&A Activity	0.293	0.118	0.130	1.387	0.132	1.365
Target - Industry Leverage	−0.005	0.009	0.000	−0.483	0.000	−0.473
Industry Specificity	0.023	0.008	0.027	−0.644	0.029	−0.874
Industry Market-to-Book	0.118	0.037	0.028	2.443	0.029	2.421
Target Volatility	0.034	0.011	0.012	1.961	0.013	1.923
$E[CAR \times x]$						
GDP growth	0.002	0.001	0.001	1.666	0.001	1.635
Market Return	0.003	0.005	0.001	0.208	0.002	0.190
Market Volatility	0.016	0.005	0.023	−1.528	0.024	−1.739
Fontaine-Garcia	0.056	0.027	0.017	1.463	0.017	1.451
Yield curve slope	0.205	0.066	0.040	2.490	0.041	2.478
× *GDP growth*	0.005	0.002			0.001	1.774
× *Market Return*	0.001	0.013			0.001	0.004

Table V: In-sample estimates of the costs of illiquidity

This table summarizes the sample distribution of the main variables in the theoretical search model, predicted using the estimates of the parameters reported specification (2) of Table III. The data used are for a sample of 114 US negotiated block trades in the Thomson One Banker's Acquisitions data between 1/1/1990 and 31/12/2010. Blocks are larger than 35% and smaller than 90% of the outstanding stock.

	Sample mean	Standard deviation	Min	First quartile	Median	Third quartile	Max
Owner's liquidity parameter (θ)	0.198	0.297	0.000	0.008	0.045	0.244	0.999
Asset's liquidity parameter (ϕ)	0.921	0.097	0.587	0.889	0.966	0.995	1.000
Marketability discount $(1 - \frac{v(\theta,\phi,\eta,.)}{v(\theta=0,\phi,\eta=1,.)})$	0.131	0.222	0.002	0.010	0.024	0.125	0.887
Illiquidity spillover discount $(1 - \frac{p(\theta,\phi,\eta,.)}{p(\theta=0,\phi,\eta=1,.)})$	0.021	0.015	0.003	0.012	0.017	0.027	0.097
Control discount $(1 - \frac{v(\theta,\phi,\eta,.)}{p(\theta,\phi,\eta,.)})$	0.125	0.223	0.001	0.005	0.016	0.110	0.886

Table VI: The costs of illiquidity by 2-digit SIC Group

This table summarizes the sample distribution of the different discounts in the theoretical search model, by 2-digit SIC Group where the target firm is in, and predicted using the estimates of the parameters reported in Table III, specification (2). The data used are for a sample of 114 US negotiated block trades in the Thomson One Banker's Acquisitions data between 1/1/1990 and 31/12/2010. Blocks are larger than 35% and smaller than 90% of the outstanding stock. Industries with fewer than 3 observations are excluded from the ranking and computations.

Marketability discount

Major Group	Top 5	N	Mean	SD	Major Group	Bottom 5	N	Mean	SD
45	Air Transportation	3	0.462	0.432	63	Insurance Carriers	3	0.024	0.009
15	Building Contractors	4	0.233	0.323	73	Business Services	5	0.022	0.013
13	Oil And Gas Extraction	8	0.219	0.265	36	Electronic And Other Electrical Equipment (Except Computers)	3	0.017	0.004
20	Food And Kindred Products	4	0.156	0.255	49	Electric, Gas, And Sanitary Services	4	0.014	0.011
80	Health Services	5	0.155	0.252	60	Depository Institutions	3	0.009	0.000

Illiquidity-spillover discount

Major Group	Top 5	N	Mean	SD	Major Group	Bottom 5	N	Mean	SD
87	Engineering, Accounting and Management Services	3	0.061	0.031	50	Wholesale Trade-durable Goods	4	0.012	0.004
15	Building Contractors	4	0.042	0.006	35	Industrial And Commercial Machinery	4	0.010	0.002
45	Air Transportation	3	0.031	0.007	37	Transportation Equipment	4	0.009	0.003
73	Business Services	5	0.030	0.028	20	Food And Kindred Products	4	0.008	0.002
36	Electronic And Other Electrical Equipment (Except Computers)	3	0.028	0.006	49	Electric, Gas, And Sanitary Services	4	0.007	0.003

Control discount

Major Group	Top 5	N	Mean	SD	Major Group	Bottom 5	N	Mean	SD
45	Air Transportation	3	0.456	0.435	63	Insurance Carriers	3	0.020	0.009
15	Building Contractors	4	0.223	0.327	49	Electric, Gas, And Sanitary Services	4	0.011	0.011
13	Oil And Gas Extraction	8	0.212	0.267	73	Business Services	5	0.008	0.006
20	Food And Kindred Products	4	0.154	0.255	36	Electronic And Other Electrical Equipment (Except Computers)	3	0.006	0.004
37	Transportation Equipment	4	0.151	0.290	60	Depository Institutions	3	0.004	0.000

Table VII: Pricing outcomes under different trading motives

This table maps the possible types of block trades into the four expected outcomes of the joint distribution of the signs of the block premium, BP, and the cumulative abnormal returns of the trade announcement, CAR. Considering only trades due to liquidity shocks and trades due to heterogeneity in private benefits we have the following categorization: L1 type trades denote liquidity-driven block sales to a blockholder that is more efficient at running the firm and increases its security benefits; L2 types refer to liquidity-driven sales to a less efficient buyer; B1 trades represent block sales in which the buyer derives more private benefits than the seller while increasing security benefits; B2 trades are those where the buyer has higher private benefits but lowers the firm's security benefits.

	$BP < 0$	$BP > 0$
$CAR > 0$	L1	L1 or B1
$CAR < 0$	L2	B2

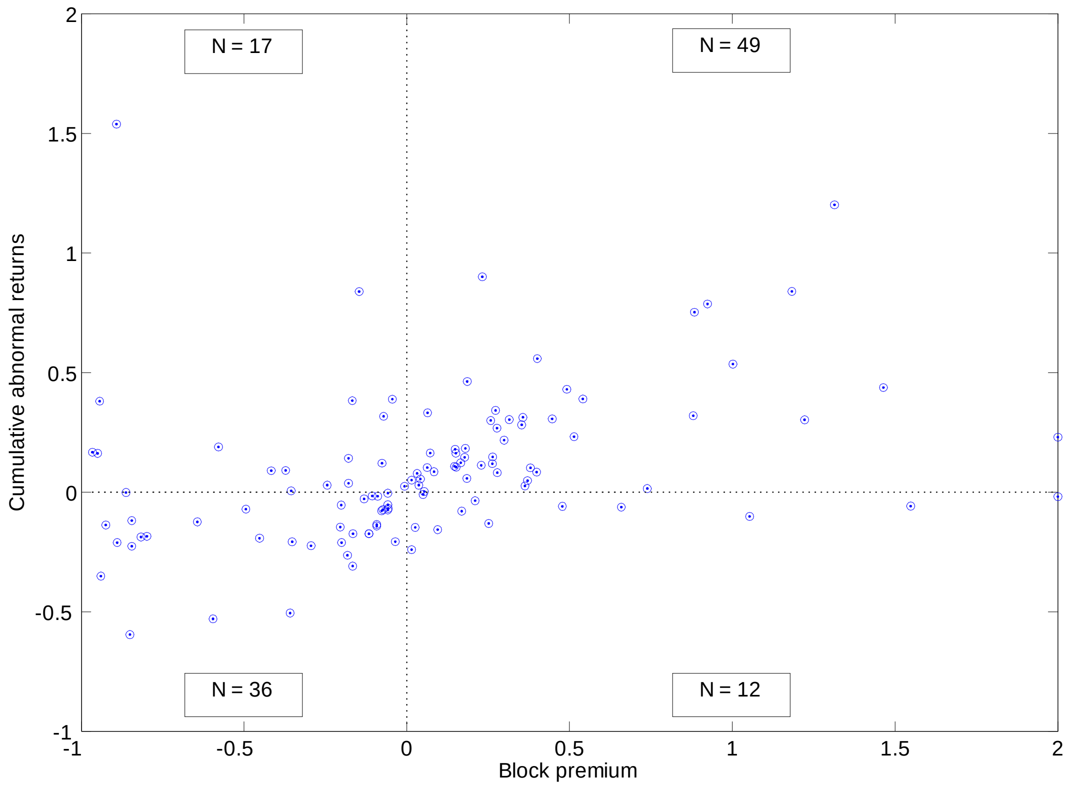

FIGURE 1: Scatter plot of the cumulative abnormal return around the announcement of the block trade against the block premium.

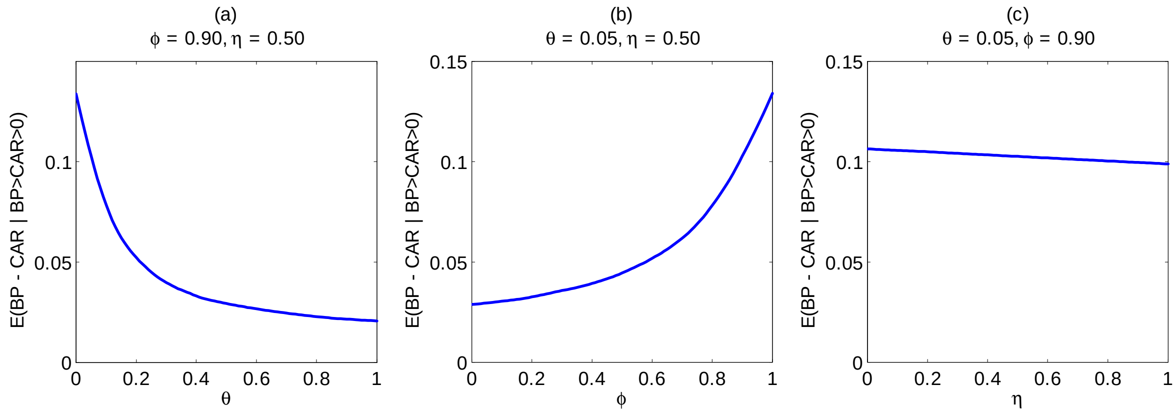

Figure 2: Expected difference between the block premium per share (BP) and the target's cumulative abnormal return (CAR), conditional on $BP > CAR > 0$, as a function of the blockholder's liquidity parameter, θ, the asset's liquidity, ϕ, and market thinness, η. When held constant, θ is set to 0.05, ϕ is set to 0.90, η is set to 0.50. For the remaining parameters, the incumbent blockholders' bargaining power, ψ, is set to 0.5, the average private benefits, B, are set to 8% per share in the block and the discount factor, δ, is set to 1/1.1. The Markov transition matrix is generated by discretizing an AR(1) cash flow process with serial correlation of 0.07, variance of 0.05 and long run mean of 0.02. The averages are computed over 10,000 simulations for each value of the varying parameter.

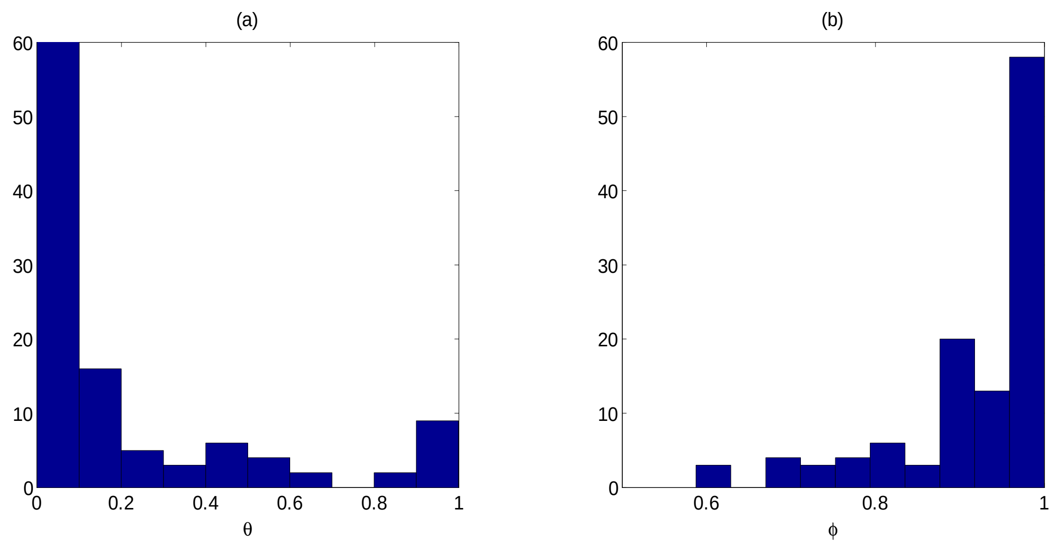

FIGURE 3: Panel (a) presents the predicted histogram of the probability that a blockholder gets a liquidity shock, θ, and panel (b) presents the predicted histogram of the liquidation value parameter, ϕ. The histograms are constructed using the coefficients in Table III, specification (2).

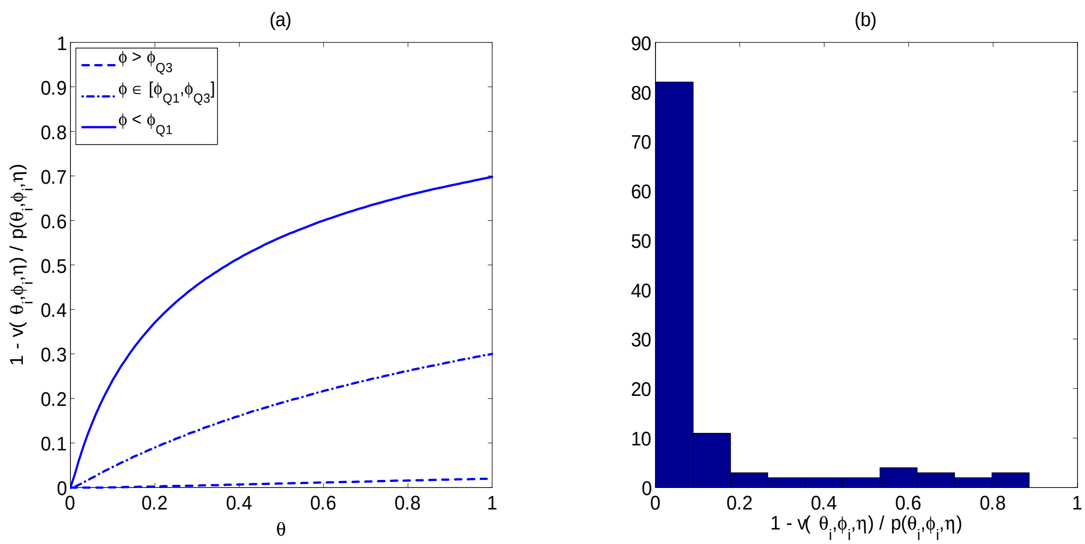

FIGURE 4: Predicted marketability discount of the controlling block from security benefits, $1 - \frac{v(\theta,\phi_i,\eta)}{v(0,1,1)}$, for every value of θ (panel (a)), and predicted histogram of the marketability discount (panel (b)) evaluated at the predicted probability that the blockholder gets a liquidity shock, θ_i, the predicted block liquidation parameter, ϕ_i, and the predicted market thinness, η. The marketability discount function and histogram are constructed using the coefficients in Table III, specification (2).

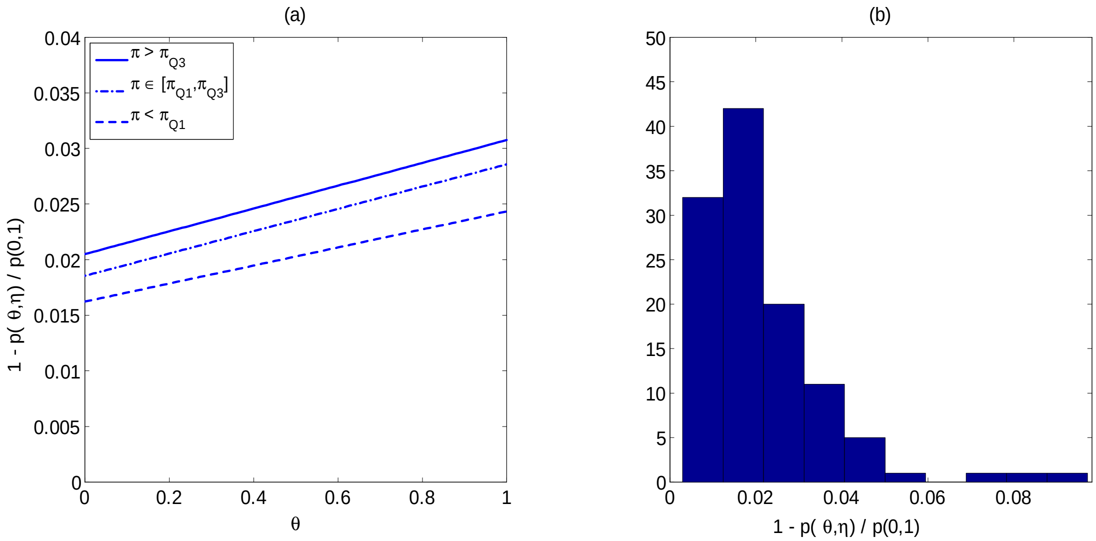

FIGURE 5: Predicted illiquidity-spillover discount of the dispersed shares, $1-\frac{p(\theta,\eta)}{p(0,1)}$, for every value of θ (panel (a)), and predicted histogram of the illiquidity spillover discount (panel (b)) evaluated at the predicted probability that the blockholder gets a liquidity shock, θ_i, the predicted block liquidation parameter, ϕ_i, and the predicted market thinness, η. The illiquidity-spillover discount function and histogram are constructed using the coefficients in Table III, specification (2).

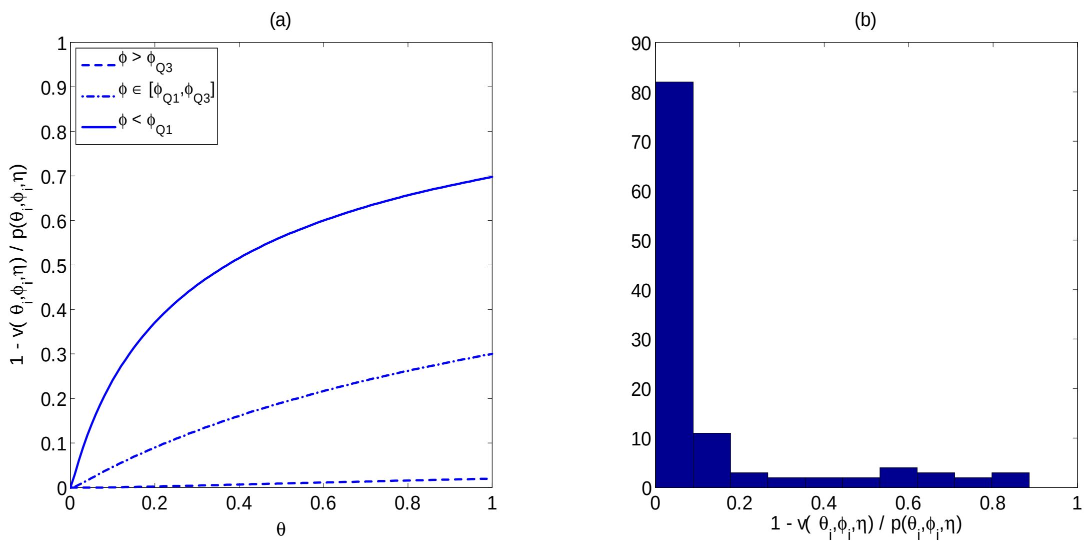

FIGURE 6: Predicted control discount of the value of security benefits in the block relative to dispersed shares, $1 - \frac{v(\theta,\phi_i,\eta)}{p(\theta,\phi_i,\eta)}$, for every value of θ (panel (a)), and predicted histogram of the control discount (panel (b)) evaluated at the predicted probability that the blockholder gets a liquidity shock, θ_i, the predicted block liquidation parameter, ϕ_i, and the predicted market thinness, η. The control discount function and histogram are constructed using the coefficients in Table III, specification (2).

Notes

[1]Contrary to a long-held belief (e.g., Berle and Means (1932)), Holderness (2009) shows, using a representative sample of U.S. public firms, that 96% of these firms have blockholders and that these blockholders own in aggregate an average of 39% of the common stock. Using a sample of large US corporations from 1996-2001, Dlugosz et al. (2006) find that 75% of all firm-year observations have blockholders that own at least 10% of the firms' equity. Holderness, Kroszner, and Sheehan (1999) report that the mean percentage share ownership of a firm's officers and directors in 1995 was 21%. See Morck (2007) for evidence outside the U.S.

[2]The Internal Revenue Service estimates that in 2007 the wealth of U.S. investors allocated to closely held stock (in companies that are not publicly traded) was 62% of the wealth allocated to publicly traded stock.

[3]The block fire sale discount estimate is similar to those in other markets: Coval and Stafford (2007) estimate a 10% discount on stocks that experience price pressure due to mutual fund outflows; Pulvino (1998) estimates a 14% fire sale discount for aircraft of some airlines; Andersen and Nielsen (2013) estimate a 12.5% discount on forced sales in the real estate market.

[4]The spillover effect is economically significant and equal to five times the size of the mean equal-weight quoted bid-ask spread on equities (see Bollen, Smith, and Whaley (2004)).

[5]The empirical literature has shown a positive association between float and liquidity of dispersed shares (e.g., Heflin and Shaw (2000); Becker, Cronqvist, and Fahlenbrach (2011); Brockman, Chung, and Yan (2008); and Dlugosz et al. (2006)).

[6]Note that the first condition in the vector of conditions in $E\left(BP \times \mathbf{x}\right)$ and $E\left(BP \times \mathbf{z}\right)$ is the same, because both $\mathbf{x}$ and $\mathbf{z}$ have a constant term. The estimation only includes one of these conditions. The same is true for $E(CAR \times \mathbf{x})$ and $E(CAR \times \mathbf{z})$.

[7]See, for example, Benmelech and Bergmann (2008) and Gavazza (2010).

[8]For specification (1), the estimated average θ is 0.1, with a standard deviation of 0.26. According to specification (1), on average a blockholder is hit by a liquidity shock that forces a sale once every ten years.

[9]The changes in the sample mostly cause changes in the estimates of B, ψ, and η, and a loss of statistical significance in general. These changes are more pronounced once we exclude 15 or more deals but, by this stage, the deals excluded have very high CAR and are therefore informative not only of liquidity shocks but also of all the other model parameters.