# The Value of Control and the Costs of Illiquidity[*]

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**Abstract**

An inherent difficulty in valuing controlling blocks of shares is the illiquidity of the market. We explore the pricing implications associated with the illiquidity of controlling blocks of shares in the context of a search model of block trades. The model considers several dimensions of illiquidity. First, following a liquidity shock, the controlling blockholder is forced to sell, possibly to a less efficient acquirer. Second, this sale may occur at a fire sale price. Third, absent a liquidity shock, a trade occurs only if a potential buyer arrives. We use a structural estimation approach and U.S. data on trades of controlling blocks of public corporations to identify these dimensions of illiquidity. We obtain estimates of counter-factual valuations that would result in the absence of illiquidity, which are used to measure the blockholders' marketability and control discounts and the dispersed shareholders' illiquidity-spillover discount.

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# 1. Introduction

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

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

The estimation of the marketability and the illiquidity-spillover discounts is notoriously difficult because it requires the quantification of a counter-factual price: what should the stock price be absent search frictions? The structural estimation adopted in the paper uses the model's pricing equations to evaluate

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

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

this counter-factual price. However, data limitations imply that the structural estimation must be able to identify the parameters associated with liquidity shocks and related search frictions without knowledge of the spell of time between trades of the same block.[3] One contribution of this paper is to show that it is possible to identify the model's parameters by using the valuations of two different types of shareholders during a block trade: the blockholders' valuation implicit in the negotiated block price and the dispersed shareholders' valuation revealed in the exchange share price.

In the model, a liquidity shock is the realization of a random variable with a Bernoulli distribution that forces blockholder turnover. 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 trade their stock at 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 if a potential new blockholder arrives and can generate 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 the stock market price reaction to the trade announcement. We allow the probability of a liquidity shock and the fire sale price to depend on economy-wide 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 (median) of 30% (12%) of the block value and a standard deviation of 32%. The marketability discount is explained by a nonlinear combination of the following two effects: an estimated average (median) probability of getting a liquidity shock within one year of 34% (20%) and an estimated average (median) fire sale price of 64% (88%) of the actual block value. The model estimates a probability of meeting a potential buyer within one year of 100%. For comparison, Pulvino (1998) estimates the liquidation value of aircraft for certain airlines to be 14% lower than the average market price. Coval and Stafford (2007) estimate gains from buying stocks that experience price pressure due to mutual fund outflows of more than 10%. The spillover effect of the block's illiquidity on the dispersed shares is on average 0.8% (median 0.6%) of the

[3] The labor search literature uses the duration of unemployment to infer the probability of a job offer (see Wolpin, 1987). 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.

share price and reaches a maximum in-sample value of 7.5%. The mean of this effect is two to three times the size of the mean equal weight quoted bid-ask spread on equities (see Bollen et al., 2004). We discuss the model's ability to estimate the various discounts and possible measurement biases and argue that these estimates constitute lower bounds to the true parameters.

We find too that economy-wide determinants of liquidity capture unobserved variation in the probability of a liquidity shock, whereas firm or industry characteristics capture unobserved variation in fire sale values. On the one hand, the probability of getting a liquidity shock is increasing in the Fontaine and Garcia (2011) measure of aggregate funding illiquidity and in the yield spread between 10-year and 3-month Treasury bills. Moreover, the illiquidity effects of higher yield spreads are more pronounced at times of high market returns and high GDP growth. On the other hand, the block's fire sale value decreases with the degree of asset specificity of the target firm's industry, with the target firm's leverage relative to that of its industry, and with the total volume of M&A of the target firm's industry. The evidence that the state of the aggregate economy determines firm-specific liquidity complements the work of Chordia et al. (2000) and Bao et al. (2008), who find commonalities in asset-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 indicated, 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. The estimations suggest that this discount is on average 30%, but that it varies significantly, highlighting the importance of conditioning on economic-wide characteristics to determine the control discount, a point ignored by the court and the literature.

The literature has considered alternative ways of measuring the value of control. One approach is to look at dual-class shares and compare the price of voting versus nonvoting shares (e.g. Masulis et al., 2009, provides a recent application). Another approach is to infer the value of control from put-call parity deviations (Kalay et al., 2011). By studying per share prices, these approaches measure the *marginal* value of control. Because in our data we have the total price of a block, we are able to comment on the total and hence *average* value of control.

There is a vast literature on the pricing of illiquid assets (see Amihud et al., 2005; and Damadoran, 2005, for comprehensive surveys). Longstaff (1995) and Kahl et al. (2003) measure the marketability discount associated with stocks with trading restrictions. We differ from these papers by considering search frictions as opposed to trading restrictions. A recent literature studies search frictions in financial markets. Duffie et al. (2005, 2007) present a search model of over-the-counter markets with atomistic investors. There is no controlling shareholder that can affect the value of assets and discounts result from a pure search cost. In our paper, a liquidity cost arises from three 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 finding a buyer. Feldhütter (2012) estimates a variant of Duffie et al. (2005) with bond market data using structural estimation. Block trading, with search frictions, is also examined by Burdett and O'Hara (1987). They study how a market maker may arise and take positions on small blocks to circumvent the lack of counterparty at any point in time.

Related theoretical work on the costs of concentrated ownership argues that it induces illiquidity in the firm's exchange traded shares.[4] Demsetz (1968) argues that, by keeping shares off the market, large blockholders reduce the 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, as a result, the price informativeness, when float is smaller. These papers focus on the price implications of a reduced float. Instead, by studying block trading events where the float is unchanged, we are able to focus on the price implications of liquidity shocks to large blockholders. Kahn and Winton (1998) and Maug (1998) argue that, if blockholders obtain value-relevant information from their monitoring, then the resulting adverse selection problem when blockholders trade their shares lowers liquidity (see also Edmans and Manso, 2008). We believe that the size of the controlling blocks studied in this paper and the fact that blocks are not partitioned suggest that this cause for illiquidity is of second order in our exercise and should not affect our results.

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

[4] The empirical literature has shown a positive association between float and liquidity of dispersed shares (e.g., Heflin and Shaw, 2000; Becker et al., 2008; Brockman et al., 2008; Dlugosz, et al., 2006; and Ginglinger and Hamon, 2007).

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 in the firm, i.e., the controlling blockholder, spill over to the pricing of the remaining investors on shares on the same firm.

The paper proceeds as follows. Section 2 presents the search model that we use to price controlling blocks and dispersed shares. Section 3 describes the empirical strategy. It describes how the model's parameters are identified, motivates the sample selection, and briefly summarizes the estimation algorithm. Section 4 summarizes the data used. Section 5 presents the main results, and section 6 discusses the robustness of the results. Finally, section 7 concludes.

## 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, and primes denote next period values. The total number of shares is normalized to one.

### *2.1. Blockholder's value*

Consider the problem faced by the owner of a block $\alpha > 50\%$ of the shares of a firm. The current block owner is called the incumbent and denoted by $I$. Under $I$, the cash flow generated by the firm is $\pi_I$. For ease of exposition, we leave to the appendix the model with time-varying stochastic cash flows. Denote by $v(\pi_I)$ the incumbent's per share value of the block and denote by $p(\pi_I)$ the dispersed shareholders' share value. 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 and network building in the case of an individual blockholder or from valuable synergies in the case of a corporate blockholder.[5]

At the beginning of every period, $I$ may face a liquidity shock with probability $\theta$. If a liquidity shock does not occur, a potential buyer, called a rival and denoted by $R$, arrives with probability $\eta$. The firm's cash flow under the rival is denoted by $\pi_R$, drawn from a distribution function $F(\pi)$, defined over a compact support. Dispersion in $F$ can be thought to depend on the dispersion of blockholder managerial skills, monitoring costs, and on other aspects through which blockholders contribute to firm value. $I$ and $R$ bargain over the block. We assume Nash bargaining and denote by $\psi$ $(1-\psi)$ the incumbent's (rival's) bargaining power absent liquidity shocks. Bargaining powers are independent of the identity of either party.

[5] 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%.

If bargaining is successful, the block changes hands for the price of $b(\pi_I, \pi_R)$. Besides private benefits, the new blockholder gets $v(\pi_R)$ and dispersed shareholders get $p(\pi_R)$. The model assumes complete information. Blockholders and dispersed shareholders know the value of cash flow under current and rival management.

If a liquidity shock occurs, then $I$ is forced to sell at a fire sale price. We do not model the trading that ensues upon a liquidity shock. Instead, we specify the fire sale price in a reduced form as $\phi \times v(\pi_R)$, where the parameter $\phi$ summarizes the resulting fire sale discount. In subsection 5.6, we discuss our estimates in light of the definitions of the parameters that describe liquidity-related frictions, $\theta$ and $\phi$. Because the incumbent sells regardless of the rival's valuation, the ex ante block price upon a liquidity shock is

$$L_v = \phi \int v(\pi)\, dF(\pi). \tag{1}$$

The incumbent's problem is best expressed in recursive form. The value of the block to the incumbent is derived from current cash flows $\pi_I$, the continuation value in the absence of a liquidity shock $\tilde{v}$, and the liquidation value $L_v$. Therefore,

$$v(\pi_I) = \pi_I + \delta\left[(1-\theta)\,\tilde{v}(\pi_I) + \theta L_v\right].$$

The continuation value absent a liquidity shock includes private benefits and an option to sell, satisfying

$$\tilde{v}(\pi_I) + B = \eta \int \max_{\text{sell, hold}} \left\{b(\pi_I, \pi), v(\pi_I) + B\right\} dF(\pi) + (1-\eta)\left[v(\pi_I) + B\right]. \tag{2}$$

The block is sold when a rival appears and the price is high enough. Under Nash bargaining, the block price for any given rival solves,

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

When a trade is mutually advantageous, i.e., $v(\pi_I) < v(\pi_R)$, the solution is

$$b(\pi_I, \pi_R) = B + v(\pi_I) + \psi\left[v(\pi_R) - v(\pi_I)\right]. \tag{3}$$

Otherwise, no trade occurs and $I$ remains the blockholder with valuation $v(\pi_I) + B$. From (3), it is clear that the block price must compensate $I$ for the value she may attain by holding onto the block plus $I$'s fraction of the added surplus that results from $R$ taking over.

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

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

The property that $v$ is strictly increasing implies that it is optimal to sell the block if and only if $\pi_I < \pi_R$. Therefore, we can simplify the block price and $\tilde{v}(\pi)$ to

$$\tilde{v}(\pi_I) + B = v(\pi_I) + B + \psi\eta \int \max_{\text{sell, hold}} \{v(\pi) - v(\pi_I), 0\} \, dF(\pi), \tag{4}$$

where the last term in $\tilde{v}$ is the value of the option to sell. The fraction $\psi$ of the option to sell accrues to $I$ but can only be captured if a rival appears, which occurs with probability $\eta$. Note that it is worth selling to an incrementally better rival because all future increases in value that result from a sale by the rival are already properly valued in $v$ and there are no fixed costs of selling.

The model's property that the block is sold if, and only if, $\pi_I < \pi_R$ (rather than if and only if $v(\pi_I) < v(\pi_R)$) is 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) and (3)) 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 $v$. This property of the model 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 search literature that assume an exogenous outside option for searchers.

### *2.2. Dispersed shareholders' value*

Dispersed shareholders own the fraction $1 - \alpha$ of the stock. In a competitive stock market, the share price $p$ is

$$p(\pi_I) = \pi_I + \delta \left[ (1 - \theta) \tilde{p}(\pi_I) + \theta L_p \right]. \tag{5}$$

Under the assumption of complete information, dispersed shareholders know that absent a liquidity shock, which occurs with probability $1 - \theta$, the block is sold if and only if a rival is present and can produce a cash flow $\pi > \pi_I$. Denote the share price contingent on a liquidity shock by $\tilde{p}$. We can write $\tilde{p}(\pi_I)$ in recursive form as

$$\tilde{p}(\pi_I) = p(\pi_I) + \eta \int \max_{\text{sell, hold}} \{p(\pi) - p(\pi_I), 0\} \, dF(\pi). \tag{6}$$

Dispersed shareholders also benefit from $I$'s option to sell. Further, we will show that $p(\pi)$ is increasing in $\pi$, which implies that $I$'s decision rule to sell is efficient. The last component of the share price is the expected value that results if a liquidity shock occurs,

$$L_p = \int p(\pi)\, dF(\pi). \tag{7}$$

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

The next proposition characterizes the function $p$.

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

There is a control discount in that $p > v$. The control discount arises because the model imposes search frictions to blockholders that have only limited impact on dispersed shareholders. We assume that blockholders cannot arbitrage this price difference by selling part of the block. This assumption can be justified by the observed empirical stability of block size and by the fact that such a sale would cause a negative price impact by signalling a loss of the public benefits from having concentrated ownership, e.g., monitoring of management. The property of a control discount is consistent with earlier theories (e.g., Bolton and von Thadden, 1998) and with empirical evidence on newly issued shares (e.g., Wruck, 1989, for an earlier paper and Barclay et al., 2007, for more recent evidence).

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

Conditional on a trade, the observed block price 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 to the pre-trade price:

$$BP(\pi_I, \pi_R) \equiv \begin{cases} \frac{\phi v(\pi_R)}{p(\pi_I)} - 1 & , \text{ if a liquidity shock occurs} \\ \frac{b(\pi_I, \pi_R)}{p(\pi_I)} - 1 & , \text{ else} \end{cases}. \tag{8}$$

We assume that, unlike the econometrician, dispersed shareholders know $\pi_R$ and whether a trade has occurred for liquidity reasons. Therefore, the post-trade price is $p(\pi_R)$. We define the price reaction to the block trade announcement by

$$CAR(\pi_I, \pi_R) \equiv \frac{p(\pi_R)}{p(\pi_I)} - 1. \tag{9}$$

Note that negative price reactions signal liquidity shocks: a negative price reaction can only occur if the block is traded after a liquidity shock and the new block owner generates $\pi_R < \pi_I$. However, the converse is not true: positive price reactions occur following a liquidity shock if the randomly drawn rival has a higher cash flow. Section 3 discusses how liquidity shocks are identified despite this difficulty.

## *2.4. Discussion*

We have developed a parsimonious and estimable search model of block trades. The following discussion points out potential weaknesses of the model and how we deal with them.

**Reasons for trading.** We model trades that occur for one of two motives: liquidity shocks or efficiency gains (i.e., a new blockholder is able to generate higher cash flows). There are, however, other reasons for trading. First, trading could occur when $I$ privately learns bad news about the firm. Such a trade could be disguised as a liquidity-driven sale provided adverse selection is not too severe in the market. We believe these trades are rare or non-existent in our data because (i) they fall under the Securities and Exchange Commission's insider trading laws (Rule 10b-5); (ii) unlike other settings where insider trading exists, in block trades the identities of both the seller and the buyer are known, which significantly increases the risk of litigation due to insider trading; (iii) buyers and sellers in this market are sophisticated investors, including financial and nonfinancial corporations, private equity firms, and wealthy individuals that are advised by financial corporations in these deals; and, (iv) 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). The model above assumes constant private benefits, but assuming that private benefits are proportional to the blockholder's value yields the same results. The critical assumption we make is rather that private benefits cannot be negatively correlated to the blockholder's value. In that case, a trade may occur where the new blockholder is able to extract significantly more private benefits than the incumbent while being detrimental to dispersed shareholders, i.e., $\pi_R < \pi_I$. While such a trade is not motivated by a liquidity shock, the estimation would infer a liquidity shock based on the negative CAR, producing an upward bias in $\theta$. While we cannot fully rule out this motive for trading, we take comfort in two pieces of evidence. Studying private benefits derived from firm cash flows, Albuquerque and Schroth (2010) find small and often statistically insignificant differences in private benefits to block sellers and buyers. Similarly, Holderness and Sheehan (1988) document that the average compensation of blockholder CEOs is not significantly different from that of CEOs of firms with dispersed share ownership.

**Investor heterogeneity.** In the model, blockholders are different from dispersed shareholders because they can manage a firm and increase share value but also because they can extract private benefits. Other forms of investor heterogeneity can also be interesting to model. First, investors may agree to disagree on the probability of liquidity shocks $\theta$, particularly if these events are rare. We return to this point in the robustness section below. Second, 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. For consistency with the assumption of risk neutral dispersed shareholders in the model, we remove from the measured stock market price a market factor to account for investor risk aversion, and a liquidity-risk factor, as in Acharya and Pedersen (2005), to account for priced liquidity risk. We attempt to deal empirically with the assumption of risk neutral blockholders by allowing for heterogeneity in their discount rate. This is done in the robustness section. Third, 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. Finally, the model abstracts from asymmetric information among dispersed investors. Empirically, we observe that bid-ask spreads appear the same before and after the block trade announcement and conclude that the price reaction and the block premium are not affected by this form of illiquidity.

## 3. Empirical strategy

The parameters to estimate are the fire sale price, $\phi$, the probability of a liquidity shock, $\theta$, the probability of meeting a buyer, $\eta$, the seller's bargaining power, $\psi$, and the block holder's private benefits, $B$. We estimate the cash flow distribution $F(\pi)$ separately and calibrate the discount rate $\delta$.

### *3.1. Identification*

The identification we propose in this paper is different from that found in the search literature in labor economics, or in the recent finance literature (Feldhütter, 2012), because we do not have information on the time between two trades of the same block nor do we have multiple trades of the same block. Instead, we rely on the information conveyed by the valuations of blockholders and dispersed shareholders at the time of the trade.

Estimation of $\phi$ relies on the fact that fire sale prices offered to large blockholders affect their own valuation of the block, $v$, but not the exchange share price, $p$. Hence variation in block prices that is not associated with variation in the price reaction to the block trade announcement is inferred by the model as coming from variation in $\phi$ when a liquidity shock has occurred.

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 a 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 normalized by $\psi$ and the price reaction, $BP/\psi - CAR$. Absent a liquidity shock, we obtain

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

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 $\pi_R - \pi_I \to 0$, then $BP/\psi - CAR$ is monotonically decreasing in $\theta$.*

This proposition reveals that *every* trade contains information about $\theta$: the use of block and stock price data around block trades identifies liquidity shocks *even* when trades are not the result of a liquidity shock. The intuition is the following: blockholders gain proportionately more than dispersed shareholders with trades that occur without a liquidity shock, because the bargaining process they are subject to implies that only a fraction of the efficiency gains that occur with the trade is already incorporated into the price of the shares in the block. When liquidity shocks are more frequent, this effect is reduced, and blockholders lose more value than dispersed shareholders.

The parameter that describes the likelihood of meeting a rival, $\eta$, captures the relevance of the option to sell to all investors. Both the block price and the price reaction increase in $\eta$, which means that both $\eta$ and $\theta$ can generate similar variation in the block premium and the price reaction. The identification of $\eta$ departs from that of $\theta$ because of the fact that only shocks to liquidity can generate negative price reactions in the model.

To identify the bargaining power parameter, $\psi$, we rely on the fact that $\psi$ moves the block price but not the $CAR$. While these facts are true also for the fire sale parameter, $\phi$, there is one important difference between $\psi$ and $\phi$: $\psi$ has a first order effect on the block price absent a liquidity shock, whereas $\phi$ has a first order effect on the block price in the presence of a liquidity shock only. Private benefits also cause variation in block prices that is unrelated to variation in $CAR$, but the effect of $B$ on the block premium occurs when the block trades at a premium.

### *3.2. Modeling liquidity*

We estimate $\theta$ and $\phi$ by expressing each as a function of their respective cross-sectional determinants. We parameterize $\theta$ and $\phi$ with the logistic functions,

$$\theta(\mathbf{x}_i, \boldsymbol{\beta}) = \frac{\exp(\mathbf{x}_i'\boldsymbol{\beta})}{1+\exp(\mathbf{x}_i'\boldsymbol{\beta})}, \tag{10}$$

$$\phi(\mathbf{z}_i, \boldsymbol{\gamma}) = \frac{\exp(\mathbf{z}_i'\boldsymbol{\gamma})}{1+\exp(\mathbf{z}_i'\boldsymbol{\gamma})}. \tag{11}$$

By construction, the logistic function guarantees 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 exogenous determinants of liquidity shocks and fire sale prices, respectively, whereas $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$ are the vectors of fixed sensitivities to be estimated. To economize on parameters, the sensitivities $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$ are constant across deals. Below we describe the variables specified in $\mathbf{x}$ and $\mathbf{z}$. Variation in $\mathbf{x}_i$ and $\mathbf{z}_i$ across deals allows us to estimate $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$ through the variation they produce on $BP$ and $CAR$.

While $\theta_i$ is allowed to vary with $\mathbf{x}_i$ and $\phi_i$ is allowed to vary with $\mathbf{z}_i$, the estimation constrains $\theta_i$ and $\phi_i$ to be constant over time for each deal $i$. This assumption is equivalent to assuming that blockholders and dispersed shareholders display a myopic attitude towards changes in these quantities. Ideally, the estimation would allow for $\mathbf{x}_i$ and $\mathbf{z}_i$ to be state variables in the investors' problems and for investors to change their valuations as their forecasts of $\theta$ and $\phi$ for each deal changed. While desirable, we choose not to pursue this approach because it is highly computationally demanding. The ability of the model to reasonably fit the data suggests that our assumption may not be too restrictive, but removing the assumption remains a goal for future research.

### *3.3. Estimation*

We estimate a more general version of the model presented above, where we allow for actual cash flow to trend at a known growth rate, $\tilde{\pi}_t = e^g \pi_t$, and the deviations from trend, $\pi_t$, to display serial correlation according to the conditional distribution function, $F(\pi_{t+1}|\pi_t)$. This more general model, which is developed in the appendix, preserves the main results of the simpler version above and has the same identification strategy. We use annual cash flow data at the 3-digit SIC level to estimate $F(.)$. We first remove a log-linear trend from 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, with its longer time series, more precise estimates. More details can be found in Appendix C.

We specify private benefits as a proportion of the block value rather than a constant dollar amount. Specifically, private benefits are $B = \tilde{B}v(\pi_I)$ for both $R$ and $I$ when they meet to bargain over the price. This specification allows the dollar value of private benefits to change across deals. We set the discount rate to 10%, so that the time discount parameter $\delta$ equals $1/(1+0.1)$.

We estimate the model's parameters, $\mathbf{\Gamma} = \left\{\psi, \eta, \tilde{B}, \boldsymbol{\beta}, \boldsymbol{\gamma}\right\}$, using the simulated method of moments. This estimator minimizes the norm function,

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

where $\mathbf{m}\left(\{BP_i, CAR_i\}_i; \mathbf{\Gamma}\right)$ is a vector of model-predicted moments of the joint distribution of the two observed endogenous variables, the block premium and the price reaction to the announcement, and $\mathbf{M}$ is the vector of the same moments in the sample. $W$ is the matrix of weights.

The estimation procedure can be summarized in three steps. In the first step, we fix a vector $\mathbf{\Gamma} = \mathbf{\Gamma}_0$. In the second step, we use the theoretical search model to simulate the vector $\mathbf{m}\left(\{BP_i, CAR_i\}_i; \mathbf{\Gamma}_0\right)$. In this step, for each deal in the data: (i) we solve the model's pricing equations (4) and (5) given the current parameters; (ii) we back out the predicted rival's cash flow state by matching the actual $CAR$ to the predicted $CAR$ grid; and (iii) we evaluate equations (8) and (9) at the given cash flow state. In this last step, we do not assume to know whether a liquidity shock occurred for a particular deal. Therefore we compute the expected block premium as a weighted average of the block premium in each liquidity state, where the probability of a liquidity shock given that a trade occurred is $\theta/\left(\theta + (1-\theta)\eta\right)$. Finally, in the third step we evaluate $\mathcal{J}$, stop if it has been minimized, or return to the first step otherwise. This procedure is explained in detail in Appendix C, including the care we take in the choice of initial conditions.

The number of parameters in the model is equal to the number of parameters in $\boldsymbol{\beta}$ plus those in $\boldsymbol{\gamma}$ plus 3. We identify these parameters through an over-identifed set of moment conditions equal to three times the number of parameters in $\boldsymbol{\beta}$ plus $\boldsymbol{\gamma}$ plus five other conditions. First, $\mathbf{m}$ includes the first-order moments $E(BP \times \mathbf{x})$, $E(CAR \times \mathbf{x})$, $E(BP \times \mathbf{z})$, and $E(CAR \times \mathbf{z})$ and the second order moments $E(BP^2)$,

$E(CAR^2)$, and $E(BP \times CAR)$.[6] The unconditional mean of $BP$ depends directly on $\widetilde{B}$, whereas $\psi$ is mostly identified off the correlation between $BP$ and $CAR$. Given that $\eta$ determines the option value of the block and dispersed shares, its identification relies on the first and second-order moments of both $BP$ and $CAR$. These moment conditions also help identify the sensitivities $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$ in that variation in the liquidity parameters also drives the first moments of $BP$ and $CAR$.

Second, $\mathbf{m}$ includes also the conditional moments $E\left[(BP/\psi - CAR) \times \mathbf{x} | CAR > 0\right]$, $E(BP \times \mathbf{z} | CAR < 0)$, $E[(BP/\psi - CAR)^2 | CAR > 0]$, and $E[(BP)^2 \,| CAR < 0]$. The first two conditions are directly aimed at capturing variation in $\theta$ as described in the identification strategy above. The last two moments describe variation in $BP$ when the price reaction is negative and serve to identify $\phi$. Finally, $\mathbf{m}$ includes the third order moments $E(BP^3)$ and $E(CAR^3)$. The inclusion of higher order moments follows from the fact that, as we shall show below, the sampling distributions of both $BP$ and $CAR$ are significantly skewed. Not matching the skewness of these distributions risks biasing our estimates of the means.[7]

# 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 U.S. 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 Jan. 1, 1990, and Dec. 31, 2010 in Thomson One Banker's M&A.[8] We use the "Type of Acquisition" field in the Thomson One Banker Acquisitions data to select which deals to include in the

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

[7] The distributions of $BP$ and $CAR$ also have a large kurtosis. However, our results (unreported) are robust to including fourth order moment conditions.

[8] While the model assumes that $\alpha > 50\%$, a sufficient condition is that the block is large enough so that an incumbent has no alternative to acquire control but to negotiate with the incumbent. Albuquerque and Schroth (2011) find that this condition is satisfied for trades above 35%.

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 receives a liquidity shock. While the blockholder could have a sudden preference for liquidity due to his own distress, this motive would not necessarily correspond to the target firm being bankrupt. For similar reasons, 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 merge the surviving deals to the target firm's CRSP record 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 risk and liquidity risk in conformity with the assumption of risk-neutral, dispersed shareholders in the model. Changes in $CAR$ are therefore more likely to provide a cleaner estimate of the effect of illiquidity on share prices due to inefficient turnover of control.

Finally, we match each deal to the target firm's Compustat record on the last December preceding the trade announcement. From the Thomson One Banker database we obtain 1,751 deals, which after merging with CRSP and Compustat yields a final sample of 114 deals. Details of this selection procedure, as well as other applied filters, are included in Appendix D.

Table II summarizes the main characteristics of our block trades: the mean block size is 59.7% with a standard deviation of 15.15%, and average deal value is \$193 millions with standard deviation of \$720 millions.

<INSERT TABLE II ABOUT HERE>

## *4.2. Cumulative abnormal returns and block premium*

We measure the pre-announcement share price, $p^0$, 21 trading days before the announcement so it excludes the build up of expectations about the unfolding block trade (see Barclay and Holderness, 1989). The post-announcement price, $p^1$, must incorporate the effects of the change of control on security benefits. Again, following the literature, we use the share price two trading days after the announcement. The average cumulative abnormal return is 9.6% (see Table II). Figure 1 plots the average price path for trades with positive $CAR$ (solid line) and trades with negative $CAR$ (dotted line). The 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% (see Table II). Our sample exhibits fewer block discounts than in Albuquerque and Schroth (2010) or Barclay and Holderness (1989), partly because the block premium is defined as the block price relative to the pre-announcement price but also partly because these studies include smaller blocks. However, the block premium distribution is significantly less right-skewed than in other studies.

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 and 48 deals (42%) where $CAR$ is negative. $BP$ and $CAR$ are positively correlated (correlation coefficient = 0.37) and are more strongly correlated when both are positive (correlation coefficient = 0.52) than when both are negative (correlation coefficient = 0.36). 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 discount.

<INSERT FIGURE 2 ABOUT HERE>

### 4.3. Determinants of block illiquidity

We group the determinants of block illiquidity into the determinants of $\theta$ and the determinants of $\phi$. In our baseline estimation, $\mathbf{x}$ includes economy-wide characteristics, such as the tightening or loosening of funding conditions that would force blockholders to liquidate their blocks because of a sudden preference for cash or lack thereof. In $\mathbf{z}$, we include characteristics of the target firm or of the industry that would make the block more or less valuable. In the robustness section, we allow $\mathbf{x}_i$ and $\mathbf{z}_i$ to share common determinants. As in Shleifer and Vishny (1992), liquidity shocks may force some investors in an industry to sell assets that would naturally be bought by other investors in the same industry, i.e., where the assets can be more effectively redeployed, which may themselves be subject to the same liquidity shocks. Hence the determinants of liquidity shocks may also have a direct effect on the fire sale price.

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

We interpret $\theta$ as a blockholder-specific shock to his preference for, or access to cash, which forces the sale of the block. We expect this shock to occur more likely in times of tighter aggregate funding liquidity. Our proxy for funding liquidity is the bond liquidity premium index in Fontaine and Garcia (2011) (*Fontaine-Garcia*). Fontaine and Garcia (2011) identify a monthly latent liquidity factor from the yield spread between US Treasury bills with the same cash flows but different ages. They interpret the higher yields on otherwise identical older Treasury bills as a premium on the liquidity of on-the-run bonds. Time series variation in this measure captures the availability of funding liquidity, and we hypothesize that it would be positively associated with $\theta$. The Fontaine and Garcia measure of funding liquidity is preferred in our setting to other measures of liquidity, e.g., Pástor and Stambaugh (2003), because it speaks directly to liquidity in the fixed income market, which is more likely to drive the blockholder's preference for cash.

We include in the determinants of liquidity shocks other variables that drive the preference for or the availability of cash. These are the growth of U.S. GDP per capita over the quarter immediately preceding the deal (*GDP growth),* the average daily return on the equally-weighted portfolio of all NYSE, AMEX, and NASDAQ stocks during the month preceding the block trade (*Market Return*), and the standard deviation of the returns on the same portfolio during the year before the trade (*Market Volatility*). We expect high GDP growth to be associated with increased liquidity and to have a negative effect on $\theta$. Likewise, 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 (see also Chordia et al., 2002). We therefore predict $\theta$ to decrease with *Market Return* and to increase with *Market Volatility.*

To measure the cost of funding, we include the slope of the yield curve, measured by the difference in interest rates on the 10-year and the 3-month Treasury bills (*Yield curve slope*). We also incorporate the interactions between the *Yield curve slope* and *GDP growth* and *Market Return.* The motivation is that high GDP growth and high returns may signal good investment opportunities that force the incumbent to sell. Since the incumbent would only sell the block if he cannot borrow to exploit such opportunities, we expect *GDP growth* and *Market Return* to have a positive effect on $\theta$ only when good investment opportunities occur at times of costly aggregate funding. A positive association between the slope of the yield curve and $\theta$ is also consistent with the interpretation that the *Yield curve slope* proxies for short term liquidity. We note, however, that determining the sign associated with the *Yield curve slope* is an empirical question because term structure theories of preferred habitat suggest that the interpretation of the slope of the yield curve as a measure of liquidity is unwarranted. Further, Estrella and Hardouvelis (1991) and others have shown that the term slope predicts future GDP growth, in which case we should expect $\theta$ and the term slope to have the same relation as $\theta$ and *GDP growth*.

#### *4.3.2.* **Determinants of $\phi : \mathbf{z}_i$**

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 the asset's 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 adopt these ideas about the liquidity of physical assets to the financial asset under consideration. We measure the *financial 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*).[9] Table II shows that, while the trades in our sample are small relative to their industry total equity (mean of 0.008), there is large variation in this measure. Based on this interpretation, we expect the liquidation value of the block, $\phi$, to decrease with the relative size of the block. However, if blockholders have a preference for relatively larger blocks in order to, say, exert control over industry policies, then $\phi$ would vary positively with *Block-to-Industry Size*.

We hypothesize that the industry's asset specificity causes a steeper fire sale discount of the controlling block. We follow Stromberg (2001) and measure *Industry Specificity* with the median proportion of machinery and equipment to total assets of all firms in the industry. As with *Block-to-Industry Size*, *Industry Specificity* directly measures the redeployability of the productive assets rather than of the controlling block. We view asset specificity as a proxy for the amount of industry-specific knowledge required by the controlling blockholder and expect more potential buyers of controlling stakes of firms that use generic productive assets and hence a negative effect.

We include the total dollar volume of M&A activity involving targets in the same 2-digit SIC group during the last quarter before the deal. On the one hand, a large *Industry's M&A Activity* could be the result of an increased supply of industry-specific assets, which would depress the liquidation value of the block. On the other hand, a large *Industry's M&A Activity* could reflect high liquidity for industry-specific

[9] This approach follows similar notions of asset liquidity in Gavazza (2010), salability in Benmelech (2009), and redeployability in Benmelech and Bergman (2008).

assets as in Schlingemann et al. (2002) and Ortiz-Molina and Phillips (2011) and, therefore, could increase the fire sale value.

We let the block's fire sale value vary with the target's leverage relative to its industry's average leverage. We define *Target minus Industry Leverage* as the difference between the target's proportion of long-term debt to assets and the median proportion of long-term debt to assets of all firms in the same 3-digit SIC code. We expect that blockholders will price in a bigger discount for firms with relatively more long term debt.

To control for the time-series variation in investment opportunities in the same industry, we include the median ratio of the market-to-book value of assets of all firms in the same 3-digit SIC code. Finally, we control for the target firm's daily return volatility over the last year before the trade. Higher volatility could signal a rebalancing need for the incumbent that would lower his bargaining position upon a liquidity shock and hence the fire sale price.

# 5. Results

## 5.1. Estimation results

Panel A of Table III presents the estimates of the model's parameters. Panel B evaluates the quality of the model's fit to the data along several dimensions. Specification (1) presents our baseline results, and specification (2) extends the baseline model to try to distinguish between liquidity shocks that represent an increase in investment opportunities and those that represent a shortage of cash. In general, specification (2) produces a better fit of the model to the data.

<INSERT TABLE III ABOUT HERE>

The point estimate of the matching probability is 1.0 in both specifications, though it is not estimated precisely. This point estimate suggests that a seller is expected to match with a buyer on average once every year. In general, and preempting our other results, the model has some difficulty estimating this parameter. We estimate the blockholder's private benefits to be equal to 11% (specification 2) of the selling blockholder's value. Panel A also reports the estimated incumbent blockholder's bargaining power *in the absence of a liquidity shock* to be 0.54 in specification (1) and 0.41 in specification (2). Conditional on measuring the buyer's and seller's valuation without bias, there is no reason to expect buyers to have a bargaining advantage over sellers in times of normal liquidity. The point estimates support this view, and in specification (2) we reject the null that this estimate is equal to zero at normal confidence levels, but we cannot reject that it is equal to 0.5.

Before turning to the results regarding the estimates of $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$, we discuss several measures of fit of the model reported in panel B. In both specifications, we reject the hypothesis that all of the model's parameters are zero ($p$-value of 0.00). Further, we cannot reject the joint hypothesis that the model is correctly specified and that the moment conditions over-identify the model's parameters. The block premium in the data has a mean of 6.8% and a standard deviation of 0.59%. Under the assumption that the econometrician cannot tell the cause of a trade, we compute the model's expected block premium as a weighted average of the block premium in each state. Specification (1) underpredicts the mean and standard deviation in the data, but specification (2) is able to improve on the point estimates of both moments of the block premium. Both specifications capture the fraction of discounts in the data well.

Regarding cumulative abnormal returns, the model predicts well the proportion of negative $CAR$ but does not generate significant cross-sectional variation in $CAR$. The inability to generate cross-sectional variation in $CAR$ underlies the fact that the distribution of $CAR$ across model specifications appears the same up to the third decimal place. While a weakness of these and other specifications of the model, the inability to generate significant cross sectional variation in $CAR$ is consistent with the general difficulty that pricing models have in explaining the large cross-sectional dispersion of stock returns.

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

### *5.1.1. Determinants of liquidity shocks*

We now focus on the results from specification (2), which we take as our main specification, and leave a comparison with the main differences from specification (1) for later. To describe the economic significance of the estimated values for $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$, we compute the predicted change in $\theta$ and $\phi$ given a one sample standard deviation change in the relevant variable.

*GDP growth* has a negative and significant effect on $\theta$, though not statistically significant. We estimate that a one standard deviation increase in *GDP growth* is associated with a decrease in $\theta$ of 0.08. The sign of the point estimate suggests that GDP growth captures changes in liquidity rather than changes in investment opportunities.

The coefficient on *Market Return* is negative and statistically significant. One sample standard deviation increase in the *Market Return* is associated with a large decrease in $\theta$ of 0.19. This result is in line with that of *GDP growth* and suggests that periods of high market returns in the sample may be capturing increased liquidity. The effect of *Market Volatility* is strong and positive, as expected, and quite large also. An increase in one standard deviation in *Market Volatility* increases $\theta$ in 0.14.

Tighter funding liquidity in the bond market, as measured by the *Fontaine-Garcia* index, has a statistically and economically significant positive effect on $\theta$. Moreover, the cost of funding as proxied by the *Yield curve slope* has the expected positive effect on $\theta$.

#### *5.1.2. Determinants of liquidation values*

The most economically significant effects on the block's liquidation value are those of *Target minus Industry Leverage* and of *Industry Specificity.* A one sample standard deviation increase in *Target minus Industry Leverage* leads to a reduction in the fire sale price of 24 percentage points, and one sample standard deviation increase in the specificity of the industry's assets is associated with a discount in the block fire sale price that is 16 percentage points larger. This result adds to the findings of Acharya, Bharath, and Srinivasan (2007) in that the industry's asset specificity not only depresses the fire sale value of the productive assets but also of controlling stakes.

The impact of *Block-to-Industry Size* on $\phi$ is positive and significant, consistent with the hypothesis that larger blocks are more valued in a fire sale, holding all else equal. A one-standard deviation increase in the size of a block relative to the total market capitalization in the same 2-digit SIC code is associated with an increase in the fire sale price of 10%. The *Industry's M&A Activity* has a negative effect on fire sale prices, consistent with the hypothesis that it represents an increased supply of industry-specific assets. One standard deviation increase in the industry's M&A activity leads to a drop of 10 percentage points in the fire sale price.

Of the remaining controls, *Industry Market-to-Book* has a negative effect on fire sale prices. According to this result, a given controlling block is worth less when there are more growth options available in the industry. *Target Volatility* has a negative sign in specification (1) but a positive sign in specification (2).

#### *5.1.3. Investment opportunities vs. funding liquidity*

As we argue above, a liquidity shock may represent an increase in investment opportunities or a shortage of cash. Specification (1) does not allow us to identify these two effects because *GDP growth* and *Market*

*Return* are only allowed to have a direct effect on $\theta$. However, good investment opportunities may force block turnover only if incumbent blockholders cannot finance their investment demand, i.e., if at the same time the cost of funding is high. To test this conjecture, specification (2) includes the interactions between *GDP growth* and *Market Return* with the *Yield curve slope*.

In specification (1), *GDP growth* and *Market Return* appear to be capturing an increase in investment opportunities, leading to a positive effect on $\theta$. But in specification (2), when we separately control for funding costs interacted with investment opportunities, *GDP growth* and *Market Return* have a negative effect on $\theta$. Instead, the interaction terms are positive and statistically significant. The positive sign on the interaction terms is consistent with the prediction that high GDP growth, and high stock returns, coupled with high funding costs results in a high probability of liquidity shocks as the blockholder may be searching for cash to fund new investment opportunities.

In addition to discriminating between these two hypotheses, specification (2) improves the statistical significance of the determinants of $\phi$ and, as discussed above, also preforms better in terms of capturing properties of the block premium.

### *5.2.* The distribution of liquidity shocks and fire sale prices

Table IV summarizes the estimated probability of a liquidity shock under specification (2). The results with specification (1) are similar and available upon request. The estimated average $\theta$ is 0.34, i.e., on average a blockholder can expect a liquidity shock once every three years. The distribution of $\theta$ is positively skewed, with 50% of the deals with estimated $\theta$ less than 20%. Figure 3 depicts the estimated distribution of $\theta$.

The frequency of deals with extremely large $\theta$ may appear low relative to the 42% of deals in the data with negative $CAR$. Table IV shows that approximately 25% of the trades have associated an estimated $\theta$ of at least 60%. This discrepancy is explained by the following reasons. First, $\theta$ is an ex ante measure of liquidity shocks computed using ex post data from each deal. A liquidity shock may have occurred despite the low ex ante probability. Second, and more mechanically, the estimate of $\theta$ is not equal to the proportion of deals with negative $CAR$ but is a nonlinear function of this statistic and also deal dependent. We further discuss in Subsection 5.6 the interpretation of the size of the estimates of $\theta$ and of $\phi$ in light of the model we propose.

<INSERT TABLE IV ABOUT HERE>

<INSERT FIGURE 3 ABOUT HERE>

Table IV shows that, conditional on a liquidity shock, we estimate the block's fire sale price to be on average 64% of the buyer's block valuation. However, the predicted distribution of $\phi$ is left-skewed with a median of 88.8% and an expected fire sale discount of at least 7/8 of the buyer's valuation in over 25% of the observations. The median value of the fire sale discount is of similar magnitude to the aircraft liquidation values reported in Pulvino (1998) and the size of the gains from trading on price pressure sales reported in Coval and Stafford (2007).

### *5.3. Marketability discount*

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

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

where we have made explicit the dependence of $v$ on $\theta$, $\eta$, and $\phi$. It is easy to show that $d^M(\theta)$ is positive, and that $v(0, \phi, 1, .) > v(\theta, \phi, \eta, .)$ for any $\phi$, provided $\theta > 0$ or $\eta < 1$. The function $d^M(\theta)$ quantifies the value of the shares *in the block* if it was possible to trade at any point in time ($\eta = 1$) and voluntarily ($\theta = 0$). This measure of the marketability discount differs from the one in Longstaff (1995) because in $v(0, \phi, 1, .)$ it is presumed that the blockholder remains in control, whereas in Longstaff there is no presumption of control.

Table IV shows that the estimated average marketability discount is 30%, with a smaller median of 12%, but with significant variation, reaching a maximum of 95%. The predicted marketability discount varies with the predicted $\theta$. Panel A of Figure 4 plots the marketability discount function for every $\theta \in [0, 1]$. We see that, for the firms in the lower quartile of $\phi$, i.e., firms with lower fire sale prices, the marketability discount increases very quickly, reaching 71% for $\theta$ just below 20%. The estimated marketability discount is also very large for blocks with intermediate fire sale prices. However, for blocks with the lowest fire sale values, the marketability discount is under 2.2% for any $\theta$. Panel B plots the predicted in-sample distribution of the marketability discount for the estimated values of $\theta$. Since the estimate of $\eta$ equals 1, the marketability discount in specification (2) is fully attributable to the liquidity shock $\theta$.

<INSERT FIGURE 4 ABOUT HERE>

### 5.4. *Illiquidity-spillover discount*

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

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

We have that $p(0, .) > p(\theta, .)$ for any $\theta > 0$ and that $d^{IS} > 0$. The illiquidity-spillover discount 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 price and of $\phi$. However, $p$ reacts to the possibility that control may change hands and that the value of assets will change as a result.

Table IV shows that the risk of forced block turnover is important to dispersed shareholders: we estimate an average illiquidity-spillover discount of 0.8% on dispersed shares (maximum of 7.5%). This effect is two to three times as large as the average quoted bid-ask spreads (Bollen et al., 2004).

Panel A of Figure 5 plots the illiquidity-spillover discount for all possible values of $\theta$, conditional on the firm's cash flow state before the trade. As the figure shows, this discount is higher for firms with historically high cash flows because these firms have more to lose if, due to a liquidity shock, the incumbent block holder is forced to sell to a less efficient rival. Panel B plots the estimated distribution of the illiquidity-spillover discount.

<INSERT FIGURE 5 ABOUT HERE>

### 5.5. *Control discount*

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

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

Given that $v < p$ for any $\theta > 0$, then $d^C > 0$. The control discount function measures the difference in valuations between controlling blockholder and dispersed shareholder and is expressed as a function of the observed share price. This estimate of the control discount ignores the private benefits afforded to the controlling shareholder. Given that $d^{IS}$ is much smaller than $d^M$, the estimated control discount shares similar properties with the marketability discount.

<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 indicated, these difficulties arise from the limited evidence on the proper size of the discount relative to the value of exchange traded shares. Our estimates of the control discount can be applied to a paired sample of comparable publicly traded firms with controlling blockholders to determine the block value. It is important to use firms with controlling blockholders so that the pricing by dispersed shareholders 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.

### *5.6. Interpreting discount estimates*

Our modeling of search frictions has potential biases in the estimation of the parameters $\theta$ and $\phi$ and hence potential biases in the measurement of the various discounts. Consider the following two possible extreme alternatives. First, suppose that $\theta$ is a pure liquidity shock. Then $\phi$ should not be viewed as a pure fire sale price because it should represent the best outcome out of all possible ways of dealing with the liquidity shock, including when the incumbent (i) borrows against the collateral represented by the block and remains the blockholder, (ii) sells to a white knight perhaps not at a fire sale price, (iii) sells a fraction of the block and possibly remains in control (though this is rare as observed by Barclay and Holderness, 1989), or (iv) sells at a fire sale price. While we chose to leave these possibilities out of the model, we note that since the fire sale is the chosen alternative in our sample, then $\phi$ is an upper bound to the fire sale price.

Second, suppose that $\theta$ captures a more restrictive event, i.e., the event of a liquidity shock conditional on having failed to deal with it in any other way including those mentioned above. In this alternative, a $\theta$-liquidity shock leads to a sale and $\phi$ becomes a pure fire sale price. A $\theta$-liquidity shock is a lower bound on a pure liquidity shock.

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

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

## 6. Robustness

This section considers a variety of additional exercises to assess the robustness of the results.

### *6.1. Random effects in $\theta$ and $\phi$*

We allow for unobservable, deal-specific effects on liquidity shocks and fire sale discounts. We are motivated by the existence of shocks to the personal wealth of individual blockholders that force them to sell. To investigate the significance of these effects and to assess the robustness of the results to unobservable causes of illiquidity, we incorporate individual random effects to our preferred specification in Table III. To be parsimonious, we consider two alternative models. In the first model, we keep $\phi_i$ as before and specify $\theta_i$ as

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

where $\xi_i$ is drawn from a normal distribution with mean zero and variance $\sigma_\xi^2$. We estimate $\sigma_\xi^2$ as an additional parameter, by randomly drawing 1000 values for $\xi_i$ for each deal and averaging them at each of the moment conditions specified above. In the second model, we keep $\theta_i$ as before and instead include a random effect to the specification of $\phi$. The results for each model are reported in Specifications (1) and (2) of Table V, respectively.

Consider first the estimates of $\sigma_\xi$, labeled "Random effect variance" in panel A. The economic significance of these estimates refers to the fraction of the variance of $\mathbf{x}_i'\boldsymbol{\beta}$ in specification (1), or of $\mathbf{z}_i'\boldsymbol{\gamma}$ in specification (2), that is explained by the variance of the random effect. Neither specification offers a statistically significant effect, though in specification (2) the point estimate indicates an economically large effect of the random effect on $\phi$: 39% of the variation in $\mathbf{z}_i'\boldsymbol{\gamma}$ is attributed to the random effect. Judging by this point estimate there do appear to be important unobserved determinants of the fire sale discount.

In general, the introduction of the random effect does not change the sign of the various effects reported in Table III. However, it reduces the economic significance of the effects almost across the board. The main exceptions are the effect of *Target minus Industry Leverage* and the effect of *Yield curve slope* whose economic significance increase slightly.

<INSERT TABLE V ABOUT HERE>

It is worthwhile to point to other results from adding the random effects. One is the poorer fit of the models to the block premium moments as shown in panel B of V: the models are unable to match the volatility of the block premium, and in specification (1), the model generates too many discounts and an average block premium that is negative. The other is the high estimate of the bargaining power for specification (1). Again, specification (2) appears to perform somewhat better, presenting an estimate of $\psi$ of 0.72. Specification (2) also gives a point estimate of $\eta$ of 0.53. According to this point estimate, sellers meet with a potential buyer once every two years. Overall, the introduction of a random effect appears to be important, at least in the specification of $\phi$, though, perhaps due to the small sample, the model fails to produce a statistically significant estimate of its effect. The small sample may also explain the inability of the model to separately estimate the remaining effects once the random effect is introduced.

### *6.2. Common drivers of liquidity shocks and fire sale prices*

In this subsection, we ask if there are common determinants of liquidity shocks and fire sale prices. The motivation for this exercise builds on the idea that, if liquidity shocks are driven by aggregate variables, in equilibrium these variables may also have pricing implications for potential buyers and their valuations as in Shleifer and Vishny (1992) and vice-versa.

For parsimony, we proceed with two separate tests. First, we allow the probability of a liquidity shock to be a function of industry-specific shocks, by incorporating *Industry Leverage* and *Industry Market-to-Book* to the baseline specification. Second, we allow for economy-wide determinants of funding liquidity to affect fire sale prices. We incorporate *GDP growth*, the *Fontaine-Garcia* index, and the slope of the yield curve to the specification of $\phi$. The results of these two models are in specifications (1) and (2) of Table VI, respectively.

<INSERT TABLE VI ABOUT HERE>

Consider the results reported in panels B and C of Table VI. Specification (1) passes the joint significance test, but specification (2) does not. However, both models have difficulty generating variation in the predicted block premium and mismatching the mean block premium. In panel A, the poor fit of these two models can be seen in the lack of statistical and economic significance of the various effects, despite the fact that the sign of the point estimates is generally consistent with the results in Table III. In specification (1), which allows for deal-specific determinants of liquidity, only *Fontaine-Garcia* remains significant as a determinant of $\theta$. In specification (2), which allows for aggregate determinants of fire sale prices, only *Industry's M&A Activity* and *Target Volatility* remain significant as determinants of $\phi$. In summary, the weak results of these models suggest that common effects may not be a first order force in explaining liquidity shocks and fire sale prices.

The inability to identify common effects to liquidity shocks and fire sale prices may also be explained, as in the previous subsection, due to the small sample size. We analyze the potential problem of overfitting the data next. We consider two exercises. First, we fix $\phi$ to be constant across deals while allowing $\theta$ to vary according to equation (10). Second, we fix $\theta$ to be constant across deals while $\phi$ varies according to equation (11). In the first exercise, we obtain $\hat{\phi} = 0.71$ (untabulated), which is between the mean and median estimates in Table IV. With a fixed $\phi$, the model cannot generate much variation in block prices conditional on a liquidity shock. Therefore, the average estimate of $\theta$ (22%) is lower than the model with variable $\phi$ (34%). In the second exercise, we obtain an average estimate of $\phi$ of 1 and $\hat{\theta} = 0$ (untabulated). This result implies that, having suppressed the variation in $\theta$, the variation in the block premium is better explained by variation in the cash flow distribution rather than in the determinants of $\phi$. However, because the cash flow volatility is low, the constrained model predicts only a block premium volatility of 0.01. We conclude that the risk of overfitting is more a concern when modeling $\phi$, consistent with the significantly poorer performance of specification (2) in Table VI.

### *6.3.* Investor heterogeneity

In subsection 2.4, we identified two sources of investor heterogeneity that could be interesting to model. One arises if investors are allowed to agree to disagree on the probability of a liquidity shock. We have re-estimated our model allowing for a different intercept in the probability of a liquidity shock as perceived by blockholders and by dispersed shareholders. The model produces a poor fit to the data (untabulated) and often the estimation does not converge. The reason is that a critical feature in the identification strategy that comes out from Proposition 3 is that investors agree on the probability of liquidity shocks $\theta$.

Allowing $\theta$ to differ implies that the spread in valuations between the two investor types no longer moves monotonically with the liquidity shock. Unless additional data are observed, such as repeat trades of the same block or prices in failed block trades, it is not possible to estimate this model specification.

The other aspect of investor heterogeneity that we discussed allows for heterogeneity in blockholders' discount rates. We conduct two exercises. In the first exercise, the blockholder's discount rate increases from 0.1 to 0.15 if the block size exceeds 65% of the common stock. In the second exercise, the blockholder's discount rate increases by 1 percentage point for every 10 percentage points increase in block size. The results are reported in Table VII.

<INSERT TABLE VII ABOUT HERE>

The best results appear in specification (1), corresponding to the first exercise. This specification produces quite similar results to those in Table VI, with the main difference being the increased economic significance of the various determinants of liquidity shocks. Specification (1) also does slightly better at predicting the various moments of the block premium. In contrast, specification (2) appears to produce a poor fit to the data, suggesting that blockholder discount rates do not vary smoothly with block size.

### *6.4.* Other explanatory variables

We verify the robustness of our results to the use of alternative measures of liquidity shocks or fire sale prices. All the results described below are included in an online appendix. First, we test whether other commonly used measures of liquidity improve the fit of specification (2) in Table III. We obtain very similar results when we use the TED spread, i.e., the spread between LIBOR and the 3-month Treasury bill instead of the *Fontaine-Garcia* index. This result is not surprising given that both are very strongly correlated (correlation coefficient of 0.63). However, the latter is economically more significant and produces a much closer in-sample forecast of the distribution of the block premium. Pástor and Stambaugh (2003) propose a monthly liquidity factor based on the argument that current order flow is followed by future stock price changes in the opposite direction when liquidity is low. We include the innovations to the liquidity index in Pástor and Stambaugh (2003) together with the *Fontaine Garcia* index in the specification of $\theta$. We find that the Pástor and Stambaugh liquidity index has the expected negative effect, while all other estimates remain qualitatively the same as in Table III. However, the effect of the Pástor and Stambaugh index is not statistically significant, whereas the effect of the *Fontaine Garcia* index remains statistically and economically significant. These results suggest that illiquidity in the bond market, rather than illiquidity in the stock market, better capture the determinants of blockholder illiquidity.

Our results do not change either when we use the logarithm of the size of the block, instead of the size of the block relative to size of the target's industry. Again, the model fit is marginally better when we use the latter. Finally, we investigate whether the negative effect of *Target Volatility* on the block's liquidation value (specification (1) of Table III) is due to the negative diversification effect of a large stake in the acquirer's portfolio. We find that the target's stock market beta has a negative effect on the fire sale discount, confirming this intuition.

## 7. Conclusion

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

The paper estimates a large average marketability discount but also shows that the marketability discount varies considerably across deals. Moreover, liquidity shocks that force the trade of controlling blocks impose nonnegligible costs on dispersed shareholders for holding shares of the target company. The paper also shows how to estimate the control discount, i.e., the private value to the blockholder with respect to the exchange traded stock price. The determinants discussed here can be applied to valuation exercises in a straightforward way.

## Appendix A: Proofs

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

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

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 $T_p : B(X) \to B(X)$ be the operator defined by

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

The first part of the proof follows the proof of Proposition 1. It remains to show that $p(\pi) > v(\pi)$. Take two functions $f_p, f_v \in B(X)$ 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, $f_p(\pi_R) > \iota f_v(\pi_R) + (1-\iota) f_v(\pi_I)$ for any $\iota < 1$. 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 $B = 0$,

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

as $\pi_R - \pi_I \to 0$. These limits exist because $v$ and $p$ are monotonic and defined over a compact support, hence differentiable almost everywhere. Differentiate (2) using (4) to obtain

$$\frac{\partial v(\pi_I)}{\partial \pi_I} = \left[1 - \delta(1-\theta)\left[1 - \eta\psi(1-F(\pi_I))\right]\right]^{-1} > 0. \tag{12}$$

Likewise, differentiate (5) to obtain

$$\frac{\partial p(\pi_I)}{\partial \pi_I} = \left[1 - \delta(1-\theta)\left[1 - \eta(1-F(\pi_I))\right]\right]^{-1} > 0. \tag{13}$$

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

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

Differentiate (12) with respect to $\theta$ to obtain

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

and differentiate (13) with respect to $\theta$ to obtain

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

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

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

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 the exogenous growth rate $g$ and that they are trend stationary, i.e.,

$$\tilde{\pi}_t = e^g \pi_t.$$

The transition probability distribution for $\pi$ is given by $F(\pi_{t+1}|\pi_t)$. We assume that $F$ has the property of first-order stochastic dominance, i.e., $F(\pi'|\pi_1) \leq F(\pi'|\pi_0)$ for any $\pi_1 > \pi_0$ with the inequality being strict for some values of $\pi'$. The value of the block to the incumbent is therefore

$$v(\pi,\theta) = \pi + \delta e^g \left[ (1-\theta) \int \tilde{v}\left(\pi,\pi',\theta\right) dF\left(\pi'|\pi\right) + \theta L(\pi,\theta) \right], \tag{14}$$

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

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

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

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

$$\tilde{v}\left(\pi,\pi',\theta\right) = \eta \int_{\pi''>\pi'} \left[ b\left(\pi',\pi'',\theta\right) - B \right] dF\left(\pi''|\pi\right) + F\left(\pi'|\pi\right) v\left(\pi',\theta\right) + (1-\eta)\left(v\left(\pi',\theta\right) + B\right). \tag{15}$$

The property of first-order stochastic dominance guarantees that, of two potential owners, the one with higher current $\pi$ is the better.

The stock price is

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

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

$$\tilde{p}\left(\pi,\pi',\theta\right) = \eta \int_{\pi''>\pi'} p\left(\pi'',\theta\right) dF\left(\pi''|\pi\right) + F\left(\pi'|\pi\right) p\left(\pi',\theta\right) + (1-\eta)\, p\left(\pi',\theta\right). \tag{17}$$

To solve the model, consider the discretized cash flow $\pi \in \{\pi_1, ..., \pi_{N_\pi}\}$. 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 $\mathbf{Q} = \left[\mathbf{q}_1^\intercal, ..., \mathbf{q}_{N_\pi}^\intercal\right]^\intercal$. Row $i$ of $\mathbf{Q}$ is given by $\mathbf{q}_i = [q_{i1}, ..., q_{ij}, ..., q_{iN_\pi}]$ and adds to one.

We may now write (15) as

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

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 $\mathbf{v}=[v_1,...,v_{N_\pi}]^\intercal$, of size $(1\times N_\pi)$. We then rewrite the previous expression in vector notation as

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

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

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

where

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

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

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

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

$$\tilde{\mathbf{v}}=\mathbf{v}\mathbf{Q}^\intercal+\eta\psi\mathbf{v}\mathbf{M}^2, \tag{18}$$

where

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

Finally, substituting (18) into (14) and solving for the $1\times N_\pi$ vector $\mathbf{v}$**,** we obtain

$$\mathbf{v}=\boldsymbol{\pi}^\intercal\left\{\mathbf{I}-\delta e^g\left[(1-\theta)\left(\mathbf{Q}^\intercal+\eta\psi\mathbf{M}^2\right)+\theta\phi\mathbf{Q}^\intercal\right]\right\}^{-1}. \tag{19}$$

Similarly, let $\mathbf{p}$, of size $(1 \times N_\pi)$ be the state-contingent share price vector. To solve for $\tilde{p}_{ij}$ in (17), we first write it in vector notation as

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

As with $\widetilde{\mathbf{v}}_i$, the vector $\tilde{\mathbf{p}}_i$ of size $(1 \times N_\pi)$ that collects all $\tilde{p}_{ij}$ can be written as

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

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

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

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

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

From (16) and then eliminating $\tilde{\mathbf{p}}$,

$$\begin{aligned}
\mathbf{p} &= \boldsymbol{\pi}^\intercal + \delta e^g \left[ (1-\theta) \widetilde{\mathbf{p}} + \theta \mathbf{p}\mathbf{Q}^\intercal \right] \\
&= \boldsymbol{\pi}^\intercal + \delta e^g \left[ \mathbf{p}\mathbf{Q}^\intercal + (1-\theta) \eta \mathbf{p} \mathbf{M}^2 \right].
\end{aligned}$$

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

$$\mathbf{p} = \boldsymbol{\pi}^\intercal \left\{ \mathbf{I} - \delta e^g \left[ \mathbf{Q}^\intercal + (1-\theta) \eta \mathbf{M}^2 \right] \right\}^{-1}. \tag{20}$$

**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 a separate Markov-transition matrix, $\mathbf{Q}$, for every trade. 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 of the de-trended logarithm of the average monthly cash flows of all firms in the same 3-digit SIC as the target, using the last five years of data preceding the trade. We generate the discrete support $\{\pi_1, \pi_2, ..., \pi_{N_\pi}\}$ 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's cash flow support by assuming that the target's cash flow grows at the industry rate, so that $\pi^i_j = \frac{p_i}{\overline{p}}\pi_j$ for every state $j = 1, ..., N_\pi$, where $p_i$ and $\overline{p}$ are the observed target share price and the 3-digit SIC average share price, respectively. We set $N_\pi$ to 15 and record the cash flow state at the time of the trade, $\pi^i_i$. Using industry data to estimate the AR(1) process for cash flows guarantees more observations per regression.

We estimate the remaining parameters, $\mathbf{\Gamma} = \left\{\psi, \eta, \tilde{B}, \boldsymbol{\beta}, \boldsymbol{\gamma}\right\}$, by the simulated method moments (SMM). That is, we solve for

$$\widehat{\mathbf{\Gamma}}_{SMM} = \arg\min_{\mathbf{\Gamma}} \mathcal{J}(\mathbf{\Gamma}),$$

where

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

$\{BP_i, CAR_i\}_i$ 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 $\phi$; $\mathbf{m}(\{BP_i, CAR_i, \mathbf{x}_i, \mathbf{z}_i\}; \mathbf{\Gamma})$ is a vector of moments derived from the joint distribution of $BP$ and $CAR$ simulated by the model; $\mathbf{M}$ is the vector of the same moments of the actual data; and $\mathbf{W}$ is a weighting matrix.

The joint distributions of $BP$ and $CAR$ are simulated conditional on whether there was a liquidity shock or not. The procedure to evaluate and maximize $\mathcal{J}$ is

1. Fix a vector of parameters $\mathbf{\Gamma}_0 = \left\{\psi_0, \eta_0, \tilde{B}_0, \boldsymbol{\beta}_0, \boldsymbol{\gamma}_0\right\}$ and evaluate for each deal $\theta_i = \Lambda(\mathbf{x}'_i \boldsymbol{\beta}_0)$ and $\phi_i = \Lambda(\mathbf{z}'_i \boldsymbol{\gamma}_0)$;

2. Evaluate $\mathbf{m}(\{BP_i, CAR_i, \mathbf{x}_i, \mathbf{z}_i\}; \mathbf{\Gamma})$ by numerical simulation, following the next steps for each trade, $i$:

(a) solve for the functions $v(\pi)$ and $p(\pi)$ from the system of equations (19) and (20), given $\mathbf{\Gamma}_0$;

(b) evaluate $CAR\left(\pi_{I,i}, \pi_{R,i}^{j}\right)$ for every state $j = 1, ..., 15$, and every trade $i$ using equation (9);

(c) pick the state $j^*$ that minimizes the distance $\left[CAR_i - CAR\left(\pi_{I,i}, \pi_{R,i}^{j}\right)\right]^2$ for each trade $i$ and evaluate $BP\left(\pi_{I,i}, \pi_{R,i}^{j}\right)$ for every $j^*$, using equation (8);

(d) compute the expected block premium, $E\left(BP\left(\pi_{I,i}, \pi_{R,i}^{j}\right)\right)$ as

$$\frac{\theta}{\theta + (1-\theta)\eta} BP\left(\pi_{I,i}, \pi_{R,i}^{j} | \text{shock occurs}\right) + \left[1 - \frac{\theta}{\theta + (1-\theta)\eta}\right] BP\left(\pi_{I,i}, \pi_{R,i}^{j} | \text{shock does not occur}\right)$$

(e) compute the moments of the simulated $\{\widehat{E(BP_i)}, \widehat{CAR_i}\}$ distribution;

3. Evaluate $\mathcal{J}(\mathbf{\Gamma}_0)$ and return to Step 1 until $\mathcal{J}(.)$ is maximized.

We estimate $\mathbf{W}$ in a first stage, running steps 1 through 3 with $\mathbf{W}$ set to the identity matrix. We then compute $\widehat{\mathbf{W}} = \frac{1}{N}\left(\mathbf{m}\left(., \widehat{\Gamma}_{Stage1}\right) \times \mathbf{m}\left(., \widehat{\Gamma}_{Stage1}\right)'\right)$ and minimize $(\mathbf{m}(., \mathbf{\Gamma}) - \mathbf{M})' \widehat{\mathbf{W}} (\mathbf{m}(., \mathbf{\Gamma}) - \mathbf{M})$.

In our search for the global maximizer, we repeat the maximization over an exhaustive set of initial conditions, $\mathbf{\Gamma}_0$. To ensure that our search for a global minimizer starts from all possible combinations of skewness of the two distributions we estimate, we use 16 different possible combinations of the mean and variance of the implied logistic distributions (high or low for each), which will also contain all four possible combinations of the skewness of both distributions (i.e., right, right; right, left; left, right; left, left). We then compute the GMM estimators of $\mathbf{\Gamma}$ that match any given arbitrary combination of the mean and variance of the logistic distributions for $\phi$ and $\theta$. These estimators yield the 16 different initial conditions used in $\mathbf{\Gamma}_0$. 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 $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$ is zero. For $\tilde{B}, \eta$ or $\psi$ we search in the whole range of possible values, i.e., [0,1].

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

**Appendix D: Data**

Our goal is to select a sample of block trades where a 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 the conditions that:

1. The size of the traded block is at least 35%, so that any attempt to acquire control requires a negotiation with the incumbent blockholder;

2. The size of the traded block is strictly smaller than 90%, and the final position is smaller than 90%, 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 corresponds 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 35% up to 90% between 1/1/1990 and 31/8/2010;

2. We exclude privatizations, tender offers, exchange offers, spin-offs, recapitalizations and repurchases, equity carveouts, joint ventures, going private deals, debt restructurings, and bankruptcies;

3. We exclude deals where the payment was made using warrants, convertible bonds, notes, liabilities, debt-equity swaps, or any form of options;

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

(continues)

**Table I: continued**

| Type | Variable name | Variable description | Source |
|---|---|---|---|
| Determinants of liquidation values (**z**) | *Block-to-Industry Size* | Ratio of the total *Block value* to the total market capitalization of all NYSE and AMEX firms in the same 2-digit SIC Code as the target. | Thomson One Banker, CRSP |
| | *Industry's M&A Activity* | Total M&A activity during the last quarter before the deal, where the target is in the same 2-digit SIC Code as the deal's target ($ Billions). | Thomson One Banker |
| | *Industry Leverage* | Median long-term debt to total assets of all the firms in the same 3-digit SIC code of the target firm, as defined by Acharya, Bharath and Srinivasan (2007). | Compustat |
| | *Industry Inverse Quick Ratio* | Median of the ratio of Current Liabilities to Cash+Marketable Securities+Accounts Receivable of all firms in the same 3-digit SIC code as the target firm. | Compustat |
| | *Industry Specificity* | Median proportion of machinery and equipment to total assets of all firms in the same 3-digit SIC code as the target firm, as defined by Stromberg (2001). | Compustat |
| | *Industry Market-to-Book* | Median ratio of the market value of the firm (book value of debt + market value of equity) to the book value of total assets of all firms in the same 3-digit SIC code as the target firm. | Compustat |
| | *Target Leverage* | Proportion of long-term target debt to total assets on the last fiscal year before the trade announcement. | Compustat |
| | *Target minus Industry Leverage* | The difference between the target's proportion of long-term debt to total assets on the last fiscal year before the trade announcement and the median of the same proportion for all firms in the same 3-digit SIC code as the target. | Compustat |
| | *Target Volatility* | Standard deviation of the target's annualized average daily return for the 12 month-period ending two months before the trade announcement (%). | Compustat |

**Table II: Sample summary statistics**

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

| Variable | Mean | Standard deviation | 5th percentile | First quartile | Median | Third quartile | 95th percentile |
|---|---|---|---|---|---|---|---|
| $\alpha$ | 59.74% | 15.15% | 38.55% | 49.32% | 54.61% | 72.33% | 87.00% |
| *Block value* | 192.92 | 719.23 | 0.80 | 7.14 | 23.02 | 100.00 | 774.23 |
| *BP* | 6.79% | 58.83% | −89.16% | −18.20% | 3.45% | 27.80% | 121.42% |
| *CAR* | 9.64% | 31.93% | −25.88% | −10.11% | 4.96% | 23.04% | 78.06% |
| *GDP growth* | 3.23% | 3.11% | −3.69% | 1.92% | 3.10% | 5.78% | 6.96% |
| *Market Return* | 12.74% | 15.78% | −19.95% | 8.89% | 14.92% | 23.58% | 30.69% |
| *Market Volatility* | 14.03% | 5.25% | 8.28% | 10.10% | 11.66% | 17.80% | 24.06% |
| *Fontaine-Garcia* | 0.812 | 0.508 | −0.154 | 0.459 | 0.914 | 1.110 | 1.396 |
| *Yield curve slope* | 1.69% | 1.17% | −0.19% | 0.69% | 1.51% | 2.82% | 3.45% |
| *Block-to-Industry Size* | 0.008 | 0.033 | 0.000 | 0.000 | 0.000 | 0.001 | 0.027 |
| *Industry's M&A Activity* | 3.879 | 3.682 | 0.173 | 1.095 | 2.761 | 6.084 | 11.667 |
| *Industry Leverage* | 0.564 | 0.191 | 0.377 | 0.437 | 0.546 | 0.629 | 0.820 |
| *Industry Inverse Quick Ratio* | 0.930 | 0.373 | 0.522 | 0.617 | 0.899 | 1.106 | 1.552 |
| *Industry Specificity* | 0.271 | 0.189 | 0.015 | 0.162 | 0.221 | 0.336 | 0.697 |
| *Industry Market-to-Book* | 1.238 | 0.475 | 1.000 | 1.000 | 1.000 | 1.249 | 2.444 |
| *Target Leverage* | 0.600 | 0.280 | 0.144 | 0.376 | 0.595 | 0.831 | 1.000 |
| *Target minus Industry Leverage* | 0.045 | 0.280 | −0.382 | −0.158 | 0.041 | 0.226 | 0.566 |
| *Target Volatility* | 39.83% | 40.13% | 5.51% | 10.77% | 23.80% | 59.08% | 110.07% |

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

This table shows the estimates of the matching probability, $\eta$, the block seller's bargaining power, $\psi$, the controlling shareholder's private benefits of control, $\tilde{B}$, and the sensitivities, $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$, of the liquidity shock probability, $\theta$, and the block's liquidation value, $\phi$, to $\mathbf{x}$ and $\mathbf{z}$, respectively. For each deal, $i$, $\theta_i$ and $\phi_i$ are given by

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

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

**Panel A: Parameter estimates**

| | (1) | | | | (2) | | | |
|---|---|---|---|---|---|---|---|---|
| | Coefficient | | Economic significance | | Coefficient | | Economic significance | |
| $\eta$ | 1.00 | (0.95) | | | 1.00 | (0.80) | | |
| $\tilde{B}^b$ | 0.12*** | (0.00) | | | 0.11*** | (0.01) | | |
| $\psi$ | 0.54 | (0.53) | | | 0.41** | (0.16) | | |
| | Liquidity shock determinants ($\mathbf{x}$) | | | | | | | |
| *GDP growth* | 5.06 | (3.09) | 0.02 | (0.01) | −19.54 | (26.60) | −0.08 | (0.10) |
| *Market Return* | 15.51*** | (0.93) | 0.32*** | (0.02) | −9.34*** | (0.83) | −0.19*** | (0.02) |
| *Market Volatility* | 41.58** | (18.33) | 0.29** | (0.13) | 20.61*** | (6.72) | 0.14*** | (0.04) |
| *Fontaine-Garcia* | 0.33** | (0.14) | 0.02** | (0.01) | 2.29*** | (0.73) | 0.15*** | (0.05) |
| *Yield curve slope* | 0.99*** | (0.04) | 0.15*** | (0.01) | 0.53* | (0.29) | 0.08* | (0.05) |
| × *GDP growth* | | | | | 54.97** | (24.69) | 0.26** | (0.12) |
| × *Market Return* | | | | | 6.19** | (2.75) | 0.12** | (0.05) |
| Constant ($\beta_0$) | −10.73 | (53.70) | | | −6.38*** | (1.82) | | |
| | Liquidation value determinants ($\mathbf{z}$) | | | | | | | |
| *Block-to-Industry Size* | −1.55 | (7.58) | 0.00 | (0.02) | 48.20*** | (10.81) | 0.10*** | (0.02) |
| *Industry's M&A Activity* | 0.04** | (0.02) | 0.01** | (0.00) | −0.45*** | (0.07) | −0.10*** | (0.01) |
| *Target minus Industry Leverage* | −14.33 | (11.15) | −0.26 | (0.21) | −14.13*** | (3.10) | −0.24*** | (0.05) |
| *Industry Specificity* | −1.40 | (1.08) | −0.02 | (0.01) | −14.04*** | (4.60) | −0.16*** | (0.05) |
| *Industry Market-to-Book* | −3.94*** | (0.49) | −0.12*** | (0.02) | −3.94*** | (0.66) | −0.11*** | (0.02) |
| *Target Volatility* | −4.57*** | (0.30) | −0.12*** | (0.01) | 2.43*** | (0.47) | 0.06*** | (0.01) |
| Constant ($\gamma_0$) | 9.13 | (9.27) | | | 11.51 | (9.67) | | |

(continues)

**Table III: continued**

**Panel B: Model fit**

| | (1) $\chi^2$ | (1) $p$ value | (2) $\chi^2$ | (2) $p$ value |
|---|---|---|---|---|
| Joint significance test ($H_0 : (\boldsymbol{\beta}, \boldsymbol{\gamma}, \eta, \psi, B) = \mathbf{0}$) | $9,070.81^{***}$ | 0.000 | $4,606.38^{***}$ | 0.000 |
| Over-identifying restrictions test ($H_0 : \mathbf{m}(\boldsymbol{\beta}, \boldsymbol{\gamma}, \eta, \psi, B) - \mathbf{M} = \mathbf{0}$) | 5.29 | 1.000 | 6.13 | 1.000 |

**Panel C: In-sample predictions**

| | (1) Mean | (1) StdD | (1) Median | (1) Proportion of negatives | (2) Mean | (2) StdD | (2) Median | (2) Proportion of negatives |
|---|---|---|---|---|---|---|---|---|
| **BP** | | | | | | | | |
| *Actual* | 0.068 | 0.588 | 0.035 | 0.465 | 0.068 | 0.588 | 0.035 | 0.465 |
| *Predicted* | 0.013 | 0.552 | 0.122 | 0.430 | 0.058 | 0.561 | 0.146 | 0.412 |
| **CAR** | | | | | | | | |
| *Actual* | 0.096 | 0.319 | 0.050 | 0.421 | 0.096 | 0.319 | 0.050 | 0.421 |
| *Predicted* | 0.002 | 0.016 | 0.000 | 0.461 | 0.002 | 0.016 | 0.000 | 0.461 |

[a] Estimates followed by ***, ** and * are statistically different from zero with 0.01, 0.05 and 0.1 significance levels, respectively.
[b] Average private benefits of control, expressed as a percentage of the seller's private block valuation.

**Table IV: In-sample estimates of the costs of illiquidity**

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

| | Sample mean | Standard deviation | Min | First quartile | Median | Third quartile | Max |
|---|---|---|---|---|---|---|---|
| Liquidity shock probability ($\theta$) | 0.342 | 0.315 | 0.001 | 0.069 | 0.205 | 0.643 | 1.000 |
| Shares' liquidation value ($\phi$) | 0.644 | 0.414 | 0.000 | 0.127 | 0.888 | 0.997 | 1.000 |
| Marketability discount ($1-\frac{v(\theta,\phi,\eta,.)}{v(\theta=0,\phi,\eta=1,.)}$) | 0.296 | 0.320 | 0.000 | 0.012 | 0.118 | 0.607 | 0.947 |
| Illiquidity spillover discount ($1-\frac{p(\theta,\phi,\eta,.)}{p(\theta=0,\phi,\eta=1,.)}$) | 0.008 | 0.010 | 0.000 | 0.002 | 0.006 | 0.013 | 0.075 |
| Control discount ($1-\frac{v(\theta,\phi,\eta,.)}{p(\theta,\phi,\eta,.)}$) | 0.303 | 0.315 | 0.003 | 0.019 | 0.128 | 0.611 | 0.946 |

**Table V: Estimates of the model's parameters with deal-specific random effects**

This table shows the estimates of the matching probability, $\eta$, the block seller's bargaining power, $\psi$, the controlling shareholder's private benefits of control, $\tilde{B}$, and the sensitivities, $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$, of the liquidity shock probability, $\theta$, and the block's liquidation value, $\phi$, to $\mathbf{x}$ and $\mathbf{z}$, respectively. A deal-specific random effect, $\xi_i$, is added to $\theta_i$ (specification (1)) or $\phi_i$ (specification (2)). For example, specification (1) is

$$\theta_i = \frac{\exp(\mathbf{x}_i'\boldsymbol{\beta} + \beta_0 + \xi_i)}{1 + \exp(\mathbf{x}_i'\boldsymbol{\beta} + \beta_0 + \xi_i)},$$

where $\xi_i \sim N(0, \sigma_\xi^2)$.The parameters are estimated using the Simulated Method of Moments, matching the actual moments, $\mathbf{M}$, of the joint distribution of the percentage block premium, $BP$, and the cumulative abnormal returns, $CAR$, to those simulated by the theoretical search model, $\mathbf{m}(\psi, \eta, \tilde{B}, \boldsymbol{\beta}, \boldsymbol{\gamma})$. The data is for a sample of 114 US negotiated block trades in the Thomson One Banker's Acquisitions data between 1/1/1990 and 31/12/2010. Blocks are larger than 35% and smaller than 90% of the outstanding stock. Standard errors are shown in parenthesis next to the coefficient estimates[a]. The economic significance of each coefficient is the change in $\theta_i$ or $\phi_i$ associated with a one sample standard deviation change in each variable in $\mathbf{x}$ and $\mathbf{z}$, respectively. The economic significance of the random effect is the ratio of $\sigma_\xi^2$ to $var(\mathbf{x}_i'\boldsymbol{\beta})$ (specification (1)) or to $var(\mathbf{z}_i'\boldsymbol{\gamma})$ (specification (2)).

**Panel A: Parameter estimates**

| | (1) | | | | (2) | | | |
|---|---|---|---|---|---|---|---|---|
| | Coefficient | | Economic significance | | Coefficient | | Economic significance | |
| $\eta$ | 0.97 | (2.52) | | | 0.53 | (0.48) | | |
| $\tilde{B}^b$ | 0.07*** | (0.01) | | | 0.05*** | (0.00) | | |
| $\psi$ | 1.00*** | (0.05) | | | 0.72*** | (0.03) | | |
| | Liquidity shock determinants ($\mathbf{x}$) | | | | | | | |
| *GDP growth* | −18.43 | (18.44) | −0.04 | (0.04) | −19.71*** | (4.47) | −0.04*** | (0.01) |
| *Market Return* | 19.51*** | (6.28) | 0.24*** | (0.08) | 8.78*** | (0.38) | 0.09*** | (0.00) |
| *Market Volatility* | 15.41** | (6.13) | 0.06** | (0.03) | 20.15* | (9.71) | 0.07* | (0.03) |
| *Fontaine-Garcia* | 3.71*** | (0.72) | 0.15*** | (0.03) | 0.35* | (0.19) | 0.01* | (0.01) |
| *Yield curve slope* | 3.13** | (1.41) | 0.28** | (0.13) | 0.15*** | (0.05) | 0.01*** | (0.00) |
| × *GDP growth* | −44.77 | (28.12) | −0.13 | (0.08) | −47.15*** | (7.79) | −0.11*** | (0.02) |
| × *Market Return* | 8.89** | (3.18) | 0.11** | (0.04) | 5.04*** | (1.13) | 0.05*** | (0.01) |
| Random effect variance ($\sigma_\xi$ ) | 2.37 | (1.65) | 0.11 | | | | | |
| Constant ($\beta_0$) | −10.60 | (8.93) | | | −6.28 | (10.51) | | |
| | Liquidation value determinants ($\mathbf{z}$) | | | | | | | |
| *Block-to-Industry Size* | 40.38 | (27.11) | 0.10 | (0.06) | 40.28 | (157.29) | 0.12 | (0.48) |
| *Industry's M&A Activity* | −0.13** | (0.06) | −0.03** | (0.01) | 0.03 | (0.12) | 0.01 | (0.04) |
| *Target minus Industry Leverage* | −12.51*** | (1.23) | −0.25*** | (0.02) | −11.80*** | (2.80) | −0.30*** | (0.07) |
| *Industry Specificity* | −7.20*** | (0.76) | −0.10*** | (0.01) | −8.67 | (9.25) | −0.15 | (0.16) |
| *Industry Market-to-Book* | 3.68*** | (0.88) | 0.12*** | (0.03) | −0.90 | (3.89) | −0.04 | (0.17) |
| *Target Volatility* | −1.92*** | (0.47) | −0.05*** | (0.01) | −0.31 | (1.57) | −0.01 | (0.06) |
| Random effect variance ($\sigma_\xi$ ) | | | | | 2.43 | (4.25) | 0.39 | |
| Constant ($\gamma_0$) | 3.96 | (7.95) | | | 9.80 | (19.16) | | |

(continues)

**Table V: continued**

**Panel B: Model fit**

| | (1) $\chi^2$ | (1) $p$ value | (2) $\chi^2$ | (2) $p$ value |
|---|---|---|---|---|
| Joint significance test ($H_0 : (\boldsymbol{\beta}, \boldsymbol{\gamma}, \sigma_\xi, \eta, \psi, \tilde{B}) = \mathbf{0}$) | $4,119.35^{***}$ | 0.000 | $6,895.29^{***}$ | 0.000 |
| Over-identifying restrictions test ($H_0 : \mathbf{m}(\boldsymbol{\beta}, \boldsymbol{\gamma}, \sigma_\xi, \eta, \psi, \tilde{B}) - \mathbf{M} = \mathbf{0}$) | 13.34 | 0.999 | 1.13 | 1.000 |

**Panel C: In-sample predictions**

| | (1) Mean | (1) StdD | (1) Median | (1) Proportion of negatives | (2) Mean | (2) StdD | (2) Median | (2) Proportion of negatives |
|---|---|---|---|---|---|---|---|---|
| **BP** | | | | | | | | |
| *Actual* | 0.068 | 0.588 | 0.035 | 0.465 | 0.068 | 0.588 | 0.035 | 0.465 |
| *Predicted* | −0.171 | 0.393 | −0.029 | 0.614 | 0.041 | 0.280 | 0.094 | 0.404 |
| **CAR** | | | | | | | | |
| *Actual* | 0.096 | 0.319 | 0.050 | 0.421 | 0.096 | 0.319 | 0.050 | 0.421 |
| *Predicted* | 0.002 | 0.016 | 0.000 | 0.461 | 0.002 | 0.016 | 0.000 | 0.461 |

[a] Estimates followed by ***, ** and * are statistically different from zero with 0.01, 0.05 and 0.1 significance levels, respectively.
[b] Average private benefits of control, expressed as a percentage of the seller's private block valuation.

**Table VI: Alternative specifications for liquidity shocks and block liquidation values**

This table shows the estimates of the matching probability, $\eta$, the block seller's bargaining power, $\psi$, the controlling shareholder's private benefits of control, $\tilde{B}$, and the sensitivities, $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$, of the liquidity shock probability, $\theta$, and the block's liquidation value, $\phi$, to $\mathbf{x}$ and $\mathbf{z}$, respectively. For each deal, $i$, $\theta_i$ and $\phi_i$ are given by

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

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

**Panel A: Parameter estimates**

| | (1) Coefficient | | (1) Economic significance | | (2) Coefficient | | (2) Economic significance | |
|---|---|---|---|---|---|---|---|---|
| $\eta$ | 1.00*** | (0.02) | | | 0.50 | (0.47) | | |
| $\tilde{B}^b$ | 0.00*** | (0.00) | | | 0.00 | (0.00) | | |
| $\psi$ | 0.74 | (82.32) | | | 1.00 | (22.86) | | |
| Liquidity shock determinants ($\mathbf{x}$) | | | | | | | | |
| *GDP growth* | −1.04 | (11.84) | 0.00 | (0.00) | −34.13 | (129.15) | −0.09 | (0.34) |
| *Market Return* | −12.34 | (37.44) | −0.02 | (0.06) | 0.75 | (3.92) | 0.01 | (0.05) |
| *Market Volatility* | −1.87 | (6.12) | 0.00 | (0.00) | 5.71 | (64.39) | 0.03 | (0.28) |
| *Fontaine-Garcia* | 3.46*** | (0.25) | 0.02*** | (0.00) | −0.26 | (2.74) | −0.01 | (0.12) |
| *Yield curve slope* | −3.15 | (123.05) | −0.04 | (1.43) | 0.21 | (0.16) | 0.02 | (0.02) |
| *Industry Leverage* | 1.18 | (46.23) | 0.00 | (0.00) | | | | |
| *Industry Market-to-Book* | 3.67 | (3.56) | 0.02 | (0.02) | | | | |
| Constant ($\beta_0$) | −11.51 | (215.31) | | | −2.42 | (7.38) | | |
| Liquidation value determinants ($\mathbf{z}$) | | | | | | | | |
| *Block-to-Industry Size* | 1.83 | (34.99) | 0.00 | (0.01) | −6.63 | (31.21) | −0.01 | (0.03) |
| *Industry's M&A Activity* | −0.61 | (0.39) | −0.02 | (0.01) | 0.60*** | (0.21) | 0.06*** | (0.02) |
| *Target minus Industry Leverage* | −17.48 | (16.31) | −0.05 | (0.04) | −3.08 | (28.15) | −0.02 | (0.20) |
| *Industry Specificity* | −12.80 | (34.29) | −0.02 | (0.06) | −0.28 | (3.92) | 0.00 | (0.02) |
| *Industry Market-to-Book* | −1.91 | (5.41) | −0.01 | (0.03) | −0.57 | (3.51) | −0.01 | (0.04) |
| *Target Volatility* | 4.57 | (10.58) | 0.02 | (0.04) | −2.40*** | (0.74) | −0.02*** | (0.01) |
| *GDP growth* | | | | | 125.96 | (985.22) | 0.10 | (0.78) |
| *Fontaine-Garcia* | | | | | 0.52 | (3.97) | 0.01 | (0.05) |
| *Yield curve slope* | | | | | 0.53 | (10.36) | 0.02 | (0.31) |
| Constant ($\gamma_0$) | 11.51 | (17.14) | | | −0.16 | (3.18) | | |

(continues)

**Table VI: continued**

**Panel B: Model fit**

| | (1) $\chi^2$ | (1) $p$ value | (2) $\chi^2$ | (2) $p$ value |
|---|---|---|---|---|
| Joint significance test ($H_0 : (\boldsymbol{\beta}, \boldsymbol{\gamma}, \eta, \psi, B) = \mathbf{0}$) | $1,792.57^{***}$ | 0.000 | 65.64 | 0.114 |
| Over-identifying restrictions test ($H_0 : \mathbf{m}(\boldsymbol{\beta}, \boldsymbol{\gamma}, \eta, \psi, B) - \mathbf{M} = \mathbf{0}$) | 0.30 | 1.000 | 11.94 | 1.000 |

**Panel C: In-sample predictions**

| | (1) Mean | StdD | Median | Proportion of negatives | (2) Mean | StdD | Median | Proportion of negatives |
|---|---|---|---|---|---|---|---|---|
| **BP** | | | | | | | | |
| *Actual* | 0.068 | 0.588 | 0.035 | 0.465 | 0.068 | 0.588 | 0.035 | 0.465 |
| *Predicted* | 0.007 | 0.164 | 0.038 | 0.070 | −0.104 | 0.276 | 0.006 | 0.377 |
| **CAR** | | | | | | | | |
| *Actual* | 0.096 | 0.319 | 0.050 | 0.421 | 0.096 | 0.319 | 0.050 | 0.421 |
| *Predicted* | 0.002 | 0.016 | 0.000 | 0.461 | 0.002 | 0.016 | 0.000 | 0.461 |

[a] Estimates followed by ***, ** and * are statistically different from zero with 0.01, 0.05 and 0.1 significance levels, respectively.
[b] Average private benefits of control, expressed as a percentage of the seller's private block valuation.

**Table VII: Alternative specifications of the blockholders discount rates**

This table shows the estimates of the matching probability, $\eta$, the block seller's bargaining power, $\psi$, the controlling shareholder's private benefits of control, $\tilde{B}$, and the sensitivities, $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$, of the liquidity shock probability, $\theta$, and the block's liquidation value, $\phi$, to $\mathbf{x}$ and $\mathbf{z}$, respectively. For each deal, $i$, $\theta_i$ and $\phi_i$ are given by

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

The parameters are estimated using the Simulated Method of Moments, matching the actual moments, $\mathbf{M}$, of the joint distribution of the percentage block premium, $BP$, and the cumulative abnormal returns, $CAR$, to those simulated by the theoretical search model, $\mathbf{m}(\psi, \eta, \tilde{B}, \boldsymbol{\beta}, \boldsymbol{\gamma})$. The baseline discount for dispersed shareholders is set to 10%. In specification (1), the blockholder's discount rate has an additional 5% if the block size exceeds 65% of the common stock. In specification (2), the blockholders additional discount increases by 1% for every 10% increase in block size, starting from 45%. The data is for a sample of 114 US negotiated block trades in the Thomson One Banker's Acquisitions data between 1/1/1990 and 31/12/2010. Blocks are larger than 35% and smaller than 90% of the outstanding stock. Standard errors are shown in parenthesis next to the coefficient estimates[a]. The economic significance of each coefficient is the change in $\theta_i$ or $\phi_i$ associated with a one sample standard deviation change in each variable in $\mathbf{x}$ and $\mathbf{z}$, respectively.

**Panel A: Parameter estimates**

| | (1) | | | | (2) | | | |
|---|---|---|---|---|---|---|---|---|
| | Coefficient | | Economic significance | | Coefficient | | Economic significance | |
| $\eta$ | 1.00*** | (0.12) | | | 1.00*** | (0.11) | | |
| $\tilde{B}^b$ | 0.12*** | (0.02) | | | 0.14*** | (0.00) | | |
| $\psi$ | 0.59* | (0.32) | | | 0.68 | (0.58) | | |
| Liquidity shock determinants ($\mathbf{x}$) | | | | | | | | |
| *GDP growth* | −62.98 | (39.87) | −0.18 | (0.12) | −59.14** | (27.06) | −0.10** | (0.05) |
| *Market Return* | 26.53*** | (5.53) | 0.39*** | (0.08) | 26.84 | (16.76) | 0.23 | (0.14) |
| *Market Volatility* | 39.80*** | (10.58) | 0.20*** | (0.05) | −44.79 | (52.55) | −0.13 | (0.15) |
| *Fontaine-Garcia* | 3.74*** | (0.98) | 0.18*** | (0.05) | 1.15 | (1.21) | 0.03 | (0.03) |
| *Yield curve slope* | 0.97*** | (0.20) | 0.11*** | (0.02) | 2.30 | (1.41) | 0.14 | (0.09) |
| × *GDP growth* | 18.27*** | (4.37) | 0.06*** | (0.02) | 54.97*** | (18.10) | 0.11*** | (0.04) |
| × *Market Return* | 13.90*** | (0.75) | 0.20*** | (0.01) | 3.10 | (11.21) | 0.03 | (0.09) |
| Constant ($\beta_0$) | −11.51*** | (2.53) | | | 3.69 | (19.71) | | |
| Liquidation value determinants ($\mathbf{z}$) | | | | | | | | |
| *Block-to-Industry Size* | 30.35*** | (5.24) | 0.06*** | (0.01) | −9.40 | (37.86) | −0.02 | (0.07) |
| *Industry's M&A Activity* | −0.16*** | (0.01) | −0.03*** | (0.00) | 0.59*** | (0.07) | 0.13*** | (0.02) |
| *Target minus Industry Leverage* | −17.48*** | (1.09) | −0.29*** | (0.02) | −17.48 | (10.24) | −0.28 | (0.17) |
| *Industry Specificity* | −13.90*** | (1.17) | −0.15*** | (0.01) | −6.07** | (2.80) | −0.07** | (0.03) |
| *Industry Market-to-Book* | −3.94*** | (0.21) | −0.11*** | (0.01) | 3.94 | (2.79) | 0.11 | (0.08) |
| *Target Volatility* | 3.12*** | (0.17) | 0.07*** | (0.00) | 4.08** | (1.58) | 0.09** | (0.04) |
| Constant ($\gamma_0$) | 8.66*** | (0.83) | | | −7.76 | (6.69) | | |

(continues)

**Table VII: continued**

**Panel B: Model fit**

| | (1) $\chi^2$ | (1) $p$ value | (2) $\chi^2$ | (2) $p$ value |
|---|---|---|---|---|
| Joint significance test ($H_0 : (\boldsymbol{\beta}, \boldsymbol{\gamma}, \eta, \psi, B) = \mathbf{0}$) | $1,179.65^{***}$ | 0.000 | $5,912.41^{***}$ | 0.000 |
| Over-identifying restrictions test ($H_0 : \mathbf{m}(\boldsymbol{\beta}, \boldsymbol{\gamma}, \eta, \psi, B) - \mathbf{M} = \mathbf{0}$) | 2.44 | 1.000 | 7.57 | 1.000 |

**Panel C: In-sample predictions**

| | (1) Mean | (1) StdD | (1) Median | (1) Proportion of negatives | (2) Mean | (2) StdD | (2) Median | (2) Proportion of negatives |
|---|---|---|---|---|---|---|---|---|
| **BP** | | | | | | | | |
| *Actual* | 0.068 | 0.588 | 0.035 | 0.465 | 0.068 | 0.588 | 0.035 | 0.465 |
| *Predicted* | 0.035 | 0.557 | 0.066 | 0.482 | −0.084 | 0.537 | 0.008 | 0.500 |
| **CAR** | | | | | | | | |
| *Actual* | 0.096 | 0.319 | 0.050 | 0.421 | 0.096 | 0.319 | 0.050 | 0.421 |
| *Predicted* | 0.002 | 0.016 | 0.000 | 0.461 | 0.002 | 0.016 | 0.000 | 0.461 |

[a] Estimates followed by ***, ** and * are statistically different from zero with 0.01, 0.05 and 0.1 significance levels, respectively.
[b] Average private benefits of control, expressed as a percentage of the seller's private block valuation.

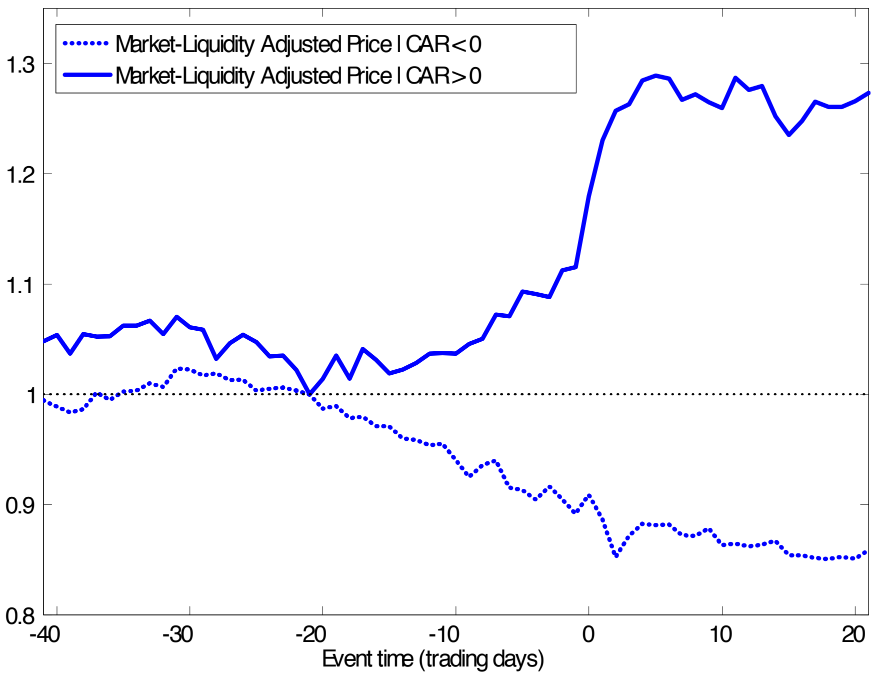


FIGURE 1: Average share price 21 trading days before and after the block trade.

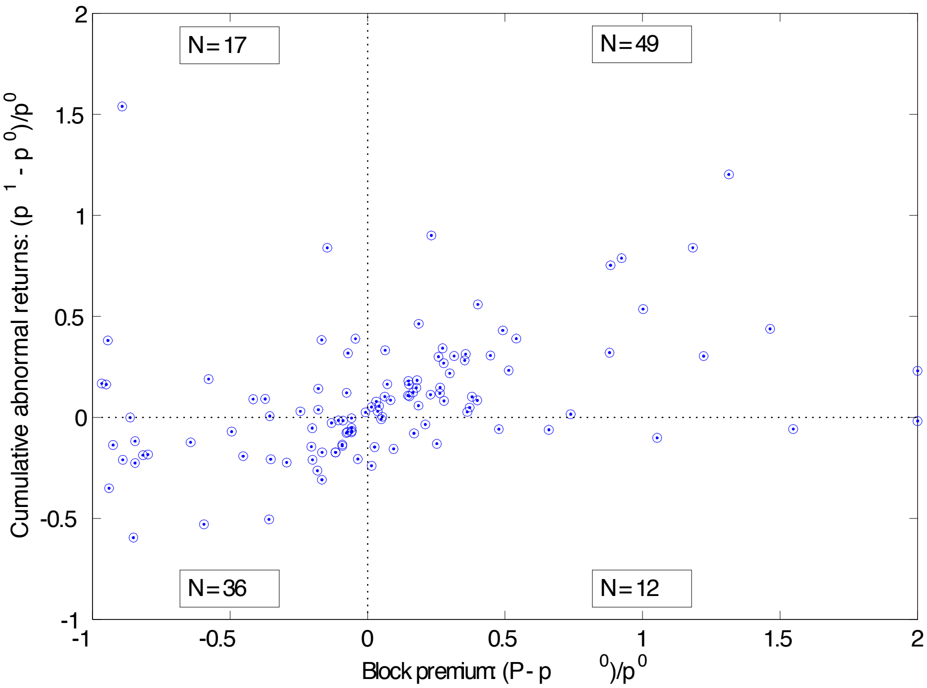


FIGURE 2: Scatter plot of the percentage block premium against the cumulative abnormal returns around the block trade announcement.

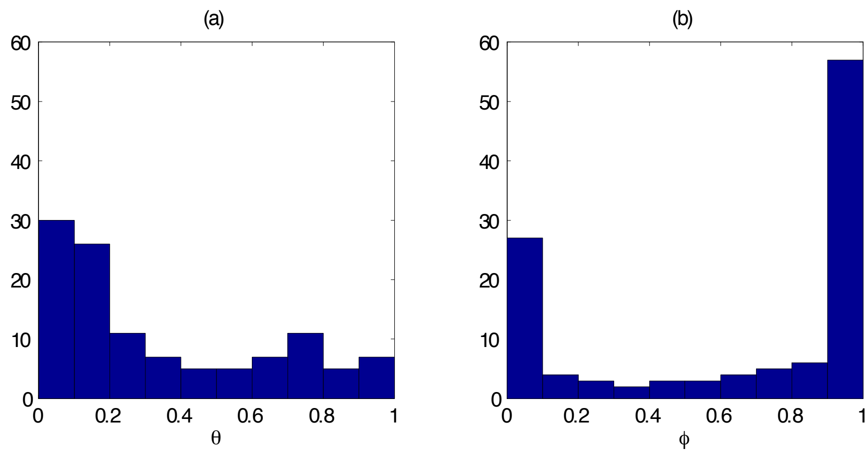


FIGURE 3: Predicted histogram of the probability that a blockholder gets a liquidity shock, $\theta$, (panel (a)) and of the liquidation value of the block, $\phi$, (panel (b)) in the estimated search model. The histograms are constructed using the coefficients in Table III, specification (2).

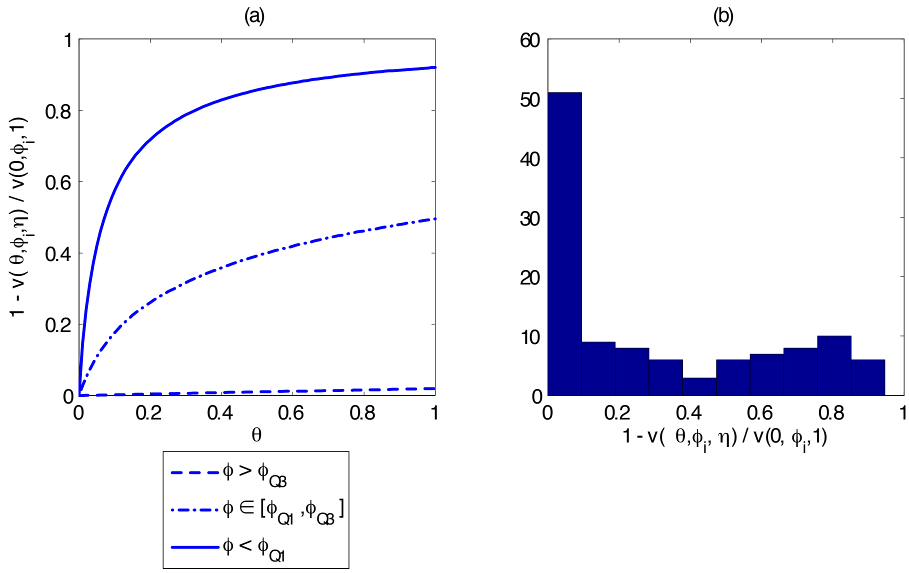


FIGURE 4: Predicted marketability discount of the controlling block, $1 - \frac{v(\theta,\phi_i,\eta)}{v(0,\phi_i,1)}$, for every value of $\theta$, (panel (a)) and predicted histogram of the marketability discount, evaluated at the predicted probability that the blockholder gets a liquidity shock, $\theta_i$,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

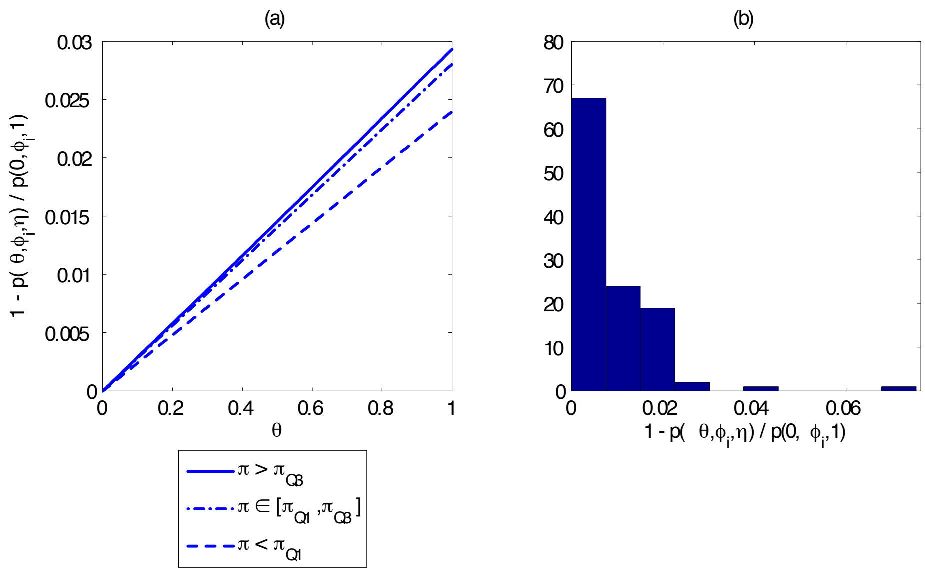


FIGURE 5: Predicted illiquidity spillover discount of the dispersed shares, $1 - \frac{p(\theta,\phi_i,\eta)}{p(0,\phi_i,1)}$, for every value of $\theta$, (panel (a)) and predicted histogram of the illiquidity spillover discount, evaluated at the predicted probability that the blockholder gets a liquidity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

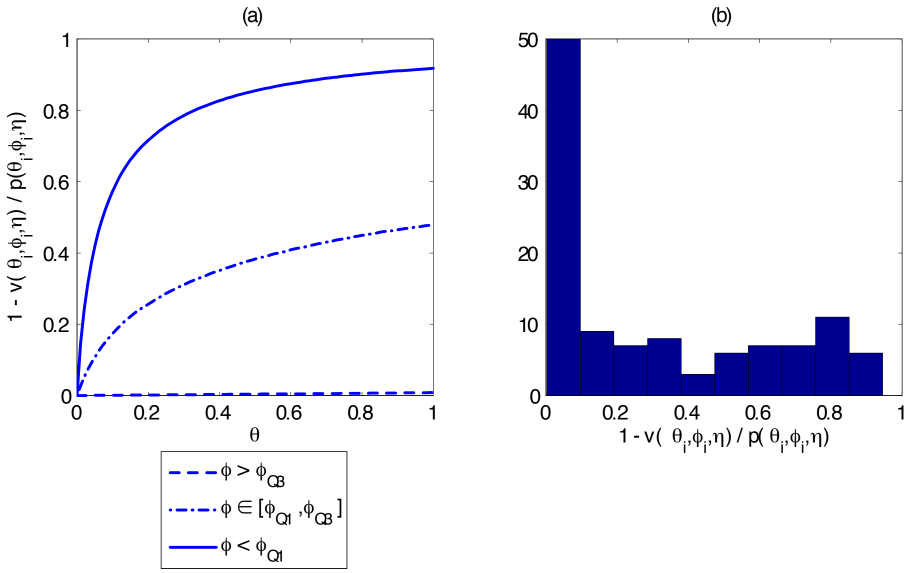


FIGURE 6: Predicted control discount of the block relative to dispersed shares, $1 - \frac{v(\theta,\phi_i,\eta)}{p(\theta,\phi_i,\eta)}$, for every value of $\theta$, (panel (a)) and predicted histogram of the control discount, evaluated at the predicted probability that the blockholder gets a liquidity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