Information Asymmetry and Investment-Cash Flow Sensitivity

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ABSTRACT

Models of capital market imperfections predict that information asymmetry increases the sensitivity of a firm's investment expenditures to fluctuations in internal funds by making external capital more costly. Previous empirical tests of the link between investment and financing decisions have relied on indirect measures of the degree to which a firm becomes financially constrained due to market frictions. In contrast, we use more direct measures of informational frictions derived from the market microstructure literature. Consistent with the theoretical prediction, our analysis shows that the scaled investment expenditures of firms with greater informed trade have greater investment- cash flows sensitivity. Our results are robust to multiple alternative measures of informed trade and liquidity.

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1. Investment – Cash Flow Sensitivity

In the pioneering work of Modigliani and Miller (1958) the financing and investment decisions of the firm can be considered independent in the absence of market frictions. Many studies of information asymmetry and capital market imperfections show that market frictions make external financing more costly than internal financing because the former contains a 'lemons' premium (e.g., Myers and Majluf (1984))[1]. In this environment, Fazzari, Hubbard, and Petersen (1988) argue that the investment decision of firms that nearly exhaust all their low-cost internal funds (i.e., have low dividend payout ratios) would be more sensitive to fluctuations in their cash flows as compared with firms that pay high dividends. Holding constant the investment opportunities of a firm, a reduction in internal funds would reduce capital expenditures by firms facing information costs. They observe "If information problems in capital markets lead to financing constraints on investment, they should be most evident for the classes of firms that retain most of their income. If internal and external finance are nearly perfect substitutes, however, then retention practices should reveal little about investment by the firm. Firms would simply use external finance to smooth investment when internal finance fluctuates," (p. 164).

To test the predicted link between investment and financing, Fazzari et. al. classify firms with low-dividend payouts as 'most financially constrained' while those with high dividend payouts as 'least constrained' firms. They argue that the 'most constrained' firms should have investment expenditures that are *more* sensitive to internal cash flows and stock of liquidity then the 'least constrained' firms. Their empirical tests show substantially higher sensitivity of investment to cash flow and liquidity for firms that retain nearly all of their income.

Kaplan and Zingales (1997) criticize Fazzari et al.'s classification procedure by pointing out that a firm's dividend policy is a choice variable, hence firms that *choose* to pay low dividends even though they could pay out more are not necessarily financially constrained. For example, firms may raise dividends in response to a reduction in personal dividend income tax rates. Using qualitative and quantitative information from financial statements and reports, they identify firms as 'never constrained' if they have more funds than needed to finance their investment and as 'likely constrained' if they are without access to more funds than needed to finance their capital expenditures. In contrast to Fazzari et al., their findings indicate that the investments of 'likely constrained' firms are *less* sensitive to cash flows than the investments of 'never constrained' firms. Kaplan and Zingales (2000) also point out that we would not expect investment cash-flow sensitivities to be a good measure of financing constraints. As Moyen (2004) demonstrates with simulated data, it is hard to identify firms with financing constraints, and the investment-cash flow sensitivity critically hinges on the classification procedure used. While some methods of financial constraint identification show low sensitivity between investments and cash flows, others show just the opposite.

Since a very important root cause of firms' financial constraints and higher external capital costs is information asymmetry between firms and uninformed investors, we use measures of asymmetric information derived from the market microstructure literature to classify firms as more or less financially constrained. Following previous theoretical work, we assume firms have private information about their investment opportunities. Informed investors invest in gathering info about firms' prospects and trade on that information, but the uninformed investors do not. Studies by Demsetz (1968), Copeland and Galai (1983), Glosten and Milgrom (1985), Kyle (1985), Glosten and Harris (1988), Fialkowski and Petersen (1994), Bessimbinder and Kaufman (1997), Easley, Hvidkjaer, and O'Hara (2002), and Easley and O'Hara (2004) indicate that measures of market liquidity (e.g., effective spread and price impact of trade measures) and probability of informed trading (e.g., *PIN)* serve to capture information asymmetry between informed and uninformed investors. That is the higher the liquidity costs, the more expensive is external financing as compared to internal financing. Therefore, we argue that firms with higher effective spreads, greater price impact of trades, and higher probability of informed trade are likely to rely more on internal cash flows and internally generated capital for investment spending than firms with lower effective spreads and *PIN*. Since we use a more *direct* measure of capital market frictions and of financing constraint, our classification procedure better addresses the Kaplan and Zingales (1997) criticism of Fazzari et al.

Our research also seeks to bridge the gap between the existing but largely distinct literature on investment in the corporate finance literature and liquidity in the market microstructure literature. A recent paper by Easley and O'Hara (2004) makes clear the link between information and the cost of capital. Recently, notable scholars in the microstructure literature (e.g., Madhavan (2004) and O'Hara (2003)) have suggested that the microstructure literature must show economic meaning to become more relevant. Our study is a modest step in that direction – specifically, linking liquidity in general and adverse selection in particular to the investment decision of the firm.

2. Data and Methodology

2.1. Sample Selection

Our original data set is the 1,224 firms of Standard and Poor's 1500 (S&P 1500) with revenues greater than $10,000,000 in 2000. The S&P 1500 is a well-known representative market index. Of the 1,224 firms in the original sample, 509 firms satisfy the following selection criteria:

(a) Accounting data available in Standard and Poor's COMPUSTAT to form the variables necessary for our study.

(b) Data available in Center for Research in Securities Prices (CRSP) daily master file

(c) Transactions data for January through June 2000 is available in the NYSE Transactions and Quote (TAQ) database.

(d) Firm's equity was traded on New York Stock Exchange (NYSE) or American Stock Exchange (AMEX) for the entire period January to June 2000 inclusive.

(e) Fiscal year-end in June or later.

(f) Firm is not in the financial services industry.

The exclusion of NASDAQ firms is to ensure that our results are not driven by and to minimize the noise due to the very different market structures. Further, the transaction-based models that we employ to measure adverse selection are developed theoretically in a specialist (not dealer) market. The exclusion of financial services industry firs in study of investment cash-flow sensitivities s standard practice in this literature (e.g. Fazzari et. al (1988), Kaplan and Zingales (1997, 2000).

2.2. *Data Sources*

The Center for Research in Security Prices (CRSP) daily master file is used to calculate average daily volume, price, and return volatility. The NYSE TAQ database is used to obtain empirical estimates of our transaction data based liquidity measures.

We use the first 6 months of year 2000 quotes and trades from TAQ data. In using the TAQ data we apply the following filters which are standard in the study of transactions data:

a) Only BBO eligible primary market quotes are retained. (NYSE quotes—if it is a NYSE listed stock, AMEX quotes if it is a AMEX listed stock)
b) Quotes and trades that have time stamp between 9:30 am to 4:00 p.m. are included.
c) Use quotations at least 15 seconds before the trade when we calculate trade execution costs
d) Use contemporaneous quotations for trade indicator identification. (See Bessembinder (2002))
e) Trade price must be > 0
f) Ask price must be > bid price must be > 0
g) Eliminate trades and quotes when trade price, ask quote, and bid quote that are lower (higher) than 7.5 standard deviations of the daily variation.
h) Keep trades with value of correction code is zero or one.
i) Exclude re-opening quotes.

2.3. *Descriptive Statistics*

Descriptive data on the final sample of 509 firms are presented in Table 1. As expected, the firms are large but do vary greatly in size, volume, and spreads. The mean (median) market value is $8.89 billion ($1.87 billion). The mean (median) daily trading volume is 888,744 (362,062) shares. The mean (median) of daily average trade weighted quoted half-spread is 7.49 cents (6.88 cents). The average (median) share price is $34.17 ($28.00).

2.4. *Empirical Measures of Liquidity and Adverse Selection*

We use various well-established measures of liquidity from the microstructure literature in our study to ensure the robustness of our results. Specifically, we use: relative effective spread, the Glosten and Harris (GH) (1988) and Huang and Stoll (HS) (1996) price impact of trade measures, and the Easley, Kiefer, O'Hara, and Paperman (EKOP) (1996) probability of informed trade measure. In this section, we discuss the estimation of each measure in turn.

2.4.1. Relative Quoted and Effective Spreads

We measure the relative quoted spread as the difference of the bid and ask quotes scaled by the quote mid-point. It is well established that the quoted spread overestimates the cost of transacting, as it does not account for trades that occur at prices inside the quotes. For example, Fialkowski and Petersen (1994) observe that for most orders executed on the New York Stock Exchange the effective spread paid by investors averages half the quoted spread. Thus, we calculate the relative effective spread as follows:

$$\mathit{Effective\,Spread} = 2 * \left| \frac{P_t - M_t}{M_t} \right|, \tag{1}$$

where P_t is the transaction price and M_t is the midpoint of the matched quote. Quotes are matched to the nearest (but not later) contemporaneous trade as suggested by Bessimbinder (2002).

2.4.2. Glosten and Harris (1988) Price Impact of a Trade

The Glosten and Harris (1988) price formation model assumes that order flow is uncorrelated through time. They show the change in transaction prices (Δp_t) can be written as

$$\Delta p_t = \lambda q_t + \psi[Q_t - Q_{t-1}] + \varepsilon_t, \tag{2}$$

where q_t is signed order flow in shares, λ is the variable (i.e., adverse selection) cost of a transacting, Q_t and Q_{t-1} are trade indicator variables, ψ measures the fixed cost of transacting, and ε_t is a zero mean disturbance term that reflects price changes due to the arrival of public information. We use the Lee and Ready (1991) algorithm is used to sign order flow (q_t) and trade indicator variables (Q_t) as modified by Bessembinder (2002). Specifically, each trade is matched to its contemporaneous quote. If the trade takes place at above the quote midpoint it is classified as a buy (i.e., Q_t =+1), if the trade occurs below the prevailing quote midpoint it is classified as a sell (i.e., Q_t =-1). If the trade occurs at the quote midpoint, it is signed according to the last price change; that is, Q_t =1 if the last price change was positive and vice versa. The signed order flow (q_t) is the size of the trade multiplied by the trade indicator variable (Q_t). The liquidity parameters (λ_{GH}) for each firm are estimated by ordinary least squares using equation (2) with a constant term added for misspecification. For each firm, we multiply λ_{GH} by the average trade size in shares (n) and scale by the average daily closing price of a share. Thus, $\lambda_{GH} * n / P$ represents the relative price impact of the average trade of a firm's stock or alternatively the adverse selection component of the relative effective spread.

2.4.3. Huang and Stoll (1996) Price Impact of a Trade

We follow Huang and Stoll (1995) as well as Bessembinder and Kaufman (1997) to decompose the effective spread into its transitory and permanent components. Uniformed trades result in a transitory change in transaction prices (i.e., price reversal), while information-motivated trades lead to a permanent price change. The realized spread (or price reversal) measures market maker revenue net of information costs. It is defined for each trade as

$$Realized\ Spread = 2Q_t(P_t - V_{t+\tau}), \quad (3)$$

where Q_t is the trade indicator variable, P_t is the transaction price, and $V_{t+\tau}$ is the post-trade value of the security at some time in the future. To empirically estimate this measure of transactions costs, a proxy for post-trade value is needed as well as a way to classify trades. The transaction price for the first trade at least 5 minutes later (i.e., $\tau \geq 5$) is used as a proxy for the post-trade value.[2] As in the Glosten-Harris estimation, trades are signed using the Lee and Ready (1991) algorithm as modified by Bessembinder (2002). The difference between the effective spread and realized spread scaled by the trade price provides an estimate of the relative price impact or information content of a trade. Specifically,

$$Relative\ Price\ Impact = 2Q_t(P_{t+\tau} - M_t) / P_t, \quad (4)$$

where M_t is the prevailing quote midpoint. In our empirical analysis we set τ equal to (at least) 5 minutes. We omit trades (rather than use the first trade of the next trading day) for which there is no later trade in the same day that permits the calculation of our trading cost measures.

2.4.4. Probability of Informed Trade

We estimate the probability of informed trading (*PIN*) using the model of Easley, Kiefer, O'Hara, and Paperman (1996). Their model is a sequential trade model that estimates the level of informed trading based on the order imbalance between buy and sell orders on any given day over a certain time period. The intuition behind the EKOP model is that order imbalance increases among buy and sell orders when informed traders are trading. The reason for that is the fact that informed traders take only one side of the market depending on their information. Therefore, *PIN* estimation is based on the level of order imbalances that are identified by the transaction data.

In the EKOP model, the probability of a news event is represented by α. A news event can be either a bad news with a probability of δ, or good news with a probability of (1- δ). On any day, both liquidity trader types (i.e., buyer and seller) arrive at a rate of ε. On the other hand, informed traders who know about the news arrive only on days with news events with an arrival rate of μ. They buy if it is good news or sell if it bad news. On days with informed trading, the imbalance of buys and sells is greater than the imbalance on days without informed trading. Therefore, the estimation of the probability of informed trade is based on the estimation of model parameters: α, μ, and ε. To obtain those parameters, we maximize the following likelihood function:

$$\begin{aligned} L(B,S\mid\theta) = {} & (1-\alpha)e^{-\varepsilon}\frac{\varepsilon^B}{B!}e^{-\varepsilon}\frac{\varepsilon^S}{S!} + \alpha\delta e^{-\varepsilon}\frac{\varepsilon^B}{B!}e^{-(\mu+\varepsilon)}\frac{(\mu+\varepsilon)^S}{S!} \\ & + \alpha(1-\delta)e^{-(\mu+\varepsilon)}\frac{(\mu+\varepsilon)^B}{B!}e^{-\varepsilon}\frac{\varepsilon^S}{S!} \end{aligned} \qquad (5)$$

where B and S represent the number of buys and the number of sells on a given day, respectively. The model assumes that days are independent, therefore the likelihood of observing the buys and sells over I days, $M = (B_i, S_i)_{i=1}^{I}$ is the product of likelihoods:

$$L(M \mid \theta) = \prod_{i=1}^{I} L(B_i, S_i \mid \theta) . \tag{6}$$

We maximize this likelihood function for each firm to find the estimates of the model parameters: α , μ , and ε . Then, the probability of informed trade (*PIN*) is calculated based on the estimated model parameters as follows:

$$PIN = \frac{\alpha\mu}{\alpha\mu + 2\varepsilon} \tag{7}$$

The numbers of buy orders and sell orders for each day are the only inputs required for the estimation of *PIN*.[3] Again, we use the Bessimbinder (2002) methodology to identify whether a trade is a buyer-initiated or a seller-initiated.

2.5. *Investment and Cash Flow Variables*

We use COMPUSTAT data for 2000 to form the variables related to investment and cash flow used in our analysis. The formation of the regression variables in our analysis is consistent with other empirical studies of investment-cash flow sensitivities (e.g. Fazzari, Hubbard, and Petersen (1988), Kaplan and Zingales (1997 and 2000)).

2.5.1. Investment Variables

Investment (*I*) in plant, property, and equipment comes from the COMPUSTAT data item for capital expenditures. This data item includes expenditures for capital leases, funds for construction, and reclassification of inventory to property. It excludes capital expenditures of discontinued operations, changes due to foreign currency fluctuations, assets of acquired companies, and decreases in funds for construction. We scale capital expenditures by the capital stock (*K*) taken as net plant, property, and equipment at the beginning of the reporting year from COMPUSTAT. Thus, our scaled investment variable is indicated as (I / K).

Tobin's Q is a measure of the investment opportunity set that the firm faces. We use the Chung and Pruitt (1994) measure of Q as follows:

$$Q = \frac{\left(MV(CS) + BV(PS) + BV(LTD) + BV(INV) + BV(CL) - BV(CA)\right)}{BV(TA)}, \qquad (6)$$

where *MV(X)* and *BV(X)* indicate the market and book variable of the argument X, respectively. *CS* is common stock, *PS* is preferred stock, *LTD* is long-term debt, *INV* is inventory, *CL* is capital leases, *CA* is current assets, and *TA* is total assets. The advantage of the Chung and Pruitt Q is the ease of computation and the anticipated larger sample size as compared to when using other more complicated formulations of Q. All variables for the computation of Q are taken from COMPUSTAT. We estimate Q as of the beginning of the reporting year to capture the investment opportunity set the firm faces before the capital investment is undertaken.

2.5.2. Cash Flow Variables

We use the COMPUSTAT data item for cash flow (*CF*), which is defined as income before extraordinary items plus depreciation and amortization. As is customary in investment-cash flow sensitivity studies (e.g., Hubbard (1988), Moyen (2004)), we scale our measure of firm cash flow by net plant, property, and equipment as of the beginning of the period from COMPUSTAT; our cash flow variable is thus denoted as (CF / K).

3. Results and Analysis

3.1. Univariate Analysis

We begin with a univariate analysis of investment, cash flow, and market liquidity measures. Looking down the column of Table 2 for scaled investment (I / K) we see positive correlation as expected with Q (ρ = +0.26) and with scaled cash flow (ρ = 0.20) indicating that firms with a greater investment opportunity set and greater cash flow invest in proportion to their capital stock. (I / K) has positive correlation (ρ ~ +0.14) with our liquidity measures such as relative effective spread, probability of informed trade, and our price impact measures indicating that higher transaction and adverse selection costs are not associated with lower scaled investment.. The liquidity measures, however, in general have negative correlations with *LNSIZE* and *Q*. Also as expected, the liquidity measures have strong negative correlations with both market value (*LNSIZE*) and trading volume (*VOLUME*) and *LNSIZE* and *VOLUME* are strongly positively correlated indicating larger firms trade more often and have, in general, better liquidity. As would be expected, our univariate analysis is exploratory and needs to be supplemented by a multivariate analysis due to the complex interactions of the control and test variables used in our analysis..

3.2. Multivariate Analysis

In our multivariate analysis, we first investigate the effect of liquidity as measured by relative effective spread on relationship the sensitivity of scaled investment (*I / K*) to scaled cashflow (*CF / K*). We then extend our analysis to include the effect of liquidity on the firm's cashflow-investment sensitivity using price impact and *PIN* measures. Fazzari, Hubbard, and Petersen (1988) draw on the *Q*-model of investment to investigate the investment-cash flow sensitivities of constrained versus unconstrained firms. We follow he general framework of Fazzari et. al. as follows:

$$\left(I/K\right)_{it} = f\left(\mathbf{X}/K\right)_{it} + g\left(CF/K\right)_{it} + \varepsilon_{it}, \qquad (7)$$

where **X** represents a vector of variables theoretically motivated as determinants of investment. A linear specification is motivated by the work of Summers (1981) and Hayashi (1982) by assuming a "quadratic adjustment cost framework." In addition to the value of *Q* at the beginning of each period, we add dummy variables to capture the potential differences in scaled investment due to the differences in capital intensity of industries and thus to avoid the bias caused by omitted explanatory variables. We also add *LNSIZE,* which is defined as the natural log of the market value of equity as an explanatory variable to control for potential differences in scaled investment due to the size of the firm. Moreover, larger (smaller) firms are generally more (less) liquid, thus by adding *LNSIZE* as an explanatory variable for control for the possibility that our liquidity partitions are proxies for firm size. Our variable of interest is a slope differential dummy variable for the slope of the investment-cash flow sensitivity for firms with the greater spreads or adverse selection costs. Specifically, we estimate the following cross-sectional specification using ordinary least squares with the White (1980) covariance matrix:

$$\left(\frac{I_i}{K_i}\right) = \alpha_0 + \beta_1\left(\frac{CF_i}{K_i}\right) + \beta_2\left(\frac{CF_i}{K_i}\right) * LIQDUM_i + \beta_3(Q_i) + \beta_4(LNSIZE_i) + \beta_5 IND1_i + \beta_6 IND3_i + \beta_7 IND4_i + \beta_8 IND6_i + \varepsilon_i, \tag{8}$$

where $LIQDUM_i$ takes on the value of unity for the more illiquid firms in our sample as indicated by our various liquidity measures , specifically the least liquid decile, and zero otherwise. Thus, the coefficient β_2 captures the difference in cash flow-investment sensitivity for the most illiquid firms in our sample. If internal and external capital are not perfect substitutes and spread serves to captures the transactions costs associated with external financing, we hypothesize that firms with greater frictions (i.e., lower liquidity) will have greater cash flow investment sensitivity ($\beta_2 > 0$) than more liquid firms. Previous research predicts (e.g. Hubbard (1998) and Kaplan and Zingales (1997)) we should expect to see a positive and significant relationship between scaled investment and Q ($\beta_3 > 0$) and also with scaled cash flow ($\beta_1 > 0$). If there are economies to firm size for investment, then β_4 is expected to be greater than zero.

3.2.1. Analysis using Relative Effective Spread

If internal and external capital are not perfect substitutes, then transactions costs would be expected to make equity capital more expensive as compared to internally generated funds. Fazzari, Hubbard, and Petersen (1998) posit that this effect would be expected to be greater for "constrained" firms. Kaplan and Zingales (1997 and 2000) counter with research to suggest greater investment-cash flow sensitivities are not indicative of firms facing greater financing constraints. We posit that higher effective bid-ask spreads serve to capture firms that are constrained, specifically due to asymmetric information problems. Amihud and Mendelson (1988) and Brennan and Subrahmanyam (1996) demonstrated that firms with greater adverse selection problems (and therefore greater spreads) will face a higher cost of capital (presumably for externally sourced equity capital). This alone serves to make the difference between internal and external capital more pronounced.

The variable *LIQDUM* is assigned a value of unity for firms with an average relative spread in the upper decile of our sample and zero otherwise. We estimate equation (8) using the White (1980) covariance matrix and present the results in Table 3. In Panel A of Table 3, we estimate the basic model of Fazzari, Hubbard, and Petersen (1988) without the slope differential dummy for the investment-cash flow sensitivity of illiquid firms. Regression #1 is estimated without the industry dummies and *LNSIZE*. As expected the slope coefficient for *Q* is positive and highly significant (t = 7.83). The coefficient on scaled cash flow (*CF / K*) is positive, as expected, and significant at the 5% level (t = 2.11). The adjusted R^2 is 0.20. In regression #2, we add *LNSIZE* as an explanatory variable. The results for *Q* and (*CF / K*) do not change materially; the coefficients have the same signs (positive as expected) and now are both highly significant. The coefficient on *LNSIZE* is negative and significant (t = -2.11) indicating a diseconomy of scale in investment. .In regression #3 we add the industry dummy variables[4] but exclude firm size as explanatory variables. The coefficient on *Q* remains positive and very highly significant and the coefficient on (*CF / K*) remains positive but is now significant at the 1% level (t = 2.63) and the adjusted R^2 increases to 0.22 The results of estimating regression #3 suggest that there are industry effects in scaled investment after controlling for *Q* and (*CF / K*). Specifically, Industry 3 (Transportation, Communications, and Public Utilities) has significantly lower scaled investment and Industry 6 (Services) has significantly greater scaled investment than Industry 2 (Construction and Manufacturing) in our sample period. In regression #4, we now add *LNSIZE* back to the explanatory variables used in regression #3; the results remain qualitatively similar. The exception being the sign on *LNSIZE* is negative as before but now insignificant (t = 1.62).

In Panel B of Table 3, we add the slope differential dummy variable, *LIQDUM*, to capture the difference in the investment-cash flow sensitivity of firms with the greatest relative effective spreads. In all four regressions presented in Panel B, *LIQDUM* is positive indicating that the investment spending of firms with the highest relative effective spreads are more sensitive to those with lower spreads, but do not meet the 10% threshold for significance (t ~ 1.45). The control variables are consistent with the regressions of Panel A and are consistent with our expectations. Overall, the regressions in Panel B of Table 3 provide weak support that the investment-cash flow sensitivities are greater for firms with greater relative effective spreads. This highlights the need to use more refined measures of information asymmetry in our analysis.

3.2.2. Analysis using Glosten and Harris (*GH*) Measure of Relative Price Impact

Effective spread is a single and imperfect measure of liquidity. It is well-documented (e.g., Glosten and Harris (1988), Glosten and Milgrom (1985), Copeland and Galai (1983), Kyle (1985)) in the microstructure literature that the bid-ask spread has an adverse selection component to compensate market-makers for the probability of dealing with better informed traders as well as a fixed component to cover order-processing costs.[5] The variable $LIQDUM_i$ is assigned a value of unity for firms with a *GH* price impact of trade measure in the upper decile of our sample and zero otherwise. We then estimate equation (8) using the White (1980) covariance matrix and present the results in Table 4. All four regressions in Table 4 have the slope coefficient on *LIQDUM* as positive but not statistically significant ($t \sim 0.85$). The results for the control variables are as expected with the estimated slope coefficients on Q and (CF/Q) are positive and at least highly significant. The results presented in Table 4 also offer only weak support for the hypothesis that firms with high adverse selection costs are likely to have greater investment cash-flow sensitivities. If we accept that firms with greater adverse selection are more constrained, the results support Fazzari et. al (1998) as compared to Kaplan and Zingales (1997, 2000). To supplement the analysis using the *GH* price impact of a trade measure, we now turn to Huang and Stoll's (1995) price impact of a trade measure.

3.2.3. Analysis using Huang and Stoll (HS) Measure of Price Impact of a Trade

The variable $LIQDUM_i$ is now assigned a value of unity for firms with a relative price impact of a trade in the upper decile of our sample and zero otherwise and interacted with the scaled cash flow variable (CF/K). We again estimate equation (8) using the White (1980) covariance matrix and present the Huang and Stoll (1995) results in Table 5. All four regressions in Table 5 have the slope coefficient on *LIQDUM* as positive and significant ($t \sim 1.80$) indicating that firms with trades that have the greatest relative price impact (i.e., informed trade) as measured by *HS* have greater cash-flow investment sensitivities. This provides confirmatory and statistically significant support for our hypothesis. Further, if we accept the Fazzari et. al. (1988) that constrained firms will have greater investment cash-flow sensitivities than unconstrained firms, then adverse selection is found to constrain the firm. If we accept Kaplan and Zingales criticism of Fazzari, et. al., we can only say the firms with the greatest adverse selection as measured by the price impact of a trade, causes its investment to be more sensitive to changes in cash-flow.

3.2.4. Analysis using EKOP Measure of Probability of Informed Trade

As a robustness check of our findings in the previous sub-section, we now repeat the analysis using a very different microstructure measure of informed trade. Easley, Keifer, O'Hara, and Paperman (1996) provide an empirically obtainable measure of the probability of informed trade (*PIN*) using transactions data. More recently, Easley and O'Hara (2004) show that the cost of capital is higher for firms with a greater probability of informed trade. Thus, we expect to find that firms with the highest probability of informed trade, will have greater investment-cash flow sensitivity. To test this proposition, we compute the probability of informed trade using the EKOP methodology. We form a dummy variable, $LIQDUM_i$, that is unity for firms in the upper decile of *PIN* values and zero otherwise. As before, we interact $LIQDUM_i$ with $(CF/K)_i$. Thus, the slope coefficient β_2 captures the difference in cash flow-investment sensitivity for firms with the highest probability of informed trade as measured by the EKOP (1996) *PIN* measure. We hypothesize that firms with greater adverse selection as measured by the probability of informed trade will be have greater cash flow investment sensitivity ($\beta_2 > 0$) than firms with a lower probability of informed trade. We estimate equation (8) with the White (1980) covariance matrix and report the results in Table 6. In all four Table 6 regressions, the coefficient (β_2) that captures the difference in slope of the investment - cash flow sensitivity for high *PIN* firms is positive and significant at the 5% level. The positive and significant coefficients for β_2 indicate greater investment-cash flow sensitivity for firms with the highest probability of informed trade. This is consistent with our hypothesis that firms with lower liquidity will have greater frictions in acquiring external financial capital thus their capital investment spending will be more sensitive to changes in internally generated capital (i.e., cash flow). Further, the slope coefficients on Q, and (CF/K) are positive as expected and very highly significant in all of the Table 6 regressions and the adjusted R^2s are approximately 0.30. The analysis of this section provides evidence that our findings with respect to price impact of a trade are robust to an alternative measure of market liquidity.

4. Conclusions

To the extent that internal and external financing are not perfect substitutes, we expect and find a positive relationship between capital investment spending and cash flow after controlling for the investment opportunities of the firm. Further, for firms with the lowest liquidity (or highest adverse selection), the difference between internal and external financing becomes more relevant due to a lemons problem. Thus, we expect firms with lower liquidity to have greater investment - cash flow sensitivities. We use both an indirect (effective spread) and direct measures (GH, HS, and PIN) of adverse selection to investigate this potential and recognized important constraint on raising external capital and its effect on firm's investment – cash flow sensitivity. Consistent with our conjecture, we do find that the firms with the greatest informed trade (i.e., lowest liquidity) in our large sample of NYSE firms have greater investment –cash flow sensitivity. Our findings are robust to various measures of informed trade and liquidity, specifically Huang and Stoll (1995) price impact of a trade and Easley, Kiefer, O'Hara, and Paperman's (1998) probability of informed trade. The results of our analysis using effective spread (a coarse measure of adverse selection) and the Glosten-Harris price impact of a trade do not contradict our findings; we do find results that are consistent but fail to rise to a conventional level of statistical significance.

If we accept a priori, that firms with greater adverse selection are more constrained, our findings support those of Fazzari, Hubbard, and Petersen (1988) as compared to Kaplan and Zingales (1997 and 2000) in the ongoing debate over whether investment – cash flow sensitivities are helpful in identifying firms that face greater financial constraints. If we accept that Kaplan and Zingales (1997 and 2000) criticism of Fazzari et. al,, we note simply that adverse selection is associated with the firm's investment being more sensitive to its internally generated cash flow. Thus, we find a role for adverse selection and liquidity in the firm's investment decision. Further, our findings are consistent with liquidity effect on the firm's investment decision as posited in Easley and O'Hara (2004) and also with Moyen (2004) who shows the investment cash flow sensitivities are highly dependent on the method of classifying a firm as constrained or not.. Our research represents a modest step in empirically establishing a direct link between market liquidity and the investment decisions of the firm.

[1] First by Akerlof (1970).
[2] Bessembinder (1999) finds that using the quote mid-point for the post trade value yields essentially the same results.
[3] We use Quant Optimization Method in GQOPT optimization package of FORTRAN to estimate PIN for each firm.
[4] Industry classifications are based on two-digit SIC codes as in Bhushan (1989). Note the base case in all of our regressions involving industry dummies is industry 2 (construction and manufacturing). Note that industry 5 (finance, real estate, and insurance) is excluded from our sample.
[5] Some theoretical models suggest an inventory component of the spread as well although the empirical support for inventory costs is weak (e.g., Madhavan and Smidt (1991)).

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Table 1

Descriptive Statistics for Sample of Non-Financial Service Industry, NYSE and AMEX-listed Firms in S&P 1500 Index for the period January 1, 2000 through June 30, 2000.

Panel A: Descriptive Statistics for Final Sample

	Average Closing Price ($)	*Market Cap. ($000)*	*Daily NYSE Volume (Shares)*	*Dollar Quoted Half-Spread ($)*	*Relative Quoted Half- Spread (%)*
(n=509)					
Mean	34.17	8,889,068	888,744	0.0749	0.3098
Median	28.00	1,873,688	362,062	0.0688	0.2467
Max.	510.26	277,717,769	20,257,390	0.5803	2.8643
Min.	2.81	43,464	9,895	0.0379	0.0726

Panel B: Distribution of Final Sample by Industry Code[c]

Industry Code (Description)	*Number of Firms*	*Proportion of Sample*
(n=509)		
IND1 (Mining)	33	0.06
IND2 (Construction and Manufacturing)	291	0.57
IND3 (Transportation, Communication, and Utilities)	87	0.17
IND4 (Wholesale and Retail Trade)	40	0.08
IND5 (Finance, Insurance, and Real Estate)	0	0.00
IND6 (Services)	58	0.11

Notes:

a. S&P 1500 List obtained from Standard and Poor's COMPUSTAT.

b. Data for Panel A is obtained from CRSP Daily Master file with the exception of quote data, which is obtained from NYSE TAQ database.

c. We follow Bhushan (1989) for industry classification. The industry groups are (1) Mining (two-digit SIC codes: 10-14), (2) Construction and Manufacturing (two-digit SIC codes: 15-39), (3) Transportation, Communication, and Public Utilities (two-digit SIC codes: 40-49), (4) Wholesale and Retail Trade (two-digit SIC codes: 50-59), (5) Finance, Insurance, and Real Estate (two-digit SIC codes: 60-67), and (6) Services (two-digit SIC codes: 70-96). Two-digit primary SIC codes are obtained from COMPUSTAT.

Table 2

Correlation Matrix of Investment and Market Liquidity Variables [a]

This table reports the correlation coefficient among the variable. *I* is the investment in plant, property, and equipment. *K* and *I/K* are the capital stock and scaled investment by capital stock, respectively. *Q* represents Tobin's Q that is a measure of the firm's investment opportunity set. We use the Chung and Pruitt (1994) measure of Q. *CF* is cash flow, defined as income before extraordinary items plus depreciation and amortization. *CF/K* is the cash flow scaled by capital stock. *LNSIZE* and *VOL* are natural log of average daily market capitalization and average daily trading volume of a firm, respectively. *ESPRD* is daily average relative effective spread calculated as the absolute difference between the transaction price and the quote mid-point scaled by the quote mid-point. *PIN* represents the information asymmetry among investors, measured by the probability of informed trading (EKOP) model. *PRIMP* is the Huang and Stoll (1995) measure of the relative price impact of a trade. *GHLAMB* is the Glosten and Harris (1988) relative price impact of a trade measure.

	I	*K*	*I / K*	*Q*	*CF / K*	*LNSIZE*	*VOL*	*ESPRD*	*PIN*	*PRIMP*	*GHLAMB*
I	1										
K	0.84	1									
I / K	-0.07	-0.21	1								
Q	0.00	-0.06	0.26	1							
CF / K	-0.13	-0.16	0.38	0.20	1						
LNSIZE	0.70	0.75	-0.04	0.21	-0.01	1					
VOLUME	0.57	0.53	-0.02	0.30	0.03	0.65	1				
ESPRD	-0.25	-0.23	0.10	-0.23	0.04	-0.05	-0.28	1			
PIN	-0.29	-0.28	0.15	-0.18	0.04	-0.28	-0.40	0.45	1		
PRIMP	-0.39	-0.37	0.14	-0.24	-0.06	-0.30	-0.56	0.78	0.59	1	
GHLAMB	-0.15	-0.15	0.39	-0.08	0.09	-0.10	-0.21	0.35	0.26	0.41	1

Note:

a. Based on 469 firms.

Table 3

Q Model of Investment using Relative Effective Spread as Liquidity Measure

This table shows the cross-sectional regression results when scaled investment (*I/K*) is regressed against scaled cash flow (CF/K), a high spread dummy variable and control variables.

Panel A shows the estimation results for the following regression:

$$\left(I_i/K_i\right) = \alpha_0 + \beta_1\left(CF_i/K_i\right) + \beta_2(Q_i) + \beta_3(LNSIZE_i) + \beta_4 IND1_i + \beta_5 IND3_i + \beta_6 IND4_i + \beta_7 IND6_i + \varepsilon_i,$$

Panel B shows the estimation results for the following regression:

$$\left(I_i/K_i\right) = \alpha_0 + \beta_1\left(CF_i/K_i\right) + \beta_2\left(CF_i/K_i\right) * SPRDDUM_i + \beta_3(Q_i) + \beta_4(LNSIZE_i) + \beta_5 IND1_i + \beta_6 IND3_i + \beta_7 IND4_i + \beta_8 IND6_i + \varepsilon_i,$$

We hypothesize that firms with greater frictions as measured by relative effective spread will be have greater cash flow investment sensitivity (β_2) than firms with lower spreads. Therefore, the slope coefficient β_2 captures the difference in cash flow- investment sensitivity for firms with higher relative effective spreads in the above regression specification.

The descriptions of the variables used are provided below:

I/K:	investment scaled by beginning of period capital stock
CF/K :	cash flow scaled by beginning of period capital stock
Q:	Tobin's *Q* measured by Chung and Pruitt (1994)
SPRDDUM:	dummy variable that takes the value of unity for firms with an average relative effective spread in the upper decile of our sample and zero otherwise.
LNSIZE:	natural log of average daily market capitalization.
IND(i):	dummy variables that represent firm's industry based on two-digit SIC code of a firm.

Panel A: OLS Regressions without Slope Dummy for High Spread Firms

Dependent Variable: Scaled Investment (*I / K)*

Regression #	*(1)*	*(2)*	*(3)*	*(4)*
Constant	0.1076***	0.3139***	0.1148***	0.2702***
	(7.83)	(3.08)	(6.22)	(2.79)
CF / K	0.0821**	0.0800***	0.0708***	0.0705***
	(2.11)	(2.88)	(2.63)	(2.63)
Q	0.0481***	0.0607***	0.0446***	0.0548***
	(3.53)	(4.16)	(3.18)	(3.57)
LNSIZE		-0.0151**		-0.0116
		(-2.11)		(-1.62)
IND1			-0.0233	-0.0187
			(-1.37)	(-1.10)
IND3			-0.0398**	-0.0308
			(-2.05)	(-1.50)
IND4			0.0267	0.0261
			(0.71)	(0.70)
IND6			0.0725**	0.0695**
			(2.32)	(2.26)
n	509	509	509	509
Adjusted R^2	0.20	0.21	0.22	0.23

Panel B: OLS Regressions with Slope Dummies for High Spread Firms

Dependent Variable: *Scaled Investment (I / K)*

Regression #/ Dep. Variable	*(1)*	*(2)*	(3)	(4)
Constant	0.1001***	0.2534***	0.1085***	0.2419**
	(6.99)	(2.69)	(5.64)	(2.34)
CF / K	0.0732***	0.0724***	0.0633**	0.0635**
	(2.78)	(2.76)	(2.53)	(2.54)
*LIQDUM * (CF / K)*	0.1590	0.1453	0.1521	0.1430
	(1.52)	(1.42)	(1.48)	(1.41)
Q	0.0525***	0.0614***	0.0489***	0.0556***
	(3.75)	(4.23)	(3.38)	(3.63)
LNSIZE		-0.0112*		-0.0079
		(-1.71)		(-1.20)
IND1			-0.0120	-0.0170
			(-1.16)	(-0.99)
IND3			-0.0369*	-0.0310
			(-1.90)	(-1.53)
IND4			0.0040	0.0049
			(0.17)	(0.21)
IND6			0.0701**	0.0682**
			(2.25)	(2.22)
n	509	509	509	509
Adjusted R^2	0.23	0.24	0.25	0.25

Table 4

Q Model of Investment using Glosten and Harris (1988) Price Impact Measure of Liquidity

This table shows the cross-sectional regression estimation results when scaled investment (*I/K*) is regressed against scaled cash flow (CF/K), a high price impact dummy variable, and control variables as follows:

$$\left(\frac{I_i}{K_i}\right)=\alpha_0+\beta_1\left(\frac{CF_i}{K_i}\right)+\beta_2\left(\frac{CF_i}{K_i}\right)*LIQDUM_i+\beta_3(Q_i)+\beta_4(LNSIZE_i)+$$
$$\beta_5 IND1_i+\beta_6 IND3_i+\beta_7 IND4_i+\beta_8 IND6_i+\varepsilon_i,$$

We hypothesize that firms with greater adverse selection as measured by the price impact of a trade will have greater cash flow investment sensitivity (β_2) than firms with lower price impacts. Therefore, in the above regression specification, the slope coefficient β_2 captures the difference in cash flow- investment sensitivity for firms with a greater relative price impact of trading a single share of stock as Glosten and Harris (GH) (1988).

The descriptions of the variables are provided below:

I/K:	investment scaled by beginning of period capital stock
CF/K :	cash flow scaled by beginning of period capital stock
Q:	Tobin's *Q* measured by Chung and Pruitt (1994)
LIQDUM:	dummy variable that takes the value of unity for firms with relative GH price impact measure in the upper decile of our sample and zero otherwise.
LNSIZE:	natural log of average daily market capitalization.
IND(i):	dummy variables that represent firm's industry based on two-digit SIC code of a firm.

Dependent Variable: Scaled Investment (I / K)

Regression #/ Dep. Variable	*(1)*	*(2)*	(3)	(4)
Constant	0.1030***	0.2795***	0.1111***	0.2422**
	(6.97)	(2.78)	(5.58)	(2.53)
CF / K	0.0746***	0.0737***	0.0652**	0.0654**
	(2.80)	(2.78)	(2.57)	(2.58)
*LIQDUM * (CF / K)*	0.1045	0.0924	0.0902	0.0820
	(0.96)	(0.87)	(0.84)	(0.78)
Q	0.0514***	0.0617***	0.0476***	0.0559***
	(3.68)	(4.19)	(3.28)	(3.60)
LNSIZE		-0.0129*		-0.0097
		(-1.85)		(-1.42)
IND1			-0.0220	-0.0182
			(-1.26)	(-1.06)
IND3			-0.0384*	-0.0310
			(-1.94)	(-1.52)
IND4			0.0215	0.0214
			(0.70)	(0.70)
IND6			0.0664**	0.0644**
			(2.07)	(2.05)
n	509	509	509	509
Adjusted R^2	0.22	0.22	0.23	0.24

Notes:

a. *t*-ratios in parenthesis below parameter estimates computed using White (1980) covariance matrix.
*, **, and ***denotes significance at the 10%, 5%, and 1% level, respectively.

Table 5

Q Model of Investment using Huang and Stoll (1995) Relative Price Impact Measure of Liquidity

This table shows the cross-sectional regression estimation results when scaled investment (*I/K*) is regressed against scaled cash flow (CF/K), a high price impact dummy variable, and control variables as follows:

$$\left(I_i/K_i\right) = \alpha_0 + \beta_1\left(CF_i/K_i\right) + \beta_2\left(CF_i/K_i\right) * LIQDUM_i + \beta_3(Q_i) + \beta_4(LNSIZE_i) +$$
$$\beta_5 IND1_i + \beta_6 IND3_i + \beta_7 IND4_i + \beta_8 IND6_i + \varepsilon_i,$$

We hypothesize that firms with greater adverse selection as measured by the probability of informed trade will have greater cash flow investment sensitivity (β_2) than firms with a lower probability of informed trade. Therefore, in the above regression specification, the slope coefficient β_2 captures the difference in cash flow- investment sensitivity for firms with a greater relative price impact of a trade as in Huang and Stoll (1995).

The descriptions of the variables are provided below:

I/K:	investment scaled by beginning of period capital stock
CF/K :	cash flow scaled by beginning of period capital stock
Q:	Tobin's *Q* measured by Chung and Pruitt (1994)
LIQDUM:	dummy variable that takes the value of unity for firms with a relative price impact measure in the upper decile of our sample and zero otherwise.
LNSIZE:	natural log of average daily market capitalization.
IND(i):	dummy variables that represent firm's industry based on two-digit SIC code of a firm.

Dependent Variable: Scaled Investment (I / K)

Regression #/ Dep. Variable	*(1)*	*(2)*	(3)	(4)
Constant	0.0984***	0.2150***	0.1065***	0.1843*
	(6.94)	(2.18)	(5.54)	(1.91)
CF / K	0.0721***	0.0716***	0.0638**	0.0639***
	(2.84)	(2.82)	(2.59)	(2.60)
*LIQDUM * (CF / K)*	0.2101*	0.1966*	0.1932*	0.1848*
	(1.94)	(1.79)	(1.78)	(1.68)
Q	0.0522***	0.0590***	0.0488***	0.0537***
	(3.82)	(4.12)	(3.44)	(3.56)
LNSIZE		-0.0085		-0.0058
		(-1.24)		(-0.84)
IND1			-0.0182	-0.0161
			(-1.06)	(-0.94)
IND3			-0.0345*	-0.0303
			(-1.76)	(-1.50)
IND4			0.0087	0.0092
			(0.34)	(0.35)
IND6			0.0594*	0.0585*
			(1.92)	(1.91)
n	509	509	509	509
Adjusted R^2	0.25	0.25	0.26	0.26

Notes:

a. *t*-ratios in parenthesis below parameter estimates computed using White (1980) covariance matrix.
*, **, and ***denotes significance at the 10%, 5%, and 1% level, respectively.

Table 6

Q Model of Investment using Probability of Informed Trade as Liquidity Measure

This table shows the cross-sectional regression estimation results when scaled investment (*I/K*) is regressed against scaled cash flow (CF/K), a high PIN dummy variable, and control variables as follows:

$$\left(I_i/K_i\right) = \alpha_0 + \beta_1\left(CF_i/K_i\right) + \beta_2\left(CF_i/K_i\right) * LIQDUM_i + \beta_3(Q_i) + \beta_4(LNSIZE_i) +$$
$$\beta_5 IND1_i + \beta_6 IND3_i + \beta_7 IND4_i + \beta_8 IND6_i + \varepsilon_i,$$

We hypothesize that firms with greater adverse selection as measured by the probability of informed trade will have greater cash flow investment sensitivity (β_2) than firms with a lower probability of informed trade. Therefore, in the above regression specification, the slope coefficient β_2 captures the difference in cash flow- investment sensitivity for firms with a greater probability of informed trade as measured Easley, Kiefer, O'Hara, and Paperman (EKOP) (1996) *PIN* measure.

The descriptions of the variables are provided below:

I/K:	investment scaled by beginning of period capital stock
CF/K :	cash flow scaled by beginning of period capital stock
Q:	Tobin's *Q* measured by Chung and Pruitt (1994)
LIQDUM:	dummy variable that takes the value of unity for firms with a probability of informed trade (PIN) in the upper decile of our sample and zero otherwise.
LNSIZE:	natural log of average daily market capitalization.
IND(i):	dummy variables that represent firm's industry based on two-digit SIC code of a firm.

Dependent Variable: Scaled Investment (I / K)

Regression #/ Dep. Variable	*(1)*	*(2)*	(3)	(4)
Constant	0.1264***	0.3712***	0.1233***	0.3267***
	(11.40)	(5.29)	(8.41)	(4.62)
CF / K	0.0621***	0.0595***	0.0503**	0.0504***
	(2.77)	(2.62)	(2.36)	(2.62)
*LIQDUM * (CF / K)*	0.2253**	0.2107**	0.2081**	0.1983**
	(2.47)	(2.40)	(2.29)	(2.26)
Q	0.0424***	0.0549***	0.0351***	0.0460***
	(3.52)	(4.05)	(3.03)	(3.40)
LNSIZE		-0.0191**		-0.0106***
		(-3.67)		(-2.78)
IND1			-0.0227	-0.0159
			(-1.37)	(-0.97)
IND3			-0.0534***	-0.0417***
			(-4.47)	(-3.26)
IND4			0.0145	0.0161
			(0.56)	(0.62)
IND6			0.0710**	0.0683**
			(2.37)	(2.30)
n^b	486	486	486	486
Adjusted R^2	0.27	0.30	0.31	0.32

Notes:

a. t-ratios in parenthesis below parameter estimates computed using White (1980) covariance matrix.

b. Sample reduced by 23 firms due to non-convergence of *PIN* estimation routine.

*, **, and ***denotes significance at the 10%, 5%, and 1% level, respectively.