Does Asymmetric Information Drive Capital Structure Decisions?*

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Abstract

Using an information asymmetry index based on measures of adverse selection developed by the market microstructure literature, we test if information asymmetry is the sole determinant of capital structure decisions as suggested by the pecking order theory. Our tests rely exclusively on measures of the market's assessment of adverse selection risk rather than on ex-ante firm characteristics. We find that information asymmetry does affect capital structure decisions of U.S. firms over the period 1973-2002, especially when firms' financing needs are low and when firms are financially constrained. We also find a significant degree of intertemporal variability in firms' degree of information asymmetry, as well as in its impact on firms' debt issuance decisions. Our findings based on the information asymmetry index are robust to sorting firms based on size and firm insiders' trading activity, two popular alternative proxies for the severity of adverse selection. Overall, this evidence explains why the pecking order theory is only partially successful in explaining all of firms' capital structure decisions. It also suggests that the theory finds support when its basic assumptions hold in the data, as it should reasonably be expected of any theory.

Keywords: Pecking Order Theory; Capital Structure; Information Asymmetry

J.E.L. Classification Code: G32.

1 Introduction

The problem of explaining firms' capital structure decisions is probably the most intensely debated issue in corporate finance. One of the most popular models of corporate financing decisions in the capital structure literature is the pecking order theory developed by Myers (1984). Myers' (1984) theory is based on the argument in Myers and Majluf (1984) that asymmetric information problems drive the capital structure of firms. Myers (1984) argues that if managers know more than the rest of the market about the firm's investment opportunities (information asymmetry), the market penalizes the issuance of securities (like equity) whose valuation is crucially related to the assessment of such opportunities. Therefore, this theory predicts that companies should recur to stock issuances only as a last resort, after cheaper alternatives (like internal cash, bank debt, or public debt) have been exhausted. In other words, firm management's superior information about the firm's prospects and value of its risky securities vis-a-vis the market should generate a hierarchy of financing policies with a preference for internal over external finance and for debt over equity. According to this hierarchy, firms should finance new investments with the least information-sensitive securities, i.e., first with retained earnings, then with safe debt, then with risky debt, and finally, under duress, with equity.

Tests of the pecking order theory have focused on this main prediction of the model, namely, on the type of securities that firms issue to cover financing deficits. Papers in this vein include Shyam-Sunder and Myers (1999), Fama and French (2002), and Frank and Goyal (2003).[1] Though Shyam-Sunder and Myers (1999) conclude that the pecking order offers a good approximation to financing behavior, their inference is challenged by Fama and French (2002) and Frank and Goyal (2003). Lemmon and Zender (2004) counter this challenge by arguing that, in testing the pecking order theory, one must account for the value of maintaining financial slack for future investment and to avoid financial distress. After controlling for these considerations, Lemmon and Zender (2004) show that the pecking order still offers a reasonable description of firms' financing behavior. Yet, Leary and Roberts

[1] Another route for the test of the pecking order theory concerns the model's predictions about capital structures. Titman and Wessels (1988), Rajan and Zingales (1995), Shyam-Sunder and Myers (1999), and Fama and French (2002) are important examples of this line of research.

(2004) incorporate financial slack in their explicit analysis of the hierarchy of financing decisions and do not find support for the pecking order theory. In short, the existing evidence on testing the pecking order is mixed at best.[2]

In sharp contrast with the above studies, in this paper we do not seek to test the predictions of the pecking order theory. Instead, we evaluate its core assumption, i.e., information asymmetry as the determinant of capital structure decisions. As Fama and French (2004) observe, ultimately the pecking order theory (albeit with some patches) posits that information asymmetry is an important (or perhaps even the sole) determinant of firms' capital structure. However, no test has ever been performed with the purpose of ascertaining the empirical viability of that basic assumption of the theory. In other words, we still do not know whether information asymmetry drives firms' capital structure decisions. That is the specific question we address in this research. In particular, we study the conformity of those decisions to the pecking order theory for different degrees of information asymmetry. If the theory correctly describes the funding process of corporations, we expect this conformity to be greater the higher is the estimated intensity of perceived information asymmetry between managers and all other market participants.

For that purpose, we construct an information asymmetry index based on several measures of adverse selection, stemming from the market microstructure literature. This represents an important innovation of our study with respect to the extant corporate finance literature. The pecking order theory of Myers (1984) and Myers and Majluf (1984) is based on adverse selection between firm managers and market participants. Market microstructure measures of information asymmetry are designed to capture adverse selection between a larger category of agents – informed traders (hatched area in Fig. I) – and the rest of the market (Uninformed traders, white area in Fig. I). In other words, firm managers (shaded area in Fig. I) constitute a subset of informed traders in the market who, in turn, constitute a subset of all traders in the market. Ideally, to test the pecking order theory, we would need to measure adverse selection between firm managers and the rest of the market. Market microstructure measures of information asymmetry are proxies for this adverse selection,

[2] Other papers testing the implications of the pecking order have used the cost of raising external capital (Galpin, 2004) or sorted firms based on distress risk (Chen and Zhao, 2004).

albeit imperfect ones since they also encompass informed traders who are not firm managers. Indeed, these proxies capture the financial markets' perception of the information advantage held by firm insiders and the resulting adverse selection costs, which are what ultimately affects the cost of issuing information-sensitive securities. In contrast, the vast majority of corporate finance studies measure companies' degree of information asymmetry surrounding their business activities according to several ex-ante firm characteristics, such as their relative size, growth opportunities, tangibility of their assets, etc. Unfortunately, these measures are often inconsistent (e.g., Huddart and Ke, 2004; Franken and Li, 2005), as well as inherently static and persistent. More important, they fail to capture the financial markets' *changing* perception of the information advantage held by firm insiders.

Our market microstructure measure of information asymmetry is derived from an extensive literature indicating that transaction costs (e.g., the bid-ask spread) consist of three primary components: order processing, inventory, and adverse selection. The latter, crucial to our research, compensates liquidity providers for transacting with better-informed traders and increases with the degree of information asymmetry. Motivated by these considerations, as well as by the often scarce availability of bid-ask spread data over longer time periods, a number of papers have developed statistical models to identify and measure this component. These models can be broken down into three groups. Within the first group, pioneered by Roll (1984), inference about the bid-ask spread is made from the serial covariance properties of the time series of observed asset returns. Within the second group, inference about adverse selection is based on the interaction between trading volume and asset returns (as in Llorente, Michaely, Saar, and Wang, 2002). Within the last group, the relevance of adverse selection considerations is gauged from the estimation of structural models of the arrival of information-based trades, as in Easley, Kiefer, O'Hara, and Paperman (1996).

In this paper, we estimate the measures of information asymmetry from each of these three classes of models that allow us to cover as many companies for as long as possible. We then use these measures to construct an index of information asymmetry. The index is constructed by (i) standardizing each of these measures across firms in each fiscal year of the sample and (ii) computing their equally weighted average for each firm in each fiscal year of the sample. We label the resulting measure as the "information asymmetry index." The components of this index, although positively correlated with each other, are not identical. Hence, they capture the many facets of information asymmetry studied by the three groups of models mentioned above. Furthermore, our index is more successful at capturing the time-varying severity of firms' adverse selection problem than the traditional information asymmetry proxies employed in the corporate finance literature. For instance, when sorting firms each fiscal year by our index into terciles, we find that, on average, 52% of these firms move to a different tercile the following year. When sorting these firms by size (a commonly employed measure of information asymmetry by the corporate finance literature) into terciles, only 18% of the firms move to a new size tercile in any given year.

Overall, we find that information asymmetry does affect capital structure decisions of U.S. firms between 1973 and 2002, especially when firms' financing needs are low and when firms are financially constrained. We also find a significant degree of intertemporal variability in both firms' degree of information asymmetry and its impact on firms' debt issuance decisions. This evidence explains why pecking order is often only partially successful in explaining the whole of firms' capital structure. Yet, it also suggests that the theory finds some support when its basic assumptions hold strongly in the data, as it should reasonably be expected of any model.

Specifically, we first examine the slope coefficient on a regression of change in debt against change in deficit (as in Shyam-Sunder and Myers, 1999) for firms sorted each fiscal year by information asymmetry terciles from the lowest to the highest. According to Shyam-Sunder and Myers (1999), a slope coefficient of one, i.e., a one-to-one correspondence between the change in debt and deficit, is evidence of the pecking order theory being the dominant description of firms' financing behavior. Yet, even when that slope coefficient is not equal to one, we expect to find it monotonically increasing across the information asymmetry terciles, if the basic tenets of the pecking order theory hold. Consistent with extant studies (e.g., Frank and Goyal, 2003), we do not find the slope coefficient to be one in any of our tests. However, we find that these slope coefficients are positive, statistically significant, and increasing across the information asymmetry terciles. This evidence suggests that while information asymmetry is an important determinant of capital structure changes, it does not seem to be the sole determinant (as predicted by the theory). These patterns are present even after sorting firms on size and estimating the slope coefficients across each size-information asymmetry subset of firms. In other words, we continue to find the increasing pattern across information asymmetry terciles in every size tercile. This result indicates that our market-based measure of adverse selection (the information asymmetry index) has incremental power over firm size, which is commonly used as an ex-ante measure of information asymmetry. We also find the slope coefficients to be monotonically increasing across the size terciles, keeping the information asymmetry quintile fixed. This result suggests that pecking order is a better description of the financing decision process of larger and more mature firms.

Issues with the power of this test have been raised in the literature (e.g., Chirinko and Singha, 2000). We address these issues by employing several alternative testing strategies. First, and to assess more directly the importance of information asymmetry in capital structure decisions, we regress the change in debt ratio (as in Frank and Goyal, 2003) on our measure of information asymmetry and four conventional firm-specific characteristics (tangibility, profitability, sales, and market-to-book ratio) over the entire sample as well as across subsets of firms sorted each fiscal year by their financing deficits into terciles. We find that our information asymmetry index is positively related to changes in debt ratio, in the overall sample as well as in each of the deficit terciles. However, the magnitude of impact of information asymmetry on debt issuance is generally decreasing as we move from the small to the large deficit terciles of firms. This result suggests that for firms with high financing needs (i.e., with large deficits), information asymmetry considerations might be of lesser importance. We also find that variables other than information asymmetry help explain changes in debt, further confirming that pecking order does not appear to provide a complete description of capital structure decisions of firms. For robustness, we also sort firms based on firm-level intensity of insider trading and estimate the above models across each resulting insider trading tercile. We find that information asymmetry has a positive and statistically significant impact on changes in debt ratio in each of these terciles. Hence, our information asymmetry index has incremental power over firm level insider trading, another commonly used measure of adverse selection.

There is mounting empirical evidence that some firms are financially constrained when attempting to satisfy their needs for funds, i.e., when financing their investments. Financial constraints may affect a firm's ability to raise capital, regardless of any other consideration. Therefore, we test whether the presence of these constraints affects the relevance of information asymmetry in firms' capital structure decisions. To do so, we construct a measure of financial constraints faced by the firms in our sample, originally developed by Whited and Wu (2005). This measure captures firms' difficulty in accessing capital markets. We then regress changes in debt ratio on our information asymmetry index across terciles of firms sorted with respect to the intensity of their financial constraints. We find that for firms in the low and medium financial constraint terciles, information asymmetry is unrelated to changes in debt ratio, in contrast with the predictions of the pecking order theory. However, consistent with the theory, information asymmetry is *positively* related to changes in debt for firms in the highest financial constraint tercile. This result suggests that, not surprisingly, information asymmetry considerations in capital structure choices matter principally for financially constrained firms, i.e., for firms whose cost of external funds is most sensitive to capital market imperfections.

We also assess the relevance of debt capacity considerations for the link between information asymmetry and firms' capital structure. Frank and Goyal (2003) argue that firms with the greatest potential for asymmetric information have the greatest incentive to follow the pecking order. As previously mentioned, large firms are commonly deemed to be affected the least by adverse selection problems. Hence, Frank and Goyal (2003) conclude that finding those large, mature firms (rather than small, high-growth firms) perform best in the Shyam-Sunder and Myers' (1999) test is contrary to the pecking order theory. In response to this criticism, Lemmon and Zender (2004) argue that it is precisely the small, high-growth firms that face the most stringent debt capacity constraints. They further show that, after controlling for debt capacity concerns, the pecking order theory still emerges as a reasonable description of firms' financing behavior. As in Lemmon and Zender (2004), we measure firms' debt capacity with their relative predicted probability of receiving a bond rating. We find that our information asymmetry index is *positively* related to changes in debt ratios of firms with either medium or high debt capacity, consistent with the pecking order theory, but is instead unrelated to changes in debt ratios of firms with low debt capacity, i.e., for firms whose ability to raise debt capital when faced with funding needs is the lowest.

Finally, we address more directly the power issue surrounding estimates of the slope coefficients of debt-deficit regressions by assessing the empirical relevance of the explicit hierarchy of firms' capital structure decisions stemming from Myers (1984) — internal resources, external debt, and equity — in our sample. Specifically, we test whether the empirical relevance of that hierarchy is related to firms' degree of information asymmetry. We do so by first estimating ordered probit models for each possible sequence of funding choices, as in de Haan and Hinloopen (2003), and then identifying the most preferred sequences across information asymmetry terciles of firms. We find that the pecking order theory is an acceptable, albeit not the prevailing description of the financing sequence adopted by the universe of U.S. firms for which information asymmetry proxies were available between 1973 and 2002. Moreover, the performance of the pecking order theory does not improve across firms with high information asymmetry. These results confirm that the pecking order theory is a partial, and often unsuccessful, first-order description of the process by which firms choose and modify their capital structure, except when the market's perceived adverse selection costs of a firm's information-sensitive securities are high and that firm is financially constrained.

The paper is organized as follows. In section 2 we describe our firm-level database, compute several information asymmetry measures and the information asymmetry index, as well as comment on their properties. In section 3 we perform several empirical tests of the pecking order theory under different degrees of information asymmetry and interpret our findings. We conclude in section 4.

2 Data

2.1 Firm Data

We obtain accounting data from the funds flow statements in the COMPUSTAT database from 1973 to 2002 for the entire universe of firms. All variables are deflated to constant 2000 dollars. Following standard practice, we exclude financial firms (SIC 6000-6999), regulated utilities (SIC 4900-4999), and firms involved in major mergers (COMPUSTAT footnote code AB). Also excluded are firms with missing book value of assets and a small number of firms that report format codes 4, 5, or 6.[3] The balance sheet and cash flow statement variables as a percentage of assets are trimmed (by removing the most extreme 0.50% in either tail of the distribution) to purge outliers and the most extremely misrecorded data from our sample. We follow Frank and Goyal (2003) to produce consistent time series of variables by merging the different format codes to a common format. The specific definition and construction of the variables used in the tests are provided in the Appendix.

2.2 Measuring Information Asymmetry

The problem of measuring the information asymmetry surrounding a firm's investment opportunity set, hence the payoffs of its securities, has been extensively analyzed both theoretically and empirically in the market microstructure literature.[4] The origins of this line of research are customarily attributed to Bagehot's (1971) idea that adverse selection stemming from the presence of better-informed traders in a financial market may affect its process of price formation. It is reasonable to believe that market players in close touch with a firm and its business (e.g., employees, analysts, traders) are those who possess better information about that firm and trade on it. For example, many studies (e.g., Seyhun, 1986, 1992; Jeng, Metrick, and Zeckhauser, 1999) show that corporate insiders (officers, directors, and owners of the firm) earn positive abnormal returns when trading in their companies' securities. Therefore, most microstructure measures attempt to estimate the degree of information asymmetry about an asset's final payoff ex post, i.e., from observed market data (quotes, bid-ask spreads, trades, and transaction prices).

Yet, most corporate finance studies instead focus on the potential, ex-ante degree of information asymmetry surrounding the activities of a firm by assessing its basic business characteristics. Firms' information asymmetry problems have been related to their relative size, growth opportunities (proxied by Tobin's Q), leverage, profitability, tangibility of their assets (e.g., Frank and Goyal, 2003), intensity of their research and development (Aboody and Lev, 2000), recent asset volatility (Halov and Heider, 2004), age (Berger and Udell, 1995), or level of institutional ownership (Best, Hodges, and Lin, 2004). Alternatively, the information

[3]COMPUSTAT does not define format codes 4 and 6. Format code 5 is for the Canadian file.

[4]See O'Hara (1995) and Clarke and Shastri (2001) for extensive reviews.

environment of a firm has been estimated by the residual volatility of its equity (e.g., Bhagat, Marr, and Thompson, 1985; Blackwell, Marr, and Spivey, 1990; Krishnaswami, Spindt, and Subramaniam, 1999), the magnitude of its earning surprises (Barclay and Smith, 1995a, b; Hoven-Stohs and Mauer, 1996), the intensity of public announcements about its business activity (Dierkens, 1991), or the dispersion of analysts' earnings forecasts (Krishnaswami and Subramaniam, 1998; Lowry, 2003).

Unfortunately, these measures, albeit commonly used, appear to be inconsistent proxies of the degree of information asymmetry between insiders and other market participants. For instance, Huddart and Ke (2004) find that institutional ownership, analyst following, book-to-market ratio, frequency of reporting of losses and R&D, and market reaction to earnings announcements fail to explain the cross-sectional variation in returns conditional on insider trades, their volume, or the resulting profits; Frankel and Li (2005) document only a weak relation between financial statement informativeness, analyst following, or voluntary disclosure and insider trading.

In this paper, we measure the degree of information asymmetry between the managers of each firm i in the sample and the rest of the market over each fiscal year τ by using four among the most widely adopted microstructure measures based on market prices and volumes: i) $RS^{*}_{i\tau}(k)$, the effective proportional bid-ask spread of Roll (1984), ii) $T^{-1}_{i\tau}$, the inverse daily turnover, iii) $C_{2i\tau}$, the relation between daily volume and first-order return autocorrelation suggested by Llorente et al. (2002), and iv) $PIN_{i\tau}$, the probability of informed trading (e.g., Easley et al., 1996). We do not use absolute bid-ask spreads in our analysis for two reasons. First, the constraints on the availability of bid-ask spreads from transactions data would severely limit the scope and time horizon of our study of U.S. firms' capital structure decisions. The measure of Roll (1984) explicitly addresses this issue. More important, the width of the bid-ask spread is affected by several factors, some of which are unrelated to adverse selection considerations (e.g., order processing costs or inventory management).[5] The proxies mentioned above are instead specifically designed to capture the significance of adverse selection risk over and above those considerations. We use these measures to

[5]For instance, Frieder and Martell (2005) and Lipson and Mortal (2006) use effective bid-ask spreads to study the relation between liquidity and leverage for U.S. firms.

construct an information asymmetry index for each firm i in each fiscal year τ, $ASY_{i\tau}$, in two steps as follows: (i) We standardize each of the above measures in each fiscal year τ by first subtracting their corresponding cross sectional mean in year τ and then by dividing the resulting difference by the corresponding cross sectional standard deviation in year τ; (ii) For each firm i and in each fiscal year τ we compute an equally weighted average of the standardized measures in the previous step using all the measures available for that firm i in fiscal year τ. By construction, the higher (lower) the resulting information asymmetry index $ASY_{i\tau}$ is, the higher (lower) is the severity of adverse selection problem for firm i in year τ. We combine all microstructure measures in an equally weighted index to capture the many facets of information asymmetry identified in the microstructure literature in a parsimonious way. Nonetheless, the analysis that follows is robust to employing each of those measures separately.[6] Finally, we employ this measure to rank each firm i in the sample over each fiscal year τ into three terciles, from the lowest (lowest adverse selection risk) to the highest (highest adverse selection risk).

We believe this approach is the most adequate to test whether information asymmetry considerations affect a firm's decision to recur to the capital markets to fund its investment activity. The advantages of this strategy over the aforementioned traditional empirical corporate finance proxies are threefold. First, these microstructure measures have been found correlated with many of those ex-ante firm characteristics (Alford and Jones, 1998; Flannery, Kwan, and Nimalendran, 1999; Clarke and Shastri, 2001). Yet, the former are able to capture the dynamic component of the degree of information asymmetry about a firm (e.g., around the time when its capital structure was modified), while the latter are by their nature essentially static. Second, there is evidence that market-based measures of information asymmetry are related to the activity of a firm's insiders (e.g., Clarke and Shastri, 2000), hence to the wedge between what the managers of a firm and all other market participants know about its investment opportunity sets. Finally, and most important, these measures capture the market's perceived intensity of information asymmetry surrounding a firm's valuation, i.e., what ultimately should affect that firm's adverse selection costs when issuing equity securities.

[6] We do not report these additional results for economy of space, but they are available on request.

In the remainder of this section, we provide the basic intuition behind each of the market microstructure proxies for adverse selection and then briefly comment on the sample properties of the resulting $ASY_{i\tau}$ measure. A more detailed description of their construction is in the Appendix. We start by observing that the basic assumption underlying most microstructure models of asymmetric information is that insiders would use their informational advantage to profit from the trading process. The resulting adverse selection risk would then induce market-makers to choose quotes not only compensating them for holding undesired inventory and providing liquidity, but also offsetting their expected losses versus informed traders with gains from uninformed traders. Therefore, observed bid-ask spreads should depend not only on inventory, transaction, and order-processing costs but also on adverse selection costs.[7] Under the assumption that the former are homogeneous across securities in competitive dealership markets, the bid-ask spread can be interpreted as a first-order approximation for these securities' relative intensity of adverse selection. Since bid and ask data are often available only over short samples, various models have been devised to determine the magnitude of the bid-ask spread and the relative importance of its components.[8] Roll (1984) was the first to suggest that, in an efficient market, trading costs induce negative serial dependence in prices, hence that the effective bid-ask spread can be estimated using return autocovariance. The lower (higher) is the resulting estimated spread, $RS_{i\tau}$, the lower (higher) is the adverse selection risk for the corresponding stock in fiscal year τ.

The investigation of the determinants of trading volume has also received increasing interest in the financial literature.[9] Portfolio rebalancing for risk sharing and speculation based on private information are two of the most commonly mentioned reasons why market participants trade. The microstructure literature exploits the different implications of these two activities for the dynamics of stock returns to gauge the corresponding extent of adverse selection risk. Hedging trades move a stock's price for liquidity reasons, but do not affect the market expectation of a stock's future payoffs; hence, they generate negatively autocorrelated returns. Speculation, however, does induce a revision of those expectations, albeit

[7]This intuition was first developed formally by Copeland and Galai (1983), then extended and refined by Glosten and Milgrom (1985), Kyle (1985), and Easley and O'Hara (1987).

[8]See Hasbrouck (2004) for a review.

[9]See Chae (2002) for a review.

generally not instantaneously, thus generating positively autocorrelated returns. There is a significant body of theoretical research suggesting that informed traders would exploit their information advantage cautiously, hence that *ceteris paribus* information asymmetry may drive down trading volume.[10] Much evidence has been provided in support of this inverse relationship (e.g., Easley et al., 1996; Chae, 2002). Accordingly, we compute the inverse of a stock's average daily turnover, $T_{i\tau}^{-1}$, as an additional measure of the intensity of information asymmetry.

In a recent study, Llorente et al. (2002) find that accounting for the intensity of trading volume can also greatly improve the direct cross-sectional identification and measurement of the extent of hedging and speculation explaining stock price movements. More specifically, they show theoretically, and confirm empirically, that a correspondence exists between the cross-sectional variation in stocks' volume-return dynamics and the relative importance of information-driven trading in stocks' price fluctuations. Their methodology generates an additional proxy for the relative importance of information asymmetry considerations among all stocks in our sample, $C_{2i\tau}$. Within each fiscal year τ, the lower (higher) are the measures $T_{i\tau}^{-1}$ or $\widehat{C}_{2i\tau}$ ($C_{2i\tau}$'s estimate), the lower (the higher) is firm i's degree of adverse selection risk.

Finally, the measures described so far extract the extent of information asymmetry about a firm's opportunity set, hence about the final payoffs of its securities, from the impact of trades on prices and returns. A series of papers by Easley, Kiefer, and O'Hara (1996, 1997a, b), and Easley et al. (1996) instead develops a model in which information asymmetry is inferred from the trading process. In their setting, market-makers' perceived probability of the arrival of informed trades is driven by the frequency and magnitude of buy-sell imbalances. Intuitively, if no information event takes place, buy and sell orders arrive randomly. Buy and sell orders instead cluster during information days. Thus, the probability of informed trading ($PIN_{i\tau}$) can be estimated from the signed order flow, under the assumption that information events occur only at the beginning of a sequence of independent trading days. Therefore, the greater the estimated $PIN_{i\tau}$ (which we obtain from Easley, Hvidkjaer, and

[10]E.g., the "No-Trade" argument in Milgrom and Stokey (1982), and the work of Black (1986) and Foster and Viswanathan (1990, 1996).

O'Hara, 2004), the greater is the intensity of information asymmetry around firm i's activity in fiscal year τ.

2.3 Summary Statistics

We construct the final database we employ in this study by merging the dataset of our information asymmetry index with the dataset of corporate-level accounting information described in Section 2.1. Table I presents summary statistics for the information asymmetry index $ASY_{i\tau}$, over the entire sample and conditional on various ex-ante firm characteristics typically associated with information asymmetry, such as size, market to book and tangibility.[11] Table II reports the corresponding correlation matrix between $ASY_{i\tau}$ and these measures, as well as two additional firm specific variables, leverage and profitability. We provide summary statistics on each of the four information asymmetry measures that constitute the asymmetric information index in the Appendix (Tables AI and AII in Section 5.2.6).

In Table I, the mean of the index $ASY_{i\tau}$ is close to zero over the entire sample, for it is an equally weighted average of cross-sectionally standardized measures.[12] Nonetheless, the mean or median of each of its constituents are positive and statistically significant (Table AI). This indicates there is evidence of information asymmetry in the U.S. stock market over our sample period. Further, their correlations (in Table AII) are mostly positive and statistically significant, but also generally small. This suggests that our procedure may allow us to capture the many facets of information asymmetry measured by those microstructure proxies. Not surprisingly, $ASY_{i\tau}$ is the greatest for small firms and monotonically declining for larger firms. It has indeed often been argued that large firms are the least plagued by adverse selection risk. Nonetheless, the correlation between size and $ASY_{i\tau}$ is only -6.7% (Table II). Table I further suggests that other popular, ex-ante, firm-level measures

[11] Detailed definitions for each of these variables are in the Appendix.

[12] Yet, this mean is not exactly zero, since the weights assigned to the constituents of our information asymmetry index for each firm-fiscal year depend upon the number of constituents available for that firm in that fiscal year. Of course, the mean (standard deviation) of each of the constituents is zero (one) by construction.

of information asymmetry (market to book and tangibility) are not monotonically related to $ASY_{i\tau}$. Consistently, Table II shows that the correlation between these two ex-ante measures of information opaqueness and $ASY_{i\tau}$ is virtually zero.[13] Overall, this evidence confirms our previous observation that our market-based proxy for information asymmetry captures different aspects of the intensity of adverse selection costs faced by firms than the commonly used proxies in the corporate finance literature.

3 Empirical Results

3.1 Debt Issuance to Cover Deficits

The pecking order theory of capital structure of Myers (1984) and Myers and Majluf (1984) predicts that firms prefer debt over equity because of information asymmetry between well-informed managers and less-informed investors. When investment needs exceed internal funds, they are met primarily with debt, while equity is used as a residual source of financing. Therefore, we regress net debt issuance ($\Delta D_{i\tau}$) on the financing deficit ($DEF_{i\tau}$) as follows:

$$\Delta D_{i\tau} = \alpha_{i\tau} + \beta_{i\tau} DEF_{i\tau} + \varepsilon_{i\tau}. \tag{1}$$

The pecking order theory predicts that the regression coefficient $\beta_{i\tau}$ should be close to one for firms with high information asymmetry. Myers (1984) and Myers and Majluf (1984) also describe a modified pecking order that recognizes the trade-off between the costs associated with information asymmetry and the costs of financial distress when too much debt is issued. Under the modified version of the theory, firms may issue equity in place of debt when faced with financing deficit to maintain both liquid assets and debt capacity for future investments. Therefore, the estimated slope coefficient in Eq. (1) should still be positive but may be lower than one.

Most existing tests on the pecking order theory, however, do not examine another key aspect of the model: the degree of information asymmetry. Given the trade-off between

[13] This evidence contradicts earlier findings by Clarke and Shastri (2001) over a much shorter sample period (1997 to 1998).

costs of information asymmetry and financial distress, higher information asymmetry costs should, on average, lead to a stricter following of the pecking order. Several studies have attempted to examine this relationship from different angles (e.g., Korajczyk, Lucas, and McDonald, 1991; Choe, Masulis, and Nanda, 1993; Bayless and Chaplinsky, 1996). We test directly the implications of different degrees of information asymmetry on firms' capital structure decisions using our microstructure-based index, $ASY_{i\tau}$, described in Section 2.2. This measure has been developed to capture information asymmetry between the investing public and certain "informed traders" such as corporate insiders. Hence, we ask the following question: "Do firms with higher information asymmetry issue more debt relative to equity than comparative firms with lower information asymmetry?"[14]

3.1.1 Firms Sorted into Informational Asymmetry Terciles

We first examine the slope coefficient $\beta_{i\tau}$ in Eq. (1), for terciles of the information asymmetry measure, $ASY_{i\tau}$. Table III reports these coefficients and their corresponding robust (heteroscedasticity consistent) t-statistics. All coefficients are positive, smaller than one, and statistically significant. More important, the estimated coefficient $\beta_{i\tau}$ is monotonically increasing from the lowest to the highest information asymmetry tercile, consistent with the pecking order theory. However, the largest estimated coefficient is only 0.2837, far below the predicted level of one based on the most restrictive interpretation of the pecking order theory. Overall, this preliminary evidence suggests that firms' net debt issue is positively related to the level of financing deficit, but also that the estimated sensitivity coefficients are smaller than one, consistent with the extant literature. Nonetheless, our results further reveal a greater preference for debt as a source of capital for firms with high levels of information asymmetry, consistent with the basic tenets of the pecking order theory.

[14]Our approach is related to Dierkens (1991), who studies the relevance of information asymmetry between managers and the market for the equity issue process. The measures of information asymmetry used in that paper are (i) the standard deviation of the market-adjusted, three-day abnormal return at the announcement of quarterly earnings; (ii) the market-adjusted residual standard deviation of daily abnormal stock returns; (iii) a dummy variable that equals one when the firm has 16 or fewer announcements in *The Wall Street Journal* for the year; and (iv) stock trading turnover. These proxies are different from the market-based variables we use in this paper. Further, Dierkens (1991) does not use them to test the pecking order theory.

3.1.2 Size and Information Asymmetry

Previous studies show that the slope coefficient varies considerably across firms of different size. In particular, the strongest support for the pecking order theory is generally found among the largest firms. Yet, those are also the firms assumed to be with the least ex-ante adverse selection costs, i.e., the costs justifying the existence of a pecking order. To address this issue, we sort all firms independently into three size terciles and three adverse selection terciles each fiscal year using the information asymmetry index $ASY_{i\tau}$ described in section 2.2. We then estimate the slope coefficient for each of the resulting 9 portfolios.[15]

We present the resulting slope coefficients in Fig. II. We plot the slopes across each of the three information asymmetry terciles and for each of the three size terciles. Fig. II shows that the estimated slope coefficient $\beta_{i\tau}$ is larger for larger firms. For the largest size firms, the coefficient is high, between 0.6025 and 0.7741 across the $ASY_{i\tau}$ firm terciles. Their magnitude is consistent with the estimates reported in Shyam-Sunder and Myers (1999) on a sample of large firms during the 1970s and 1980s. Fig. II also shows that the estimated coefficient $\beta_{i\tau}$ declines monotonically with size. Again, this is consistent with the extant literature (e.g., Frank and Goyal, 2003). In addition, however, Fig. II reveals that for each size tercile, higher levels of information asymmetry are strongly associated with higher estimated slope coefficients. Overall, this evidence suggests that our measure of information asymmetry has incremental explanatory power for the financing decisions of firms even after controlling for firm size.

3.2 Debt Issuance, Information Asymmetry, and Financial Deficit

The model used in the previous section, estimating the relation between the amount of debt issuance to cover financial deficits, was first introduced by Shyam-Sunder and Myers (1999) as a test of the pecking order theory. Chirinko and Singha (2000) question that interpretation by showing that equity issues can induce a negative bias in the test. The argument is as follows: Suppose that firms actually follow the pecking order theory, but nonetheless issue an empirically observed amount of equity. In that case, Chirinko and Singha (2000) prove

[15] Since the sorts are independent, rather than conditional, the number of firms in each portfolio is different.

the predicted regression coefficient would actually be 0.74 rather than one. They also show that if firms follow a policy of using debt and equity in fixed proportions, the regression will identify this ratio. Hence, finding a coefficient near one cannot be construed as support for the pecking order theory. This result raises the need for additional tests to support or refute the pecking order theory. It is therefore important to examine the assumptions behind the theory from a number of points of view rather than relying on a single test. We do so by outlining and performing several alternative tests below.

To begin with, we run a year-by-year cross-sectional regression of debt issuance (measured as net debt issued in any fiscal year) against $ASY_{i\tau}$ (the information asymmetry index defined in Section 2.2) for the same year, across terciles of firms sorted according to the magnitude of their deficit from the lowest to the highest, as follows:

$$\Delta D_{i\tau} = \alpha_{i\tau} + \beta_{i\tau} ASY_{i\tau} + \varepsilon_{i\tau}, \tag{2}$$

where $D_{i\tau}$ is defined as the ratio of firm i's total debt to market capitalization in fiscal year τ, as in Frank and Goyal (2003). If pecking order is a good description of financing behavior, we expect $\beta_{i\tau}$ in Eq. (2) to be positive and significant across all terciles. Further, if information asymmetry is the sole determinant of capital structure decisions, regardless of the level of financial deficit, we expect the sensitivity $\beta_{i\tau}$ in Eq. (2) to be the same across terciles.

The results of this estimation are presented in panel A of Table IV. Over the entire sample, we find evidence of a statistically significant positive relationship between our information asymmetry index and changes in debt ratio: $\beta_{i\tau}$ is equal to 0.1530 and is significant at the 5% level. This relationship is strongest (and conformity with pecking order predictions the highest) when financing deficits are low. On the other hand, for medium and high deficit firms, information asymmetry is still positively related to $\Delta D_{i\tau}$ but statistically insignificant at the 10% level. Overall, this evidence indicates that (i) information asymmetry concerns are important mostly for firms with low financing needs (as the significant positive relationship in the low deficit terciles suggests), and (ii) information asymmetry may not be the crucial driver of capital structure decisions when firms are faced with large funding needs (as the positive but insignificant coefficients $\beta_{i\tau}$ in the medium and high deficit terciles suggests).

Next, in order to assess the importance of information asymmetry as compared to conventional factors in empirical analyses of capital structure decisions, we estimate the following multivariate specification:

$$\Delta D_{i\tau} = \alpha_{i\tau} + \beta_{1i\tau} ASY_{i\tau} + \beta_{2i\tau} \Delta TAN_{i\tau} + \beta_{3i\tau} \Delta \Pi_{i\tau} + \beta_{4i\tau} \Delta LS_{i\tau} + \beta_{5i\tau} \Delta MB_{i\tau} + \varepsilon_{i\tau}, \quad (3)$$

where $TAN_{i\tau}$ is a proxy for firm i's tangibility defined as the ratio of fixed assets to book value of total assets, $\Pi_{i\tau}$ is a proxy for firm i's profitability defined as the ratio of operating income to book value of total assets, $LS_{i\tau}$ is the natural logarithm of firm i's sales, and $MB_{i\tau}$ is the market-to-book ratio defined as the ratio of market value of assets (book value of assets plus the difference between market value of equity and book value of equity) to book value of assets. Eq. (3) is estimated via a standard Fama-MacBeth procedure. If asymmetric information is an important determinant of capital structure decisions, we expect $\beta_{1i\tau}$ in Eq. (3) to be again positive and significant. If asymmetric information is the sole driver of capital structure decisions, we do not expect the other coefficients in Eq. (3) to be significant in this estimation.

The results of this estimation are presented in panel B of Table IV. Sign and significance of the coefficients for each of the proxies defined above are generally consistent with the extant literature (e.g., Frank and Goyal, 2003). However, the overall regression shows again a positive relationship between our information asymmetry index $ASY_{i\tau}$ and changes in debt ratio, consistent with pecking order predictions. This pattern of sensitivity is statistically significant (but generally declining) in all the three deficit terciles of firms. These results indicate that (i) even after controlling for various firm characteristics, information asymmetry is still positively related to changes in debt ratio for each level of firm financing needs, (ii) information asymmetry concerns are more important for firms with low financing needs even in the presence of other determinants of capital structure changes, and (iii) information asymmetry is not the sole driver of capital structure decisions. Hence, Table IV suggests that, across firms, pecking order can explain, albeit not fully, firms' financing behavior as long as the assumption of information asymmetry (the driving force behind the theory) holds.

We also plot the time series of sensitivity coefficients $\beta_{i\tau}$ and $\beta_{1i\tau}$ for both the univariate and multivariate overall regressions described above (Eq. (2) and Eq. (3)) in Fig. III.

Clearly, there is a large variation in both sensitivity coefficients over time. Nonetheless, the coefficients for the information asymmetry index $ASY_{i\tau}$ are positive over most of our sample period. When occasionally negative, these estimates indicate that the assumption that information asymmetry drives capital structure decisions might not hold. This provides further support to the claim that the contradictory results on the viability of pecking order as a theory might be due to the violation of its core assumption, namely that information asymmetry is the sole determinant of capital structure decisions.

3.2.1 Robustness: Controlling for Insider Trading

The pecking order theory crucially depends on the information asymmetry between firm managers (insiders) and markets being the source of friction leading to a hierarchy of financing choices adopted by the firm. This hierarchy is to minimize adverse selection costs of security issuance. Our market microstructure measures (and the resulting index $ASY_{i\tau}$) capture the degree of information asymmetry among market participants, which may arise from information asymmetry between insiders and outsiders of the firm. Yet, as shown in Fig. I, these measures may also proxy for asymmetry between a broader category of agents — informed traders — and uninformed traders. Hence, our inference might be biased insofar as these informed traders are not (related to) the insiders (managers) of the pecking order theory.

Thus, as a robustness check, we construct an alternative measure of information asymmetry using the intensity of insider trading activity for each firm and in each fiscal year of the sample. We estimate such intensity for each firm i in each fiscal year τ‘ as the ratio between the total volume of insider purchases and sales and the corresponding overall trading volume, $IT_{i\tau}$.[16] Intuitively, the greater is $IT_{i\tau}$, the more intense is the trading activity of firm i's insiders in year τ, hence the greater is their information advantage with respect to

[16]Further details on the construction of $IT_{i\tau}$ are in Section 5.2.5 of the Appendix. Insider trading data is available to us only between 1978 and 2000. $IT_{i\tau}$ is on average positive (Table AI) and weakly positively correlated to the information asymmetry index (Table AII). Similar inference can be drawn by computing $IT_{i\tau}$ exclusively from insider sales, as suggested by Lakonishok and Lee (2001).

outsiders. We use $IT_{i\tau}$ to sort firms into terciles from the lowest (lowest intensity of insider trading) to the highest (highest intensity of insider trading). We then estimate again Eq. (2) and Eq. (3) across each insider trading tercile of firms. We report the resulting estimates in Table V. Since the coefficient estimates for the other control variables are similar to those reported in Table IV in both magnitude and significance, we do not report those estimates in the remainder of the paper.

The overall results are qualitatively similar to those reported in table IV: Our information asymmetry index is significantly positively related to changes in debt ratios.[17] In addition, Table V reveals that the coefficient on $ASY_{i\tau}$ is remarkably similar across all the terciles of insider trading. These results indicate the robustness of our inference to insider-based measures of information asymmetry. In other words, they suggest that our market-based information asymmetry index has incremental explanatory power for firms' debt issuance decisions even after controlling for the firms' intensity of insider trading.

3.3 Debt Issuance, Financial Constraints, and Information Asymmetry

A firm is financially constrained if it requires outside capital but faces imperfections in the capital markets. Further, a firm can be considered more financially constrained than another firm if it faces a higher cost of raising any given amount of capital. The cost of raising such capital depends on the extent of capital market imperfections, some of which possibly stem from asymmetric information between a firm and its investors. Thus, our tests of pecking order need to control for the degree of financial constraints faced by the firm while making capital structure decisions.

We do so first by constructing an index of external finance constraints $FC_{i\tau}$ being low (tercile 1), medium (tercile 2), or high (tercile 3), from Whited and Wu (2005) for all firms in our sample. $FC_{i\tau}$ is computed from a GMM estimation of an investment Euler equation. In

[17]The overall coefficients on $ASY_{i\tau}$ in Table V are slightly different from those in Table IV, since the former regressions are estimated over a shorter sample period (1978-2000) over which insider trading data is available.

particular, we compute $FC_{i\tau}$ using the factor loadings in Whited and Wu (2005) as follows:

$$FC_{i\tau} = -0.091CF_{i\tau} - 0.062I_{i\tau}^{Div} + 0.021LEV_{i\tau} - 0.044LNA_{i\tau} + 0.0255ISG_{i\tau} - 0.0088SG_{i\tau}, \quad (4)$$

where $I_{i\tau}^{Div}$ is a dummy equal to one if firm i paid dividends over fiscal year τ and zero otherwise, $CF_{i\tau}$ and $LEV_{i\tau}$ are firm i's cash flow and leverage, $LNA_{i\tau}$ is the natural logarithm of firm's total assets, and $ISG_{i\tau}$ and $SG_{i\tau}$ are firm i's 3-digit SIC code industry and own sales growth over fiscal year τ. We then estimate the univariate and multivariate specifications of our tests outlined in section 3.2. Eq. (2) and Eq. (3) across those terciles of firms sorted on $FC_{i\tau}$ to assess the differential impact of $ASY_{i\tau}$ on firm's changes in debt ratios.

We report the results of this estimation in Panels A and B of Table VI. Panel A indicates that the strong relationship between our $ASY_{i\tau}$ measure and changes in debt ratio seems to arise exclusively among firms with high financial constraints. This result is consistent with pecking order predictions, if we interpret financial constraints as a measure of degree of information asymmetry faced by the firm. The multivariate specification in Panel B produces the same qualitative results. Overall, the above results suggest that information asymmetry concerns are important only for financially constrained firms, i.e., for firms whose cost of capital is most likely to be sensitive to market frictions.

3.4 Debt Issuance, Information Asymmetry, and Debt Capacity

Shyam-Sunder and Myers (1999) argue that the pecking order offers a good approximation to firms' financing behavior. Yet, their research studies only firms for which uninterrupted financing histories are available. However, Fama and French (2002) and Frank and Goyal (2003) challenge this inference studying all the existing firms in COMPUSTAT.

Lemmon and Zender (2004) counter this challenge by arguing that in testing the pecking order theory, one must account for the value of maintaining financial slack for future investment and to avoid financial distress. As Fama and French (2004) note, debt capacity is a valuable option for future financing, but the pecking order theory implicitly assumes that debt capacity is not constraining firms' financing choices. After accounting for debt capacity considerations, Lemmon and Zender (2004) show that the pecking order still offers a reasonable description of firms' financing behavior. Yet, Leary and Roberts (2004) incorporate debt capacity in their explicit analysis of the hierarchy of financing decisions and still do not find support for the pecking order theory. In this section, we examine if debt capacity considerations are important in our tests of the relationship between information asymmetry and capital structure decisions.

For that purpose, we follow Lemmon and Zender (2004) and define debt capacity as $Prob_{i\tau}$, the estimated probability that firm i has a bond rating in fiscal year τ being low (tercile 1), medium (tercile 2), or high (tercile 3). $Prob_{i\tau}$ is computed from a predictive logit regression in which the dependent variable is one if a firm has rated debt outstanding in a particular year (S&P long-term domestic issuer credit rating, i.e., Data 280 in COMPUSTAT) and zero otherwise, while the regressors are the following lagged (by one fiscal year) firm characteristics: profitability, tangibility, market-to-book ratio, leverage, size, age, stock return volatility, and industry dummies for each 2-digit SIC code in the sample.[18] The estimation uses only data from 1986-2002, the interval when bond ratings are available in COMPUSTAT, but the resulting coefficients are then used to compute $Prob_{i\tau}$ for each year between 1973 and 2002, again as in Lemmon and Zender (2004).

We then estimate the univariate and multivariate regressions of changes in debt ratio on our information asymmetry index $ASY_{i\tau}$, as in the previous sections (Eqs. (2) and (3), respectively), but sorting firms based on their debt capacity. The results of this estimation are reported in Panels A and B of Table VII. There we find that information asymmetry is important in explaining debt ratio changes for firms with medium and high debt capacity. On the other hand, firms with low debt capacity are insensitive to the severity of adverse selection risk. This result is consistent with Lemmon and Zender (2004): Controlling for debt capacity, the pecking order appears to be a viable description of firm financing, albeit not the dominant one.

[18] Specifically, size is the natural logarithm of total assets; age is the natural logarithm of the number of years since a firm was first included in COMPUSTAT; stock return volatility is the annualized standard deviation of a firm's stock returns over each fiscal year.

3.5 Financing Hierarchy and Information Asymmetry

Ultimately, the pecking order theory is a description of the hierarchy or preference order followed by managers: (i) internal finance, (ii) debt, and (iii) equity issues. This sequence is justified by the existence of asymmetric information between managers and markets. In a recent paper, de Haan and Hinloopen (2003) estimate an ordered probit model for Dutch firms using data from 1984-1997 for every possible hierarchy of financing choices, and test which of these best suits the data. We use their methodology in this paper. The ordered probit model is specifically designed for choices with a specific hierarchy. We model the imposed order using two threshold parameters. When the parameter value is exceeded, the model selects the next choice in the order. Therefore, coding different financing types (internal finance, debt, equity) with the ordinal discretes (0, 1, 2, respectively) imposes the pecking order in the estimation of the ordered probit model. By estimating all possible models for our financing choices (three combinations in our case) and performing bilateral likelihood ratio comparisons, we can determine which hierarchy fits the data best, i.e., rank the three possible financing hierarchies of U.S. firms in our sample from the most preferred (1) to the least preferred (3).

Specifically, we obtain these rankings by means of likelihood ratio tests from the estimation of a series of ordered probit models, for each of the following three hierarchies: h_1: Internal funds (0), External debt (1), Equity (2), i.e., the pecking order theory; h_2: Internal funds (0), Equity (1), External debt (2); and h_3: External debt (0), Internal funds (1), Equity (2). We limit our analysis to these orderings because each of them has a twin ordering that yields coefficient estimates of equal magnitude and opposite sign, but identical likelihood values. This twin ordering is the unique ordering that has a perfect inverse correlation with the original ordering. For example, the ordering Internal funds (0), External debt (1), Equity (2) has a correlation of -1 with, and only with, the ordering Equity (2), External debt (1), Internal funds (0). Therefore, we can limit our likelihood comparisons to the three hierarchies listed above to determine the best fit ordering.

The discrete issuance decision series are generated in each fiscal year τ only among firms with a non-negative deficit ($DEF_{i\tau} \geq 0$) as follows: Debt issuance by firm i in fiscal year

τ takes place if that firm's net change in long-term debt from $\tau - 1$ to τ, normalized by book assets in year $\tau - 1$, is greater than or equal to 5%; equity issuance by firm i in fiscal year τ takes place if the ratio between the change in the market value of equity adjusted for capital gains[19] and the firm's book assets in year $\tau - 1$ is greater than or equal to 5%; finally, internal funding takes place if neither debt nor equity issuances take place over year τ. We remove the few cases in which dual issuances (i.e., debt and equity) take place. We use the following independent variables for the ordered probit model: contemporaneous sales, Q ratio, tangibility, profitability, 2-year stock returns, and deviation from a target leverage ratio.[20] We use the resulting log-likelihood values from the estimation to compute likelihood ratio (LR) tests across hierarchies as follows: $LR_{12} = -2 * (lnL_{h_1} - lnL_{h_2})$, $LR_{13} = -2 * (lnL_{h_1} - lnL_{h_3})$, and $LR_{23} = -2 * (lnL_{h_2} - lnL_{h_3})$. We then assume that one hierarchy prevails over the other if the corresponding LR test is significant at the 1% level.

The results of this estimation are presented in Table VIII for each tercile of firms sorted according to our information asymmetry index $ASY_{i\tau}$ described in Section 2.2. All rankings (i.e., all LRs) are statistically significant. Thus, no two hierarchies are ranked equally. The final ranking is determined by comparing the magnitude of the likelihood functions, from the lowest (1) to the highest (3). Hence, a ranking of 1 (3) indicates that the corresponding hierarchy fits the data the best (worst). The evidence in Table VIII is remarkably consistent, either for the overall sample or across each information asymmetry quintile: h_3: External debt (0), Internal funds (1), Equity (2) is the most preferred hierarchy. The pecking order is always the second best in these estimations. Based on this evidence, we conclude that the pecking order is not a complete, dominant description of firm financing decisions. Table VIII also reveals that external debt always precedes equity issuances; yet, this sub-hierarchy is independent of the intensity of information asymmetry unlike what is implied by the basic tenet of the pecking order theory.

[19]The change in the market value of equity adjusted for capital gains is defined in Fama and French (2005) as $\frac{1}{2}\left(Shares_\tau Adjust_\tau - Shares_{\tau-1} Adjust_{\tau-1}\right)\left(Price_{\tau-1}/Adjust_{\tau-1} + Price_\tau/Adjust_\tau\right)$, where $Shares_\tau$ is the total number of shares outstanding, $Adjust_\tau$ is the split adjustment factor, and $Price_\tau$ is the stock price at the end of fiscal year τ in COMPUSTAT

[20]This target is constructed as one year lagged leverage minus a leverage target given by the corresponding (2-digit SIC) industry median leverage in fiscal year τ.

4 Conclusion

Using an information asymmetry index based on adverse selection measures developed by the market microstructure literature, we test if information asymmetry is the sole determinant of capital structure decisions as suggested by the pecking order theory. Our tests rely exclusively on measures of the market's assessment of adverse selection risk rather than on ex-ante firm characteristics. We find that information asymmetry does affect capital structure decisions of U.S. firms over the period 1973-2002, especially when firms' financing needs are low and when firms are financially constrained. We also find a significant degree of intertemporal variability in firms' degree of information asymmetry, as well in its impact of firms' debt issuance decisions. Our findings based on the information asymmetry information index are robust to sorting firms based on size and firm insiders' trading activity, two popular alternative proxies for the severity of adverse selection. Overall, this evidence explains why the pecking order theory is only partially successful in explaining all of firms' capital structure decisions. It also suggests that the theory finds support when its basic assumptions hold in the data, as it should reasonably be expected of any theory.

5 Appendix

5.1 Variable Definitions

Information Asymmetry measures

(For construction of these variables refer to the subsection below)

$RS_{i\tau}$: Roll (1984)'s effective bid-ask spread

$T_{i\tau}^{-1}$: Average inverse daily turnover

$\widehat{C}_{2i\tau}$: Relation between daily volume and first-order return autocorrelation suggested by Llorente et al. (2002).

$PIN_{i\tau}$: the probability of informed trading (in percentage) suggested by Easley et al. (1996).

Firm Specific Variables

(Computed from the COMPUSTAT database)

Size : Data6

Q / $MB_{i\tau}$: (Data6-Data60+(Data24*Data25))/(Data6)

Leverage : Data9 / Data6

Tangibility $TAN_{i\tau}$: Data8/Data6

Profitability $\Pi_{i\tau}$: Data13/Data6

Log(sales) $LS_{i\tau}$: Log(Data12)

Change in debt $\Delta D_{i\tau}$: Data111 - Data114

Financial deficit $DEF_{i\tau}$: DIV+INV+ΔWC-INTCF where each of these calculations follow Shyam-Sunder and Myers (1999).

$I_{i\tau}^{Div}$: a dummy equal to one if firm i paid dividends over fiscal year τ and zero otherwise

Cash flow $CF_{i\tau}$: (data123+data124+data125+data126+data106+data213+data217+data218), if data318 = 1,2 or 3.

(data123+data124+data125+data126+data106+data213+data217+data314), if data 318 = 7.

Leverage $LEV_{i\tau}$: Data9 / Data6

$LNA_{i\tau}$: log(total assets=Data6)

$ISG_{i\tau}$ and $SG_{i\tau}$: firm i's 3-digit SIC code industry growth and own sales growth over fiscal year τ.

5.2 Construction of Information Asymmetry Measures

5.2.1 The Roll measure

In his seminal study, Roll (1984) showed that the serial covariance properties of stock returns can be used to infer RS_{it}, the quoted proportional spread for any stock i over day k in year t, as

$$RS_{it} = 200 I_{it} \sqrt{-Cov\left[r_{it}\left(k\right), r_{it}\left(k-1\right)\right]} - 200\left(1 - I_{it}\right)\sqrt{Cov\left[r_{it}\left(k\right), r_{it}\left(k-1\right)\right]},$$

where $Cov\left(r_{it}, r_{it-1}\right)$ is the return series $r_i\left(k\right)$'s first-order autocovariance over period t and $I_{it} = 1$ if $Cov\left[r_{it}\left(k\right), r_{it}\left(k-1\right)\right] < 0$ and $I_{it} = 0$ otherwise. The latter adjustment is necessary, for Roll (1984) finds that around 50% of resulting spreads estimated from daily data without I_{it} are actually negative (i.e., $Cov\left[r_{it}\left(k\right), r_{it}\left(k-1\right)\right] > 0$). We compute this measure for each company in the CRSP database between 1973 and 2002 for which the estimation of $Cov\left[r_{it}\left(k\right), r_{it}\left(k-1\right)\right]$ was possible over their corresponding fiscal years τ, i.e., $RS_{i\tau}$ from $Cov\left[r_{i\tau}\left(k\right), r_{i\tau}\left(k-1\right)\right]$. In each fiscal year τ, we rank all companies into 5 terciles based on their resulting $RS_{i\tau}$, from the lowest (i.e., lowest adverse selection risk) to the highest (i.e., highest adverse selection risk). Within this process, we read estimated $RS_{i\tau} < 0$ as circumstances where no adverse selection risk was present.

5.2.2 Turnover

Much evidence has been provided in support of an inverse relationship between information asymmetry and trading volume. For example, Easley et al. (1996) found that their empirical measure of the probability of informed trading is decreasing in trading volume. Chae (2002) documented that trading volume is consistently related to various measures of information asymmetry and consistently decreases before important information events like earnings announcements. In this paper, we compute the inverse of the average daily trading volume for each of the stocks in the CRSP database over each of the fiscal years in the sample period, $T_{i\tau}^{-1}$, as an additional proxy for the degree of information asymmetry surrounding these firms' investment opportunity sets. Consistently with Lo and Wang (2000), we define each stock's daily trading volume as its daily turnover, computed as the ratio between the total number of shares traded on a single day and the corresponding total number of shares outstanding. Then, in each fiscal year τ, we rank all available companies into 5 terciles based on their $T_{i\tau}^{-1}$, from the lowest (i.e., lowest information asymmetry) to the highest (i.e., highest information asymmetry).

5.2.3 Return autocorrelation

The methodology of Llorente et al. (2002) consists of two steps. First, we measure trading volume for each stock i in each day k of each fiscal year τ, $V_{i\tau}(k)$, as the natural logarithm of the daily turnover (since turnover is nonstationary) plus a small constant (0.00000255, to avoid the problem of zero turnover), and detrend the resulting series using its mean over the past 200 available observations. Second, we estimate the following regression for each stock in the sample within each fiscal year τ :

$$r_{i\tau}(k+1) = C_{0i\tau} + C_{1i\tau} r_{i\tau}(k) + C_{2i\tau} V_{i\tau}(k) r_{i\tau}(k) + \eta_{i\tau}(k).$$

We interpret the resulting relative magnitude of the coefficients $\widehat{C}_{2i\tau}$ as a robust proxy for the cross-sectional importance of information asymmetry considerations among all stocks for which they could be estimated over period τ.[21] More specifically, and consistently with Llorente et al. (2002), $\widehat{C}_{2i\tau}$ should be positive and significant for stocks for which speculative trading is important, negative and significant if hedging is predominant, and a monotonic function of the significance of speculative trading versus hedging in stock return dynamics. Within this process, we interpret estimated $\widehat{C}_{2i\tau} < 0$ as circumstances where no adverse selection risk was present.

[21] Llorente et al. (2002) show that the assessment of cross-sectional intensity of speculation stemming from the cross-section of estimated $\widehat{C}_{2i\tau}$ is robust to alternative definitions of volume, nonsynchronous trading, and alternative time horizons for stock returns.

5.2.4 The PIN measure

The construction of this measure is unfortunately limited by the availability of transaction data (specifically, trade signs). For example, the Trade and Quote (TAQ) database on the Wharton Research Data Services (WRDS) Web site provides intraday transactions data (trades and quotes) for all securities listed on the NYSE, AMEX, and NASDAQ only starting from 1993. Thus, in this paper, we employ the time series of annual stock PINs, PIN_{it}, estimated by Easley, Hvidkjaer, and O'Hara (2004) between 1983 and 2001. These time series were made available by the authors on Hvidkjaer's Web site, at http://www.rhsmith.umd.edu/Finance/hvidkjaer/data.htm. They painstakingly construct these series for all NYSE and AMEX stocks for which transaction data were available over that sample period, with the exception of REITs, stocks of companies incorporated outside of the U.S., closed-end funds, stocks with less than 60 days of quotes or trades within a year, and stocks for which the estimation algorithm failed to converge (only about 1% of nearly $40,000$ stock-years, according to Easley, Hvidkjaer, and O'Hara, 2004). Since the annual stock PINs were constructed over calendar years, we can only match them to companies whose fiscal year ends in December, i.e., $PIN_{i\tau} = PIN_{it}$ only if $t = \tau$ and unavailable otherwise for each company i. In each fiscal year τ, we rank all companies into three terciles based on their $PIN_{i\tau}$, from the lowest (i.e., lowest information asymmetry) to the highest (i.e., highest information asymmetry).

5.2.5 Insider Trading measure

We construct this measure using the Securities and Exchange Commission (SEC) Ownership Reporting System (ORS) data file following Lakonishok and Lee (2001). The ORS data start in 1973 and end in 2000, but the data become populate starting in 1978 and contain all transactions by insiders that are subject to disclosure according to Section 16(a) of the Securities and Exchange Act of 1934. We classify management as insiders. This group includes CEOs, CFOs, chairmen of the board, directors, officers, presidents, and vice presidents. We examine two types of trading: Purchases and Sales. Purchases include open market or private purchases and purchase of shares through the exercise/conversion of options, warrants, or convertible bonds. Sales include open market or private sales and sales of shares acquired through the exercise of options. In this paper, we employ the time series of annual insider trading $IT_{i\tau}$, estimated for each fiscal year, as the ratio of the sum of insider purchases and sales to the trading volume (obtained from CRSP) and expressed in percentage during the same period.

5.2.6 Summary statistics of these measures

Table AI:

Variable	n	Mean	S.D.	Min	Mdn	Max
$ASY_{i\tau}$	90607	-0.0075	0.6547	-9.9917	-0.0257	33.50
$RS_{i\tau}$	90606	1.6521	4.65	-48.01	1.0782	88.02
$\widehat{C}_{2i\tau}$	78849	0.0145	0.15	-18.63	0.0189	11.98
$T_{i\tau}^{-1}$	84531	1605.20	70958.63	0.26	373.12	1.70E+07
$PIN_{i\tau}$	12992	0.2014	0.08	0.03	0.1900	0.85
$IT_{i\tau}$	84245	1.3920	6.08	0.00	0.0000	99.95

Note: All means and medians are significantly different from zero at the 1% level of significance. The corresponding correlation matrix is:

Table AII:

	$ASY_{i\tau}$	$RS_{i\tau}$	$\widehat{C}_{2i\tau}$	$T_{i\tau}^{-1}$	$PIN_{i\tau}$	$IT_{i\tau}$
$ASY_{i\tau}$	1					
$RS_{i\tau}$	0.519	1				
$\widehat{C}_{2i\tau}$	0.875	-0.010	1			
$T_{i\tau}^{-1}$	0.175	0.106	-0.034	1		
$PIN_{i\tau}$	0.601	0.053	0.090	0.134	1	
$IT_{i\tau}$	0.047	-0.079	0.036	0.06	-0.043	1

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Table I. Information Asymmetry Index: Summary Statistics

This table reports summary statistics for the information asymmetry index $ASY_{i\tau}$, described in section 2 over our merged CRSP-COMPUSTAT database of U.S. stocks between 1973 and 2002. We report the overall mean and the mean within stocks belonging to the low (1), medium (2), and high (3) terciles of three firm characteristics: size, market to book (MB), and tangibility. ***,**,* indicates significance at the 1%, 5% and 10% level, respectively.

Variable	Terciles	Adverse selection proxy $ASY_{i\tau}$
All		-0.0075***
	low	0.1508 ***
Size	medium	0.0060***
	high	-0.1760***
	low	0.1149 ***
MB	medium	-0.0245***
	high	-0.1171***
	low	0.0065 ***
Tangibility	medium	-0.3060***
	high	0.0014***

Table II. Measures of Information Asymmetry: Correlation Matrix

This table reports the correlation matrix for the information asymmetry index $ASY_{i\tau}$, described in section 2 over our merged CRSP-COMPUSTAT database of U.S. stocks between 1973 and 2002. We compute the correlation between the above index and five firm characteristics, defined in the Appendix: size, market to book (MB), leverage, tangibility, and profitability. ***,**,* indicates significance at the 1%, 5%, and 10% level, respectively.

	$ASY_{i\tau}$	Size	MB	Leverage	Tangibility	Profitability
$ASY_{i\tau}$	1					
Size	-0.067***	1				
MB	-0.001	-0.002	1			
Leverage	0.007**	0.018***	0.023***	1		
Tangibility	0.007**	0.037**	-0.007**	0.197***	1	
Profitability	-0.014***	0.006*	-0.941***	0.001	0.011***	1

Table III. Sensitivity of Debt Issuance to Financial Deficit

This table reports ordinary least square (OLS) estimates for the coefficients of the regression of change in debt $\Delta D_{i\tau}$ on financial deficit $DEF_{i\tau}$:

$$\Delta D_{i\tau} = \alpha_{i\tau} + \beta_{i\tau} DEF_{i\tau} + \varepsilon_{i\tau}.$$

The change in debt is defined as the amount of long-term debt issued by firm i during fiscal year τ. The financial deficit is defined in the Appendix and computed using COMPUSTAT sample of U.S. firms between 1973 and 2002. We estimate the coefficient for terciles of the information asymmetry index $ASY_{i\tau}$ described in section 2. Robust (heteroscedasticity consistent) t-statistics are reported in parentheses.

	Information Asymmetry Index		
$ASY_{i\tau}$	low	medium	high
$\beta_{i\tau}$	0.2116	0.2639	0.2837
	(31.59)	(30.66)	(33.99)

Table IV. Debt Issuance and Information Asymmetry

This table contains ordinary least square (OLS) estimates for the coefficients of Fama-MacBeth cross-sectional regressions of firms' change in debt $\Delta D_{i\tau}$ (where D is the ratio of total debt to market capitalization as in Frank and Goyal, 2003), on the information asymmetry index $ASY_{i\tau}$ described in the appendix, in our merged CRSP-COMPUSTAT sample of U.S. stocks between 1973 and 2002. More specifically, in Panel A, we report the average estimate for the coefficient $\beta_{i\tau}$ over 30 observation-years and its corresponding t-statistic in the following univariate regressions across all firms i for which both an information asymmetry index measure and accounting information were available in fiscal year τ:

$$\Delta D_{i\tau} = \alpha_{i\tau} + \beta_{i\tau} ASY_{i\tau} + \varepsilon_{i\tau}.$$

The same estimation is then repeated each fiscal year τ within each of three subsets of firms identified according to the relative magnitude of their financing deficit $DEF_{i\tau}$ defined in the appendix as the sum of dividends, investments, change in working capital, current portion of long-term debt, minus the cash flow after interest and taxes being low (tercile 1), medium (tercile 2), or high (tercile 3). In Panel B, we report the average estimate for the coefficient $\beta_{1i\tau}$ as well as their standard errors and corresponding t statistics in the following multivariate regressions across all firms i for which both an information asymmetry index measure and accounting information were available in fiscal year τ :

$$\Delta D_{i\tau} = \alpha_{i\tau} + \beta_{1i\tau} ASY_{i\tau} + \beta_{2i\tau} \Delta TAN_{i\tau} + \beta_{3i\tau} \Delta \Pi_{i\tau} + \beta_{4i\tau} \Delta LS_{i\tau} + \beta_{5i\tau} \Delta MB_{i\tau} + \varepsilon_{i\tau},$$

where $TAN_{i\tau}$ is a proxy for firm i's tangibility defined as the ratio of fixed assets to book value of total assets, $\Pi_{i\tau}$ is a proxy for firm i's profitability defined as the ratio of operating income to book value of total assets, $LS_{i\tau}$ is the natural logarithm of firm i's sales, and $MB_{i\tau}$ is the market-to-book ratio defined as the ratio of market value of assets (book value of assets plus the difference between market value of equity and book value of equity) to book value of assets. ***,**,* indicates significance at 1%, 5%, and 10% level, respectively, for the two-sided t test of the null hypothesis that $\beta_{i\tau} = 0$ (Panel A) or $\beta_{1i\tau} = 0$ (Panel B).

	Panel A: Univariate regressions			
Deficit	all	low	medium	high
mean $\widehat{\beta}_{i\tau}$	0.1530**	0.2666**	0.1053	0.1430
t-stat	2.13	2.37	1.46	1.60

	Panel B: Multivariate regressions			
Deficit	all	low	medium	high
mean $\widehat{\beta}_{1i\tau}$	0.1582**	0.2550**	0.1245*	0.1534*
t-stat	2.20	2.27	1.91	1.65
mean $\widehat{\beta}_{2i\tau}$	1.6276***	1.5425**	1.0003*	1.6798***
t-stat	4.18	2.18	1.86	3.85
mean $\widehat{\beta}_{3i\tau}$	0.0360	-0.1418**	0.0018	0.1197
t-stat	0.64	-2.05	0.05	1.43
mean $\widehat{\beta}_{4i\tau}$	0.1175	-0.0492	0.0556	0.0437
t-stat	1.21	-0.37	0.47	0.27
mean $\widehat{\beta}_{5i\tau}$	-1.2591***	-1.7457***	-1.0878***	-1.2048*
t-stat	-3.56	-7.59	-3.03	-1.74

Table V. Insider Trading, Information Asymmetry and Debt Issuance

This table contains ordinary least square (OLS) estimates for the coefficients of Fama-MacBeth cross-sectional regressions of the firms' change in debt $\Delta D_{i\tau}$ (where D is the ratio of total debt to market capitalization as in Frank and Goyal, 2003) on the information asymmetry index $ASY_{i\tau}$ described in section 2, in our merged CRSP-COMPUSTAT sample of U.S. firms, sorted into terciles based on their insider trading $IT_{i\tau}$. Due to data limitations, the sample of firms for which insider trading data is available and can be grouped into terciles covers the period 1978-2000. More specifically, in Panel A, we report the average estimate for the coefficient $\beta_{i\tau}$ over 23 observation-years and its corresponding t-statistic in the following regressions across all firms i for which insider trading, information asymmetry index measure, and accounting information were available in fiscal year τ:

$$\Delta D_{i\tau} = \alpha_{i\tau} + \beta_{i\tau} ASY_{i\tau} + \varepsilon_{i\tau}.$$

The same estimation is then repeated each fiscal year τ within each of three subsets of firms identified according to the relative magnitude of their insider trading $IT_{i\tau}$ defined in the Appendix being low (tercile 1), medium (tercile 2) or high (tercile 3). In Panel B, we report the average estimate for the coefficient $\beta_{1i\tau}$ as well as their standard errors and corresponding t statistics in the following multivariate regressions across all firms i for which insider trading, information asymmetry measure, and accounting information were available in fiscal year τ:

$$\Delta D_{i\tau} = \alpha_{i\tau} + \beta_{1i\tau} ASY_{i\tau} + \beta_{2i\tau} \Delta TAN_{i\tau} + \beta_{3i\tau} \Delta \Pi_{i\tau} + \beta_{4i\tau} \Delta LS_{i\tau} + \beta_{5i\tau} \Delta MB_{i\tau} + \varepsilon_{i\tau},$$

where $TAN_{i\tau}$ is a proxy for firm i's tangibility defined as the ratio of fixed assets to book value of total assets, $\Pi_{i\tau}$ is a proxy for firm i's profitability defined as the ratio of operating income to book value of total assets, $LS_{i\tau}$ is the natural logarithm of firm i's sales, and $MB_{i\tau}$ is the market-to-book ratio defined as the ratio of market value of assets (book value of assets plus the difference between market value of equity and book value of equity) to book value of assets. ***,**,* indicates significance at 1%, 5%, and 10% level, respectively, for the two-sided t test of the null hypothesis that $\beta_{i\tau} = 0$ (Panel A) or $\beta_{1i\tau} = 0$ (Panel B).

	Panel A: Univariate regressions			
Insider Trading	all	low	medium	high
mean $\widehat{\beta}_{i\tau}$	0.1858**	0.2272**	0.2918**	0.2587**
t-stat	2.08	2.09	2.18	1.90
	Panel B: Multivariate regressions			
Insider Trading	all	low	medium	high
mean $\widehat{\beta}_{1i\tau}$	0.2022**	0.2274**	0.2996**	0.2920**
t-stat	2.22	2.09	2.19	2.07

Table VI. Financial Constraints, Debt Issuance, and Information Asymmetry
This table contains ordinary least square (OLS) estimates for the coefficients of Fama-MacBeth cross-sectional regressions of the firms' change in debt $\Delta D_{i\tau}$ (where D is the ratio of total debt to market capitalization as in Frank and Goyal, 2003), on the information asymmetry index $ASY_{i\tau}$ described in section 2, in our merged CRSP-COMPUSTAT sample of U.S. firms between 1973 and 2002, sorted into terciles based on their degree of financial constraints $FC_{i\tau}$. $FC_{i\tau}$ is the index of external finance constraints from Whited and Wu (2005). More specifically, in Panel A, we report the average estimate for the coefficient $\beta_{1i\tau}$ over 30 observation-years and its corresponding t-statistic in the following regressions across all firms i for which a financial constraint measure, information asymmetry index measure, and accounting information were available in fiscal year τ:

$$\Delta D_{i\tau} = \alpha_{i\tau} + \beta_{i\tau} ASY_{i\tau} + \varepsilon_{i\tau}.$$

The same estimation is then repeated each fiscal year τ within each of three subsets of firms identified according to the relative magnitude of $FC_{i\tau}$ as low (tercile 1), medium (tercile 2), or high (tercile 3). $FC_{i\tau}$ is computed from the GMM estimation of an investment Euler equation. In particular, we compute $FC_{i\tau}$ using the factor loadings in Whited and Wu (2005) as follows:

$$FC_{i\tau} = -0.091 CF_{i\tau} - 0.062 I_{i\tau}^{Div} + 0.021 LEV_{i\tau} - 0.044 LNA_{i\tau} + 0.0255 ISG_{i\tau} - 0.0088 SG_{i\tau}.$$

where $I_{i\tau}^{Div}$ is a dummy equal to one if firm i paid dividends over fiscal year τ and zero otherwise, $CF_{i\tau}$ and $LEV_{i\tau}$ are firm i's cash flow and leverage, $LNA_{i\tau}$ is the natural logarithm of firm's total assets, and $ISG_{i\tau}$ and $SG_{i\tau}$ are firm i's 3-digit SIC code industry and own sales growth over fiscal year τ. In Panel B, we report the average estimate for the coefficient $\beta_{1i\tau}$ (as well as their standard errors and corresponding t statistics) in the following multivariate regression across all firms i for which a financial constraint measure, an information asymmetry measure, and accounting information were available in fiscal year τ :

$$\Delta D_{i\tau} = \alpha_{i\tau} + \beta_{1i\tau} ASY_{i\tau} + \beta_{2i\tau} \Delta TAN_{i\tau} + \beta_{3i\tau} \Delta \Pi_{i\tau} + \beta_{4i\tau} \Delta LS_{i\tau} + \beta_{5i\tau} \Delta MB_{i\tau} + \varepsilon_{i\tau},$$

where $TAN_{i\tau}$ is a proxy for firm i's tangibility defined as the ratio of fixed assets to book value of total assets, $\Pi_{i\tau}$ is a proxy for firm i's profitability defined as the ratio of operating income to book value of total assets, $LS_{i\tau}$ is the natural logarithm of firm i's sales, and $MB_{i\tau}$ is the market-to-book ratio defined as the ratio of market value of assets (book value of assets plus the difference between market value of equity and book value of equity) to book value of assets. ***,**,* indicates significance at 1%, 5%, and 10% level respectively for the two-sided t test of the null hypothesis that $\beta_{i\tau} = 0$ (Panel A) or $\beta_{1i\tau} = 0$ (Panel B).

	Panel A: Univariate regressions			
$FC_{i\tau}$	all	low	medium	high
mean $\widehat{\beta}_{i\tau}$	0.1530**	-0.0168	0.0898	0.2891***
t-stat	2.13	-0.20	1.03	3.17

	Panel B: Multivariate regressions			
$FC_{i\tau}$	all	low	medium	high
mean $\widehat{\beta}_{1i\tau}$	0.1582**	-0.0238	0.1189	0.2759***
t-stat	2.20	-0.31	1.36	3.18

Table VII. Debt Capacity, Debt Issuance, and Information Asymmetry

This table contains ordinary least square (OLS) estimates for the coefficients of Fama-MacBeth cross-sectional regressions of the information asymmetry index measure $ASY_{i\tau}$ described in section 2, on firms' change in debt $\Delta D_{i\tau}$ (where D is the ratio of total debt to market capitalization as in Frank and Goyal, 2003), in our merged CRSP-COMPUSTAT sample of U.S. firms between 1973 and 2002, sorted into terciles by the firm's debt capacity. More specifically, in Panel A, we report the average estimate for the coefficient $\beta_{i\tau}$ over 30 observation-years and its corresponding t-statistic in the following univariate regression across all firms i for which both an information asymmetry measure, and accounting information were available in fiscal year τ:

$$\Delta D_{i\tau} = \alpha_{i\tau} + \beta_{i\tau} ASY_{i\tau} + \varepsilon_{i\tau}.$$

The same estimation is then repeated each fiscal year τ within each of three subsets of firms identified according to their relative debt capacity $Prob_{i\tau}$ (defined as the estimated probability that firm i has a bond rating in fiscal year τ as low (tercile 1), medium (tercile 2), or high (tercile 3). $Prob_{i\tau}$ is computed from a predictive logit regression in which the dependent variable is one if a firm has rated debt outstanding in a particular year (S&P long-term domestic issuer credit rating, i.e., Data 280 in COMPUSTAT) and zero otherwise, while the regressors are the following lagged (by one fiscal year) firm characteristics: Profitability, tangibility, market-to-book ratio, leverage, size, age, stock return volatility, and industry dummies for each 2-digit SIC code in the sample, similarly to Lemmon and Zender (2004). Size is the natural logarithm of total assets; age is the natural logarithm of the number of years since a firm was first included in COMPUSTAT; stock return volatility is the annualized standard deviation of a firm's stock returns over each fiscal year. The estimation uses only data from 1986-2002, the interval when bond ratings are available in COMPUSTAT, but the estimated coefficients are used to compute $Prob_{i\tau}$ for each year between 1973 and 2002, again as in Lemmon and Zender (2004). In Panel B, we report the average estimate for the coefficient $\beta_{1i\tau}$ (as well as their standard errors and corresponding t statistics) in the following multivariate regressions across all firms i for which both an information asymmetry measure and accounting information were available in fiscal year τ:

$$\Delta D_{i\tau} = \alpha_{i\tau} + \beta_{1i\tau} ASY_{i\tau} + \beta_{2i\tau} TAN_{i\tau} + \beta_{3i\tau} \Pi_{i\tau} + \beta_{4i\tau} LS_{i\tau} + \beta_{5i\tau} MB_{i\tau} + \varepsilon_{i\tau},$$

where $ASY_{i\tau}$ is as before, while $TAN_{i\tau}$ is a proxy for firm i's tangibility defined as the ratio of fixed assets to book value of total assets, $\Pi_{i\tau}$ is a proxy for firm i's profitability defined as the ratio of operating income to book value of total assets, $LS_{i\tau}$ is the natural logarithm of firm i's sales, and $MB_{i\tau}$ is the market-to-book ratio defined as the ratio of market value of assets (book value of assets plus the difference between market value of equity and book value of equity) to book value of assets. ***,**,* indicates significance at 1%, 5%, and 10% level respectively for the two-sided t test of the null hypothesis that $\beta_{i\tau} = 0$ or $\beta_{1i\tau} = 0$.

	Panel A: Univariate regressions			
Debt Capacity	all	low	2	high
mean $\widehat{\beta}_{i\tau}$	0.1530**	0.0507	0.2926**	0.3013*
t-stat	2.13	1.12	2.23	1.72

	Panel B: Multivariate regressions			
Debt Capacity	all	low	2	high
mean $\widehat{\beta}_{1i\tau}$	0.1582**	0.0684	0.3239***	0.3310**
t-stat	2.20	1.46	2.62	2.04

Table VIII. Financial Hierarchy and Information Asymmetry

This table contains rankings (from the most preferred, 1, to the least preferred, 3) of financing hierarchies of U.S. firms in our merged CRSP-COMPUSTAT sample of U.S. stocks between 1973 and 2002, as in de Haan and Hinloopen (2003). Specifically, these rankings are obtained from the estimation of a series of ordered probit models for each of the following three hierarchies: h_1: Internal funds (0), External debt (1), Equity (2), i.e., the Pecking Order theory; h_2: Internal funds (0), Equity (1), External debt (2); and h_3: External debt (0), Internal funds (1), Equity (2). We consider only three hierarchies since other combinations are mirror images of these three (for example, Equity (0), External Debt (1), Internal Funds (3) is a mirror image of h_1). Each ordinal discretes 0, 1, and 2 impose the corresponding hierachy when estimating the model. The discrete issuance decision series are generated in each fiscal year τ only among firms with a non-negative deficit $DEF_{i\tau} \geq 0$ as follows: Debt issuance by firm i in fiscal year τ takes place if that firm's net change in long-term debt (defined in the Appendix) from $\tau - 1$ to τ normalized by book assets in year $\tau - 1$ is greater than or equal to 5%; equity issuance by firm i in fiscal year τ takes place if the ratio between the change in the market value of equity adjusted for capital gains (defined in Fama and French (2005) as $\frac{1}{2}\left(Shares_{\tau}Adjust_{\tau} - Shares_{\tau-1}Adjust_{\tau-1}\right)$ $\left(Price_{\tau-1}/Adjust_{\tau-1} + Price_{\tau}/Adjust_{\tau}\right)$, where $Shares_{\tau}$ is the total number of shares outstanding, $Adjust_{\tau}$ is the split adjustment factor, and $Price_{\tau}$ is the stock price at the end of fiscal year τ in COMPUSTAT and the firm's book assets in year $\tau-1$ is greater than or equal to 5%; finally, internal funding takes place if neither debt nor equity issuances do over year τ. We remove the few cases in which dual (debt and equity) issuances take place. For each hierarchy, we estimate an ordered probit model with the following independent variables (defined in the Appendix unless otherwise mentioned): contemporaneous sales, Q ratio, tangibility, profitability, 2-year stock returns, and deviation from a target leverage ratio constructed as lagged leverage minus a leverage target given by the corresponding (2-digit SIC) industry median leverage in year τ. We use the resulting log-likelihood values from the estimation to compute likelihood ratio (LR) tests across hierarchies as follows: $LR_{12} = -2 * (lnL_{h_1} - lnL_{h_2})$,$LR_{13} = -2 * (lnL_{h_1} - lnL_{h_3})$, and $LR_{23} = -2 * (lnL_{h_2} - lnL_{h_3})$. We then assume that one hierarchy prevails over the other if the corresponding LR test is significant at the 1% level (6.63). All rankings (i.e., all LRs) were statistically significant; thus, no two hierarchies are ranked equally. Finally, an overall ranking is determined by comparing the magnitude of the likelihood functions, from the lowest (1) to the highest (3). Hence, a ranking of 1 (3) indicates that the corresponding hierarchy fits the data the best (worst). We repeat this procedure for the entire sample and across each information asymmetry tercile of firms, where the terciles (from the lowest, 1, to the highest, 3) are constructed using our information asymmetry $ASY_{i\tau}$.

Table VIII (*Continued*).

	Information asymmetry			Preferred hierarchies			
				all	low	medium	high
	Hierarchy						
	0	1	2		$ASY_{i\tau}$		
h_1	Internal	Debt	Equity	2	2	2	2
h_2	Internal	Equity	Debt	3	3	3	3
h_3	Debt	Internal	Equity	1	1	1	1

Fig. I: Microstructure measures of information asymmetry and their relationship to information asymmetry in Myers and Majluf (1984)

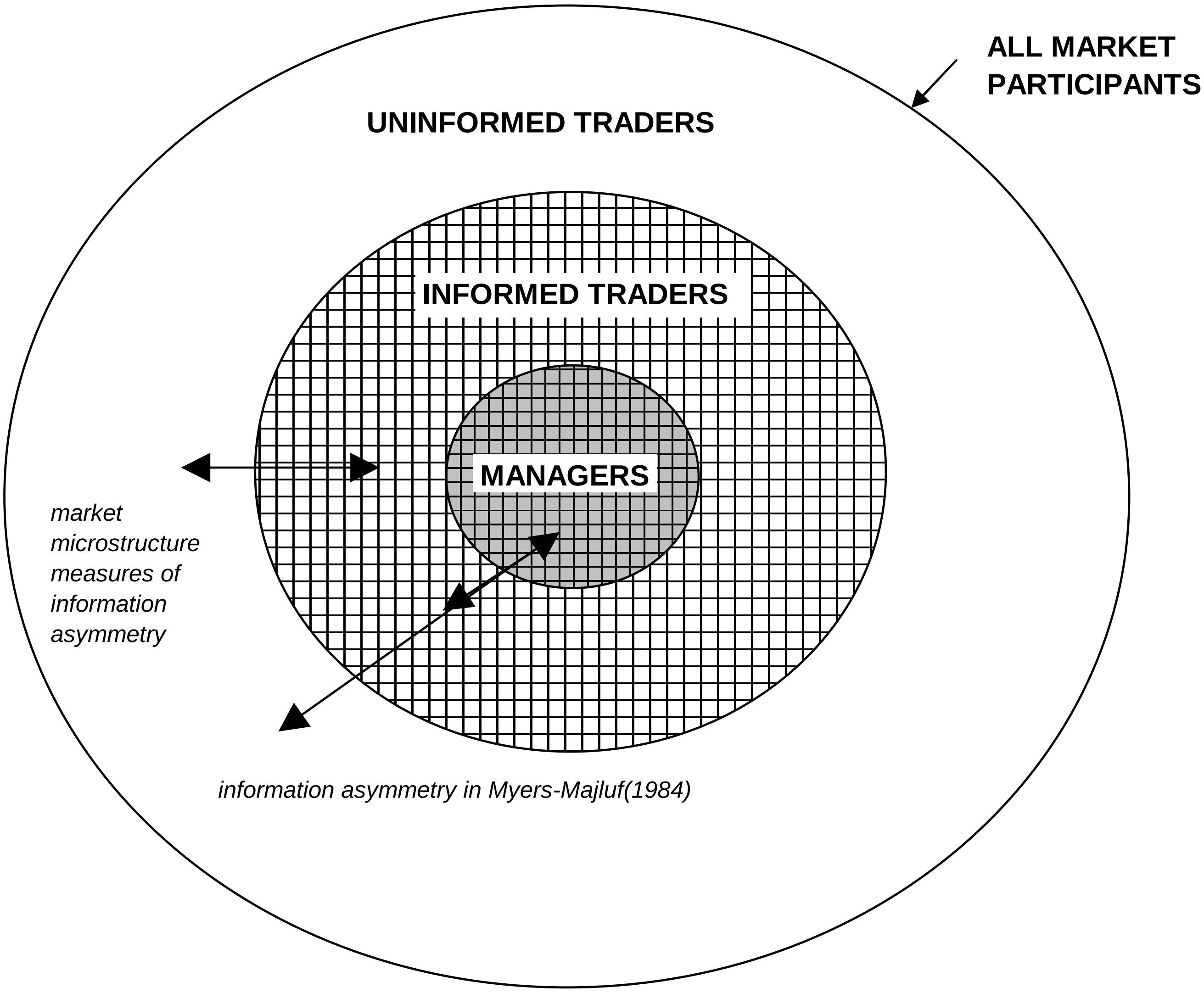

Fig. II: Sensitivity of Debt Issuance to Financial Deficit: Two Way Sort on Size and Information Asymmetry

This figure plots ordinary least square (OLS) estimates for the coefficients of the regression of change in debt $\Delta D_{i\tau}$ on financial deficit $DEF_{i\tau}$.

$$\Delta D_{i\tau} = \alpha_{i\tau} + \beta_{i\tau} DEF_{i\tau} + \varepsilon_{i\tau}.$$

The change in debt is defined as the amount of long-term debt issued by firm i during fiscal year τ. The financial deficit is defined in the appendix and computed using COMPUSTAT sample of U.S. firms between 1973 and 2002. We first sort firms into terciles based on size each year (Total Assets). We then estimate the coefficient for terciles of the asymmetry index $ASY_{i\tau}$, defined in Section 2.

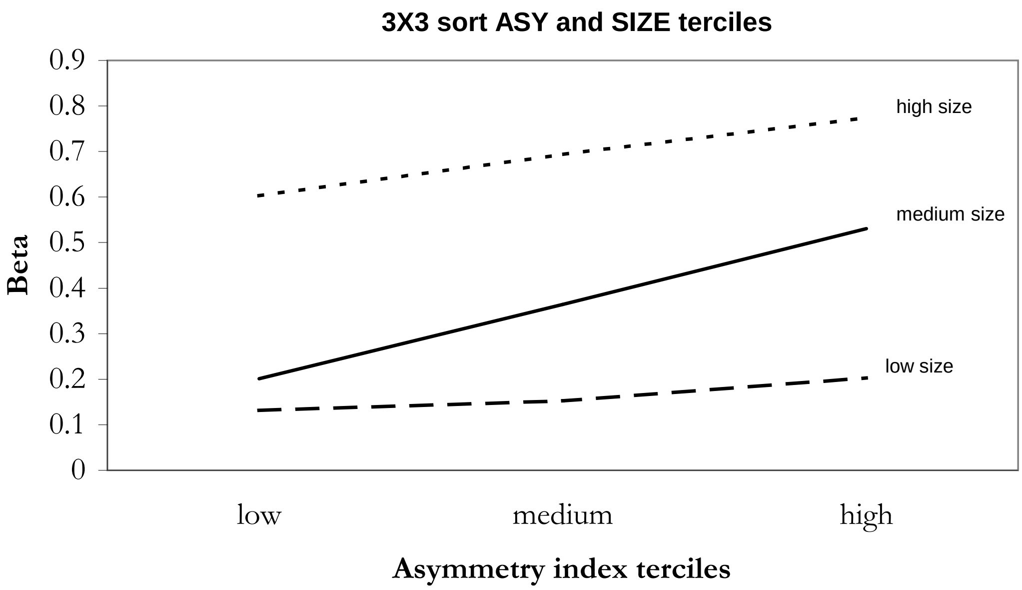

Fig. III: Deficit, Debt, and Information Asymmetry: Intertemporal Dynamics
This figure plots ordinary least square (OLS) estimates for the coefficients of Fama-MacBeth cross-sectional regressions of firms' debt issuance decision $\Delta D_{i\tau}$ (where D is the ratio of total debt to market capitalization as in Frank and Goyal, 2003), on $ASY_{i\tau}$, the information asymmetry index described in section 2, in our merged CRSP-COMPUSTAT sample of U.S. firms between 1973 and 2002. More specifically, the solid line in the figure plots the estimates for the coefficient $\beta_{i\tau}$ in the following univariate regressions across all firms i for which both an information asymmetry measure and accounting information were available in fiscal year τ:

$$\Delta D_{i\tau} = \alpha_{i\tau} + \beta_{i\tau} ASY_{i\tau} + \varepsilon_{i\tau}.$$

This estimation is repeated each fiscal year τ. Similarly, the dotted line in the figure plots the estimates for the coefficient $\beta_{1i\tau}$ in the following multivariate regressions across all firms i for which both an information asymmetry measure and accounting information were available in fiscal year τ:

$$\Delta D_{i\tau} = \alpha_{i\tau} + \beta_{1i\tau} ASY_{i\tau} + \beta_{2i\tau} TAN_{i\tau} + \beta_{3i\tau} \Pi_{i\tau} + \beta_{4i\tau} LS_{i\tau} + \beta_{5i\tau} MB_{i\tau} + \varepsilon_{i\tau},$$

where $TAN_{i\tau}$ is a proxy for firm i's tangibility defined as the ratio of fixed assets to book value of total assets, $\Pi_{i\tau}$ is a proxy for firm i's profitability defined as the ratio of operating income to book value of total assets, $LS_{i\tau}$ is the natural logarithm of firm i's sales, and $MB_{i\tau}$ is the market-to-book ratio defined as the ratio of market value of assets (book value of assets plus the difference between market value of equity and book value of equity) to book value of assets.