

# Search Frictions and the Liquidity of Large Blocks of Shares\*

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## Abstract

This paper investigates empirically the illiquidity of majority blocks of shares in the context of a search model of block trades. Combining search frictions with the risk of aggregate liquidity shocks incorporates two dimensions of illiquidity: first, following a sudden preference for cash, the controlling blockholder may be forced to sell to a less efficient acquirer. Second, the block liquidity sale may occur at a fire-sale price. We structurally estimate the model using data on majority block trades in the U.S. The structural estimation is particularly useful in this exercise as it allows us to identify (i) the (aggregate) probability of being illiquid from (ii) the (firm-specific) cost of fire-selling the block conditional on a liquidity shock. Such distinction is useful also to value large blocks, which are affected by both components (the "marketability discount"), and dispersed shares, which are affected only by the risk of inefficient turnover (the "illiquidity-spillover discount")

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# 1. Introduction

This paper investigates empirically the illiquidity of concentrated share ownership by studying what happens when majority blocks trade. Because of their size, majority blocks may be sensitive to aggregate liquidity shocks, such as the tightening of aggregate funding, which would trigger blockholders into fire-selling the block to meet a sudden preference for cash. Therefore, majority block trading may be a natural setting to study the impact and the determinants of aggregate liquidity shocks. Moreover, and contrary to popular belief, recent literature points to the presence of large blockholders as a prevalent feature in many publicly held corporations in the U.S.<sup>1</sup>, underscoring the need to quantify the liquidity costs of concentrated ownership.

Our starting point is the observation that a controlling blockholder affects the value of the assets (Holderness and Sheehan, 1988, and Barclay and Holderness, 1989). Unless he is forced to, the controlling shareholder of a public corporation will only sell his block to a bidder who can further increase asset value. But if the controlling blockholder has a liquidity shock and is forced to sell, he may sell to a party that generates a lower asset value and be paid a fire sale price. Therefore, the possibility of a liquidity shock induces a known *marketability discount* on the price of shares owned by the blockholder. In addition, we argue that the possibility that the new blockholder generates a lower security value induces an *illiquidity-spillover discount* on the dispersed shares traded in the stock market. In the first part of the paper, we provide a search model of controlling-block trading and pricing. In the second part of the paper, we estimate the model using data on majority-block trades in the U.S. Our results allow us to shed light into the size of these discounts and the determinants of aggregate liquidity.

The estimation of the marketability discount (and of the illiquidity-spillover discount) is notoriously difficult since it requires the quantification of a counter-factual price: What should the share price be absent liquidity shocks? The structural estimation uses the model pricing equations to evaluate this counter-factual price. However, data limitations imply that the structural estimation must be able to identify liquidity costs and related search frictions without knowledge of the spell of time between trades of the same block.<sup>2</sup> One contribution of this paper is to show that it is possible to identify liquidity shocks and fire sale values by using the valuations of two different investors on the firm: the blockholders' valuation in the negotiated block price, and the dispersed shareholders' valuation in the exchange share price.

In the model, a liquidity shock is the realization of a random variable with Bernoulli distribution that

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<sup>1</sup>Holderness (2009) constructs a representative sample of U.S. public firms and shows that 96% of these firms have blockholders and that these blockholders own in aggregate an average 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.

<sup>2</sup>The labor search literature uses the duration of the unemployment spell to infer the probability of a job offer (see Wolpin, 1987). Similarly, in the first estimation of search models in Finance to our knowledge, Feldhütter (2010) uses the fact that a bond is traded in different amounts to infer selling pressure.

forces blockholder turnover. The new blockholder may be more or less efficient than the old blockholder in generating cash flow but, because he is buying from a distressed seller, he is assumed to pay a fire sale price equal to a fraction of his valuation of the block. In contrast, dispersed shareholders are not directly hit by the liquidity shock and do not sell unless paid a price that reflects the present discounted value of future cash flows under the new blockholder. This distinction allows us to identify fire sale prices. If the liquidity shock does not occur, the block changes hands only if the potential new blockholder generates more cash flow. The outcome from the bargaining that ensues produces another pricing disparity relative to dispersed shareholders, which we use to identify liquidity shocks. In short, we estimate both the probability of a liquidity shock and the fire sale price of the block using information from block prices and abnormal stock market price run-ups around these events. We allow the probability of a liquidity shock and the fire sale price to depend on aggregate and deal-specific determinants of liquidity in order to match the cross-sectional and time-series variation in the observed prices.

We find that the marketability discount varies significantly across our sample, with an average that ranges between 6% to 7% of the block value, and a maximum between 36% to 63%. The marketability discount is explained by a combination of a rather low estimated probability of getting a liquidity shock (mean of 0.06) but a rather high and heterogeneous estimated fire sale value: on average, blocks are sold for between 10% and 48% of the buyer's valuation, conditional on the seller being illiquid. The spillover effect of the block's illiquidity on dispersed shares is very small. While the illiquidity-spillover discount can reach up to 3% upon the realization of a liquidity shock, we estimate it to be lower than 0.5% unconditionally. The low illiquidity spillover to dispersed shares results from it depending on the probability of a liquidity shock but not on the block liquidation value.

The marketability discount is largest for blocks of firms in industries that are underperforming relative to other industries in the sample (e.g., electronic and electrical equipment or transportation equipment), or in times of tighter aggregate financing conditions, e.g., of low market returns, high volatility and low GDP growth. The marketability discount is also high for firms in industries with low tangibility and more restricted asset redeployability (e.g., electronics or specialized equipment manufacturers). Similarly, the marketability discount is lowest for firms in industries of high tangibility (e.g., wholesalers of tradeable goods, food producers) or in times of high liquidity. Therefore, liquidity costs depend both on aggregate conditions and firm-specific characteristics.

We find too that aggregate determinants of liquidity capture unobserved variation in the probability of a liquidity shock, whereas firm or industry characteristics that measure asset redeployability explain well the variation in liquidation values. On the one hand, the probability of getting a liquidity shock is increasing in the market return and decreasing in the market return volatility. It is also very sensitive to, and increasing in, the Pástor and Stambaugh (2003) measure of aggregate liquidity. On the other hand, the block's liquidation value decreases with the target's stock's past performance volatility, increases with the target firm's proportion of tangible assets and decreases with the dollar size of the block relative to

the industry's market capitalization. This evidence that the state of the aggregate economy determines firm-specific liquidity complements the work of Chordia et al. (2000), who find commonalities in firm-specific liquidity measures, and of Chordia et al. (2001) who discuss the time series properties of aggregate liquidity (see also Amihud, 2002, Jones, 2002, and Bekaert et al., 2005).

Our results on block trades of public corporations can be extended to the case of privately held corporations. The many difficulties in determining the appropriate marketability discount in privately held corporations are clearly enunciated in *Mandelbaum, et al. v. Commissioner of Internal Revenue* (1995). As the Court indicates, these difficulties arise from the limited evidence on the proper size of the discount relative to the value of exchange traded shares. We provide an estimate of the control discount that should apply relative to exchange traded shares of comparable firms. Our estimations suggest that this discount can range from just under 1% to a maximum of 37% of the stock market share value across different specifications. In addition, our framework allows us to condition on aggregate characteristics to determine the control discount, a point ignored by the Court and in the literature.

There is a vast literature on the pricing of illiquid assets (see Amihud et al., 2005, and Damadoran, 2005, for comprehensive surveys).<sup>3</sup> Longstaff (1995) and Kahl et al. (2003) measure the marketability discount associated with stocks with trading restrictions. Longstaff (1995) derives an upper bound for the marketability discount as the value of a look-back option on the maximum price of the stock during the restricted period with strike price equal to the security value at the end of this period. We differ from Longstaff by considering search frictions as opposed to trading restrictions and by giving point estimates of the marketability discount.

There is a more recent literature that studies search frictions in financial markets.<sup>4</sup> Duffie et al. (2005, 2007) present a search model of OTC markets with atomistic investors. There is no controlling shareholder who can affect the value of assets, and discounts result from a pure search cost. In contrast, in our paper, a liquidity cost arises from two sources: the drop in value from potentially selling the block at a fire sale price and to a less efficient buyer, and the likelihood of such events, induced by the search cost. Feldhütter (2010) estimates a variant of Duffie et al. (2005) with bond market data using structural estimation. An earlier paper of block trading with search frictions is proposed by Burdett and O'Hara (1987). They study how a market maker may arise and take positions to circumvent the lack of counterparty at any point in time. Their argument is necessarily one for small blocks, not the majority blocks we study.

Vayanos and Wang (2007) and Weill (2008) study illiquidity spillovers in search models with multiple securities. They find that search frictions can lead to lower liquidity premiums concentrated in stocks with larger float. Amihud et al. (1997) find positive liquidity spillovers across related stocks in reaction

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<sup>3</sup>One aspect of this literature is to incorporate the impact of transactions costs in pricing (e.g. Amihud and Mendelson, 1986).

<sup>4</sup>See Rust and Hall (2003), Duffie et al. (2005, 2007) and Miao (2006).

to improvements in the trading mechanism. Chordia et al. (2005) 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 one investor, i.e., the majority blockholder, spill over to the pricing of the remaining investors of shares on the same firm.

Related theoretical work on the costs of concentrated ownership argues that concentrated ownership induces illiquidity in the firm's stock. Demsetz (1968) argues that by keeping shares off the market, large blockholders reduce liquidity of traded shares. Holmstrom and Tirole (1993) argue that dispersed shareholders have fewer incentives for information production if the float on a stock is smaller. Bolton and von Thadden (1998) argue that the threat of takeovers is reduced and so is price informativeness when float is smaller. These papers focus on the pricing implications of a reduced float whereas we focus on the pricing implications of liquidity shocks to large blockholders. Closer to us in spirit is the work of Kahn and Winton (1998) and Maug (1998). They argue that because large blockholders obtain value-relevant information from their monitoring, an adverse selection problem arises when blockholders trade their shares, which may also lead to lower liquidity (see also Edmans and Manso, 2008). In our setting, the pricing implications arise from trades that are caused by liquidity shocks. The evidence on ownership concentration and liquidity is generally supportive of the theory, but it cannot usually tell which mechanism is at work (e.g., Hefflin and Shaw, 2000, Becker et al., 2008, Brockman et al., 2008, Dlugosz, et al., 2006, and Ginglinger and Hamon, 2007). The various potential confounding aspects of blockholder-induced illiquidity costs are less likely to be an issue for the large, majority blocks we focus on.

The paper proceeds as follows. Section 2 presents the search model that we use to price majority blocks and dispersed shares. Section 3 describes the empirical strategy. It describes how the model's parameters are identified using this data, motivates the sample selection, and briefly summarizes the estimation algorithm. Section 4 summarizes the data used and section 5 presents the results. Finally, section 6 presents concluding remarks.

## 2. A search theory of block trades

All agents are risk neutral, infinitely lived and discount future payoffs at rate  $\delta < 1$ . Time is discrete. We use primes to denote next period values.

### 2.1. *Blockholder's value*

Consider the problem faced by the owner of a block of shares  $\alpha$  representing more than 50% of the shares of a firm. For simplicity assume one share per firm. The current block owner is called the incumbent and

denoted by  $I$ . Under  $I$ , the cash flow generated by the firm is  $\pi_I$ .<sup>5</sup> Denote by  $v(\pi_I)$  the incumbent's per share value of the block and denote by  $p(\pi_I)$  the value of each stock to dispersed shareholders. In addition, the holder of the block derives private benefits  $B$ . We assume that these private benefits do not come directly from the firm's cash flows, but rather from social prestige, network building, in case of an individual blockholder, or valuable synergies in the case of a corporate blockholder.<sup>6</sup>

At the beginning of every period, the incumbent faces a potential buyer, called a rival, and denoted by  $R$ . The firm's cash flow under the rival is denoted by  $\pi_R$ . The cash flow distribution under different potential rivals is  $F(\pi)$ , defined over a compact support. Unless  $I$  is forced to sell,  $I$  and  $R$  bargain over the block. We assume Nash bargaining. Let the bargaining power of  $I$  be  $\psi \in [0, 1]$  and that of  $R$  be  $1 - \psi$ . Bargaining powers are fixed and independent of the identity of the incumbent or that of the rival. If bargaining is successful, the block changes hands for the price of  $b(\pi_I, \pi_R)$ . The new blockholder values the block at  $v(\pi_R)$  – aside from private benefits  $B$  – and dispersed shareholders value the stock at  $p(\pi_R)$ .

The model assumes complete information. Blockholders and dispersed shareholders know the value of cash flow under current and rival management. This is in line with theories where controlling shareholders are able to extract value from their monitoring, even when this value is realized in the future, because it is reflected in the price (e.g. Faure-Grimaud and Gromb, 2004).

At the beginning of every period, and coincidental with the arrival of  $R$ ,  $I$  may face a liquidity shock with probability  $\theta$ . Liquidity shocks are events when  $I$  is forced to sell possibly at a fire sale price. If a liquidity shock is realized,  $I$  sells to whomever bids for the block. In that case, the block price is  $\phi v(\pi)$ , where  $R$  can generate security benefits of  $\pi$ , and a fire sale occurs when  $v(\pi_I) > \phi v(\pi)$ . The parameters  $\phi$  and  $\theta$  thus describe the search frictions in the model. The ex-ante block price upon a liquidity shock is:

$$L_v = \phi \int v(\pi) dF(\pi). \quad (1)$$

The incumbent's problem is best expressed in recursive form. Aside from private benefits, the value of the block to the incumbent is

$$v(\pi_I) = \pi_I + \delta [(1 - \theta) \tilde{v}(\pi_I) + \theta L_v], \quad (2)$$

where  $\tilde{v}(\pi_I)$  is the continuation value if a liquidity shock does not occur and is given by

$$\tilde{v}(\pi_I) + B = \int \max_{sell, hold} \{b(\pi_I, \pi); v(\pi_I) + B\} dF(\pi). \quad (3)$$

If the block is sold, then  $I$  gets  $b(\pi_I, \pi)$ , which, as will be shown, compensates  $I$  for both security benefits and private benefits. If the block is not sold, then  $I$  remains the blockholder with total value of  $v(\pi_I) + B$ .

<sup>5</sup>For simplicity, in the main text we present the case with no growth in security benefits and leave the more general case with growth—used for the estimations—to the Appendix.

<sup>6</sup>Albuquerque and Schroth (2010) show that private benefits diverted by the controlling blockholder from the firm's cash flow decrease with block size and are zero for blocks larger than 35%.

Before continuing we solve for the block price under Nash bargaining. The block price  $b$  solves

$$\max_b (b - (v(\pi_I) + B))^\psi ((v(\pi_R) + B) - b)^{1-\psi}.$$

It is straightforward to show that

$$b(\pi_I, \pi_R) = B + \psi v(\pi_R) + (1 - \psi) v(\pi_I). \quad (4)$$

This solution holds when a trade is mutually advantageous, i.e.,  $v(\pi_I) < v(\pi_R)$ . Otherwise, no trade occurs.

The next proposition characterizes the function  $v$ . The proof is provided in the Appendix.

**Proposition 1** *The value function  $v$  exists and is unique. The function  $v(\pi)$  is strictly increasing in  $\pi$ .*

The property that  $v$  is strictly increasing allows us to simplify the block pricing problem and the decision of whether to sell or to keep the block. We have that the block price in the absence of a liquidity shock is  $b(\pi_I, \pi_R) \geq v(\pi_I) + B$  if and only if  $\pi_I < \pi_R$ . Therefore, we can rewrite  $\tilde{v}(\pi)$  as

$$\tilde{v}(\pi_I) = \int_{\pi > \pi_I} [b(\pi_I, \pi) - B] dF(\pi) + F(\pi_I) v(\pi_I). \quad (5)$$

The simple decision rule obtained above is a result that relies on the assumption that  $R$  and  $I$  are heterogeneous only with respect to the cash flow they generate. Any two blockholders generating cash flow  $\pi$ , have identical valuations,  $v(\pi)$ . This allows the valuation of rival holders to be endogenously determined and contrasts with the standard formulations in the labor literature, which assume an exogenous outside option for searchers that take a job.

The model's property that the block is sold if and only if  $\pi_I < \pi_R$  will prove extremely useful in obtaining a numerical solution to the valuation problem defined above. As the Appendix shows, when  $\pi$  is a discrete random variable, this property implies that the fixed point problem that defines  $v$  (equations (2)-(4)) can be solved via a perfectly identified system of linear equations and requires only that a matrix be inverted. In contrast, the fixed point problem would be harder to solve if the decision to sell the block depended on the exact shape of the value function  $v$ .

## 2.2. *Dispersed shareholders' value*

Dispersed shareholders own the fraction  $1 - \alpha$  of the stock. Under the assumption of complete information, dispersed shareholders know that if there is no liquidity shock, a sale can only occur if and only if  $\pi_R > \pi_I$ . This allows us to derive the per share stock price  $p$ . We have

$$p(\pi_I) = \pi_I + \delta [(1 - \theta) \tilde{p}(\pi_I) + \theta L_p], \quad (6)$$

where

$$\tilde{p}(\pi_I) = \int_{\pi > \pi_I} p(\pi) dF(\pi) + F(\pi_I) p(\pi_I). \quad (7)$$

With probability  $1 - \theta$ , a liquidity shock does not occur, in which case the block is sold if and only if the rival can produce a cash flow  $\pi > \pi_I$ . With probability  $\theta$ ,  $I$  is forced to sell the block. In that case, the dispersed shareholders' expected value is

$$L_p = \int p(\pi) dF(\pi). \quad (8)$$

Dispersed shareholders differ from blockholders in three ways. First, they do not receive any private benefits from holding the stock. Second, they do not have to bargain over the sale of the block and will take full advantage from the cash flow that the new holder generates. Third, dispersed shareholders are not hit with liquidity shocks and are not forced to sell at a fire sale price. They do, however, lose value if upon a liquidity shock to the incumbent, the rival generates less security benefits. These differences are critical for the model to identify the search frictions.

Combining equations (6) and (7), we obtain

$$p(\pi_I) = \pi_I + \delta \left[ (1 - \theta) \left[ \int_{\pi > \pi_I} p(\pi) dF(\pi) + F(\pi_I) p(\pi_I) \right] + \theta L_p \right]. \quad (9)$$

The next proposition characterizes the function  $p$ .

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

This proposition highlights the control discount implied by  $p > v$ . This control discount is due to the fact that the model imposes search frictions to blockholders that have only limited impact on dispersed shareholders. We assume that  $B + v(\pi) > p(\pi)$  so that majority blockholders do not want to sell their shares at price  $p(\pi)$ . This assumption is sufficient in our setting to restrict trading between the blockholder and dispersed shareholders, but would not be necessary in a model where the sale of stock creates a moral hazard problem and reduces share prices. Our structural estimation allows us to verify the validity of this assumption.

### 2.3. The block premium and the price reaction to the trade

The observed block price when  $R$  can generate security benefits  $\pi_R$  is  $\phi v(\pi_R)$  if a liquidity shock occurs, and  $b(\pi_I, \pi_R)$ , otherwise. The block premium is defined as the ratio of the block price relative to the pre-announcement price:

$$BP(\pi_I, \pi_R) \equiv \begin{cases} \frac{\phi v(\pi_R)}{p(\pi_I)} - 1 & , \text{ if a liquidity shock occurs} \\ \frac{b(\pi_I, \pi_R)}{p(\pi_I)} - 1 & , \text{ else} \end{cases}. \quad (10)$$

Since we assume that dispersed shareholders know whether or not a trade has occurred for liquidity reasons, they can infer from the block price the value of  $\pi$  under the new blockholder.<sup>7</sup> Because  $v$  is strictly increasing, dispersed shareholders can determine the value of  $\pi_R$ , whether the block sells for price  $\phi v(\pi_R)$  or for price  $b(\pi_I, \pi_R)$ . Therefore, the post-announcement stock price is  $p(\pi_R)$  and the price reaction to the trade announcement is  $p(\pi_R)/p(\pi_I)$ . We define the price reaction to the block trade announcement by

$$CAR(\pi_I, \pi_R) \equiv \frac{p(\pi_R)}{p(\pi_I)} - 1. \quad (11)$$

Negative price reactions always signal liquidity shocks in this model: a negative price reaction can only occur if the block is traded after a liquidity shock and the new block owner generates  $\pi_R < \pi_I$ .

#### 2.4. Discussion

We have developed a parsimonious and estimable search model of block trades. It is necessarily an incomplete description of how block trades are conducted, though it contains important features associated with block trades. The following discussion is intended to point some potential weaknesses of the model and our approach to dealing with them.

**Reasons for trading.** We model trades that occur for one of two reasons: liquidity shocks or efficiency improvements (i.e., new blockholder generates more security value). There are, however, other potential reasons for trading. First, trading could occur due to bad news. If the incumbent learns bad news about the firm, he may try to sell the firm while disguising the sale as a liquidity-driven sale. If the adverse selection is not too severe, the market would not collapse and trades would occur, not due to liquidity shocks, but to asymmetrically informed blockholders. We assume these trades are rare as they would fall under the Securities and Exchange Commission’s insider trading laws (Rule 10b-5). In our sample, we do not observe any deal that was later subject to prosecution due to insider trading.

Second, trades could occur due to differences in private benefits of control as in Burkart et al. (2000) and Albuquerque and Schroth (2010). Albuquerque and Schroth model private benefits derived from firm cash flows. They find differences in private benefits to block sellers and buyers, but these differences are often not statistically significant. Likewise, Holderness and Sheehan (1988) document that even average compensation is not significantly different for blockholders that are also CEOs versus CEOs with dispersed share ownership. Quantifying private benefits that are not derived from firm cash flows, such as non-pecuniary private benefits, appears even harder to do and for lack of guidance we assume that there is no heterogeneity on such private benefits across block holders.

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<sup>7</sup>We use this assumption here for the purpose of exposition. This assumption is relaxed in the more general version of the model, which we estimate, and develop in Appendix B.

**Investor heterogeneity.** In the model, blockholders are different from dispersed shareholders in that they can manage a firm and increase share value but also because they can extract private benefits. Other forms of investor heterogeneity can be potentially interesting to model. First, different investors may agree to disagree on the probability of liquidity shocks  $\theta$ . Such behavior may be more acceptable when these events are harder to identify possibly due to disagreement about the sensitivity of blockholders to the various determinants of liquidity shocks. We return to this point in the estimation below. Second, if blockholders also assume management positions in the firm, they may be able to extract value in a manner that is not proportional to their cash flow rights. The evidence in Holderness and Sheehan (1988) cited above suggests that this is of second order. Third, blockholders may not be as diversified as dispersed shareholders, in which case their risk aversion may affect the implied block values and introduce another disparity relative to dispersed shareholders' valuation. Larger blocks would then carry a larger risk premium. We attempt to deal empirically with this valuation issue by allowing for heterogeneity in the discount rate.

**Other liquidity costs.** The model abstracts from illiquidity that arises from transactions costs and asymmetric information among dispersed investors. Hence, the stock market price we model does not capture the discount associated with these costs. Suppose to the contrary that transactions costs increased substantially with the new blockholder, giving rise to a higher liquidity discount and a negative price run-up. By using the search model above, we would be wrongly inferring a blockholder liquidity shock. We document that firm bid-ask spreads and turnover are approximately the same before and after the block trade announcement and conclude that the price impact or block premium are not affected by these forms of illiquidity. Moreover, our measure of *CAR* excludes returns that are systematically correlated with aggregate liquidity.

### 3. Empirical strategy

The problem at hand consists of estimating the parameters of the model, i.e., the bargaining power  $\psi$ , the private benefits  $B$ , the probability of liquidity shocks  $\theta$ , and the fire sale block price  $\phi$ . We will also estimate the cash flow distribution  $F(\pi)$  in a first stage, and shall fix the discount rate  $\delta$ . In this section, we discuss the data set that is required for the purpose, and the restrictions imposed by the theoretical search model that allow the identification of these parameters using data on block prices and price reactions to trade announcements.

#### 3.1. Data set requirements

The importance of choosing the proper setting to estimate the model is two fold. First, the data has to be rich enough to allow the identification of the parameters. This is discussed in the next subsection. Second, the setting must minimize the risk that our model may fail to properly estimate search frictions when in

the presence of other known costs associated with the existence of large shareholders.<sup>8</sup> Thus, careful design of the sample is needed to eliminate such alternative, confounding effects.

If large shareholders receive private benefits of control (whether or not they are derived from firm cash flows), they may pay a higher block premium (e.g. Barclay and Holderness, 1989, and Albuquerque and Schroth, 2010). While we incorporate private benefits of control through  $B$ , these are not of the type that are derived from the firm's cash flow. By restricting our sample to majority blockholders, we expect that the incentive effect of increased ownership is large enough and that blockholders internalize most of the inefficiency in extracting private benefits. Indeed, Albuquerque and Schroth (2010) estimate that private benefits from cash flow are zero for blocks larger than 35% of the firm's stock.

In our paper as in the corporate governance literature, large blockholders are often modeled as affecting share value (e.g., due to tighter monitoring of management), but also as reducing firm liquidity. It is therefore important that we are able to distinguish empirically our search frictions from other illiquidity stories. First, Demsetz (1968) argues that a smaller float carries higher transactions costs. Holmstrom and Tirole (1993) argue that a reduced float decreases the incentives for information production in the stock market. Bolton and von Thadden (1998) argue that by keeping shares out of the market, large blockholders limit the threat of takeovers and reduce price informativeness. By studying what happens around a block trading event we are able to condition on the presence of these costs: they should exist before and after the trade and should not affect either the block premium paid or the price reaction to the trade.

Second, Kahn and Winton (1998) and Maug (1998) argue that blockholders have access to value-relevant information which they may use for trading. This may introduce an adverse selection problem and reduce liquidity. Several papers show that the presence of a blockholder appears associated with lower firm liquidity in the form of, say, higher spreads and smaller quoted depths (Heflin and Shaw, 2000, Becker et al., 2008, Brockman et al., 2008, and Ginglinger and Hamon, 2007). This potential confounding aspect of blockholder costs and induced illiquidity is less likely to be an issue for large, majority blocks, which are harder to trade.

Third, Burdett and O'Hara (1987) argue that a market maker may arise and take positions in trading blocks of shares due to investor segmentation. They argue that, when a seller enters the market and is not matched with the best possible buyer, a market maker may decide to be the counterparty to the trade. This practice, however, introduces inventory risk into the market maker's portfolio, where the size of the desired inventory affects the liquidity of the stock. In our sample of majority block trades, there is no market maker and thus no concern due to inventory risk.

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<sup>8</sup>Additional issues were raised in subsection 2.4. above.

### 3.2. Identification

The identification we propose in this paper is quite different from that found in the labor literature that models search frictions in the labor market, or in the recent finance literature (Feldhütter, 2010), because we do not have multiple trades of the same block nor do we have information on the time between two trades of the same block. Instead, we rely on the information conveyed by the different known valuations of blockholders and dispersed shareholders at the time of the block trade to infer the search frictions present in these trades.

Estimation of  $\phi$  relies on the fact that fire sale prices offered to large blockholders affect their valuations of the block  $v$ , but not the share price in the market place,  $p$ . Hence, variation in block prices that is not associated with variation in the price reaction to the block trade announcement tends to be inferred by the model as coming from variation in  $\phi$ , especially if the block is traded at a discount. Note that private benefits also cause variation in block prices that is unrelated to variation in the price reaction, but this occurs when the block trades at a premium.

The critical issue is the identification of the probability of a liquidity shock  $\theta$  without multiple trades of the same block. Our identification works through two channels. First, a negative price reaction  $p(\pi_R) < p(\pi_I)$ , or  $\pi_R < \pi_I$ , can only be the outcome of a liquidity shock (though the converse is not true). Second, even in the absence of an actual liquidity shock, in which case  $\pi_R > \pi_I$ , it is possible to infer variation in  $\theta$  from the block price and the price reaction. To show this, consider the difference between the block premium and the price reaction,  $BP/\psi - CAR$ . Absent a liquidity shock,

$$BP/\psi - CAR \approx \frac{b(\pi_I, \pi_R) - v(\pi_I)}{\psi v(\pi_I)} - \frac{p(\pi_R) - p(\pi_I)}{p(\pi_I)}.$$

The approximation results from replacing  $p(\pi_I)$  in the denominator of the first term by  $v(\pi_I)$ . The next proposition describes how this quantity varies with  $\theta$ . The proof is relegated to the Appendix.

**Proposition 3** *Suppose  $B = 0$  and assume that a trade occurs without a liquidity shock, i.e.,  $\pi_R - \pi_I > 0$ . If  $\pi_R - \pi_I \rightarrow 0$ , then  $BP/\psi - CAR$  is monotonically decreasing in  $\theta$ .*

To understand the intuition behind this result note that a higher  $\pi$  increases value for all investors, but by giving blockholders more of the surplus in future bargaining it increases their valuation more so than dispersed shareholders' valuation who have no such benefit. Formally,  $\partial v(\pi_I)/\partial \pi_I > \partial p(\pi_I)/\partial \pi_I$ . This effect is stronger the likelier it is that they sell to a higher-value blockholder, i.e. the lower is  $\theta$ . Therefore, a lower probability of a liquidity shock is inferred from the data if the difference  $BP/\psi - CAR$  is larger. The use of block pricing and stock price data around block trades can then help us identify liquidity shocks even when trades are not the result of a liquidity shock and in the absence of multiple trades of the same block.

### 3.3. Modeling liquidity

It is not feasible to estimate  $\theta$  and  $\phi$  as parameters specific to each trade. Instead, we estimate  $\theta$  and  $\phi$  by expressing each as a function of its cross-sectional determinants and respective parameters, which are constant across trades. We model the trade-specific  $\theta_i$  and  $\phi_i$  with the logistic functions,

$$\theta(\mathbf{x}_i, \boldsymbol{\beta}) = \frac{\exp(\mathbf{x}'_i \boldsymbol{\beta})}{1 + \exp(\mathbf{x}'_i \boldsymbol{\beta})}, \text{ and} \quad (12)$$

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

By construction, these functions guarantee that  $\theta$  and  $\phi$  are bounded between 0 and 1. In these functions,  $\mathbf{x}_i$  and  $\mathbf{z}_i$  are the vectors of the determinants of liquidity shocks and fire sale prices, whereas  $\boldsymbol{\beta}$  and  $\boldsymbol{\gamma}$  are the vectors of fixed parameters to estimate. The next section describes the variables specified in  $\mathbf{x}$  and  $\mathbf{z}$ . Essentially,  $\mathbf{x}$  includes characteristics of the aggregate economy, such as the tightening or loosening of funding conditions, that would force blockholders to liquidate their blocks because of a sudden extreme preference for cash. In the case of  $\mathbf{z}$ , we include characteristics of the target firm or of the market that would make the block more or less redeployable.

Note that (12) and (13) are flexible enough to allow for unobservable characteristics in the form of random effects. Random effects subsume all the determinants of  $\theta$  and  $\phi$  that are known to the block traders but not to the econometrician. They are used extensively in the context of labor economics to control for workers' heterogeneous reservation wages or non-market productivity (see Van den Berg and Ridder (1993) for a survey in the context of the labor literature). Specifically, we allow for random effects,  $\xi_i$ , drawn independently across deals from a normal distribution with mean 0 and variance  $\sigma_\xi^2$ , where this variance is a parameter to be estimated.

### 3.4. Estimation

We estimate a more general version of the model presented above, where we allow for the future cash flow to trend at a known growth rate and the deviations from trend,  $\pi$ , to display serial correlation according to the conditional distribution function,  $F(\pi'|\pi)$ . This more general model, which is developed in Appendix B, preserves the main results of the simpler version above and has the same identification strategy. Also, we specify private benefits as a constant ratio of total block value rather than a constant dollar amount. That is, we specify and estimate the parameter  $B$ , such that private benefits are  $Bv(\pi_I)$  for both  $R$  and  $I$  when they meet to bargain over the price. The dollar value of private benefits is allowed to change over time and across deals. The discount rate  $\delta$  is calibrated to 1/1.1.

Before estimating the model, we estimate the conditional distribution of each target's cash flow,  $F(\pi'|\pi)$ , using annual cash flow data at the 3-digit SIC industry level. We first remove a log-linear trend on the data and then use the residuals to obtain a grid for  $\pi$  and its associated Markov transition matrix. 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 more precise estimates with longer data series. This estimation step is done separately from the rest of the estimation. More details can be found in Appendix C.

Our estimator of the model’s parameters maximizes the simulated likelihood function of the block premium and  $CAR$  data. The simulated maximum likelihood procedure consists of specifying directly the likelihood function for the two observed endogenous variables, the block premium  $BP_i$  and the cumulative abnormal return around the announcement,  $CAR_i$ , and computing the joint density by numerical simulation. One advantage of the simulated maximum likelihood is that we do not need to make any assumptions ex-ante on whether a liquidity shock occurred for a particular deal nor do we need to assume what the security benefits are that  $R$  brings to the table.

The estimation procedure can be summarized in three steps. In the first, we fix a vector of parameters  $\Gamma = \{\beta, \gamma, \psi, B\}$ . In the second, we use the theoretical search model to numerically simulate the likelihood function of the data,  $\mathcal{L}(\{BP_i, CAR_i\}_i; \Gamma | \text{trade occurs})$ , which is defined as

$$\ln \prod_{i=1}^N \left[ \begin{array}{l} \theta_i f_L(BP_i, CAR_i; \Gamma | \text{liquidity shock occurs}) \\ + (1 - \theta_i) f_N(BP_i, CAR_i; \Gamma | \text{no liquidity shock occurs}) \end{array} \right].$$

The product is over the  $N$  block trades in our sample. In this step, for each trade we (i) solve the model’s pricing equations (2) and (9) given the current parameters, (ii) use the estimated conditional distribution of cash flows to simulate many paths for next period cash flow (the block trading period) starting from the observed (and fixed) pre-trade cash flow, and (iii) evaluate equations (10) and (11) at each simulated path, dropping all realizations for which there are no gains from trade. The functions  $f_L(\cdot)$  and  $f_N(\cdot)$  are the joint densities conditional on whether or not a liquidity occurs, respectively. They are computed numerically using a bivariate kernel density estimator. Finally, in the third step we verify if  $\mathcal{L}(\{BP_i, CAR_i\}_i; \Gamma | \text{trade occurs})$  has been maximized, and return to the first step if it hasn’t. This procedure is explained in detail in Appendix C.

## 4. Data

We construct our data set by combining four databases: Thomson One Banker’s Mergers and Acquisitions, CRSP, Compustat and Thomson-Reuters’ Institutional Holdings. We complement these with characteristics of the aggregate economy, which are obtained mostly from the Board of Governors of the Federal Reserve. Table I describes in detail the variables constructed from these sources.

<INSERT TABLE I ABOUT HERE>

#### 4.1. *Sample selection*

We include all U.S., disclosed-value acquisitions of a block of more than 35% but less than 90% of the stock between 1/1/1990 and 31/12/2010 in Thomson One Banker’s M&A. We use the ‘Type of Acquisition’ field in the Thomson One Banker Acquisitions data to select which deals to include in the analysis. We rule out acquisitions due to a bankruptcy of the target firm. Indeed, in our model the block is sold either because there are gains from trade or the blockholder is illiquid. While the blockholder could have a sudden preference for liquidity due to own distress, this motive would not correspond to the target firm being bankrupt. We also exclude block trades between parent companies and subsidiaries, privatizations, exchange offers, spin-offs, recapitalizations, repurchases, equity carve-outs, going private deals, and debt restructurings. We end up with 1,751 observations. Details of this selection procedure, as well as other applied filters, are included in Appendix D.

We merge the surviving deals to the target’s CRSP tapes, imposing the additional restrictions that the target’s traded share price is observable for at least 20 trading days after the announcement and 51 trading days before the announcement. We compute each stock’s alpha, market beta and liquidity beta from the regression of each stock’s daily returns on the contemporaneous value-weighted CRSP portfolio return and the innovations in the Pástor-Stambaugh market liquidity index, with a time window of all available prices from day  $t - 252$  up to  $t - 21$  from the announcement. The estimated parameters are used to adjust the share price for changes in systematic market and market liquidity risk. We also match each deal to the target firm’s Compustat record on the last December preceding the trade announcement. The end result is a sample of 114 deals.

The top of Table II summarizes the main characteristics of our selected trades. Our selection has a similar block size distribution as the total universe of block trades above 35%: mean of 59.7% (standard deviation 15.15%) vs. 60.3% (standard deviation 17.7%), respectively. However, the average deal value in our sample is \$193 M, whereas the average deal value in the universe of deals is \$123 M.

<INSERT TABLE II ABOUT HERE>

#### 4.2. *Block premium and cumulative abnormal returns*

We measure the pre-announcement share price,  $p^0$ , at a date that precedes the build up of expectations about the unfolding block trade. As in Barclay and Holderness (1989) and others, we choose the share price 21 trading days before the announcement. The post-announcement price,  $p^1$ , must incorporate the effects of the change of control on security benefits. Again, following the previous literature we use the share price two trading days after the announcement. Figure 1 plots the average price path for trades with positive  $CAR$  (blue plot) and trades with negative  $CAR$  (red plot). This figure supports our choice of dates to measure the deal’s cumulative abnormal returns.

<INSERT FIGURE 1 ABOUT HERE>

The average block premium in our sample is 6.79%, which is smaller than the block premium in previous studies of minority block trades only (19.6% in Albuquerque and Schroth, 2010) or of both minority and majority block trades (e.g., 20.4% in Barclay and Holderness, 1989). Even though our sample exhibits fewer block discounts than these other studies, the block premium distribution is significantly less right-skewed. Figure 2, which plots the scatter of the block premium and the cumulative returns, shows that there are 53 deals (47%) where the block price is below the pre-announcement share price.

The average cumulative abnormal returns ( $CAR$ ) are 9.6%. However,  $CAR$  is negative in 42% of the trades. Therefore, we expect that at least 42% of our matched trades occur due to liquidity shocks to the blockholder. In general,  $BP$  and  $CAR$  are positively correlated (correlation coefficient = 0.37), and are more strongly correlated when both are positive (correlation coefficient = 0.52). In our sample, 78% of all trades with positive  $CAR$  exhibit a block premium and 75% of the trades with a negative  $CAR$  show a premium.

<INSERT FIGURE 2 ABOUT HERE>

### 4.3. *Determinants of liquidity costs*

Liquidity affects the value of the block through two channels: the probability that a liquidity shock occurs,  $\theta$ , and the fire sale value of the block,  $\phi$ . These variables are modelled in equations (12) and (13) as logistic functions of their determinants and their associated parameters.

#### 4.3.1. *Determinants of $\theta$ : $\mathbf{x}_i$*

Following Pástor and Stambaugh (2003) and Acharya and Pedersen (2005), we focus on aggregate determinants of liquidity. These authors have shown that stock prices are affected more by the covariance between the stock's payoff and market liquidity rather than by the stock's liquidity itself. Pástor and Stambaugh (2003) propose a monthly liquidity factor based on the argument that current order flow will be followed by future stock price changes in an opposite direction when liquidity is low. We include the innovations to the index of liquidity in Pástor and Stambaugh (2003) (*PS Liquidity*), which is expected to have a negative effect on  $\theta$ .

We conjecture that blockholders may face a sudden preference for more liquid assets, forcing them to sell their block, when aggregate financing conditions tighten. Following Gromb and Vayanos (2002) and Brunnermeier and Pedersen (2009), liquidity providers themselves face tighter funding constraints when market returns are low and volatility is high, and thereby diminish their role as liquidity providers. Chordia, et al. (2002) provide evidence that aggregate excessive stock selling imbalances are related to low

S&P 500 returns. We therefore include the average daily returns on the equally-weighted portfolio of all NYSE, AMEX and NASDAQ stocks through the last month preceding each block trade (*Market Return*) and the standard deviation of the returns on the same portfolio through the last year before the trade (*Market Volatility*). We expect  $\theta$  to decrease with *Market Return* and to increase with *Market Volatility*. For robustness, we include alternatively the changes in volatility and the Chicago Board Options Exchange daily market volatility index (*VIX*), which is implied by CBOE traded index options on the S&P 500.

Longstaff et al. (2005) find a significant non-default component in the corporate yield spread, i.e., the difference between the yield of corporate bonds and a risk-free bond of equal maturity. Moreover, they find that the non-default component is strongly related to measures of bond-specific illiquidity and overall liquidity, such as money market mutual fund inflows. We include in  $\mathbf{x}$  the difference between the yields on the BAA and AAA rated corporate bonds, and expect it to have a positive effect on  $\theta$ .

We include also the slope of the yield curve, measured by the difference in interest rates on the 10 year and 1 year Tbills. Since an increase in the slope of the yield curve is consistent with an increase in the preference for liquidity, we expect this variable to be positively associated with  $\theta$ . However, term structure theories of preferred habitat suggest that the interpretation of the slope of the yield curve as a measure of liquidity is unwarranted, in which case this variable may have too much noise. As an alternative to the slope of the yields curve, we use the *3-month-Tbill* rate, hypothesizing that increases in the short term interest rate are associated with low aggregate liquidity. Finally, we use the growth of US GDP per capita over the last quarter prior to the deal (*GDP growth*) to measure income effects that, if positive, make the blockholder less likely to liquidate the block and contribute to a lower  $\theta$ .

Following the identification strategy described in subsection 3.2., we quickly inspect the ability of these various determinants to explain variation in  $\frac{BP}{\psi} - CAR$ . The model predicts a negative correlation between this difference and  $\theta$  conditional on no liquidity shock. The first column of Panel A in Table III, where  $\psi$  is set to 0.5, shows that of all aggregate variables discussed above, only the *Corporate Spread* and the *Market Return*, correlate with  $\frac{BP}{\psi} - CAR$  in the whole sample, if only weakly. Recall however, that the whole sample contains 42% of observations where  $CAR < 0$ , i.e., where the model infers that a liquidity shock occurred. Because the subsample of trades with positive  $CAR$  may still include those where a liquidity shock occurred, we subsequently drop those deals where  $CAR > 0$  but where the block premium was negative, as those would be more likely to be liquidity trades as well. Column 3 shows that the correlation coefficients increase significantly, giving preliminary support to our conjecture that the determinants of a liquidity shock are mostly indicators of the aggregate economy.

<INSERT TABLE III ABOUT HERE>

Note that these raw correlations may give an incomplete picture as they do not condition on any other information. For example, the correlation of *Market Return* and  $\frac{BP}{\psi} - CAR$  is negative, contrary to predicted. In the estimation below, we control for the cash flow level at the target firm and obtain a negative sign for *Market Return* as a predictor of liquidity shocks.

#### 4.3.2. *Determinants of $\phi : z_i$*

We specify the fire sale value of the block as a function of characteristics of the target firm and of its industry. Williamson (1988) argues that asset liquidation values should be closely related to their redeployability. Shleifer and Vishny (1992) add that, because distressed assets tend to be put to the best use by liquidating them within the same industry, redeployability is a function of the industry’s capacity to absorb them. We measure the redeployability of the block as 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*).<sup>9</sup> Table 2 shows that, while the trades in our sample are small relative to their industry total equity (mean of 0.008), there is a large variation in this measure. We expect the liquidation value of the block,  $\phi$ , to decrease with the relative size of the block.

We also 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. On one hand, a large *Industry’s M&A Activity* could be the reflection of high liquidity for assets specific to that industry, and therefore increase the fire sale value. On the other, a large *Industry’s M&A Activity* could also be the result of an increased supply of industry-specific assets, which would depress the liquidation value of the block.

We take as a potential determinant of the fire sale value the *Tangibility* of target firm assets, measured by the proportion of tangible to total assets. We expect the impact of tangibility on  $\phi$  to be positive because these assets are generally easier to price than intangible assets.

We control too for the target firm’s average daily return and return volatility over the last year before the trade. Higher returns and lower volatility could imply higher liquidation values through their effect on the expected growth rate and discount rates, respectively, used to calculate the firms terminal value. Additionally, higher returns and lower volatility also reflect a larger distance to default, and therefore lower expected bankruptcy costs. Further, a more volatile past performance could also increase the relative bargaining power of the buyer, increasing the discount on the block. In short, we expect  $\phi$  to be increasing in *Target Return* and decreasing in *Target Volatility*. Clearly, we cannot identify these three effects from each other because they all work in the same direction. However, we note that the bankruptcy costs and valuation effects may already be incorporated into the buyers value,  $v(\pi_R)$ , given that this is a majority block.

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<sup>9</sup>This approach follows similar notions of asset liquidity in Gavazza (2010), salability in Benmelech (2009) and redeployability in Benmelech and Bergman (2008).

The identification strategy described in subsection 3.2. suggests that movements in the block premium that are unrelated to movements in  $CAR$  may be used to identify the determinants of fire sale values. For a quick assessment of the joint validity of our identification strategy and our determinants of  $\phi$ , we take the variation in  $BP$  that is orthogonal to variation in  $CAR$  and regress it on  $z_i$ . Because the determinants of  $\phi$  should be correlated with these residuals only when a liquidity shock has occurred, we perform the regression over two subsamples of trades (i)  $CAR < 0$  or  $CAR > 0$  but  $BP < 0$  and (ii)  $CAR < 0$ . The former subsample drops those trades with positive cumulative returns and positive block premiums, as these are unlikely to be liquidity trades. The latter includes only trades where the model infers that a liquidity shock has occurred with certainty. Panel B of Table III shows how the adjusted  $R^2$  increases significantly as we restrict the sample to include only those trades that are more likely to have been liquidity trades. The proxy for liquidation values correlates stronger, and with the predicted sign, as we move across columns for most of the determinants discussed above.

Note too that we have explored the possibility that the aggregate variables in  $\mathbf{x}$  may be correlated with the determinants of  $\theta$  (Panel A) or that the firm and industry-specific variables in  $\mathbf{z}$  be correlated with the determinants of  $\phi$  (Panel B). The evidence rejects these alternative specifications.

## 5. Results

Table IV shows the model's parameter estimates under two different specifications of  $\theta_i$ . In specification (1),  $\theta$  is determined by observable aggregate variables. Specification (2) allows for a deal-specific random effect,  $\xi_i$ , which is unobservable to the econometrician but is known to the investors and common to both  $I$  and  $R$ . In general, we observe that most of the coefficient estimates of the determinants of  $\theta$  and  $\phi$  have the expected sign and are statistically significant. In both specifications, we reject the hypothesis that all the model's parameters are zero. To evaluate the economic significance of these estimates, we compute the predicted change in  $\theta$  given a one sample standard deviation change in the relevant determinant.

<INSERT TABLE IV ABOUT HERE>

In both specifications, we estimate the incumbent blockholder's bargaining power in the absence of a liquidity shock to be very close to 0.5. We therefore conclude that neither the buyer, nor the seller, have a significant bargaining advantage in the absence of a liquidity shock, *over and above* all the other determinants of the block price. Indeed, conditional on measuring the buyer's and seller's valuation without bias, there is no reason to expect one party to have a larger bargaining power over the other unless they have significantly different risk aversion coefficients. The data seems to reject this interpretation.

In specification (1), we estimate blockholder's private benefits to be 2% of the blockholder's value. However, this estimate is not statistically significant. The addition of a random effect in  $\theta$  decreases this

estimate to 0%, although the standard error is 2.1%. This difference in estimates can be explained with the differences in estimates of  $\theta$  and of  $\phi$  in the two specifications. We return to this point below.

## 5.1. Determinants of liquidity costs

### 5.1.1. Probability of liquidity shocks

In both specifications, *Market Return* has a negative effect and *Market Volatility* has a positive effect on the probability of a liquidity shock. The effects are stronger in specification (2), where a one standard deviation increase in the *Market Return* is associated with a decrease in  $\theta$  of 0.052. Given that the predicted average  $\theta$  for this specification is 0.06 (Table V), this change almost doubles the probability of a liquidity shock. We have also replaced *Market Volatility* for the implied volatility index, *VIX*. The results, unreported here but available upon request, are very similar qualitatively, although the effect of *VIX* is weaker and not significant at the 5% level. This difference is perhaps due to the much higher volatility of the realized market return volatility than that of implied volatility (see Table II).

The coefficient associated with the *Corporate Spread* has the opposite sign to that predicted, and it is not statistically significantly different from zero in specification (1). The *Yield Curve slope* coefficient is negative, which is consistent with the slope of the term structure being a noisy signal of aggregate illiquidity as discussed above. In untabulated results, we find that this result does not change after we control for the short term interest rate, whose coefficient is also insignificant.

*GDP growth* and *PS liquidity* have the predicted, negative and significant effect on  $\theta$ . We estimate that a one standard deviation increase in *GDP growth* is associated with a decrease in  $\theta$  of 21 basis points, which represents 33% of the average  $\theta$ . For the *PS liquidity* measure, the effect is equally strong.. We note too that innovations to the *VIX* index do not have any significant explanatory power beyond the Pástor and Stambaugh (2003) liquidity measure: when both determinants are included, only the latter has a significant effect on  $\theta$ .

The estimate of  $\sigma_\xi$  is 0.011 (and different from zero with 0.01 significance). To evaluate its economic significance we compute the statistic  $\frac{\sigma_\xi^2}{\text{var}(\mathbf{x}'\beta)}$ , which measures the ratio of the variance generated by the unobservable determinants of  $\theta$  to the variance generated by the observables determinants. This ratio is 0.051, implying that the random effect alone accounts for almost 5% of the total explained variation in  $\theta$ .

Table V gives statistics for the estimated probability of a liquidity shock. The estimated average  $\theta$  in specification (1) is 0.009 and in specification (2) is 0.064. Figure 3 shows that the distribution of  $\theta$  is concentrated between zero and 0.3, but a few mass points between 0.4 and 0.92. These numbers appear low relative to the 42% of deals in the data with negative *CAR*. However, we note that the estimate of  $\theta$  is highly non-linear and is deal dependent, and does not equal the proportion of deals with negative *CAR*. Nevertheless, it is possible that the model is unable to capture further variation in the probability of liquidity, for example for lack of additional determinants of liquidity.

### 5.1.2. *Liquidation values*

The coefficients of *Target Return* and *Target Volatility* on  $\phi$  have the expected sign and are both statistically significant in both specifications. A one sample standard deviation increase in the target firm’s daily return volatility during the year prior to the trade decreases the block’s liquidation value by 22% in specification (1), and 12% in specification (2). This result is consistent with our hypothesis that a more volatile past performance may increase the buyer’s relative bargaining power in case of a fire sale.

The coefficient on *Tangibility* is positive and significant for both specifications reported. In specification (1), *Tangibility* has a relatively large economic effect on liquidation values, in spite of its small coefficient of variation of .37. An increase of one standard deviation in *Tangibility* is associated with an increase of 6.5 percentage points in the block’s fire sale value. The impact of *Block-to-Industry Size* on  $\phi$  is also consistent with the hypothesis that asset’s redeployability is the main determinant of its liquidation value. The coefficient of this variable is always negative, statistically and economically significant, and robust also across all unreported specifications. The total M&A activity in the same industry as the target does not always significantly explain the estimated cross-sectional variation in  $\phi$ . As we argued above, the expected ambiguity of the effect of the *Industry’s M&A Activity* is consistent with the lack of statistical significance, or the change in sign, of its coefficient.<sup>10</sup>

Table V shows that, conditional on a liquidity shock, we estimate the block’s fire sale price to be have an average of 48.3% (specification (1)) or 9.3% (specification (2)) of the buyer’s valuation. Recall that specification (2) implies larger estimated average probability of a liquidity shock to the blockholder than specification (1). To understand these differences, note that the block premium is sensitive to  $\phi$  only when there is a liquidity shock. Therefore, a possible interpretation for the different fit of specifications (1) and (2) is that, by allowing for a random effect, we can generate more variation in  $\theta$  and therefore infer a larger proportion of liquidity trades. With a higher  $\theta$ , the model has to match relatively more fire-sale discounts and, as a consequence,  $\phi$  has to be lower.

<INSERT TABLE V ABOUT HERE>

<INSERT FIGURE 3 ABOUT HERE>

### 5.2. *Marketability discount*

We define the *marketability discount* of a majority block,  $d^M$ , as

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

---

<sup>10</sup>We have also tested for the presence of random effects in the determinants of  $\phi$ . We found that they do not add significant variation in  $\phi$ .

where we have made explicit the dependence of  $v$  on both  $\phi$  and  $\theta$ . It is easy to show that  $v(0, \phi, \cdot) > v(\theta, \phi, \cdot)$  for any  $\phi$ , and that  $d^M(\theta)$  is positive. The function  $d^M(\theta)$  quantifies the value of the shares *in the block* absent liquidity shocks. This measure of the marketability discount differs from the one in Longstaff (1995). Longstaff presents an upper bound on the marketability discount on restricted shares, but the sale of the shares is not assumed to imply a loss of control.

Table V shows the estimated marketability discount. In specification (1), where  $\theta$  is low but  $\phi$  is, on average, high, the marketability discount is on average 6.6% (median 5.8%) and it can reach a maximum of 36%. For specification (2), the estimated marketability discount is higher, with an average of 7.3% and a maximum of 63.2%.

Panel (a) of Figure 4 plots the marketability discount function for every  $\theta \in [0, 1]$ , using the parameter estimates from specification (2). We see that for the firms in the lower quartile of  $\phi$ , i.e., firms with higher liquidation costs, the marketability discount increases very quickly reaching 70% for  $\theta$  equal to 0.2 (bold line). The estimated marketability discount is also very large for blocks with intermediate liquidation values (solid line). Further, even for blocks with the lowest liquidation costs (dashed line), the marketability discount is 35% with a  $\theta$  of 0.1 and reaches a maximum of over 80% when  $\theta$  equals one. Panel (b) plots the predicted in-sample distribution of the marketability discount for the estimated values of  $\theta$ .

<INSERT FIGURE 4 ABOUT HERE>

### 5.3. *Illiquidity-spillover discount*

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

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

Again, it is easy to show that  $p(0, \cdot) > p(\theta, \cdot)$ , for any  $\theta \in [0, 1]$  and that  $d^{IS} > 0$ . The illiquidity-spillover discount function quantifies the price of dispersed shares that would prevail in the absence of liquidity shocks. It is a spillover effect in that the liquidity shock does not affect dispersed shareholders directly. Indeed,  $p$  is independent of the block trade price and of  $\phi$ . However,  $p$  reacts to the possibility that control may change hands and the value of assets will change as a result.

Table V shows that the illiquidity-spillover discount on dispersed shares is estimated to be very small. For a low estimated  $\theta$ , as in specification (1), the illiquidity-spillover discount is at most 0.1% of the share price. For specification (2), this discount is at most 0.4%. Panel (a) of Figure 5, which plots the illiquidity-spillover discount for all possible values of  $\theta$ , shows that  $d^{IS}$  can be significant but only for very large values of  $\theta$ .

<INSERT FIGURE 5 ABOUT HERE>

#### 5.4. *Control discount*

We define the control discount,  $d^C$ , as

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

The control discount function measures the difference in valuations between controlling majority blockholder and dispersed shareholder and is expressed as a function of the observed share price. The control discount ignores the private benefits afforded to the controlling shareholder. Note that the control discount is recovered from the marketability and the illiquidity-spillover discount from

$$1 - d^C = \frac{1 - d^M}{1 - d^{IS}},$$

because  $v(0, \cdot) = p(0, \cdot)$ . Because  $v < p$  for any  $\theta > 0$ ,  $d^C > 0$ .

Given that  $d^{IS}$  is close to zero in sample, the estimated control discount is very similar to the marketability discount, if slightly bigger: on average it is between 7.8% and 9.6% and can reach an in-sample maximum of 37.6% (specification (1)) or 64.4% (specification (2)).

<INSERT FIGURE 6 ABOUT HERE>

The estimates on 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 indicates, 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. It is important to use firms with controlling blockholders so that the pricing already incorporates the added value of the blockholder. In the absence of such a sample, the control discount we calculate constitutes an upper bound to the actual discount because it assumes that blockholders have no beneficial impact in the cash flows themselves.

#### 5.5. *Liquidity costs by industry*

In this subsection we ask whether our estimated discount measures are cross-sectionally associated with other observable characteristics of the target firm, not already specified in  $\theta$  or  $\phi$ . To search for differences in the estimated discounts across different industries, we aggregate deals by the 2-digit SIC code group of the target firm. We exclude 2-digit SIC groups with fewer than 3 observations. The results are shown in Table VI.

<INSERT TABLE VI ABOUT HERE>

Panel A shows that the largest estimated marketability discounts are for different machinery and equipment suppliers (e.g., electronic and electrical (code 36), transportation (code 37), industrial machinery (code 35)) consulting services (e.g., advertising (code 73)) and general communications providers (e.g., telephone services, cable television, (code 48)). Because the illiquidity-spillover discount is very small, these groups also have the largest average control discounts. In the case of machinery or transport equipment, the *CAR* are among the lowest in the sample with an average of  $-18\%$  and  $-2\%$ , respectively. This suggests that the determinants of  $\theta$  are important for explaining the discount in these sector. Indeed, these trades occur when the *Market Return*, *GDPgrowth* and when *PS Liquidity* are lowest in the sample. While the trades of blocks in these 2-digit SIC group are well spread out over time rather than clustered, they all occur at times when the determinants of aggregate illiquidity are stronger than the average for other industries.

The case of communication providers tells a different story: the control discount appears to be large because of the determinants of fire sale values rather than liquidity shocks. Indeed, the blocks traded in this 2-digit SIC group are, on average, among the top five largest relative to the total industry equity and have the third lowest *Tangibility*. The deals are clustered between late 1999 and mid 2001, where the M&A activity in this 2-digit group is the largest in the sample. Moreover, the average block premium for this group is  $33\%$  and the *CAR* is  $7.7\%$ .

The marketability discount, as well as the control discount, is lowest for restaurants (code 58), food producers (code 20), durable goods wholesalers (code 50), various retailers (code 59) and accounting consultants (code 87). Food producers and wholesalers have small marketability discounts because the blocks are small relative to the industry market capitalization and their assets are highly tangible. Controlling blocks of retailers or accounting consultants occur when *PS Liquidity* and *GDPgrowth* are high relative to other industries in the sample. As a result, they have the lowest average marketability discount .

## 6. Conclusion

This paper has shown that the costs of concentrated ownership to the blockholder, and the spillover effects on the dispersed shareholders, can be identified with data on majority block trades and the theoretical restrictions imposed by a search model. Unobservable to the econometrician, the probability that a block is traded because the blockholder has a sudden preference for liquidity can be estimated from the difference between the block price premium and the share price reaction to the trade announcement.

The paper shows that the marketability discount on a block can be large. However, there is great heterogeneity in the marketability discount across deals in our sample. The marketability discount depends on the aggregate macroeconomic conditions, which determine the probability of a liquidity shock, and firm

and industry-specific characteristics, which determine the liquidation value of the block. We also estimate the control discount, i.e., the private value to the blockholder with respect to the exchange traded stock price. Therefore, the determinants discussed here can be applied to valuation exercises in a straightforward way.

One possible shortcoming of this study is that our estimates of the liquidity shock arrival probability seem small and, as a result, the model does not generate sufficient variation in the control discounts or the predicted block premium and cumulative returns around the trades. Pending is the need to find additional determinants of blockholders' illiquidity.

## Appendix A: Proofs

**Proof of Proposition 1.** Define the support of  $\pi$  as  $X$ . Let  $B(X)$  be the space of bounded, continuous functions  $f : X \rightarrow \mathbf{R}$  with the sup norm. Let  $T_v : B(X) \rightarrow B(X)$  be an operator defined by

$$T_v(f)(\pi) = \pi_I + \delta \left[ (1 - \theta) \int \max_{sell, hold} \{b(f)(\pi_I, \pi) - B; f(\pi_I)\} dF(\pi) + \theta L_v \right],$$

where

$$b(f)(\pi_I, \pi) = B + \psi f(\pi_R) + (1 - \psi) f(\pi_I),$$

if  $f(\pi_I) < f(\pi_R)$  and 0 otherwise. It is straightforward to show that the operator  $T_v$  satisfies Blackwell's sufficient conditions of monotonicity and discounting and is therefore a contraction. By the contraction mapping theorem (see Stokey and Lucas, 1989),  $T_v$  has a unique fixed point  $v$ . Theorem 4.7 in Stokey and Lucas can then be used to show that  $v$  is a strictly increasing function. ■

**Proof of Proposition 2.** Let  $T_p : B(X) \rightarrow B(X)$  be the operator defined by

$$T_p(f)(\pi_I) = \pi_I + \delta [(1 - \theta) [(1 - F(\pi_I)) E[f(\pi) | \pi > \pi_I] + F(\pi_I) f(\pi_I)] + \theta L_p].$$

The first part of the proof follows the proof of Proposition 1. It remains to show that  $p(\pi) > v(\pi)$ . Take two functions  $f_p, f_v \in B(X)$  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,  $f_p(\pi_R) > \psi f_v(\pi_R) + (1 - \psi) f_v(\pi_I)$  for any  $\psi < 1$ . Therefore,  $T_p(f)(\pi_I) > T_v(f_v)(\pi_I)$ , for any  $\theta < 1$ . ■

**Proof of Proposition 3.** Absent a liquidity shock, a trade occurs if  $\pi_R > \pi_I$ . When  $B = 0$ ,

$$\begin{aligned} BP/\psi - CAR &\approx \frac{v(\pi_R) - v(\pi_I)}{v(\pi_I)} - \frac{p(\pi_R) - p(\pi_I)}{p(\pi_I)} \\ &\rightarrow \frac{\partial v(\pi_I)}{\partial \pi_I} - \frac{\partial p(\pi_I)}{\partial \pi_I}, \end{aligned}$$

as  $\pi_R - \pi_I \rightarrow 0$ . These limits exist because  $v$  and  $p$  are monotonic and defined over a compact support, hence differentiable almost everywhere. Differentiate (2) using (5) to obtain

$$\frac{\partial v(\pi_I)}{\partial \pi_I} = [1 - \delta(1 - \theta)[1 - \psi(1 - F(\pi_I))]]^{-1} > 0. \quad (14)$$

Likewise, differentiate (9) to obtain

$$\frac{\partial p(\pi_I)}{\partial \pi_I} = [1 - \delta(1 - \theta)F(\pi_I)]^{-1} > 0. \quad (15)$$

We want to show monotonicity of  $BP/\psi - CAR$  with respect to  $\theta$ , or

$$\frac{\partial}{\partial \theta} [BP/\psi - CAR] = \frac{\partial^2 v(\pi_I)}{\partial \theta \partial \pi_I} - \frac{\partial^2 p(\pi_I)}{\partial \theta \partial \pi_I}.$$

Differentiate (14) with respect to  $\theta$  to obtain

$$\frac{\partial^2 v(\pi_I)}{\partial \theta \partial \pi_I} = - \frac{\delta [1 - \psi (1 - F(\pi_I))]}{[1 - \delta (1 - \theta) [1 - \psi (1 - F(\pi_I))]]^2},$$

and differentiate (15) with respect to  $\theta$  to obtain

$$\frac{\partial^2 p(\pi_I)}{\partial \theta \partial \pi_I} = - \frac{\delta F(\pi_I)}{[1 - \delta (1 - \theta) F(\pi_I)]^2}.$$

We conclude that for  $\psi < 1$ ,  $\frac{\partial v(\pi_I)}{\partial \pi_I} > \frac{\partial p(\pi_I)}{\partial \pi_I}$ , and

$$\frac{\partial^2 v(\pi_I)}{\partial \theta \partial \pi_I} < \frac{\partial^2 p(\pi_I)}{\partial \theta \partial \pi_I} < 0.$$

Therefore,  $BP/\psi - CAR$  is decreasing in  $\theta$ . ■

## Appendix B: A general estimable model

This appendix describes a generalized version of the model in section 2, where we model the cash flow dynamics around a constant growth path. This is the version of the model that we estimate. We assume that actual cash flows,  $\tilde{\pi}_t$ , grow at some exogenous growth rate  $g$  and that they are stationary around this trend, i.e.,

$$\tilde{\pi}_t = e^{gt} \pi_t,$$

where  $F(\pi_{t+1}|\pi_t)$  describes the transition probability distribution for  $\pi$ . The value of the block to the incumbent is therefore

$$v(\pi, \theta) = \pi + \delta e^g \left[ (1 - \theta) \int \tilde{v}(\pi, \pi', \theta) dF(\pi'|\pi) + \theta L(\pi, \theta) \right], \quad (16)$$

where  $L(\pi, \theta) = \phi \int v(\pi', \theta) dF(\pi'|\pi)$  and  $\tilde{v}(\cdot)$  is defined as

$$\tilde{v}(\pi, \pi', \theta) + B = \int \max_{\text{sell, hold}} \{ b(\pi', \pi'', \theta); v(\pi', \theta) + B \} dF(\pi''|\pi).$$

In keeping with stationarity, we assume that private benefits also grow at rate  $g$ , i.e.,  $B_t = B \exp^{gt}$ .

Because  $I$  and  $R$  draw independent values of  $\pi$ , it may happen that  $I$  draws a bad shock  $\pi' < \pi$  while  $R$  draws a shock  $\pi > \pi'' > \pi'$ , but they share a common aggregate state  $\theta$ . The block price and the decision to rule to sell are the same as in the model in section 2. Therefore,  $\tilde{v}(\pi, \pi', \theta)$  can be simplified to

$$\tilde{v}(\pi, \pi', \theta) = \int_{\pi'' > \pi'} [b(\pi', \pi'', \theta) - B] dF(\pi''|\pi) + F(\pi'|\pi) v(\pi', \theta). \quad (17)$$

The stock price is

$$p(\pi, \theta) = \pi + \delta e^g \left[ (1 - \theta) \int \tilde{p}(\pi, \pi', \theta) dF(\pi'|\pi) + \theta L(\pi, \theta) \right], \quad (18)$$

where  $L(\pi, \theta) = \int p(\pi', \theta) dF(\pi'|\pi)$  and

$$\tilde{p}(\pi, \pi', \theta) = \int_{\pi'' > \pi'} p(\pi'', \theta) dF(\pi''|\pi) + F(\pi'|\pi) p(\pi', \theta). \quad (19)$$

To solve the model, consider the discretized cash flow  $\pi \in \{\pi_1, \dots, \pi_{N_\pi}\}$ . Let the conditional probability distribution  $\Pr[\pi = \pi_j | \pi = \pi_i] = q_{ij}$  with  $q_{ij} > 0$  and  $\sum_j q_{ij} = 1$  and the matrix  $\mathbf{Q} = [\mathbf{q}_1^\top, \dots, \mathbf{q}_{N_\pi}^\top]^\top$ . Row  $i$  of  $\mathbf{Q}$  is given by  $\mathbf{q}_i = [q_{i1}, \dots, q_{ij}, \dots, q_{iN_\pi}]$  and adds to one.

We may now write (17) as

$$\begin{aligned} \tilde{v}_{ij} &= \sum_{\pi_l > \pi_j} q_{il} (\psi v_l + (1 - \psi) v_j) + \sum_{\pi_l \leq \pi_j} q_{il} v_j \\ &= v_j + \psi \sum_{\pi_l > \pi_j} q_{il} (v_l - v_j). \end{aligned}$$

Define  $\mathbf{I}_i$  as a diagonal matrix with ones only on the diagonal elements  $i + 1$  through  $N_\pi$ . Thus,  $\mathbf{I}_{N_\pi}$  is the null matrix. Let  $\mathbf{1}$  be a column vector of ones. Also, define the column vector  $\mathbf{v} = [v_1, \dots, v_{N_\pi}]^\top$ , of size  $(1 \times N_\pi)$ . We then rewrite the previous expression in vector notation as

$$\tilde{v}_{ij} = v_j + \psi \mathbf{q}_i \mathbf{I}_j (\mathbf{v} - \mathbf{1}v_j).$$

Letting  $\tilde{\mathbf{v}}_i$  be the  $1 \times N_\pi$  vector collecting all terms  $\tilde{v}_{ij}$ . We have

$$\begin{aligned} \tilde{\mathbf{v}}_i &= \mathbf{v} + \psi ((\mathbf{M}_i^0 - \mathbf{M}_i^1) \mathbf{v}^\top)^\top \\ &= \mathbf{v} + \psi \mathbf{v} (\mathbf{M}_i^0 - \mathbf{M}_i^1)^\top \end{aligned}$$

where

$$\mathbf{M}_i^0 = \begin{bmatrix} \mathbf{q}_i \mathbf{I}_1 \\ \dots \\ \mathbf{q}_i \mathbf{I}_{N_\pi} \end{bmatrix}, \quad \mathbf{M}_i^1 = \text{diag} \left( \begin{bmatrix} \mathbf{q}_i \mathbf{c}_1 \\ \dots \\ \mathbf{q}_i \mathbf{c}_{N_\pi} \end{bmatrix} \right),$$

and  $\mathbf{c}_i = [0, \dots, 0, 1, \dots, 1]^\top = \mathbf{I}_i \mathbf{1}$  with the first 1 in row  $i + 1$ . Integrating over possible future states  $\pi'$ , the scalar  $\tilde{v}_i$  simplifies to

$$\tilde{v}_i = \mathbf{v} \mathbf{q}_i^\top + \psi \mathbf{v} (\mathbf{M}_i^0 - \mathbf{M}_i^1)^\top \mathbf{q}_i^\top.$$

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

$$\tilde{\mathbf{v}} = \mathbf{v} \mathbf{Q}^\top + \psi \mathbf{v} \mathbf{M}^2, \tag{20}$$

where

$$\mathbf{M}_{(N_\pi \times N_\pi)}^2 = \left[ (\mathbf{M}_1^0 - \mathbf{M}_1^1)^\top \mathbf{q}_1^\top, \dots, (\mathbf{M}_{N_\pi}^0 - \mathbf{M}_{N_\pi}^1)^\top \mathbf{q}_{N_\pi}^\top \right].$$

Finally, substituting (20) into (16), and solving for the  $1 \times N_\pi$  vector  $\mathbf{v}$ , we obtain

$$\mathbf{v} = \boldsymbol{\pi}^\top \left\{ \mathbf{I} - \delta \exp^g [(1 - \theta) (\mathbf{Q}^\top + \psi \mathbf{M}^2) + \theta \phi \mathbf{Q}^\top] \right\}^{-1}. \tag{21}$$

Similarly, let  $\mathbf{p}$ , of size  $(1 \times N_\pi)$  be the state-contingent share price vector. To solve for  $\tilde{p}_{ij}$  in (19), we first write it in vector notation as

$$\begin{aligned} \tilde{p}_{ij} &= \sum_{\pi_l > \pi_j} q_{il} p_l + \sum_{\pi_l \leq \pi_j} q_{il} p_j \\ &= \sum_{\pi_l > \pi_j} q_{il} p_l + \left( \sum_{\pi_l \leq \pi_j} q_{il} p_j + \sum_{\pi_l > \pi_j} q_{il} p_j - \sum_{\pi_l > \pi_j} q_{il} p_j \right) \\ &= \sum_{\pi_l > \pi_j} q_{il} (p_l - p_j) + p_j \\ &= p_j + \mathbf{q}_i \mathbf{I}_j (\mathbf{p} - \mathbf{1}p_j). \end{aligned}$$

As for  $\tilde{\mathbf{v}}_i$ , the vector  $\tilde{\mathbf{p}}_i$  of size  $(1 \times N_\pi)$  can be written as

$$\tilde{\mathbf{p}}_i = \mathbf{p} + \mathbf{p} (\mathbf{M}_i^0 - \mathbf{M}_i^1)^\top.$$

Integrating over possible future states  $\pi'$ , the scalar  $\tilde{p}_i$  is

$$\tilde{p}_i = \mathbf{p} \mathbf{q}_i^\top + \mathbf{p} (\mathbf{M}_i^0 - \mathbf{M}_i^1)^\top \mathbf{q}_i^\top.$$

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

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

Eliminating  $\mathbf{M}^2$ , we obtain

$$\begin{aligned} \mathbf{p} &= \boldsymbol{\pi}^\top + \delta e^g \left[ (\mathbf{I}_{N_z} - \mathbf{M}^\theta) \tilde{\mathbf{p}} + \mathbf{M}^\theta \mathbf{p} \mathbf{Q}^\top \right] \\ &= \boldsymbol{\pi}^\top + \delta e^g \left[ \mathbf{p} \mathbf{Q}^\top + (\mathbf{I} - \mathbf{M}^\theta) \mathbf{p} \mathbf{M}^2 \right]. \end{aligned}$$

Finally, solving for  $\mathbf{p}$  gives

$$\mathbf{p} = \boldsymbol{\pi}^\top \left\{ \mathbf{I} - \delta \exp^g [\mathbf{Q}^\top + (1 - \theta) \mathbf{M}^2] \right\}^{-1}. \quad (22)$$

## Appendix C: Details of the estimation procedure

This appendix describes the procedure used to estimate the discretized general version of the theoretical search model, which is developed in Appendix B. The first step consists of estimating the Markov-transition matrix,  $\mathbf{Q}$ , for every observation. Recall that this matrix is the discretized version of the conditional cumulative density  $F(\pi'|\pi)$ . To do so, we estimate an AR(1) process for the time series, including the last 5 years preceding each trade, of the de-trended logarithm of the average monthly cash flows of all firms in the same 3-digit SIC code as the target. For each trade, we generate the discrete support  $\{\pi_1, \pi_2, \dots, \pi_{N_\pi}\}$  and the Markov transition  $\mathbf{Q}_{N_\pi \times N_\pi}$  for a yearly frequency, using the quadrature-based method of Tauchen and Hussey (1991). Finally, we recover the target  $i$ 's cash flow support by assuming that it grows at the same permanent rate that the industry, so that  $\pi_j^i = \frac{p_i}{\bar{p}} \pi_j$  for every state  $j = 1, \dots, N_\pi$ , where  $p_i$  and  $\bar{p}$  are the observed target share price and the 3-digit SIC average share price, respectively. We set  $N_\pi$  to 5 and record the cash flow state at the time of the trade,  $\pi_j^i$ . Using industry data to estimate the AR(1) process for cash flows guarantees more observations per regression. We set the discount rate to be  $\delta = 1/1.1$ .

We estimate the remaining parameters,  $\Gamma = \{\beta, \gamma, \psi, B\}$ , by simulated maximum likelihood (SML). That is, we solve for

$$\hat{\Gamma}_{SML} = \arg \max_{\Gamma} \mathcal{L}(\{BP_i, CAR_i\}_i; \Gamma, \{\mathbf{x}_i, \mathbf{z}_i\} | \text{trade occurs}),$$

where  $\mathcal{L}(\{BP_i, CAR_i\}_i; \Gamma, \{\mathbf{x}_i, \mathbf{z}_i\} | \text{trade occurs})$  is given by

$$\ln \prod_{i=1}^N \left[ \begin{array}{l} \theta_i f_L(BP_i, CAR_i; \Gamma, \mathbf{x}_i, \mathbf{z}_i | \text{liquidity shock occurs}) \\ + (1 - \theta_i) f_N(BP_i, CAR_i; \Gamma, \mathbf{x}_i, \mathbf{z}_i | \text{no liquidity shock occurs}) \end{array} \right].$$

$\{BP_i, CAR_i\}_i$ , are the block premium and cumulative abnormal returns data,  $\{\mathbf{x}_i, \mathbf{z}_i\}_i$  are the data on the determinants of  $\theta$  and  $\phi$  and the functions  $f_L(\cdot)$  and  $f_N(\cdot)$  are the joint densities of  $BP$  and  $CAR$  conditional on whether there was a liquidity shock or not. The procedure to evaluate and maximize the simulated likelihood follows the steps below:

1. Fix a vector of parameters  $\Gamma_0 = \{\beta_0, \gamma_0, \psi_0, B_0\}$  and evaluate for each deal  $\theta_i$  and  $\phi_i$ ;
2. Evaluate  $\mathcal{L}(\{BP_i, CAR_i\}_i; \Gamma, \{\mathbf{x}_i, \mathbf{z}_i\} | \text{trade occurs})$  by numerical simulation, following the next steps for each trade,  $i$  :
  - (a) solve for the functions  $p(\pi)$  and  $v(\pi)$  from the system of equations (22) and (21), given  $\Gamma_0$ ;
  - (b) simulate  $S = 1000$  pairs  $\left(\pi_{R,t+1}^s, \pi_{I,t+1}^s\right)_{s=1, \dots, S}$  of future cash flows using the estimated Markov matrix,  $\mathbf{Q}$ , and starting off at the cash flow state observed prior to the trade;
  - (c) evaluate the current  $v(\pi_{I,t}), p(\pi_{I,t}^s)$  and the future  $v(\pi_{R,t+1}^s), p(\pi_{R,t+1}^s), v(\pi_{I,t+1}^s)$ , and  $p(\pi_{I,t+1}^s)$  for every  $s$ ;

- (d) evaluate  $BP\left(\pi_{I,t+1}^s, \pi_{R,t+1}^s\right)$  and  $CAR\left(\pi_{I,t+1}^s, \pi_{R,t+1}^s\right)$  for every  $s$ , using equations (10) and (11)
- (e) compute  $f_L$  and  $f_N$  as the bivariate kernel density for the simulated  $\{BP_i, CAR_i\}$  conditional on a liquidity shock or not, using Botev et al.'s (2009) procedure; note that absent a liquidity shock, all draws where  $\pi_{R,t+1}^s < \pi_{I,t+1}^s$  violate the gains-from-trade condition and are dropped from the computation;

3. Evaluate  $\mathcal{L}_0 = \ln \prod_{i=1}^N (\theta_i f_{L,i} + (1 - \theta_i) f_{N,i})$  and return to Step 1 until  $\mathcal{L}(\cdot)$  is maximized.

In order to be confident that the maximizer is global, we repeat the maximization over an exhaustive set of initial conditions,  $\Gamma_0$ . This is done over a combination of 3 initial conditions (lower bound, middle, upper bound) on four parameters ( $4^3 = 64$  points) :  $\beta_0, \gamma_0, B$  and  $\psi$ .

To gain speed, we restrict our search for the maximizer within the set of parameter values where the elasticity of  $\theta$  or  $\phi$  with respect to the variable associated to each parameter in  $\beta$  and  $\gamma$  is zero. For  $B$  or  $\psi$  we search in the whole range of possible values, i.e.,  $[0,1]$ .

We estimate the covariance matrix of the estimator,  $var\left(\widehat{\Gamma}_{SML}\right)$ , with the inverse of the negative of the numerical Hessian,  $\left(-H\left(\widehat{\Gamma}_{SML}\right)\right)^{-1}$  of the likelihood function. We verify that our solution is locally identified by checking that the Hessian  $H\left(\widehat{\Gamma}_{SML}\right)$  is non-singular.

## Appendix D: Data

Our goal is to select a sample of block trades where a majority controlling block is traded. Our selection criteria aims to include block purchases where (i) a private negotiation is necessary and (ii) there remains a float of publicly traded shares. Therefore, we impose that:

1. The size of the traded block is at least 50%, so that any attempt to acquire control requires a negotiation with the incumbent majority blockholder ;
2. The size of the traded block is strictly smaller than 100%, so that some float of shares remains;
3. The transfer price must be observable;
4. The transfer price reported by SDC is confirmed by the deal synopsis;
5. The block must be paid with instruments that do not lead to further acquisition of shares (e.g., warrants, convertible bonds, swaps), so that any future changes in the block size are not predictable at the trade moment;
6. The target's shares are covered by CRSP and its balance sheets are available in Compustat;
7. Additionally, we exclude transactions where:
  - (a) the transfer is between subsidiaries or parent companies, where the block pricing may be more complex;
  - (b) the acquirer makes a simultaneous or announces a subsequent tender offer, so the block size remains unchanged;
  - (c) the target is bankrupt, which correspond to the firm, rather than the blockholder, being illiquid.

The procedure to meet the criteria above is therefore:

1. Select from Thomson One Banker's M&A all US, disclosed value, acquisitions of 50% up to 99.99% between 1/1/1990 and 31/8/2009; resulting in 3,120 trades;
2. We exclude: Privatizations, Tender Offers, Exchange Offers, Spin-offs, Recapitalizations and Repurchases, Equity Carveouts, Joint Ventures, Going Private deals, Debt Restructurings and Bankruptcies; resulting in 2,615 trades;
3. We exclude deals where the payment was made using warrants, convertible bonds, notes, liabilities, debt-equity swaps or any form of options; resulting in 1,625 trades;
4. We merge the 1,625 trades to the target's CRSP tapes, with the additional restrictions that:

- (a) 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;
- (b) 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.

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Table I: Description of variables used and their sources

Type	Variable name	Variable description	Source	
Outcome variables	$p^0, p^1$	Market-model adjusted share prices, 21 trading days before ( $t = 0$ ) and 2 trading days after ( $t = 1$ ) the trade announcement (\$).	CRSP	
	$P$	Market-model adjusted price per share in the block (\$).	Thomson One Banker	
	$\alpha$	Block size (%).	Thomson One Banker	
	<i>Block value</i>	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	
	$CAR$	Price impact of the block trade announcement, defined as $\frac{p^1-p^0}{p^0}$ (%).	Constructed	
Determinants of aggregate liquidity ( $\mathbf{x}$ )	<i>Market Return</i>	Annualized average daily returns on the equally-weighted portfolio of all NYSE, AMEX and NASDAQ stocks for the last month before the deal (%).	CRSP	
	<i>Market Volatility</i>	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	
	<i>Corporate Spread</i>	Difference between the average interest rate on BAA and AAA rated corporate bonds (%).	FED Board of Governors	
	<i>Yield curve slope</i>	Difference between the interest rate on the 10 and 1 year Treasury bill (%).	FED Board of Governors	
	<i>3-month-Tbill</i>	Interest rate on the 3-month Treasury bill (%).	FED Board of Governors	
	<i>GDP growth</i>	Average annual US GDP per capita growth rate in the last quarter prior to the trade (%).	FED Board of Governors	
	<i>PS liquidity</i>	Pástor and Stambaugh's (2003) measure of innovations to monthly aggregate liquidity.	Robert Stambaugh's webpage	
	$VIX$	Chicago Board Options Exchange daily market volatility index, implied by CBOE traded S&P 500 index options (%).	CBOE	
				(continues)

Table I: continued

Type	Variable name	Variable description	Source
Determinants of liquidation values ( $\mathbf{z}$ )	<i>Target Return</i>	Target's annualized average daily return for the 12 month-period ending two months before the trade announcement (%).	Compustat
	<i>Target Volatility</i>	Standard deviation of the target's annualized average daily return for the 12 month-period ending two months before the trade announcement (%).	Compustat
	<i>Tangibility Block-to-Industry Size</i>	Target's proportion of tangible to total assets. Ratio of the total <i>Block value</i> to the total market capitalization of all NYSE and AMEX firms in the same 2-Digit SIC Code as the target.	Compustat Thomson One Banker, CRSP
	<i>Industry's M&amp;A Activity</i>	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

**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 99% of the target's outstanding stock.

Variable	Mean	Standard deviation	5th percentile	First quartile	Median	Third quartile	95th percentile
$\alpha$	59.74%	15.15%	38.55%	49.32%	54.61%	72.33%	87.00%
<i>Block value</i>	192.917	719.231	0.750	7.140	23.017	100.000	810.000
<i>BP</i>	6.79%	58.83%	-89.16%	-18.20%	3.45%	27.80%	121.42%
<i>CAR</i>	9.64%	31.93%	-25.88%	-10.11%	4.96%	23.04%	78.06%
<i>Market Return</i>	12.74%	15.78%	-19.95%	8.89%	14.92%	23.58%	30.69%
<i>Market Volatility</i>	14.03%	5.25%	8.28%	10.10%	11.66%	17.80%	24.06%
<i>Corporate Spread</i>	0.81%	0.21%	0.56%	0.62%	0.80%	0.91%	1.25%
<i>Yield curve slope</i>	3.24%	3.00%	-1.00%	1.00%	2.00%	6.00%	8.80%
<i>3-month-Tbill</i>	4.38%	1.66%	1.20%	3.17%	4.98%	5.21%	6.29%
<i>GDP growth</i>	3.23%	3.11%	-3.69%	1.92%	3.10%	5.78%	6.96%
<i>PS liquidity</i>	0.011	0.050	-0.082	-0.007	0.003	0.039	0.100
<i>VIX</i>	19.60%	7.91%	11.70%	13.77%	16.89%	23.92%	36.07%
$\Delta$ VIX	0.03%	0.03%	-0.04%	0.02%	0.03%	0.06%	0.07%
<i>Target Return</i>	50.06%	106.76%	-86.06%	-9.23%	30.28%	80.10%	243.32%
<i>Target Volatility</i>	39.83%	40.13%	5.51%	10.77%	23.80%	59.08%	110.07%
<i>Tangibility</i>	0.487	0.240	0.104	0.322	0.519	0.592	0.954
<i>Block-to-Industry Size</i>	0.008	0.033	0.000	0.000	0.000	0.001	0.027
<i>Industry's M&amp;A Activity</i>	3.879	3.682	0.173	1.095	2.761	6.084	11.667

**Table III: Reduced-form analysis**

This table summarizes the cross-sectional relationship between the different determinants of liquidity shocks,  $\mathbf{x}$ , and of the block liquidation value,  $\mathbf{z}$ . The first three columns report the correlation coefficient between each variable in  $\mathbf{x}$  or  $\mathbf{z}$  and the difference between the percentage block premium ( $BP$ ) divided by the seller's bargaining power,  $\psi$ , and the cumulative abnormal returns ( $CAR$ ) in three subsamples of the data.  $\psi$  is set to 0.5. The remaining columns report the coefficients of the regression of  $\epsilon$  on  $\mathbf{x}$  or  $\mathbf{z}$  on different subsamples.  $\epsilon$  is the residual from the regression of  $BP$  on  $CAR$ . 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 99% of the outstanding stock. Standard errors are shown in parenthesis next to the coefficient estimates<sup>a</sup>.

**Panel A: Aggregate variables (x)**

	$\rho(\frac{BP}{\psi} - CAR, x)$				Dependent variable: $\epsilon_i = BP_i - \beta_{OLS} \times CAR_i$	
	All trades (N = 114)	CAR > 0 (N = 85)	CAR > 0 and BP > 0 (N = 66)	All trades (N = 114)	CAR < 0 or (CAR > 0 and BP < 0) (N = 72)	CAR < 0 (N = 47)
<i>Market Return</i>	-0.142*	-0.146	-0.197**	1.050** (0.425)	0.608 (0.596)	0.111 (0.696)
<i>Market Volatility</i>	0.078	0.026	0.151*	1.535* (0.907)	0.473 (1.087)	2.116 (1.327)
<i>Corporate Spread</i>	0.156**	0.170*	0.247**	0.759* (0.391)	0.284 (0.536)	1.022 (0.664)
<i>Yield curve slope</i>	0.025	0.114	0.119	0.050 (0.818)	-0.654 (1.088)	-0.749 (1.161)
<i>3-month-Tbill</i>	-0.054	-0.149	-0.135	-0.033 (0.044)	-0.072 (0.059)	0.004 (0.068)
<i>GDP growth</i>	-0.069	-0.010	0.198**	2.205 (2.855)	0.633 (3.525)	-0.212 (4.026)
<i>PS liquidity</i>	-0.004	-0.080	0.083	-0.501 (1.247)	1.480 (1.547)	2.675 (1.978)
<i>VIX</i>	-0.043	0.031	-0.041	-0.013 (0.009)	-0.011 (0.010)	-0.030** (0.012)
$\Delta VIX$	-0.069	-0.010	-0.068	0.042 (0.050)	-0.016 (0.064)	0.049 (0.083)
Constant				-0.535 (0.460)	0.056 (0.595)	-0.420 (0.726)
F statistic				2.16**	0.67	1.47
Adjusted R squared				0.09	0.04	0.09

(continues)

Table III : continued

Panel B: Firm and industry-specific variables (z)		Dependent variable: $\epsilon_i = BP_i - \beta_{OLS} \times CAR_i$			
	$\rho(\frac{BP}{\psi} - CAR, z)$	All trades	All trades	All trades	
		$CAR > 0$ (N = 85)	$CAR > 0$ and $BP > 0$ (N = 66)	$CAR < 0$ or $(CAR > 0$ and $BP < 0)$ (N = 72)	$CAR < 0$ (N = 47)
<i>Target Return</i>	0.003	-0.024	0.120	0.138* (0.058)	0.198 (0.123)
<i>Target Volatility</i>	-0.171**	-0.250**	-0.144*	-0.304** (0.135)	-0.733 (1.583)
<i>Tangibility</i>	-0.027	0.027	0.097*	-0.177 (0.243)	1.504** (0.639)
<i>Block-to-Industry Size</i>	-0.039	0.000	-0.080	-2.472 (4.518)	-32.203** (13.256)
<i>Industry's M&amp;A Activity</i>	-0.017	-0.037	-0.137	-0.182 (0.294)	-24.667* (13.453)
Constant				0.179 (0.139)	-0.595 (0.357)
F statistic				2.09	20.05***
Adjusted R squared				0.04	0.46

<sup>a</sup> Estimates followed by \*\*\*, \*\* and \* are statistically different from zero with 0.01, 0.05 and 0.1 significance levels, respectively.

**Table IV: Estimates of the model's parameters**

This table shows the estimates of the block seller's bargaining power,  $\psi$ , of the controlling shareholder's private benefits of control,  $B$ , and the sensitivities,  $\beta$  and  $\gamma$ , of the probability of a liquidity shock,  $\theta$  and of the block's liquidation value,  $\phi$ , respectively, to their determinants. For each deal,  $i$ ,  $\theta_i$  and  $\phi_i$  are given by

$$\theta_i = \frac{\exp(\mathbf{x}'_i\beta + \beta_0 + \xi_i)}{1 + \exp(\mathbf{x}'_i\beta + \beta_0 + \xi_i)} \quad \text{and} \quad \phi_i = \frac{\exp(\mathbf{z}'_i\gamma + \gamma_0)}{1 + \exp(\mathbf{z}'_i\gamma + \gamma_0)}.$$

The vectors  $\mathbf{x}$  and  $\mathbf{z}$  are specified below, and  $\xi_i \sim N(0, \sigma_\xi^2)$ . The parameters are estimated by maximizing the joint likelihood of the percentage block premium ( $BP$ ), and the cumulative abnormal returns ( $CAR$ ), which is simulated by the theoretical search model. 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 99% of the outstanding stock. Standard errors are shown in parenthesis next to the coefficient estimates<sup>a</sup>. Unless noted otherwise, the economic significance of each coefficient is given by the change in  $\theta_i$  or  $\phi_i$  associated with a change of one sample standard deviation of the variable in  $\mathbf{x}$  and  $\mathbf{z}$ , respectively.

	(1)		(2)	
	Coefficient	Economic significance	Coefficient	Economic significance
<b>Liquidity shock determinants (x)</b>				
<i>Market Return</i>	-7.993*** (1.619)	-0.009*** (0.002)	-8.518*** (0.020)	-0.052*** (0.001)
<i>Market Volatility</i>	7.744** (3.843)	0.003** (0.001)	9.499*** (0.115)	0.019*** (0.001)
<i>Corporate Spread</i>	-4.775 (16.243)	-0.007 (0.024)	-2.362*** (0.012)	-0.019*** (0.001)
<i>Yield curve slope</i>	-13.748*** (2.754)	-0.012*** (0.002)	-13.318*** (0.003)	-0.062*** (0.002)
<i>GDP growth</i>	-17.148*** (0.998)	-0.004*** (0.001)	-17.135*** (0.341)	-0.021*** (0.001)
<i>PS liquidity</i>	-10.301*** (1.138)	-0.004*** (0.001)	-10.734*** (0.001)	-0.021*** (0.001)
Constant ( $\beta_0$ )	-4.592*** (1.008)		-4.529*** (0.002)	
Random effect variance ( $\sigma_\xi$ ) <sup>b</sup>			0.011*** (0.002)	0.051*** (0.012)
<b>Liquidation value determinants (z)</b>				
<i>Target Return</i>	0.260*** (0.093)	0.055*** (0.020)	0.534*** (0.003)	0.042*** (0.002)
<i>Target Volatility</i>	-2.800*** (0.091)	-0.224*** (0.007)	-3.977*** (0.003)	-0.117*** (0.001)
<i>Tangibility</i>	1.360*** (0.094)	0.065*** (0.004)	0.493*** (0.010)	0.009*** (0.001)
<i>Block-to-Industry Size</i>	-2.150*** (0.091)	-0.014*** (0.001)	-4.538*** (0.001)	-0.011*** (0.001)
<i>Industry's M&amp;A Activity</i>	0.040 (0.094)	0.030 (0.069)	-0.114*** (0.001)	-0.031*** (0.001)
Constant ( $\gamma_0$ )	0.010 (0.075)		-1.514*** (0.013)	
$\psi$	0.503*** (0.106)		0.408*** (0.058)	
$B$	0.020 (0.094)		0.000 (0.021)	
$\chi^2$ statistic	771.800***		1,032.274***	
$p$ value ( $H_0 : (\beta, \gamma, \sigma_\xi, B, \psi) = \mathbf{0}$ )	0.000		0.000	

<sup>a</sup> Estimates followed by \*\*\*, \*\* and \* are statistically different from zero with 0.01, 0.05 and 0.1 significance levels, respectively.

<sup>b</sup> The economic significance is the ratio of the variance of the random effect,  $\sigma_\xi^2$ , to the variance generated by the observable determinants, i.e.,  $\text{var}(\mathbf{x}'\beta)$ . The F test's null hypothesis is that this ratio equals 1, and the alternative that it is smaller than 1.

**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 in Table IV. 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 99% of the outstanding stock.

	(1)			(2)						
	Sample mean	Standard deviation	Min	Median	Max	Sample mean	Standard deviation	Min	Median	Max
Liquidity shock probability ( $\theta$ )	0.009	0.039	0.000	0.001	0.322	0.064	0.145	0.000	0.014	0.918
Shares' liquidation value ( $\phi$ )	0.483	0.226	0.008	0.563	0.963	0.093	0.109	0.000	0.078	0.810
Marketability discount ( $1 - \frac{v(\theta,.)}{v(\theta=0,.)}$ )	0.066	0.046	0.002	0.058	0.360	0.073	0.081	0.004	0.054	0.632
Liquidity-spillover discount ( $1 - \frac{p(\theta,.)}{p(\theta=0,.)}$ )	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.004
Control discount ( $1 - \frac{v(\theta,.)}{p(\theta,.)}$ )	0.078	0.046	0.013	0.070	0.367	0.096	0.081	0.028	0.080	0.644

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

This table summarizes the sample distribution of the main variables 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 IV, 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 99% of the outstanding stock.

<b>Panel A: Marketability discount</b>									
<b>Top 5</b>					<b>Bottom 5</b>				
Major Group	Group description	N	Mean	Std. Dev.	Major Group	Group description	N	Mean	Std. Dev.
36	Electronic and Other Electrical Equipment, Except Computers	3	0.244	0.337	58	Restaurants	3	0.046	0.029
73	Business Services (Advertising, Consulting)	5	0.157	0.215	50	Wholesale Trade-durable Goods	4	0.045	0.022
37	Transportation Equipment	4	0.115	0.155	20	Food and Kindred Products	4	0.044	0.024
35	Industrial and Commercial Machinery	4	0.092	0.077	87	Accounting, Engineering and Management Services	3	0.036	0.002
48	Communications (Radio, Cable, Telephone)	5	0.089	0.033	59	Miscellaneous Retail (Stores)	5	0.026	0.017
<b>Panel B: Illiquidity-spillover discount</b>									
<b>Top 5</b>					<b>Bottom 5</b>				
Major Group	Group description	N	Mean	Std. Dev.	Major Group	Group description	N	Mean	Std. Dev.
36	Electronic and Other Electrical Equipment, Except Computers	3	0.001	0.002	58	Restaurants	3	0.000	0.000
37	Transportation Equipment	4	0.001	0.001	50	Wholesale Trade-durable Goods	4	0.000	0.000
48	Communications (Radio, Cable, Telephone)	5	0.000	0.000	49	Electric, Gas and Sanitary Services	4	0.000	0.000
15	Building Contractors	4	0.000	0.000	63	Insurance Carriers	3	0.000	0.000
60	Depository Institutions	3	0.000	0.000	20	Food and Kindred Products	4	0.000	0.000

(continues)

Table VI: continued

Panel C: Control discount									
Top 5					Bottom 5				
Major Group	Group description	N	Mean	Std. Dev.	Major Group	Group description	N	Mean	Std. Dev.
36	Electronic and Other Electrical Equipment, Except Computers	3	0.271	0.323	49	Electric, Gas and Sanitary Services	4	0.063	0.032
73	Business Services (Advertising, Consulting)	5	0.191	0.210	87	Accounting, Engineering and Management Services	3	0.062	0.002
37	Transportation Equipment	4	0.128	0.154	50	Wholesale Trade-durable Goods	4	0.061	0.022
35	Industrial and Commercial Machinery	4	0.116	0.071	20	Food and Kindred Products	4	0.057	0.024
48	Communications (Radio, Cable, Telephone)	5	0.111	0.032	59	Miscellaneous Retail (Stores)	5	0.045	0.021

<sup>a</sup> Industries with fewer than 3 observations are excluded from the ranking and computations.

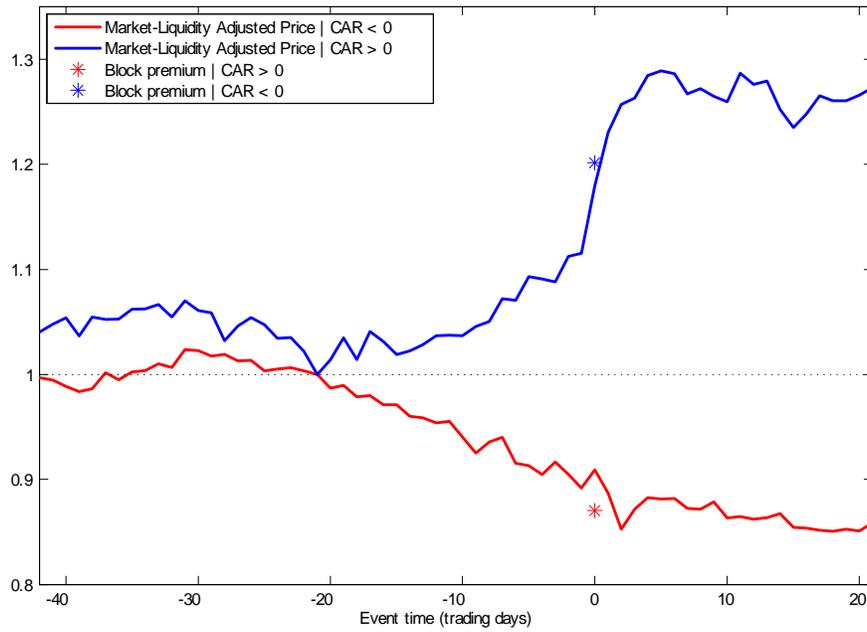


FIGURE 1: Average share price 21 trading days before and after the block trade.

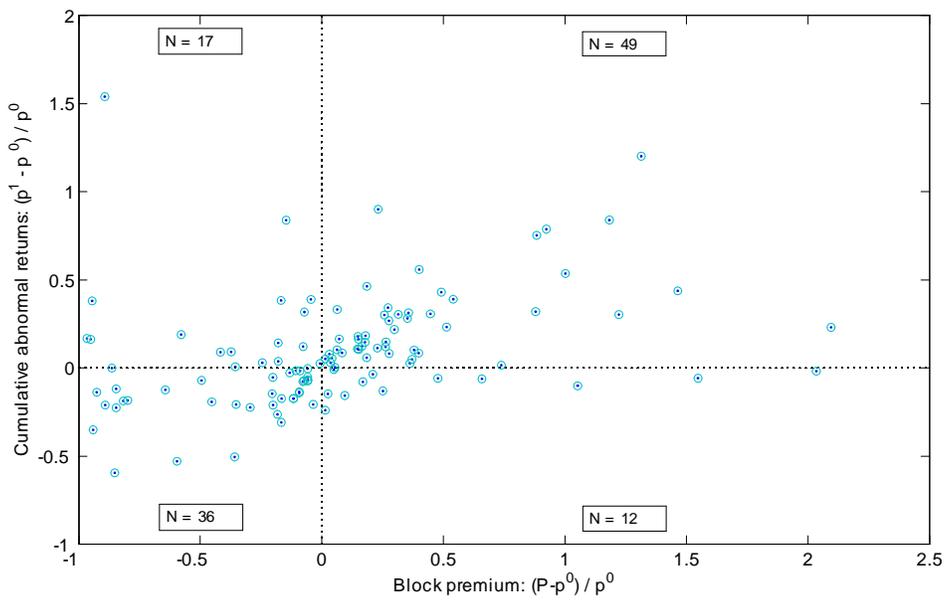


FIGURE 2: Scatter plot of the percentage block premium against the cumulative abnormal returns around the block trade announcement.

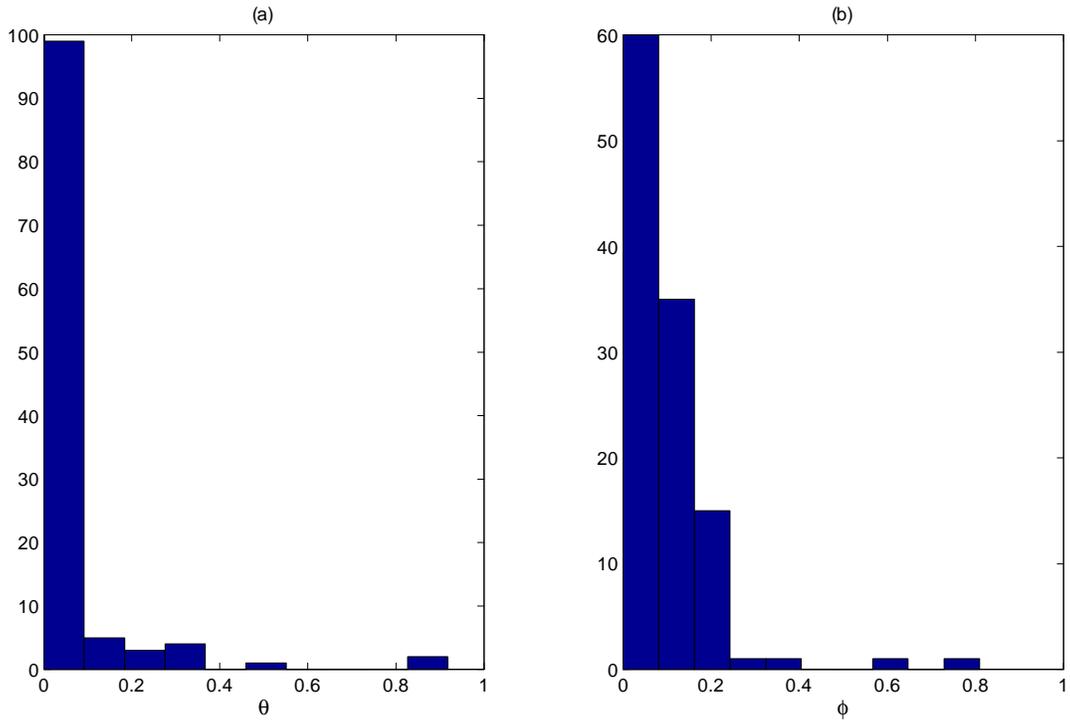


FIGURE 3: Predicted histogram of the probability that a blockholder gets a liquidity shock,  $\theta$ , (panel (a)) and of the liquidation value of the block,  $\phi$ , (panel (b)) in the estimated search model. The histograms are constructed using the coefficients of specification (2) in Table IV.

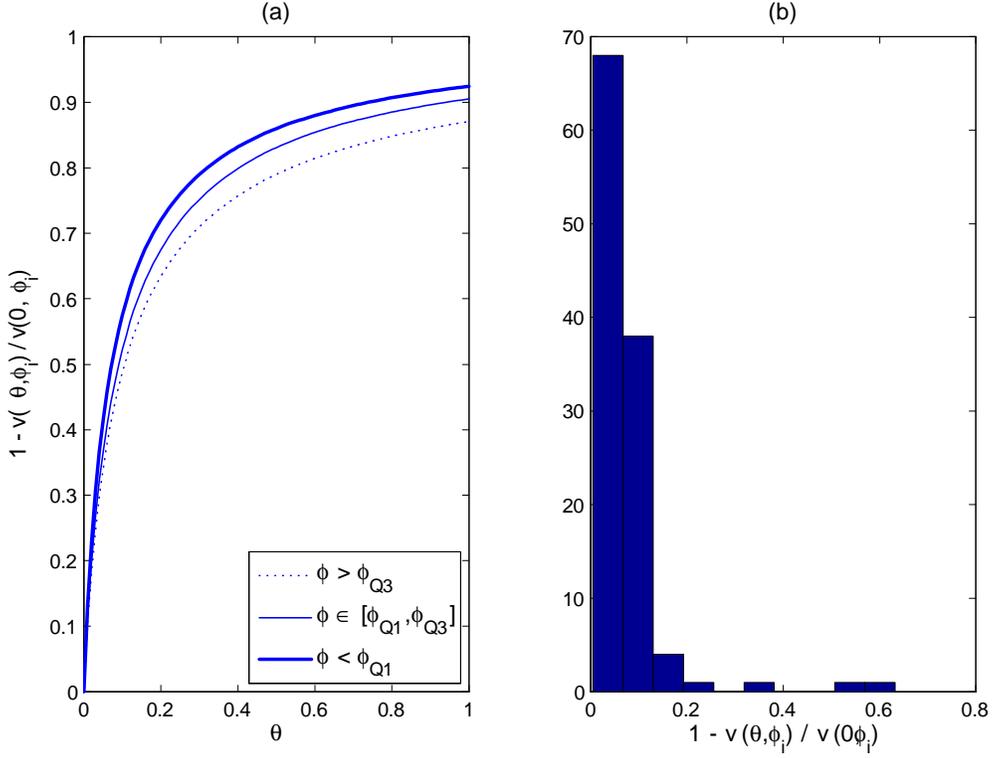


FIGURE 4: Predicted marketability discount of the block,  $1 - \frac{v(\theta, \phi_i)}{v(0, \phi_i)}$ , for every value of  $\theta$ , (panel (a)) and predicted in-sample histogram of the marketability discount, evaluated at the predicted probability that the blockholder gets a liquidity shock,  $\theta_i$ , as a function of the predicted block liquidation value,  $\phi_i$ , (panel (b)) in the estimated search model. The marketability discount function and histogram are constructed using the coefficients of specification (2) in Table IV.

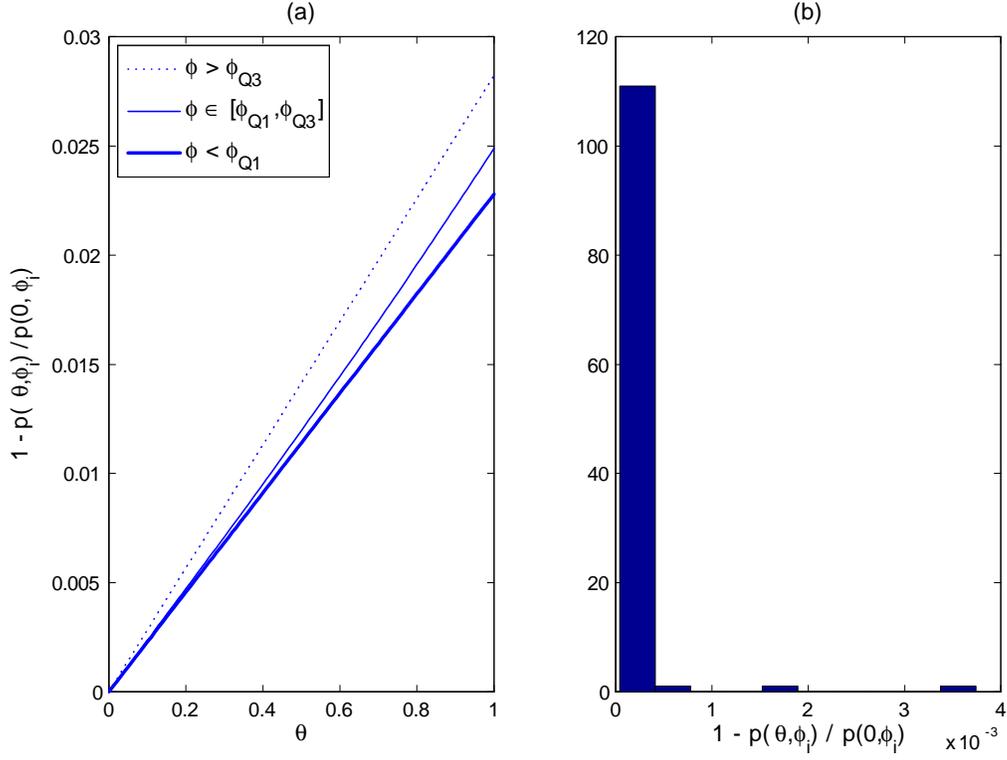


FIGURE 5: Predicted illiquidity-spillover discount of the dispersed shares,  $1 - \frac{p(\theta, \phi_i)}{p(0, \phi_i)}$ , for every value of  $\theta$ , (panel (a)) and predicted histogram of the in-sample liquidity spillover discount, evaluated at the predicted probability that the blockholder gets a liquidity shock,  $\theta_i$ , as a function of the predicted block liquidation value,  $\phi_i$ , (panel (b)) in the estimated search model. The liquidity spillover discount function and histogram are constructed using the coefficients of specification (2) in Table IV.

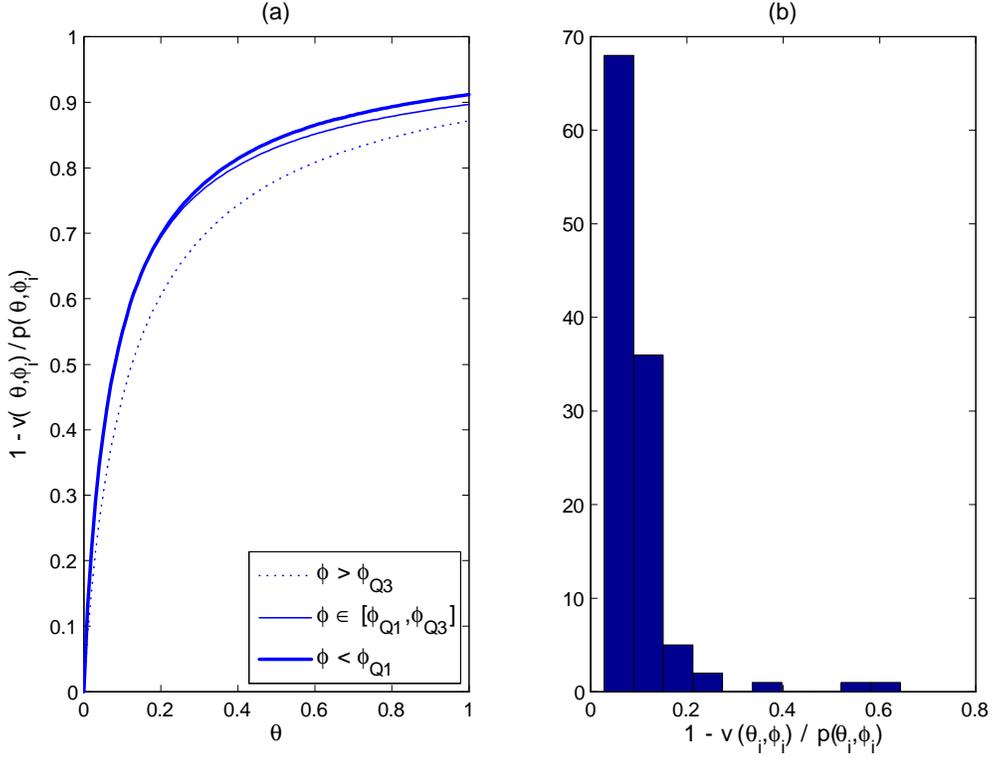


FIGURE 6: Predicted control discount of the block relative to dispersed shares,  $1 - \frac{v(\theta, \phi_i)}{p(\theta, \phi_i)}$ , for every value of  $\theta$ , (panel (a)) and predicted in-sample histogram of the control discount, evaluated at the predicted probability that the blockholder gets a liquidity shock,  $\theta_i$ , as a function of the predicted block liquidation value,  $\phi_i$ , (panel (b)) in the estimated search model. The control discount function and histogram are constructed using the coefficients of specification (2) in Table IV.