Financial Slack and Tests of the Pecking Order's Financing Hierarchy

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Abstract

We empirically examine the pecking order theory of capital structure using a new empirical model and testing strategy. Our approach solves the power problem associated with previous tests and reveals that 62% and 29% of firms adhere to the first (internal-external) and second (debt-equity) rung of the pecking order, respectively. We then show that this inability to accurately classify debt and equity issuance decisions is due to neither debt capacity concerns nor leverage targeting, both of which also fail to adequately explain security issuance decisions. However, when we integrate alternative considerations (e.g., tradeoff) into the pecking order framework, we find that our empirical model is able to accurately classify almost 70% of debt and equity issuances in our sample, suggesting that future research work on bridging the gap between these existing theories, as opposed pitting one against the other. Finally, we show that, empirically, information asymmetry does not appear to be related to pecking order behavior, despite its importance in issuance decisions. Thus, while the mispricing story of Myers and Majluf (1984) offers an empirically reasonable explanation for equity issuances, this mispricing does not result in a pecking order of financing decisions.

The pecking order theory of capital structure, posited by Myers (1984) and Myers and Majluf (1984), predicts that information asymmetry between managers and investors creates a preference ranking over financing sources. Beginning with internal funds, followed by debt, and then equity, firms work their way up the pecking order to finance investment in an effort to minimize adverse selection costs. While often thought of as a consequence of adverse selection, pecking order behavior can also be generated by other economic forces including agency costs (e.g., see Myers (2003)) and taxes (e.g., see Stiglitz (1973) and Hennessy and Whited (2004)). Thus, two empirical questions concerning the pecking order naturally arise: First, to what extent do firms follow the pecking order in their decision making? And, second, which economic force(s) generate pecking order behavior?

Regarding the first question, the evidence is mixed. Earlier studies (e.g., Titman and Wessels (1988), Chaplinsky and Niehaus (1990), Rajan and Zingales (1995), and Fama and French (2002), among others) cite the negative association between leverage and profitability as evidence consistent with the pecking order since more profitable firms can more easily finance investment with internal funds instead of debt. However, Strebulaev (2004) generates an inverse leverage-profitability association in a theoretical model absent any financing hierarchy, while Hovakimian, Opler, and Titman (2001) present empirical evidence that profitability is positively associated with leverage increasing financing decisions. More recent studies by Shyam-Sunder and Myers (1999) and Lemmon and Zender (2004) argue that the pecking order offers a good description of financing behavior in large firms, as well as small firms once one accounts for debt capacity concerns (i.e., the ability to fund *future* investment with debt). Although, Helwege and Liang (1996), Frank and Goyal (2003), and Fama and French (2004) suggest that the pecking order fails to accurately portray financing behavior when one examines issuance decisions or extends the analysis to a broader sample.

While each of these papers make important contributions beyond their conclusions regarding the pecking order, the extent to which firms adhere to a financing hierarchy is still unclear. Additionally, the question of what economic force may be driving pecking order behavior has yet to be empirically examined, as noted in the recent survey paper by Frank and Goyal (2005). The goal of this paper is to address both of these questions using a new empirical approach that enables us to: 1) provide a statistically powerful test of the pecking order, 2) quantify the degree to which corporate financing decisions adhere to the financing hierarchy, 3) assess the relative appropriateness of pecking order versus alternative concerns as they pertain to issuance decisions, and 4) shed light on the empirical link between information asymmetry and the pecking order.

We begin by developing an empirical model of the pecking order's financing hierarchy as an implication of the theory's primary prediction: When investment exceeds internal resources firms turn to external finance, and when investment exceeds firms' abilities to borrow they turn to equity finance. Despite the centrality of this prediction to the theory, we are unaware of any previous studies that explicitly model this ordering of decisions.[1] Additionally, we model the entire hierarchy, internal funds followed by debt and then equity. Incorporating the first rung of the hierarchy (internal versus external) proves important for two reasons. First, we find that in many instances firms turn to external capital markets despite having sufficient internal resources for investment. Second, the ability of the pecking order to accurately identify elements of the second rung (debt versus equity) depends, in part, on the ability of the theory to accurately identify external issuances.

We then construct a series of hypothesis tests that can distinguish between varying degrees of adherence to the financing hierarchy by firms in our sample. This feature is particularly important in light of Chirinko and Singha's (2000) critique of Shyam-Sunder and Myers' (1999) testing strategy. Chirinko and Singha note that the empirical test of Shyam-Sunder and Myers suffers from statistical power problems that "[raise] serious questions about the validity of inferences based on [this] new testing strategy," a strategy that cannot detect violations of the financing hierarchy (i.e., ordering of decisions). By focusing on the pecking order's ability to accurately characterize observed financing decisions, our test avoids this problem, which we illustrate via a simulation experiment.

An important by-product of our testing approach and simulation experiment is that they enable us to identify the fraction of the sample adhering to a particular rung of the hierarchy. This quantification is similar to that made in a recent paper by Fama and French (2004), who argue that equity issuances (and retirements) occur too frequently for financing behavior to be consistent with the pecking order. Their study, which is most closely related to ours, both avoids and raises several questions that we hope to answer with our analysis. In particular, we look at the extent to which all financing decisions adhere to the hierarchy, how other theories (e.g., tradeoff) compare to the pecking order,

[1] de Haan and Hinloopen (2003) estimate an ordered probit model of financing decisions but ignore the decision rule governing the order. Hence, the ordering implicit in their model could arise for reasons other than those dictated by the pecking order. Helwege and Liang (1996) look at the correlation between financing decisions and the financing deficit for a small sample of IPO firms but do not model the ordering of the decisions either.

and what motivates the pecking order behavior that is observed in the data.[2] Additionally, we illustrate that without a benchmark for comparison, interpreting the quality of a theory based on its absolute predictive ability is difficult. As our simulations reveal, even if all firms adhere to the pecking order all of the time, the econometrician will only accurately identify approximately 85% of the internal and external issuance decisions, and less than 70% of the debt and equity issuance decisions.

Our results show that 64% of the firms in our sample adhere to the hierarchy in their choice between internal resources and external capital, while 29% of the firms adhere to the hierarchy in their decision between debt and equity. This inability to classify debt and equity decisions for the majority of firms implies that an alternative mechanism is at work. Lemmon and Zender (2004) suggest that this mechanism is debt capacity concerns, which allows firms to violate the financing hierarchy should concerns over future investment opportunities overwhelm current adverse selection costs. The tradeoff theory suggests that the mechanism is the deviation of leverage from an optimal level that balances the costs (e.g., bankruptcy costs, agency costs) and benefits (e.g., taxes, mitigation of free cash flow problems) associated with financial leverage.

With respect to debt capacity concerns, we analyze a large dataset of corporate loans and find that this concern does not appear to be the motivation for the majority of equity issuers, consistent with the findings of Korajczyk, Lucas, and McDonald (1990). While equity issuers, on average, tend to be smaller and have larger future investment opportunities then their debt issuing counterparts, consistent with Lemmon and Zender (2004), the majority of equity issuers are similar to their debt issuing counterparts and have a stronger financial profile (i.e., lower leverage, higher current ratio, higher interest coverage ratio). Further analysis reveals that most equity issuers would face borrowing rates similar to those faced by private borrowers, and those rates are only slightly higher than that found on investment grade public debt. With respect to the tradeoff theory, only 27% of the firms in our sample make issuance decisions consistent with leverage targeting. Thus, independent of one another, neither the pecking order nor the tradeoff theory appear to offer an adequate explanation of security issuance behavior.[3]

[2]Fama and French also identify equity issuances using a broad classification that includes stock option exercise and stock grants. This definition raises the concern that the violations of the pecking order that they find may simply be due to the theory's inability to explain stock issuances that amount to payment-in-kind, whereas Myers and Majluf (1984) develop the pecking order theory in the context of investment financing.

[3]We note, however, that the inability of the tradeoff theory to accurately classify equity issuances is not a rejection of the theory. Indeed several studies (e.g., Chen and Zhao (2003), Hovakimian, Opler,

These findings lead us to examine Myers' (1984) suggestion that "one start with a story based on asymmetric information and expand it by adding only those elements of that static tradeoff which have clear empirical support." In doing so, we are able to quantify the effectiveness of Myers' proposed strategy, as well as investigate the relative importance of various theoretical factors in identifying financing decisions. When we integrate alternative considerations into the pecking order framework, we find that the fraction of firms adhering to the first rung of the pecking order increases by approximately 15%. However, we find that almost 70% of the firms in the sample adhere to the second rung in our integrated model, an improvement due to the inclusion of both traditional tradeoff forces (e.g., taxes and bankruptcy costs), as well as measures of investment opportunities and security mispricing. We interpret these results as pointing future research towards bridging the gap between these explanations, as opposed to pitting them against one another or completely dismissing them.

Our final analysis looks at the second question posed above by testing the association between various measures of information asymmetry and the likelihood of adhering to the pecking order. If information asymmetry is the driving force behind the pecking order, then variation in this factor should correlate positively with adherence to the hierarchy so that when adverse selection costs are large (small), firms should be more (less) inclined to adhere to the hierarchy. We find no significant empirical link between various measures of information asymmetry and prediction accuracy. That is, information asymmetry appears to have little, if any, association with whether or not firms adhere to or violate the pecking order's financing hierarchy.

We find this last result of particular interest because it illustrates the distinction between the pecking order financing hierarchy and information asymmetry. On the one hand, we show that firms often violate the hierarchy and these violations have no association with measures of information asymmetry, counter to the prediction of Myers and Majluf (1984). On the other hand, we show that mispricing/information asymmetry is important in identifying debt and equity issuance decisions, consistent with Myers and Majluf (1984).[4] Reconciling these seemingly conflicting results lies in the fact that

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and Titman (2001), Hovakimian (2004), and Leary and Roberts (2004)) show that leverage rebalancing is executed primarily through retirements and repurchases.

[4]Many papers have demonstrated empirically the importance of recent equity returns in predicting issuances, albeit in different forms and contexts. (See, for example, studies by Asquith and Mullins (1986), Jung, Kim and Stulz (1996), Marsh (1982), and Mikkelson and Partch (1986).) Additionally, recent studies by Brav (2004), Chang, Dasgupta, and Hilary (2004), and Gomes and Phillips (2004) show directly that various measures of information asymmetry are strongly correlated with financing

a pecking order of financing decisions is not a necessary implication of the Myers and Majluf model (see Yilmaz (2004)), or of information asymmetry in general (Lukin and Fulghieri (2001) and Halov and Heider (2003)). Thus, our findings show that while information asymmetry may be an important determinant of financial policy, this asymmetry does not manifest itself in a pecking order of financing decisions.

The remainder of the paper is as follows. Section 1 reviews the pecking order theory and discusses the empirical predictions. Section 2 describes the empirical model. Section 3 outlines the data and sample selection. Section 4 presents results on the appropriateness of the pecking order as a descriptor of financing behavior, as well as those pertaining to alternative explanations. Section 5 presents the results concerning the empirical link between pecking order behavior and information asymmetry. Section 6 provides additional robustness checks beyond those discussed in earlier sections. Section 7 concludes.

1. The Pecking Order

1.1 Theory

The conventional view of the pecking order hypothesis (Myers (1984) and Myers and Majluf (1984)) is that firms have a preference ranking over securities because of information asymmetry between firm's well-informed managers and its less-informed investors. Managers use their informational advantage to issue securities when they are overpriced, but investors, aware of management's incentive, discount the price that they are willing to pay for the securities. The result of this discounting is a potential underinvestment problem, as managers forgo profitable investment opportunities.

To avoid the underinvestment problem, firms prefer to use internal funds because they avoid informational problems entirely. When internal funds are insufficient to meet financing needs (i.e., financing deficit), firms turn first to risk-free debt, then risky debt, and finally equity, which is at the top of the pecking order. Any internal funds in excess of financing needs (i.e., financing surplus) are used to repurchase debt, as opposed to equity, because of similar adverse selection problems. Thus, the pecking order hypothesis implies the existence of a financing hierarchy: internal funds first, debt second, and equity last.

The rigidity of this hierarchy, coupled with the insignificant role of equity lead Myers and Majluf (1984) and Myers (1984) to also describe a "modified" (or dynamic) pecking order that recognizes both asymmetric information and costs of financial distress. This

decisions but not necessarily with a financing hierarchy.

modification allows equity financing to play a more important role by relaxing the ordering of the hierarchy's second rung, the choice between debt and equity. Firms may issue equity in place of debt or internal financing to maintain both liquid assets and debt capacity for future investments, thereby avoiding potential underinvestment problems and lowering expected bankruptcy costs. Thus, the modified pecking order relaxes the strict dollar-for-dollar matching of debt with net financing need by allowing the use of equity when firms desire financial slack for future investment.

1.2 Empirical Predictions: The Financing Hierarchy

Panel A of Figure 1 illustrates the pecking order's financing hierarchy. Firms finance investment with internal resources up to the cash threshold C^*, which represents the amount of internal funds that the firm has available for investment. When the size of current investment exceeds C^*, the firm then turns to external finance to fill the financing deficit. Debt finance is applied first and used up to the point D^*, where $(D^* - C^*)$ represents the amount of debt the firm can issue without producing excessive leverage (i.e., without becoming financially distressed). Investment needs beyond D^* require that the firm turn to equity financing. Thus, Panel A illustrates the traditional financing hierarchy and the dependence of that hierarchy on the thresholds C^* and D^*.[5]

In the modified pecking order, the ranking of debt and equity in the hierarchy can reverse, as illustrated by Panel C of Figure I. This graph shows a situation in which firms will turn first to equity financing before debt in order to preserve the ability to borrow in the future to take advantage of upcoming investment options. Thus, the modified pecking order implies that those firms issuing equity for reasons other than current financial distress or overwhelming investment must be doing so to preserve debt capacity for future investment or to avoid significantly increasing expected bankruptcy costs.

[5] We note that if one allows for transaction costs, then the number of financing decisions may be affected, though the financing hierarchy and, consequently, the empirical implications, are not. As Stafford (2001) shows, cash balances tend to increase after large investments, consistent with firms substituting capital raising funds for internal funds. Thus, rather than exhausting internal resources before turning to external capital markets, firms may simply go directly to external capital markets to finance all of their investment demand with debt if investment is greater than C^* but less than D^*, or entirely with equity if investment is greater than D^*. Regardless, the empirical implications under this alternative structure are unaffected: firms avoid external capital when investment is less than C^* and avoid equity capital when investment is less than D^*.

1.3 Empirical Predictions: Information Asymmetry

While most discussions refer to the pecking order as an implication of adverse selection in the Myers and Majluf (1984) framework, this implication is not unique. For example, Stiglitz (1973) shows that the asymmetric tax treatment of capital flows from investors to corporations and payouts from corporations to investors can lead to a financial policy similar to the pecking order. Hennessy and Whited (2004) also use an asymmetric tax environment to generate pecking order behavior in a dynamic model of corporate investment and financial policy. Finally, Myers (2003) discusses how agency costs of equity finance, as in Jensen and Meckling (1976), can also lead to a pecking order of finance.

Additionally, the notion that adverse selection is sufficient to generate a financing hierarchy is not clear. Dybvig and Zender (1991) discuss how properly designed managerial compensation contracts can limit the impact of asymmetric information on capital structure and dividend policy. Fulghieri and Lukin (2001) illustrate how endogenizing the degree of information asymmetry can alter the preference ranking over external securities such that risky debt or composite securities (e.g., convertible debt) can emerge as the preferred choice. Halov and Heider (2004) present a similar result by showing that information asymmetry concerning the investment project, as opposed to the quality of the firm, can lead to a preference of equity over debt. Finally, a recent note by Yilmaz (2004) shows that even within the original framework of Myers and Majluf (1984), the pecking order between debt and equity can be reversed when the expected payoff of the investment project is sufficient to overcome the dilutive effects of equity.

These theoretical results suggest that empirical evidence on the motivation behind pecking order behavior is needed, a sentiment echoed by Frank and Goyal's (2005) recent survey paper. From the perspective of Myers and Majluf (1984), if information asymmetry is the primary factor behind the financing hierarchy, we should see a positive correlation between measures of information asymmetry and firms' adherence to the hierarchy. That is, when adverse selection costs are extreme the dilution resulting from equity issuances (or risky debt) should be greatest and firms will have a large incentive to follow the hierarchy.

2. The Empirical Model

As described above, the pecking order's financing hierarchy implies a decision making process uniquely determined by the relationship between investment and the thresholds C^* and D^*. The first decision that firm i makes in period t is between internal and external funds, $External_{it}$, and is determined by the relative magnitudes of investment (Inv_{it}) and C^*_{it}. When current investment is less than the available internal resources, the firm chooses to finance its investment solely with cash and liquid assets. Otherwise, the firm turns to external capital markets (debt or equity). This decision is represented mathematically as

$$External_{it} = \begin{cases} 1 & Inv_{it} > C^*_{it} \\ 0 & \text{otherwise.} \end{cases} \tag{1}$$

In measuring investment, we follow previous empirical studies of the pecking order (Shyam-Sunder and Myers (1999) and Frank and Goyal (2003)) and define this variable as the sum of capital expenditures, increase in investments, acquisitions, and other use of funds, less the sale of PPE (plan, property and equipment), and the sale of investment. However, in our robustness checks (Appendix A) we also examine alternative measures of investment that include research and development expenditures and advertising expenditures in an effort to account for a broad notion of what investment means to our large sample of heterogeneous firms.[6]

The second decision facing the firm is whether to use debt or equity. This decision is determined by the relative magnitudes of investment, C^*_{it}, and D^*_{it}. When investment exceeds C^*_{it}, so that the firm has decided to use external finance, but is less than D^*_{it} then the firm uses debt finance. When investment outstrips the firm's debt threshold (i.e. greater than D^*_{it}), then the firm turns to equity finance. This decision is represented mathematically as

$$Equity_{it} = \begin{cases} 1 & Inv_{it} > D^*_{it} \\ 0 & C^*_{it} \leq Inv_{it} < D^*_{it}. \end{cases} \tag{2}$$

The remainder of this section discusses the specification of the thresholds and compares the model to those found in previous studies. We then perform a simulation experiment to highlight how the model can distinguish between varying degrees of pecking order behavior found in the data, whereas previous models (e.g., Shyam-Sunder and Myers (1999)) struggle. Our simulations also provide the null hypotheses for our empirical tests, as well as a useful benchmark by which the results may be judged.

[6] We thank Mitchell Petersen for this suggestion.

2.1 The Available Cash Threshold (C^*)

The available cash threshold (C^*_{it}) is defined as

$$C^*_{it} = CashBal_{it-1} + CashFlow_{it} - CashTarget^*_{it}, \tag{3}$$

where $CashBal_{it-1}$ is the firm's stock of cash and marketable securities at the end of period $t-1$, $CashFlow_{it}$ is the after-tax earnings, net of dividends, minus the change in working capital (excluding cash and short-term debt) of the firm during period t, and $CashTarget^*_{it}$ is the firm's target level of cash and marketable securities at the end of period t.[7] In the context of the pecking order, there is no cash target, per se, and therefore this term is specified as:

$$CashTarget^*_{it} = \alpha_C + \varepsilon_{it} \tag{4}$$

where α_C is an unknown parameter and ε_{it} is a mean zero normal random variable assumed to be independent across firms but correlated within firm observations. Thus, our assumption here is that firms share a common component in their minimum cash requirement, which relaxes the unrealistic assumption that firms exhaust all of their internal resources before turning to external capital markets. As we will see later in our extension of this framework, the specification of $CashTarget$ will incorporate determinants associated with alternative theories of capital structure and, therefore, offer a natural comparison with this more restrictive specification.

Equation (3) shows that a firm has available internal resources for investment if the sum of last period's cash balance and the current period's cash flow are greater than a baseline level of cash balances at the end of the period. With this construction, the difference $Inv_{it} - C^*_{it}$ implicit in equation (1) is close to the "financing deficit" (Frank and Goyal (2003)) but for two important differences. First, we replace the change in cash balance by the difference between the beginning cash balance and its end-of-period target. This enables us to evaluate the first decision in the pecking order (internal vs. external finance) by breaking the link between external finance raised and external finance needed.[8] Second, we treat issuances of short-term debt as a financing activity

[7] Since the relevant comparison is between investment and C^*, this treatment of working capital implies that an increase in working capital can be viewed either as an increase in investment or a decrease in cash flow. However, the predicted financing choice is unaltered if we view an increase in inventory as a strategic investment and add it to the investment measure, or as a use of cash and subtract it from C^*.

[8] For example, consider a firm with no current investment opportunity and a cash balance in excess

and include it in our measure of debt issuance, though our results are unchanged if we focus our attention on long-term debt (see the robustness section in Appendix A).

In order to limit potential endogeneity issues, we require all determinants of the financing choice to be in the manager's information set at the beginning of year t. Therefore, rather than use observed year t cash flows, we use year $t-1$ cash flows as a proxy for expected cash flow for each year.[9]

2.2 The Debt Threshold (D^*)

The debt threshold is an aggregate of the liquidity requirements of the firm (C^*) and the firm's ability to issue debt without jeopardizing its financial stability ($D^*_{it} - C^*_{it}$). We specify this second term as:

$$DC^*_{it} \equiv D^*_{it} - C^*_{it} = MaxDebt^*_{it} - Debt_{it-1}, \tag{5}$$

where $Debt_{it-1}$ is the total debt of the firm outstanding at time $t-1$ and $MaxDebt^*_{it}$ is the maximum amount of debt the firm can issue before risking financial distress. Therefore, we model the debt threshold as

$$\begin{aligned} D^*_{it} &= C^*_{it} + DC^*_{it} \\ &= CashBal_{it-1} + CashFlow_{it} - CashTarget^*_{it} + MaxDebt^*_{it} - Debt_{it-1}. \end{aligned} \tag{6}$$

Relative to tradeoff theories of capital structure, the maximum amount of debt the firm can issue according to the pecking order is not a well defined concept. Thus, we take a similar approach as with the $CashTarget$ above and specify

$$MaxDebt^*_{it} = \alpha_M + \eta_{it}, \tag{7}$$

where α_M is an unknown parameter and η_{it} is a mean zero normal random variable assumed to be independent across firms but correlated within firm observations and contemporaneously correlated with ε_{it}. The correlation between the errors in equations (4) and (7) is economically important as the cash and debt thresholds are likely related.

α_C. If the firm issues debt, only to further pad its cash balance, its financing deficit will equal the amount of the debt issuance, apparently consistent with the pecking order in the context of the Shyam-Sunder and Myers (1999) framework. However, the lack of investment opportunity coupled with a relatively high cash balance suggests that $Inv \ngtr C^*$ (assuming cash flow is not sufficiently negative) and, therefore, the model can identify this pecking order violation.

[9] Using observed year t cash flows has not material effect on the results.

The correlation is statistically important, as it requires equations (1) and (2) be estimated simultaneously to avoid biasing the parameter estimates. Thus, as with our cash target, equation (7) assumes that firms share a common component in the upper bound on the amount of debt that they can issue, which relaxes the assumption that firms never issue equity.

For estimation purposes, it is easier to focus on the difference between $MaxDebt$ and $CashTarget$, as opposed to treating $MaxDebt$ separately.[10] Thus, we employ the following formulation in the estimation:

$$(MaxDebt^*_{it} - CashTarget^*_{it}) = \alpha_{M'} + \omega_{it}, \tag{8}$$

where $\alpha_{M'}$ is an unknown parameter and ω_{it} is a mean zero normal random variable assumed to be independent across firms but correlated within firm observations and contemporaneously correlated with ε_{it}. As with the $CashTarget$ above, our extension of this framework below will expand the specification in equation (8) to incorporate determinants associated with alternative theories of capital structure.

2.3 Some Comments Concerning the Model

Substituting equations (3) and (4) into equation (1) reveals that the decision between internal and external funds is governed by

$$External_{it} = \begin{cases} 1 & y^*_{1it} > 0 \\ 0 & y^*_{1it} \leq 0, \end{cases} \tag{9}$$

where

$$y^*_{1it} = Inv_{it} - CashBal_{it-1} - CashFlow_{it} + \alpha_C + \varepsilon_{it}. \tag{10}$$

Substituting equations (6) and (8) into equation (2) reveals that the decision between debt and equity is governed by

$$Equity_{it} = \begin{cases} 1 & y^*_{2it} > 0 \\ 0 & y^*_{2it} \leq 0, \end{cases} \tag{11}$$

[10]The difficulty arises from the fact that the scale term of discrete choice models is not identifiable. Thus, imposing cross-equation restrictions on slope coefficients requires that either the scale terms of the two equations be identical, or that the scale term of one of the equations be estimated. If the cross-equation restrictions or, more generally, the model, is inconsistent with the data, obtaining sensible parameter estimates or convergence of the optimization program is uncertain at best.

where

$$y^*_{2it} \;=\; Inv_{it} - CashBal_{it-1} - CashFlow_{it} + Debt_{it-1} - \alpha_{M'} - \omega_{it}. \qquad (12)$$

For identification purposes, we assume that the variances of ε and ω are unity, so that α_C and α'_M are implicitly in σ_ε and σ_ω units, respectively. This is a standard identifying restriction in discrete choice models and is innocuous as the observable data is governed only by the sign of the latent variables and not the magnitude. We also scale all variables by the book assets of the firm as of the end of the previous fiscal year to control for scale effects and mitigate heteroscedasticity. Appendix B derives the likelihood function.

The model specification in equations (10) and (12) imposes the restriction that the slope coefficients on Inv, $CashBal$, $CashFlow$, and $Debt$ are each equal to one (or minus 1). Imposing this restriction on the model, however, is infeasible because of the unidentifiability of the scale term associated with the errors. In the estimation, we require the coefficients on these terms to be equal in their respective equations, a less restrictive condition. Thus, the model contains five parameters: the two slope coefficients on $(Inv - CashBal - CashFlow)$ and $(Inv - CashBal - CashFlow + Debt)$, the two intercepts ($\alpha_C$ and $\alpha_{M'}$), and the correlation between the two error terms (ρ).

Before continuing we make several comments concerning the model and its relation to previous studies. Equations (9) through (12) specify a partially observed (or censored) bivariate probit. The censoring is due to the unobservability of the decision between debt and equity if the firm chooses to use internal funds. Because $CashTarget^*$ and $MaxDebt^*$ are not observable, we can not directly estimate equations (4) and (7) (or equation (8)). Rather, the coefficients of these equations are attained from the bivariate probit estimation. That is, given the pecking order's decision rule, and our specifications for $CashTarget^*$ and $MaxDebt^*$, our model finds those parameter values that best match the observed financing decisions with those predicted by the pecking order. This methodology has the advantage of not introducing additional error through a first-stage estimation of the cash and debt thresholds.

However, perhaps the most important aspect of the model is that it respects the ordering of financing decisions implied by the pecking order and does so in a manner consistent with the theory's decision rule relating investment to the availability of funds. This approach differs from previous discrete choice models, such as the multinomial logit specifications found in Helwege and Liang (1996) and Chen and Zhao (2004). These models contain no sense of "order" among the financing decisions and, as such, do not model the pecking order's financing hierarchy. Further, their specifications ignore the pecking order's decision rule in determining why firms make various financing decisions. In other words, the decision to issue debt or equity in their models is not governed by the relation between investment and cash and debt thresholds, as in equations (1) and (2). Finally, multinomial and conditional logit models require that the independence of irrelevant alternatives assumption is satisfied by the data. Our results, as well as those in a recent paper by Gomes and Phillips (2004), show that this assumption is violated by the data, which results in inconsistent parameter estimates.[11] While these previous models can tell us what types of firms tend to make certain financing decisions, they are silent on when and why those decisions are made: precisely the issues on which the pecking order speaks most clearly.

2.4 Statistical Power

Statistical power is an important issue when testing the pecking order because, as Chirinko and Singha (2000) note, the testing framework developed by Shyam-Sunder and Myers (1999) can produce both false positives and false negatives.[12] That is, firms may be following a perverse financing hierarchy where they always issue equity before debt but, so long as they issue relatively little equity, the test can fail to reject the pecking order null. Similarly, firms may be adhering to the hierarchy by issuing debt before equity but if equity issuances represent a large enough fraction of external financing, the test can reject the pecking order null.

Though Chirinko and Singha identify the power problem, they do not propose a solution. As such, we present a simulation experiment that highlights how the model presented above solves the power problem by distinguishing between pecking order and non-pecking order behavior, whereas the model of Shyam-Sunder and Myers struggles. Additionally, our simulation results provide null hypotheses and a quantitative benchmark for the analysis below, enabling us to measure the degree to which the pecking order accurately characterizes financing behavior. The remainder of this subsection discusses

[11] Multinomial models place other, unnecessary restrictions on the data that are avoided in our bivariate framework. The multinomial logit requires that the data be firm specific (i.e., the same variables affecting the cash threshold also affect the debt capacity, and vice versa). The conditional logit, instead, assumes that the data are choice specific but then requires that the marginal affect of each covariate is the same across alternatives. While these restrictions are less of an issue in the context of the current specification, they become important when we extend this framework to incorporate additional variables.

[12] Though Chirinko and Singha direct their critique at Shyam-Sunder and Myers, more recent studies by Frank and Goyal (2003) and Lemmon and Zender (2004) also employ this testing strategy in their analysis of the pecking order.

the simulation and presents the results of our power study. The details of the simulation are discussed in Appendix C.

The simulation is based on random draws of investment (Inv_{it}), the cash threshold (C^*_{it}) and the debt threshold (D^*_{it}), corresponding to 100 years of data for 1,000 firms. Because there are components of each threshold that are not observable in the data ($CashTarget^*$ in C^* and $MaxDebt$ in D^*), we use empirical proxies to aid in the construction of the thresholds. The generation of the simulated series is such that all first and second moments of the simulated data match those of their empirical counterparts. This matching ensures that the simulation is representative of the data generating process found in the data.

With these three series, two sets of financing decisions (*External* and *Equity*) are constructed. The first set is generated according to the pecking order decision rule: use internal funds if $Inv < C^*$ ($External = 0$), use debt finance if $C^* \leq Inv < D^*$ ($External = 1$ and $Equity = 0$), and use equity finance if $Inv \geq D^*$ ($External = 1$ and $Equity = 1$). In the process of generating the financing decisions, we parameterize the simulation to ensure that the ratios of internal-to-external and debt-to-equity decisions match those found in our sample.[13] The second set of financing decisions is generated by a random decision rule, calibrated only to ensure that the ratio of internal to external and debt to equity decisions match those found in our sample.

These two sets of decisions correspond to two extreme situations: one in which all financing decisions are generated by the pecking order decision rule and the other in which all financing decisions are removed from the pecking order decision rule, absent chance error. In order to gauge intermediary results, we vary the fraction of firms (equivalently, observations) that adhere to the pecking order's decision rule by increments of 10%. This procedure gives us 11 sets of financing decisions varying in the degree to which the sample adheres to the financing hierarchy. For each of these 11 sets of financing decisions, we estimate the empirical model via maximum likelihood.

From the estimated models, we map the predicted probabilities into predicted financing decisions as follows. If $\hat{Pr}(y^*_{1it} > 0) > 0.5$ then the firm's predicted financing decision is external, where $\hat{Pr}(y^*_{1it} > 0)$ is the estimated probability from the internal-external equation (9). If $\hat{Pr}(y^*_{1it} > 0) \leq 0.5$ then the firm's predicted financing choice is internal.

[13] See Panel A of Table 3 for the sample ratios and Appendix C for a discussion of how this is accomplished. The ratios of financing decisions are "balanced" (i.e., equal to one) because of the random sampling that we perform, which is discussed in detail below.

Conditional on a predicted external financing, we define the model's prediction to be an equity issuance if $\hat{Pr}(y^*_{2it} > 0|y^*_{1it} > 0) > 0.5$, where the first term is the conditional probability of an equity issue as estimated by the model If $\hat{Pr}(y^*_{2it} > 0|y^*_{1it} > 0) \leq 0.5$ then the predicted financing decision is a debt issuance. We choose a prediction threshold of 0.5 because of the normality assumption underlying our empirical model, as well as the symmetric nature of our sample which we discuss below.

Panel A of Table 1 presents the simulation results. The classification accuracy of the model for various financing decisions is given in the rows denoted: internal funds, external funds, debt issuances, equity issuances. For example, when 50% of the sample is assumed to follow the pecking order's decision rules, the model accurately identifies 66% of the internal financings, 67.1% of the external security issuances, 38.2% of the debt issuances, and 50.4% of the equity issuances. The model fit is summarized by the two "Average Correct" rows, which represent an equal-weighted average of the accuracy rates for internal and external decisions, and debt and equity decisions, respectively.

The last row, "Improvement", illustrates the importance of accounting for the ability of the pecking order to accurately identify the first decision between internal and external funds. The lower bound for accurately identifying debt and equity issuances using a naive predictor (e.g., guessing debt or equity with equal probability) changes with the fraction of external issuances accurately identified. To see this, consider two extreme situations where in the first, the model does not correctly identify any external issuances and in the second, the model correctly identifies all external issuances. In the first case, the model will not identify any debt or equity issuances correctly because all of the external issuances have incorrectly been identified as internal issuances. In the second case, simply flipping a coin or always choosing one type of issuance will ensure that, on average, half of the debt and equity issuances are properly identified. In the more realistic situation, such as when 50% of the sample firms are adhering to the hierarchy, a naive predictor would get half of the accurately classified external issuances (67.1%/2 = 33.55%) correct, on average. Since our model accurately classifies 44.3% in this case, the improvement is thus, 44.3% - 33.55% = 10.7%. Thus, in order to gauge the performance of the model in identifying debt and equity decisions, one must account for the predictive accuracy in the first stage.

The results in Panel A highlight several important points. First, the average predictive accuracy of the model increases monotonically with the fraction of firms following the pecking order, ranging from 50.1% to 85.8% for the internal-external decision and from 26.0% to 65.3% for the debt-equity decision. This pattern shows that the model is not only able to distinguish between pecking order and non-pecking order behavior but also the degree to which pecking order behavior is observed in the data. Second, we note that even when every firm adheres to the pecking order (the 100% column), the model "only" gets 85.8% (65.3%) of the internal-external (debt-equity) decisions correct. This outcome is due to the error terms, ε_{it} and ω_{it}, which correspond to the econometrician's inability to perfectly measure $CashTarget$ or $MaxDebt$. The larger the variance of these error terms, the more difficult it becomes to accurately identify financing decisions.

These points have immediate implications for the study of Fama and French (2004), who, though focusing only on equity issuances and retirements, attempt to identify whether these decisions adhere to or violate the pecking order. In so far as their (implicit) estimates of the threshold D^* contain error, the expected fraction of the observed equity issuances that are classified as adhering to the pecking order will be well below 100% even when all of the sample firms are adhering to the hierarchy. On the other hand, by not examining the performance of the model in identifying external issuance, they are implicitly assuming that the pecking order accurately identifies all external issuances, an assumption that is false given our results below. While Fama and French interpret their results as warranting a dismissal of the theory, the fact that between 70% and 80% of significant equity issuances (and retirements in their case) are correctly identified by the pecking order suggests that an even larger fraction of firms in the sample are adhering to the financing hierarchy. However, by conditioning on an external issuance and therefore assuming that firms adhere to first rung of the hierarchy, these numbers are likely to be inflated. Thus, without a benchmark and complete examination of the hierarchy, it is difficult to interpret their results.

We now contrast our model's predictive results with the coefficient estimates and R-squares from the Shyam-Sunder and Myers (1999) model, presented in Panel B of Table 1. These estimates correspond to their regression model,

$$\Delta Debt_{it} = \alpha + \beta FinDef_{it} + \varepsilon_{it}, \tag{13}$$

where $FinDef_{it}$ is net financial need or the "financing deficit", defined as[14]

$$FinDef_{it} = Dividends_{it} + Inv_{it} + \Delta WorkingCapital_{it} - CashFlow_{it}. \tag{14}$$

Equation (13) is simply a rearrangement of the flow of funds identity, where the change in equity is treated as the residual (ε_{it}). The pecking order hypothesis implies that

[14]Shyam-Sunder and Myers (1999) also include the current portion of long-term debt, beyond its role in the change in working capital. Estimation of equation (13) is carried out after normalizing the change in debt and financing deficit by book assets.

$\alpha = 0$ and $\beta = 1$, so that debt changes dollar-for-dollar with the financing deficit. In their analysis of 157 firms that traded continuously from 1971 to 1989, Shyam-Sunder and Myers find that the intercept is economically small (usually less than $|0.01|$) and the slope, though statistically different from one, is economically close (approximately 0.7 in most of their results). They conclude that the pecking order offers an "excellent first-order descriptor of corporate financing behavior, at least for our sample of mature corporations." (P. 242)

In order to estimate equation (13) using our simulated data, we compute the change in debt, change in equity and financing deficit implied by each sequence of simulated financing decisions. If the firm uses internal funds then $\Delta Debt = \Delta Equity = 0$. If the firm uses debt financing, then $\Delta Debt =$ Investment and Δ Equity = 0. If the firm uses equity financing, then $\Delta Debt = 0$ and Δ Equity = Investment.[15]

Panel B of Table 1 presents the estimation results, which are consistent with Shyam-sunder and Myers (1999) findings as well as the discussion in Chirinko and Singha (2000). Specifically, the regression is unable to distinguish between data generated according to the pecking order and data generated randomly but constrained to maintain a fixed proportion of debt and equity issuances. There is virtually no change in the estimated coefficients and R-squares as the proportion of pecking order firms in the sample is changed. This invariance shows that the empirical specification in equation (13) tells us more about the proportion of debt and equity issues in the data, rather than when and why firms are issuing these two securities. Thus, by modeling the actual decision making process, as opposed to the relative magnitude of debt issuances, our empirical model provides a more powerful means of testing the pecking order.

3. Data and Summary Statistics

3.1 Sample Selection

For consistency with previous studies and the broadest coverage, our data are drawn from firms on both the CRSP and annual Compustat databases over the period 1971-2001. We exclude financial firms (SIC codes 6000-6999) and utilities (SIC codes 4900-4999) to avoid capital structures governed by regulation. In line with previous capital structure

[15]We use this rule since dual issuances in the data are relatively rare and, as Stafford (2001) shows, cash balances tend to increase after large investments suggesting that capital raising activities substitute for internal fund usage. We also perform the simulation using the rule that firms may use multiple sources of capital to finance investment (e.g., internal funds and debt financing). The results are unaffected.

studies, we trim the upper and lower 1% of each variable used in the analysis to mitigate the impact of data errors and outliers. We also restrict leverage measures to lie in the unit interval and the market-to-book ratio to be less than 20. The final sample consists of 36,031 firm-year observations, with nonmissing data for all of the variables used in our analysis.[16]

3.2 Identifying Financing Decisions

Our construction of $External_{it}$ and $Equity_{it}$ is motivated by previous studies such as Chen and Zhao (2003), Hovakimian (2004), Hovakimian et al. (2001), Korajczyk and Levy (2003), and Leary and Roberts (2004), who identify financing decisions by the relative changes in debt and equity. Specifically, a debt issuance is defined as a net change in total debt from period $t-1$ to t, normalized by book assets in period $t-1$, in excess of 5%. Total debt is defined as the sum of short-term and long-term debt.[17] While there may be instances of misclassification using this scheme, such as when convertible debt is called, the previous studies employing this scheme have shown that their analysis is unaffected by using the SDC database to classify issuances. More importantly, this scheme enables us to identify private debt issuances, which represent the most important source of funds for firms (see Houston and James (1996)).

While these previous studies define equity issuances using the statement of cash flows, namely, the sale of common and preferred stock during period t in excess of 5% of book assets in period $t-1$, a recent paper by Fama and French (2003) points out a potential shortcoming of this classification. Fama and French argue that firms often issue equity through channels that may not affect the cash flow of the firm (e.g., employee stock options, grants, and stock mergers) and, as such, will not be captured by the cash flow measure. As an alternative, they suggest that net equity issuances be defined as the change in the market value of common equity, adjusted for capital gains.[18]

[16]Several studies of capital structure impose a minimum size threshold for sample selection to avoid dealing with issues related to financial distress. We choose not to exclude small firms for two reasons, although our results are unchanged if we do impose such a restriction. First, a small asset base or low sales could simply reflect a small firm, as opposed to a distressed firm. Second, removing firms based on financial distress potentially excludes observations for which there is a great deal of information. Further, if the financing behavior of these excluded firms is systematically related to the factors in our study, their exclusion can lead to potential selection biases in the results.

[17]We also estimate the model using net debt issuance from the statement of cash flows, as well as considering only long term debt issues, with no material change to the results (see section IV.E).

[18]they define net equity issued for year t as the product of (1) the split-adjusted growth in shares and

The choice between these two measures of equity issuance is not immediate. While stock-based mergers, an important form of investment for some firms, will be captured by the Fama and French measure, their results suggest that a significant fraction of stock issuances during the 1990s come in the form of stock-based compensation, such as employee stock option exercise and outright grants, which has little do with investment financing. Thus, requiring the pecking order theory to account for what amounts to payment-in-kind may be asking more of the theory than its original intent. For robustness we perform all of our analysis using both the statement of cash flow definition and Fama and French's definition in conjunction with the 5% cutoff. The results are qualitatively very similar and as such we present those obtained using the measure based on the statement of cash flows, which is consistent with the investment measure used here and in previous studies.

A second issue concerning the definition of financing decisions is the magnitude of the cutoff, which, admittedly is somewhat arbitrary. While the studies mentioned above use a 5% cutoff, Fama and French (2003) do not specify a positive cutoff, though as a robustness check they do examine a 1% cutoff. Interestingly, their estimate of the percentage of equity issues and repurchases that are consistent with the pecking order increases from 40%-50% to 70%-80% when the 1% cutoff is imposed. This suggests that this distinction is not innocuous, as our Table 2 confirms. The majority of changes in equity are a very small fraction of total assets. Many of these issuances may correspond not to investment financing but, rather, to payment-in-kind, which we believe is not in the spirit of the pecking order as a theory of investment financing. Regardless, in our robustness section, we examine alternative thresholds (1% and 3%) and show that they do not have a significant impact on our conclusions.

If a firm issues neither debt nor equity, the firm is assumed to have used internal resources to fund investment, if any. Also, in the spirit of the pecking order, we classify the relatively few dual issuances as equity issuances since the pecking order rule dictates that a firm will not issue equity (regardless of whether it is accompanied by a debt issue) unless investment needs exceed its internal resources and debt capacity.

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(2) the average of the split adjusted stock price at the beginning and end of the fiscal year, where both terms are obtained from Compustat data.

3.3 Balancing the Sample

Because we focus on prediction accuracy in our empirical tests, the skewness of the decision variables becomes important for interpreting our results. As show in Panel A of Table 3, the ratio of internal to external and debt to equity decisions are X and Y, respectively. The consequence of this skewness in our framework is that prediction accuracy will be biased towards the relatively more popular decisions, internal and debt.[19] To avoid this bias, we take a random sample of external issuances and debt issuances to ensure that our sample is approximately "balanced", in the sense that the ratios of decisions in each equation (9) and (11)) approximately equal unity. This balancing is accomplished by first taking a random sample of debt issuances, without replacement, so that the number of debt issuances is equal to the number of equity issuances. Given these external issuances (debt plus equity), we then draw a random sample of internal issuances, without replacement, so that the number of internal issuances is equal to the number of external issuances.

The resulting sample contains 26,452 total observations. The summary statistics of both the full and balanced samples are presented in Panels A and B of Table 3 for comparison with one another. A quick inspection reveals that the random sample's firm characteristics are nearly identical to those of the original sample for all variables. Additionally, both panels reveal results that are broadly consistent with those found in previous studies. However, to ensure that our results are not an artifact of the sampling procedure, we repeat the random sampling procedure and all corresponding analysis 100 times. That is, after drawing each of the 100 samples, we estimate our model and compute the predicted financing decisions. We then average the prediction accuracy results across the 100 samples. These results are negligibly different from those obtained with our original random sample and, as such, are not presented.

4. Results 1: The Pecking Order and Alternative Explanations

In this section, we examine how closely actual financing decisions coincide with the pecking order's financing hierarchy, using the simulation results presented above as a benchmark. This analysis enables us to then examine and compare alternative explanations, such as the debt capacity argument put forth by Lemmon and Zender (2004) and the tradeoff theory's leverage targeting argument.

[19] See the discussion in Greene (2003).

Because of the restrictive nature of the model, it is difficult to attach an economic interpretation to the estimated coefficients and, thus, the estimates are not presented here. However, we do mention the following two points. First, a likelihood ratio test of the restrictions that the slope coefficients on Inv, $CashBal$, and $CashTarget$ in equation (10) are equal and the slope coefficients on Inv, $CashBal$, $CashTarget$, and $Debt$ in equation (12) are equal is rejected at all conventional significance levels.[20] Second, our estimate of the correlation between the error terms ε and ω is 0.77, which is highly significant. This result is analogous to the result found by Gomes and Phillips (2004), who show that the independence of irrelevant alternatives (i.e., independence between error terms) is violated in their issuance data. Thus, multinomial specifications relying on this assumption will produce inconsistent estimates. We avoid this problem in our framework by modeling the dependence explicitly, whereas Gomes and Phillips use a nested logit framework.

4.1 Pecking Order Prediction Accuracy

After estimating the model, we construct predicted financing decisions from the estimated probabilities in the same manner as discussed above. Panel A of Table 4 presents the prediction accuracy results. For the internal-external decision, the pecking order accurately identifies 72% of internal and external financing decisions. As mentioned above, this relatively high accuracy is not surprising given the close link between the decision rule and the flow of funds identity. However, based on the simulation benchmark in Table 1, this accuracy rate corresponds to approximately 62% of the sample observations adhering to the first rung of the pecking order. Further, almost 30% of external issuances are made despite the presence of internal resources. Thus, a significant fraction of firms are visiting external capital markets despite having internal resources.

For the debt-equity decision, the classificatory ability of the model breaks down relative to the first rung. The model accurately identifies 38% of the debt issuances and 47% of equity issuances for an average accuracy rate of 42.6%. Given the fraction of external issuances accurately identified in the first stage (72%), the lower bound on the prediction accuracy in the second stage is 36%. The improvement is thus $42.6\% - 36\% \approx 6.5\%$, which corresponds to 34% of the sample adhering to the pecking order. Panel A also shows that even for equity issuing firms, a significant fraction appear to have sufficient internal funds, as well as the capacity to issue debt.

[20] Of course, this rejection also suggests that the more restrictive hypothesis assuming that all coefficients equal one would be rejected, as well.

These results suggest that, by itself, the pecking order's financing hierarchy offers a seemingly poor description of the choice between debt and equity. Firms violate the rule of issuing debt before equity more often than not. Additionally, firms turn to external capital markets a significant number of times, despite the presence of internal resources sufficient for investment. These results are complimentary to those of Fama and French (2004) who, focusing solely on equity financing, argue that firms issue and retire equity more often than they should according to the pecking order. However, we interpret our results, in conjunction with the existing empirical evidence, as indicative of either an alternative mechanism or combination of mechanisms at work. We investigate these possibilities below.

4.2 Are Equity Issuances Due to Debt Capacity Concerns?

Lemmon and Zender (2004) suggest that equity issuers outside of financial duress and not facing overwhelming current investment issue equity to preserve future investment options. To test this claim, we compare the equity issuing firms identified above as violating the financing hierarchy ("Equity Violators") with a large sample of borrowers in the private debt market. This comparison is particularly useful since equity issuers are, on average, relatively smaller and younger so that their primary source of financing outside of equity markets is private lenders, as opposed to public debt markets which are restricted to larger, more established firms.[21] Importantly, the large majority of our equity issuers have a strictly positive leverage, suggesting that they are not restricted from the debt markets because of transaction costs or other barriers to entry (Faulkender and Petersen (2004)). With this analysis, we can see whether equity issuers are significantly different from private borrowers along the dimensions that Lemmon and Zender suggest.

Our private lender data for this analysis is an August 2002 extract of the Dealscan database, marketed by Loan Pricing Corporation (LPC). The data consists of dollar denominated private loans made by bank (e.g., commercial and investment) and non-bank (e.g., insurance companies and pension funds) lenders to U.S. corporations during the period 1990-2001. According to Carey and Hrycray (1999), the database contains between 50% and 75% of the value of all commercial loans in the U.S. during the early 1990s. From 1995 onward, Dealscan contains the "large majority" of sizable commercial loans. According to LPC, approximately half of the loan data are from SEC filings (13Ds, 14Ds, 13Es, 10Ks, 10Qs, 8Ks, and registration statements). The other half is obtained

[21] See Denis and Mihov (2003) for an analysis of the lender decision.

from contacts within the credit industry and from borrowers and lenders. Borrower characteristics are obtained by merging Dealscan with the Compustat database using the historical header file and matching company names and dates. Our final sample consists of 22,166 unique, dollar denominated loans corresponding to 5,615 nonfinancial U.S. firms during the period 1987-2001.

Table 5 presents a comparison of the Equity Violators' firm characteristics with the firm characteristics of our sample of private borrowers. Because our private borrower data is limited to the time period 1987-2001, we restrict our attention to the sample of Equity Violators over the same period. The first four columns present a synopsis of the distribution of each firm characteristic for the sample of private borrowers: the 25th percentile, median, 75th percentile and average. The fifth and sixth columns present the median and average values for the sample of Equity Violators. The last column presents t-statistics testing the difference in means between the two samples.[22]

Consistent with Lemmon and Zender's argument, the equity issuers are, on average, smaller (Market Cap.), less profitable (EBITDA / Assets), and have a shorter term debt maturity structure (Long Term Debt / Total Debt), higher cash flow volatility, lower Z-score, and a higher financing deficit. However, equity issuers also have lower leverage, and a higher current ratio (current assets / current liabilities) and interest coverage ratio (EBITDA / interest expense). However, more important than these paired mean and median comparisons is a comparison of the entire distributions. In other words, the more relevant question is what is the overlap in the distributions of both samples? For example, the median financing deficit of the Equity Violators is double that of the private borrowers but far from the tail of the distribution or even the 75th percentile. Similarly, more than half of the equity issuers have market-to-book ratios that fall below the 75th percentile of the borrowers. In many instances, the majority of equity issuers have firm characteristics that fall in the interquartile range of the borrower's distribution, as opposed to the tail suggesting that equity issuers *as a group* are not much different from their counterparts that turn to the private lending market.

Though suggestive, the above analysis is unconditional. Our next analysis addresses this issue by estimating a model of loan yields, following the analysis of Bradley and Roberts (2003), in an effort to compute the (expected) promised yields that Equity Violating firms would face if they had turned to the private lending markets. The goal of

[22]We perform a two-sided test of the null hypothesis that the population means are equal, assuming the underlying sampling distribution is normal. The standard error is computed after adjusting for clustering at the firm level.

this analysis is not a precise model of loan pricing but, rather, a method to address the conditional nature of the borrowing process. Because of obvious data constraints, we are restricted to including characteristics in our model that are observable for both groups of firms: bank borrowers and Equity Violators. Thus, our model incorporates firm-specific characteristics and macroeconomic factors but does not incorporate information specific to the loan, as this is unobservable for the sample of Equity Violators.

This omission raises the concern that the group of equity issuers might enter into loans different, in terms of contract structure, from our sample of private borrowers (i.e., are the samples different across unobservable characteristics?). We attempt to mitigate this problem by including both industry and year fixed effects to control for possible selection differences between the two groups based on their industry or timing of investment opportunities. Additionally, we note that the financial deficit facing the Equity Violators is not much different from that facing the private borrowers, as inferred from Table 5. As such, there is no reason to believe that the size of the loans would be vastly different for the Equity Violators.

Panel A of Table 6 presents the coefficient estimates from the loan yield equation, except for the fixed effects. We avoid discussing these results, only noting that they are broadly consistent with those found in Bradley and Roberts (2003). Instead we focus attention on Panel B, which presents a comparison of yield distributions across three groups of firms. The first group (Borrowers) corresponds to our sample of private borrowers. The second group (Equity Issuers) corresponds to all of the equity issuers in our sample. The third (Equity Violators) and fourth (Equity Non-Violators) groups are firms that issued equity in violation of or adherence to, respectively, the pecking order prediction from the empirical model of equations (1) and (2) These last three groups are restricted to observations during the period 1987-2001 to coincide with the lending data.

The yield distribution for the sample of bank borrowers has a median (mean) promised yield of 225 (219) basis points above the 6-month LIBOR. The median (mean) estimated spread for the Equity Violators is 25 (34) basis points higher than that of the borrowers. The median (mean) estimated spread for the Equity Non-Violators is 35 (48) basis points higher than that of the borrowers. Thus, for some of the equity issuers, debt capacity concerns may well be important, however, this argument appears applicable to a relative small fraction of equity issuers, as a whole. The predicted yields for all equity issuers is only moderately shifted to the right, suggesting that most equity issuers are similar to their debt issuing counterparts even in a conditional analysis.

Another potential concern with this analysis is that our sample of loans might consist of risky securities, which face adverse selection costs similar in magnitude to equity.[23] In this instance, the distinction between debt and equity is less clear according to the pecking order. To address this issue we compare the duration matched credit spreads of our loans to that of investment grade public debt. Specifically, we take each loan and subtract off the yield of the treasury security with the closest maturity. The average of these spreads is 2.0%, compared to an average spread between BAA 30-year bonds and 30-year T-bills of 1.7% for the same 1987-2000 period.[24] This 30 basis point spread is more likely to be a liquidity premium than a difference in default risk, suggesting that our sample of loans have a risk profile similar to that of a BAA bond. Coupled with higher recovery rates (Altman and Suggitt (2000)) and greater propensity to be secured relative to public debt (Bradley and Roberts (2003)), these results suggest that our sample of loans are on the lower end of the risk spectrum for debt instruments.

4.3 Does Leverage Targeting Explain the Security Issuance Decision?

Another alternative explanation for the pecking order's poor performance in identifying debt and equity issuances is that firms are behaving according to a leverage targeting strategy, as various tradeoff theory's predict. Thus, we now examine the ability of leverage targeting to identify debt and equity issuance decisions, noting that this is not a test of the tradeoff theory, per se, but, rather, a comparison between the ability of the two theories to describe financing decisions. And, by focusing on somewhat narrow interpretations of the two theories, we can more easily separate their implications, which often overlap (Fama and French (2002)).

While different versions of the tradeoff theory weigh different costs and benefits associated with financial leverage, most imply the existence of an optimal level or range of leverage.[25] In this setting, financing decisions are governed by the deviation from the optimum so that when leverage is above the optimum firms will lever down and vice versa. This rule raises two issues. First, firms do not always adjust the capital structure in response to deviations from the optimum, as is the case when adjustment costs are present (e.g., Fischer, Heinkel, and Zechner (1989)). However, since we are modeling

[23]We thank Michael Lemmon for pointing out this possibility.

[24]The interest rate data come from the FRED database.

[25]This is not universally true, as illustrated by Hennessy and Whited (2004), however, there exist far more examples where this is the case (e.g., Bradley, Jarrell, and Kim (1984), Fischer, Heinkel, and Zechner (1989), Goldstein, Ju, and Leland (2001), Leland (1994,1998), Leland and Toft (1996), Mauer and Triantis (1995), Myers (1977), Strebulaev (2004), and Titman and Tsyplakov (2003)).

observed financing decisions, according to a tradeoff theory the benefit of adjusting must outweigh the cost. So, the presence of adjustment costs do not cloud our inferences. Second, firms can adjust their capital structures through repurchases and retirements, as well as issuances. Thus, we restrict our inferences here to statements only about the tradeoff theory's ability to characterize issuance decisions.[26]

Mathematically, our implementation of the tradeoff hypothesis is:

$$Equity_{it} = \begin{cases} 1 & (Leverage_{it-1} - Leverage^*_{it}) > 0 \\ 0 & otherwise \end{cases} \tag{15}$$

where $Leverage_{it-1}$ is the book leverage (total debt / total assets) for firm i in period $t-1$ and $Leverage^*_{it}$ is the optimal or target level of leverage. Following the existing empirical literature, we characterize the optimum as a function of various determinants prescribed by theory:

$$Leverage^*_{it} = W_{it-1}\delta + \zeta_{it}, \tag{16}$$

where W is a vector of determinants, δ an unknown parameter vector, and ζ is a random error term. As tradeoff theories are somewhat ambiguous about the internal-external decision, we assume that this first stage decision is governed by the same process as the pecking order (equations (9) and (10)). This assumption also facilitates comparisons between the results.

In specifying the determinants, W, we follow Frank and Goyal (2004), who provide an exhaustive analysis of the determinants of corporate leverage. They classify various factors into two categories: Tier I (most robust) and Tier II (less robust).[27] We use both sets of their factors in specifying W. For robustness, we also use the target specification in Hovakimian, Opler, and Titman (2001) (results not presented), whose framework is similar to ours.[28] As such, we also follow their estimation strategy here by first regressing

[26]In the case of dual issuances, we look at the net effect on leverage. A resulting increase (decrease) in excess of 5% of asset value is treated as a debt (equity) issuance. We also examine 1% and 3% thresholds in our robustness checks discussed in Appendix A.

[27]Their tier I factors include: median industry leverage, Altman's Z-score, Sales, an indicator for whether the firm paid a dividend, market-to-book ratio, intangible assets, and collateral. The tier II factors include: variance of asset returns, net operating loss carry forwards, an indicator for financially constrained, Profitability, log change in asset value, the top statutory tax rate, and short term interest rate. The Compustat definitions of each of these variables are outlined in Table 1 of their paper and, by and large, follow conventions used throughout the capital structure literature.

[28]Their determinants are three-year mean return on assets (EBITDA divided by total assets), two-

book leverage on the determinants W to obtain predicted values that serve as our estimate of target leverage. We estimate these parameters outside of the probit model to preserve their interpretation as sensitivities of target leverage to the determinants, as opposed to sensitivities of the financing decisions to the determinants.

However, a departure of our model from that of Hovakimian, Opler, and Titman is that we do not include other variables that they suggest may be correlated with the deviation from the target. We do this for two reasons. First, as they note, the additional variables have several alternative interpretations that would only serve to cloud the interpretation of the model as one in which financing decisions are dictated solely by a concern to adjust towards a target. Second, our goal here is not a test of the tradeoff theory but, rather, a comparison of the relative importance of leverage targeting versus pecking order behavior.

Panel B of Table 4 presents the results, which show that leverage targeting does slightly worse in identifying debt and equity issuance decisions, with 32% of firms in our sample adhering to a leverage targeting strategy in their debt and equity issuance decisions.[29] This result is consistent with the findings of Hovakimian, Opler, and Titman (2001), as well as others, who find that leverage targeting behavior appears to be concentrated in retirement decisions. Thus, the motivation behind issuance decisions appears not to be governed exclusively by either pecking order, debt capacity, or leverage targeting concerns.

5. Integrating Tradeoff Concerns Into a Pecking Order Framework

The results thus far lead us now to examine Myers' (1984) suggestion to integrate pecking order and tradeoff concerns into one framework. We operationalize this integration in our current framework by modifying the specification of the $CashTarget$ and $MaxDebt$ to include various determinants of optimal cash balances and optimal leverage, as prescribed by the corresponding literatures. Thus, the section tests the possibility that different concerns are relevant under different circumstances, as well quantifying how well existing theories can describe actual financing behavior. This last point is particularly relevant

year stock return, market-to-book ratio (market value of equity plus book value of debt divided by total assets, log(total assets), R&D expenditures divided by sales, Selling expense divided by sales, tangible assets divided by total assets, and net operating loss carryforwards divided by total assets.

[29] The prediction accuracy results in the first rung (internal-external) is not identical to that in Panel A because the sample changed slightly as a result of missing observations for the estimated leverage target.

in light of the conclusion of Fama and French (2004) that suggests existing theories (i.e., pecking order and tradeoff) fail to adequately describe financing behavior.

The economic implication of our integrated model is that alternative considerations may now justify deviating from the pecking order's financing hierarchy. For example, Panel B of Figure 1 illustrates a situation in which the firm has a negative cash threshold, implying that its internal resources are less than it desires. Such a situation might arise due to a negative shock to cash flows or greater anticipated growth. Rather than expending most of the internal resources that it has, as the pecking order predicts, the integrated model enables this firm to turn immediately to the external capital markets. Similarly, Panel C of Figure 1 shows an overlevered firm, a situation that may arise from a negative equity shock, for example. If investment outstrips C^*, and consequently D^*, the integrated model allows the firm to turn directly to equity without first issuing debt. We now turn to a discussion of what those alternative considerations may be.

5.1 The Integrated Cash Threshold

Several studies (see, for example, Kim et al. (1998) and Opler et al. (1999)) argue that firms have an optimal cash level that balances the marginal costs and benefits of holding cash. The costs include a lower rate of return due to a liquidity premium and possible tax disadvantage. The benefits include the avoidance of transaction costs and other external financing costs, such as asymmetric information. Following these studies, we now specify the cash target as:

$$CashTarget^*_{it} = X_{it-1}\beta + \varepsilon_{it} \tag{17}$$

where β is a vector of unknown parameters, X_{it-1} is a vector of observed covariates lagged one period to mitigate any potential endogeneity problems, and ε_{it} is a mean zero normal random variable assumed to be independent across firms but correlated within firm observations. Dependence across firms each fiscal year is addressed by including year dummy variables (Petersen (2004)).

Since our focus here is not on the determinants of corporate liquidity, we only briefly discuss the variables and their motivation, referring the reader to the aforementioned studies for more detail. Firm size, as measured by the log of book assets, is used by Kim et al. to proxy for external financing costs and Opler et al. to capture economies of scale in cash management. The market-to-book ratio, defined as the ratio of total assets minus book equity plus market equity to total assets, proxies for growth opportunities. While we, like many previous studies (e.g., Titman and Wessels (1998), Kim et al. (1998), Opler et al. (1999) and others) use the market-to-book ratio to measure investment opportunities, it is a less than perfect proxy (see Erickson and Whited (2000)). As such, we include two additional measures of future investment opportunities: research and development expenditures and a forward looking measure of anticipated investment, which we measure with the average of actual investment over the next two years: $t + 1$ and $t + 2$.[30] We similarly define a forward looking measure of anticipated cash flows to capture expected profitability. Assuming firms are rational, these forward looking averages should represent a reasonable approximation of anticipated investment needs and profitability.[31]

We measure cash flow volatility by the historical standard deviation (using data during the previous 10 years, as available) of the ratio of EBITDA to total assets. Leverage is measured by the ratio of total debt (long term plus short term) to total assets. We also examine a measure of market leverage whose denominator is the sum of total debt and market equity but this has no consequences for the results and is not presented. Unlevered Altman's Z-score, defined as the sum of 3.3 times earnings before interest and taxes plus sales plus 1.4 times retained earnings plus 1.2 times working capital divided by book assets, is used to proxy for the likelihood of financial distress, as in previous studies by Mackie-Mason (1990) and Graham (1996). Net working capital is defined as total current assets, excluding cash, minus total current liabilities net of short term debt.

Several fixed effects are included in the model, beginning with a binary indicator for whether or not the firm paid a dividend in year $t-1$. This measure is intended to capture precautionary savings motives for the firm's payout policy, as well as possible financial constraints.[32] Finally, we include year and industry (2-digit SIC level) binary variables to account for any longitudinal or industry fixed effects.[33]

[30] We assume that missing values for the research and development variable are zero, and include a dummy variable equal to 1 for firms with zero or no reported R&D, similar to other studies such as Fama and French (2002) and Kayhan and Titman (2003).

[31] Excluding these forward-looking measures from the specification has little effect on the results, as does replacing them with one-period forecasts from an AR(1) model.

[32] Almeida, Campello and Weisbach (2003) and Faulkender and Wang (2004) use the ratio of total dividends plus repurchases to earnings as a proxy for financial constraints.

[33] Though Mackay and Phillips (2004) note that most variation in debt-equity ratios is firm-specific, there is still a significant amount of residual variation at the industry level.

5.2 The Integrated Debt Threshold

Many studies of capital structure (e.g., Titman and Wessels (1988), Hovakimian, Opler, and Titman (2001), Frank and Goyal (2003)) suggest that firms have an optimal leverage that balances the costs and benefits of financial leverage. The costs include financial distress costs and agency costs. The benefits include the tax deductibility of interest payments and the mitigation of free cash flow problems. As such, we specify the difference between $MaxDebt$ and $CashTarget$ as:

$$(MaxDebt^*_{it} - CashTarget^*_{it}) = Z_{it-1}\gamma + \omega_{it}, \tag{18}$$

where γ is a vector of unknown parameters, Z_{it-1} is a vector of observed covariates lagged one period to mitigate any potential endogeneity problems, and ω_{it} is a normal random variable assumed to be independent across firms but correlated within firm observations and contemporaneously correlated with ε_{it}.[34] Modeling the difference in equation (18) eases estimation, as discussed earlier, and enables us to interpret the sign of the coefficients as increasing (positive) or decreasing (negative) financial slack.

Because the specification in equation (18) aggregates the effect of the covariates, Z, on $CashTarget$ and $MaxDebt$, we begin by including all of the determinants of the cash target discussed above into our specification of Z. Relying on the existing capital structure literature, we recognize that many of the determinants of the cash target are also determinants of debt policy. As such, we include only four additional variables in Z, beyond what is specified in the cash target. The first variable is the ratio of physical plant, property and equipment to total assets and is intended to measure the ability of firms to secure physical assets in order to reduce the cost of debt capital. The second variable is the amount of time that the firm has been listed on Compustat, which proxies for the age of the firm (Lemmon and Zender (2003)). We also include last year's stock return, which captures both investment opportunities, as well as potential mispricing or information asymmetry in the sense of Myers and Majluf (1984). Finally, we include Graham's (1996) before-financing marginal tax rate to capture the tax benefit associated with debt financing.

5.3 Parameter Estimates

The parameter estimates are presented in Table 7 and are broadly consistent with expectations. For the cash target, we see that larger firms maintain relatively lower cash

[34] Again, cross-sectional dependence within years is captured by year dummy variables.

targets. This result is unsurprising as Table 3 suggests that internal resources are the primary source of investment funding for larger firms, who also have relatively lower future investment and consequently less need for financial slack. Larger firms are also more likely to access external capital markets at lower cost, resulting in a potentially lower liquidity requirement. Greater future investment, as captured by *Future Investment, R&D / Sales,* and *Market-to-Book*, is associated with greater cash targets, as it should be if internal funds are the first rung of the pecking order and financial slack is important. We also see that larger anticipated cash flows result in lower cash targets. As expected, Net Working Capital, which can be viewed as a substitute for cash, is negatively associated with cash targets.

However, several estimated coefficients are inconsistent with expectations. Dividend paying firms also have lower cash targets, which is a bit difficult to explain given this cash requirement and the fact that many firms maintain cash reservoirs earmarked for dividends (Kalay (1982)).

As with the cash target, most coefficients in the debt threshold have the expected sign. Higher cash flow volatility and lower Z-scores are associated with a greater need for financial slack, consistent with the importance of bankruptcy costs. Greater investment opportunities as captured by *Future Investment, R & D / Sales* and *Market-to-Book*, require more financial slack. Older firms and those with greater asset tangibility appear to require less financial slack.

5.4 Predictive Accuracy

Panel C in Table 4 presents the prediction accuracy results for the integrated model. The accuracy rates for the internal-external decision increase significantly from 62% under the pecking order to 71% in the integrated specification. For the debt-equity choice, the improvement is even more striking. Moving from the pecking order model to the integrated model enables us to accurately identify the financing decisions of almost 75% of our sample.

We also perform likelihood ratio tests (not reported) comparing this integrated specification with the pecking order and tradeoff specifications above. Consistent with the increase in predictive ability, the test rejects the restrictions imposed by both pecking order and tradeoff at all conventional significance levels. These results suggest Myers' strategy can be fruitful in identifying a predictive model of issuance choice. They also illustrate that previous examinations pitting pecking order and tradeoff theories against one another may be somewhat misplaced. The integrated model shows that different considerations take precedent at different times. Thus, one possible direction for future research is to bridge the gap between these two theories, as well as looking for alternative explanations for those minority of firms whose financial policy is unexplained by the integrated model.

An additional benefit of our integrated specification is that it enables us to measure the relative contributions of various determinants in identifying debt and equity decisions by estimating the model on different subsets of the variables. Thus, we can attempt to distinguish among the importance of competing explanations in so far as the proxies allow for this delineation. To perform this comparison across specifications though, we require that the specification of the first stage decision (internal-external) be the same since the predictive ability in the debt-equity decision varies with that in internal-external decisions, as discussed earlier. The predictive accuracy results for various specifications appear in Table 8.

What the results show is that extending the pecking order to include alternative considerations in the debt-equity decision leads to a significant improvement in the explanatory ability of the model. Incorporating proxies for the tax benefit (Graham's (1996) before-financing marginal tax rate, net operating loss carry-forwards) and bankruptcy costs (tangible assets, Altman's Z-Score) associated with debt leads to an improvement from accurately characterizing 35% of the sample financing decisions to 53% of those decisions.[35] Just incorporating variables related to investment opportunities and equity mispricing (future investment, market-to-book, stock returns) leads to an even greater improvement, accurately identifying the financing decisions of 61% of our sample. Disentangling the interpretation of market-to-book and stock returns as proxies for investment opportunities and mispricing is difficult, however, we believe that realized future investment is less likely to capture security mispricing relative to the other two proxies. Thus, column four presents the results of using just future investment, which suggest that mispricing may play a relatively important role in the equity issuance decision, consistent with previous studies. Ultimately, it is the combination of these alternative explanations (tradeoff forces, security mispricing) within the pecking order framework that result in a relatively high prediction accuracy rate.

[35]The results for the pecking order are not identical to those in Panel A of Table 4 because the sample is constrained to nonmissing data for all variables used in the integrated model. This ensures that our comparisons are based on the same set of observations, though the difference in results between the two samples is negligible.

6. Information Asymmetry and the Pecking Order

We now turn to the second question posed at the outset: What economic force is driving pecking order behavior? If information asymmetry is the primary driver behind the pecking order's financing hierarchy, as suggested by Myers and Majluf (1984), the variation in this factor should correlated positive with firms' adherence to the hierarchy. When information asymmetry is high (low), it is costly (not costly) for firms to deviate from the hierarchy. In order to test this hypothesized relation and determine the significance of the link between information asymmetry and the pecking order, we examine several measures of information asymmetry motivated by previous empirical studies.

Korajczyk, Lucas and McDonald (1990, 1991), Choe, Masulis and Nanda (1993), and Bayless and Chaplinsky (1996)) identify the impact of time-variation in adverse selection costs on security issuance decisions. Choe, Masulis and Nanda document that the variation in asymmetric information costs is associated, at least in part, with business cycle movements. Therefore, we split the years in our sample period into "hot" (high equity issuance), "cold" (low equity issuance), and neutral years, following Bayless and Chaplinsky (1996). We then estimate our model separately on the "hot" and "cold" subsamples. If our previous results are being driven by time-varying asymmetric information costs, we would expect the model to perform significantly better in the "cold" periods (high cost) than in the "hot" periods.

We define hot and cold years in three ways. First, we use the periods defined by Bayless and Chaplinsky, who use monthly data. If at least seven months of a sample year are designated a hot period by Bayless and Chaplinsky (and no months in that year designated cold), we define that year to be hot, and vice versa for cold years. Since their sample only extends through 1990, we define two alternative measures to utilize our entire sample period. We rank each year according to either the number of issuances scaled by the number of sample firms or the total net issuance volume scaled by the total market value of equity in the sample. (This last measure controls for market value fluctuations and most closely matches the measure reported by Bayless and Chaplinsky.) We then define hot years to be those years in the upper quartile (low information asymmetry) and cold years to be those years in the bottom quartile (high information asymmetry).

We also examine several firm-specific measures of information asymmetry including the ratio of intangible assets to total assets (Harris and Raviv (1991)), the dispersion in analyst forecasts (Gomes and Phillips (2004)), and analyst coverage of the firm (Chang, Dasgupta, and Hilary (2004)). For the first two measures, we stratify the sample into low, medium, and high information asymmetry according to the lower, middle, and upper third of the measures' distributions. For analyst coverage, we identify firm-years for which there was either no analyst coverage (high information asymmetry) or at least one analyst covering the firm (low information asymmetry). We also examine alternative breakpoints for the analyst coverage proxy (e.g., low information asymmetry is less than or equal to 1, 2 analysts covering the firm) but these changes have little effect on the results and are therefore not presented.

As a final proxy for information asymmetry, we incorporate issuance data from SDC, Dealscan, and FISD to identify public and private, debt and equity issuances. The motivation is that public and private issuances are exposed to more or less, respectively, information asymmetry between managers and investors. For each of the three databases, we attach GVKEY and PERMNO identifiers in several ways using the historical header file in CRSP. For SDC, we use information on cusips and ticker symbols, in conjunction with company names. For Dealscan, we use ticker symbols and company names. Finally, for FISD, we rely on cusips and company names. For all matches with CRSP/Compustat, company names are checked, as are issuance dates to ensure that the information in the header file is contemporaneous with the issuance. While the issuance data spans the period 1970 to 2003, the coverage is significantly more complete beginning in the late 1980s. With this data, we are able to identify 38% of the security issuances defined using the 5% cutoff.[36]

Table 9 presents the results of the analysis by showing the average prediction accuracy for the debt-equity decision. Panel A presents results using the pecking order specification, while Panel B presents the results using the integrated model.[37] Contrary to what one would expect if information asymmetry drives firms to following a pecking order of financing choices, we find no evidence of improvement in model fit as the degree of information asymmetry increases. This inference is true for both pecking order and integrated models, and is robust across most all of the various proxies for information asymmetry.

[36]There are many reasons for not finding a one-to-one correspondence. First, most financing decisions are private debt issuances for which we have the least amount of information. Further, even when a firm enters into a private debt agreement, most tranches (67%) are lines of credit that need not be drawn down at inception. There may also be misclassifications due to calendar time and fiscal year-end differences, as well as non-overlap between the various datasets.

[37]In unreported analysis, we also examine the predictive accuracy across information asymmetry measures for the internal- external decision and find similar results. However, given the high correlation between our PO variable and our measure of external finance, these results are less informative.

Focusing first on the pecking order model in Panel A, we see that, if anything, prediction accuracy *decreases* with our measures of information asymmetry. For example, for firm-years in which forecast dispersion was highest (i.e., high information asymmetry), the model correctly identifies 35% of the external issuance decisions but, when the forecast dispersion was lowest (i.e., low information asymmetry), the model correctly identifies 40%. For each measure of information asymmetry, with the exception of public vs. private issuances, the model's prediction accuracy either decreases with information asymmetry or is negligibly different, counter to the hypothesis that information asymmetry implies a pecking order of financing decisions. Even when we focus on firms that have the least amount of risk-free debt capacity (as identified by the lower third of Altman's Z-score distribution), the results (not presented) are unaffected.

When we examine the integrated model in Panel B, we see a similar result. For all but one (firm age) measure of information asymmetry, prediction accuracy either decreases or is unchanged as information asymmetry increases. The one measure that showed a consistent pattern with predictive accuracy in the pecking order model, public vs. private issuances, no longer shows a difference here. Overall, these results suggest that the link between adherence to the pecking order and information asymmetry is empirically weak at best. However, we emphasize that this is a statement only about the relevance of information asymmetry as the force behind the pecking order and not a statement about the importance of information asymmetry as a determinant of capital structure. Thus, for the pecking order behavior that we do observe there must be some other economic force, such as taxes or agency costs, that is driving this behavior. We leave further examination of this issue to future research.

7. Concluding Remarks

We develop an empirical model and test of the pecking order hypothesis. Our simulation experiment shows that our tests can both identify and quantify pecking order behavior in the data, whereas the testing framework proposed by Shyam-Sunder and Myers (1999) cannot. Our results suggest that the pecking order, as well as the tradeoff theory, struggle in characterizing the issuance decisions of firms when the two theories are examined in isolation. However, integrating the two views offers a substantial improvement in the model's predictive ability, which accurately identifies almost 75% of the decisions in our sample. Thus, our results lead us to first conclude that an integration of pecking order and tradeoff theories offers a reasonable description of the large majority of financing decisions observed in the data, and that future research might aim to bridge the gap between these two views.

An closer examination of the factor(s) responsible for this improvement reveals that while traditional tradeoff factors (taxes, bankruptcy costs, investment opportunities) have a significant impact on the financing decision, variables most closely related to investment opportunities and mispricing (in the sense of Myers and Majluf (1984)) have the economically largest impact. This results proves particularly interesting because it shows how the mispricing story put forth by Myers and Majluf (1984) appears consistent with the data, whereas the pecking order financing hierarchy is less appropriate. Indeed, our examination of the association between measures of information asymmetry and adherence to the pecking order's financing hierarchy reveal little, if any, link between the two. Thus, we show empirically, what Yilmaz (2004) illustrates theoretically, that the pecking order does not seem to be an implication of information asymmetry.

Appendix A: Robustness Checks

Though we have briefly addressed various robustness concerns throughout the paper, we report the results of several specific tests in Table 10. While we focus our discussion on changes to our integrated model specification, all of the inferences carry over to the original pecking order specification and, as such, these results are not presented. The first column reproduces the prediction accuracy results of our integrated model. The second column shows the results when we expand our definition of investment to include both advertising and research and development expenditures. Many of the small firms issuing equity in the 1990s were likely to be focused on the development of intellectual property (e.g. high tech and pharmaceutical companies) or young firms trying to establish a brand image (e.g. internet start-ups). While R & D and advertising are often expensed in their accounting treatment, for such firms they may be significant strategic investments. However, the results indicate that this adjustment does not increase the model's ability to explain firms' financing choices. If anything the predictive accuracy is slightly worse for debt and equity issuers. Thus, while there may be important investments for some firms beyond that measured by capital expenditures, this does not seem to account for those issuances that the pecking order fails to predict.

We also examine the robustness of our results to changes in the definition of a debt issuance. The third column displays the results when debt issuance is defined as the sum of net long term debt issuance and the change in short debt from the statement of cash flows. Since the change in short term debt is often missing, especially prior to 1987, this significantly reduces the sample size. However, as can be seen, the results are largely unaffected. The fourth column uses only long term debt issuance to identify debt issues. This addresses the concern that since most of the assets in our original investment measure are likely long-lived assets, firms may not be actively financing these assets with short term debt. While this change has a slight effect on the model's ability to distinguish between internal financing and external financing choices, it has no affect on its ability to predict debt and equity issuances.

We then examine the effect of using alternative (1% and 3%) thresholds in our definition of debt and equity issuances. The results are shown in columns 5 and 6. Again, the results are not altered substantially, but if anything, the model is less able to classify financing decisions as the threshold is lowered. This suggests that either the model is simply better able to identify relatively larger financing decisions or those decisions more likely related to investment financing, in so far as non-investment financing is more prevalent among smaller issuance sizes.

Finally, we further examine the sensitivity of our results to changes in the cash target and debt capacity specification. The results presented thus far have been flexible in terms of including what we believe to be all the relevant determinants of these thresholds. However, thus far we have only considered linear functions of those determinants. In column 7 we expand our specification to include second and third order polynomial terms of all of our independent variables. Despite a large increase in the model degrees of freedom, the improvement in predictive ability is slight, suggesting that limiting our attention to linear functions is does not appear to be overly restrictive.

In column 8, we add to this polynomial specification several additional variables that are related to alternative capital structure theories, but not necessarily in the spirit of the pecking order. These include Graham's before-financing marginal tax rate, as well as lagged firm-specific and market-wide stock returns. We do this to ensure that our results are not being driven by the omission of some important factor and to see how well the model can do if we are "liberal" in what we include. The results improve slightly with the inclusion of these additional variables, though not enough to change any inferences.

Appendix B: Likelihood Derivation

This appendix derives the likelihood function for the integrated (i.e., most general) specification. Alternative specifications examined in the body of the paper correspond to either parameter restrictions and/or changes in the covariate specification.

In the data, there are three possible outcomes beginning with the decision to use internal funds (i.e., $External_{it} = 0$). In this case, we do not observe the decision between debt and equity and thus the likelihood of this outcome is simply:

$$\begin{aligned}
\Pr(External_{it} = 0) &= \Pr(y^*_{1it} \leq 0) \\
&= \Pr\left(Inv_{it} - CashBal_{it-1} - CashFlow_{it} + X_{it-1}\beta\right. \\
&\quad \left. + \varepsilon_{it} \leq 0\right) \\
&= \Phi\left(-Inv_{it} + CashBal_{it-1} + CashFlow_{it} - X_{it-1}\beta\right) \quad (19)
\end{aligned}$$

where $\Phi(x)$ is the probability that $\varepsilon \leq x$ and ε is distributed N(0,1).

The second scenario is when the firm chooses to go to the external capital markets and then decides to use debt financing. This outcome occurs with probability:

$$\begin{aligned}
& \Pr(External_{it} = 1 \cap Equity_{it} = 0) \\
= \; & \Pr(y^*_{1it} > 0 \cap y^*_{2it} \leq 0) \\
= \; & \Pr\left(\{\varepsilon_{it} > -Inv_{it} + CashBal_{it-1} + CashFlow_{it} - X_{it-1}\beta\}\right. \\
& \left. \cap \{\omega_{it} \leq -Inv_{it} + CashBal_{it-1} + CashFlow_{it} + Z_{it-1}\gamma - Debt_{it-1}\}\right) \\
= \; & \Pr\left(\{\varepsilon_{it} \leq Inv_{it} - CashBal_{it-1} - CashFlow_{it} + X_{it-1}\beta\}\right. \\
& \left. \cap \{\omega_{it} \leq -Inv_{it} + CashBal_{it-1} + CashFlow_{it} + Z_{it-1}\gamma - Debt_{it-1}\}\right) \\
= \; & \Phi_2\left(Inv_{it} - CashBal_{it-1} - CashFlow_{it} + X_{it-1}\beta,\right. \\
& \left. -Inv_{it} + CashBal_{it-1} + CashFlow_{it} + Z_{it-1}\gamma - Debt_{it-1}, -\rho\right) \qquad (20)
\end{aligned}$$

where Φ_2 is the bivariate standard normal with correlation coefficient ρ.

The third and final scenario occurs when firms choose to go to the external capital market and then decide to use equity financing. This outcome occurs with probability:

$$\begin{aligned}
& \Pr(External = 1 \cap Equity = 1) \\
= \; & \Pr(y^*_{1it} > 0 \cap y^*_{2it} > 0) \\
= \; & \Pr\left(\{\varepsilon_{it} > -Inv_{it} + CashBal_{it-1} + CashFlow_{it} - X_{it-1}\beta\}\right. \\
& \left. \cap \{\omega_{it} > -Inv_{it} + CashBal_{it-1} + CashFlow_{it} + Z_{it-1}\gamma - Debt_{it-1}\}\right) \\
= \; & \Pr\left(\{\varepsilon_{it} \leq Inv_{it} - CashBal_{it-1} - CashFlow_{it} + X_{it-1}\beta\}\right. \\
& \left. \cap \{\omega_{it} \leq Inv_{it} - CashBal_{it-1} - CashFlow_{it} - Z_{it-1}\gamma + Debt_{it-1}\}\right) \\
= \; & \Phi_2\left(Inv_{it} - CashBal_{it-1} - CashFlow_{it} + X_{it-1}\beta,\right. \\
& \left. Inv_{it} - CashBal_{it-1} - CashFlow_{it} - Z_{it-1}\gamma + Debt_{it-1}, \rho\right) \qquad (21)
\end{aligned}$$

Let ψ_{1it}, ψ_{2it}, and ψ_{3it} denote the three terms in equations (19), (20), and (21), respectively. The log likelihood is thus:

$$\begin{aligned}
\log L_{it} = \; & \textstyle\sum_{i=1}^{N} \sum_{t=1}^{T_i} \; (1 - External_{it}) \log(\psi_{1it}) + External_{it}(1 - Equity_{it}) \log(\psi_{2it}) \\
& \qquad + External_{it}(Equity_{it}) \log(\psi_{3it}) \qquad (22)
\end{aligned}$$

The standard errors are adjusted for clustering by employing the generalized estimation equation approach of Liang and Zeger (1986)

Appendix C: Simulations

This appendix details the simulations. We begin by discussing the mechanics of the simulations, followed by a discussion of its parametrization.

B.1: Mechanics

Our simulation proceeds in two concurrent steps. First, we draw random triplets from a trivariate normal distribution with mean vector $[\mu_{Inv}, \mu_C, \mu_D]$ and covariance matrix:

$$\begin{bmatrix} \sigma^2_{inv} & \sigma_{C,inv} & \sigma_{D,inv} \\ \sigma_{inv,C} & \sigma^2_C & \sigma_{D,C} \\ \sigma_{inv,D} & \sigma_{C,D} & \sigma^2_D \end{bmatrix}$$

where C and D (note the lack of *) correspond to:

$$C \rightarrow CashBal + CashFlow - X\beta \quad (23)$$

$$D \rightarrow CashBal + CashFlow - Debt + Z\gamma \quad (24)$$

from equations (10) and (12) and each term is implicitly normalized by assets as of the previous period. Thus, C and D are simply C^* and D^* less the error terms, ε and ω, respectively.

Second, we independently draw random pairs from a bivariate normal distribution with zero mean vector and covariance matrix:

$$\begin{bmatrix} \sigma^2_\varepsilon & \sigma_{\omega,\varepsilon,} \\ \sigma_{\varepsilon,\omega} & \sigma^2_\omega \end{bmatrix}$$

These random draws correspond to the error terms ε and ω in equations (10) and (12). The simulated error terms are then added to the simulated C and D above to obtain the C^* and D^* required for simulating the financing decisions. The normality assumption is made to coincide with our empirical model, a bivariate probit.

With a simulated triplet (Inv, C^*, D^*), we construct financing decisions using two different decision rules. The first rule corresponds to the pecking order hypothesis and is defined by equations (9) and (11). That is, internal funds are used if $Inv > C^*$, otherwise external funds are used. Conditional on using external funds, debt finance is used if $Inv < D^*$, otherwise equity finance is used. The second decision rule randomly chooses the financing decision (internal, debt, or equity), independent of the simulated data, but with probabilities equal to that in our observed data. Since our sample is chosen to ensure an equal number of internal and external (debt and equity) issuances, the probability of an internal or external issuance is 0.5 and, conditional on an external issuance, the probability of a debt or equity issuances is also 0.5.

These two sets of decisions correspond to 100% and 0% of the sample adhering to the hierarchy, respectively. To obtain intermediate realizations, we vary the fraction of the simulations that use the pecking order decision rule and the random decision rule by increments of 10%. This produces 11 sets of financing decisions, each of which is used in conjunction with the simulated data (Inv, C, D) to estimate the model by maximum likelihood. For each of the 11 sets of estimates, we map the predicted probabilities into predicted financing decisions using the following mapping. If the predicted probability of an external issuance exceeds 0.5, then the predicted decision is an external issuance. Otherwise, the predicted decision is an internal issuance. And, conditional on an external issuance, if the predicted probability of an equity issuance exceeds 0.5, then the predicted financing decision is an equity issuance. Otherwise, the predicted decision is a debt issuance.

To reduced simulation error, this entire process is repeated 500 times and the resulting predictions are averaged across the 500 simulations. The results are presented in Table 1.

B.2: Parametrization

Before implementing the procedure described above, we must specify the means, variances and covariances in a manner consistent with the data. That is, the characteristics of the simulated data, (Inv, C, D) and (ε, ω), must match those of their counterparts in the data. For example, we specify the first two moments of Inv, μ_{Inv} and σ^2_{Inv}, as the sample mean and sample variance of capital expenditures divided by assets. Other elements of the simulation, however, have no directly observable counterpart in the data and, as such, we require empirical proxies. In what follows, all variables are normalized by total assets as required by the empirical implementation.

Beginning with $C = CashBal + CashFlow - X\beta$, we require an estimate of β, which we obtain from the following regression:

$$\frac{CashBal_{it}}{Assets_{it-1}} = X_{it-1}\beta_C + \varepsilon_{it} \tag{25}$$

where the design matrix X consists of the variables used in the integrated model presented in the body of the paper. Thus, our proxy of the cash target $(CashTarget = X\beta + \varepsilon)$ follows that found in the cash holdings literature (e.g., Opler et al. (1999), and Kim, Mauer and Stohs (1998)). With the predicted values from this regression, we construct our empirical proxy of C:

$$\hat{C}_{it} = CashBal_{it-1} + CashFlow_{it} - X_{it-1}\hat{\beta}_C,$$

where all variables are scaled by $Assets_{it-1}$. Using $\hat{C}$, we define σ_C as the sample variance of $\hat{C}$ and $\sigma_{Inv,C}$ as the covariance between capital expenditures divided by assets and $\hat{C}$. We use the variance of the estimated residuals from equation (25) to specify σ_ε^2 since they represent our proxy for ε, the error term of the cash target (equation (17)). We note that this estimate represents an upper bound on the variance of ε because our proxy is a noisy measure of the true, unobservable, target.

We follow an analogous procedure in deriving empirical proxies for $D = CashBal + CashFlow - Debt + Z\gamma$ and ω. We estimate the following regression:

$$\frac{Debt_{it} - CashBal_{it}}{Assets_{it-1}} = Z_{it-1}\beta_D + \omega_{it} \tag{26}$$

where the design matrix Z consists of the variables used in the integrated model presented in the body of the paper. Thus, our proxy for the debt target follows that found in the capital structure literature (e.g., Hovakimian, Opler, and Titman (2001)). We take the predicted values from equation (26) to construct our empirical proxy of D:

$$\hat{D}_{it} = CashBal_{it-1} + CashFlow_{it} - Debt_{it-1} + Z_{it-1}\hat{\beta}_D,$$

where all variables are scaled by $Assets_{it-1}$. Using $\hat{D}$, we define σ_D^2 as the sample variance of $\hat{D}$, $\sigma_{Inv,D}$ as the sample covariance between capital expenditures divided by assets and $\hat{D}$, $\sigma_{C,D}$ as the sample covariance between $\hat{C}$ and $\hat{D}$. We use the variance of the estimated residuals from equation (26) to specify σ_ω^2 since they represent our proxy for ω, the error term of difference in the maximum debt level and cash target (equation (18)). The covariance between ε and ω is used to specify $\sigma_{\varepsilon,\omega}$.

The two parameters remaining to be specified, μ_C and μ_D, are chosen so that the proportion of internal to external issuances and debt to equity issuances match those found in the data (50-50 in our balanced sample). Note that adjusting these means in this way is not a departure from consistency with the data, since these variables are not observed and, therefore, their sample means cannot be measured. Rather, consistency with the data is ensured by matching the proportion of financing decisions in the simulated data with that found in the observed data.

A final comment on the parametrization pertains to the variances of the two error terms, σ_ε and σ_ω. These are arguably the most important parameters as they have the largest impact on the prediction accuracy rates. Intuitively, the larger the error variance the more difficult it is for the econometrician to identify financing decisions from the observed data since it is "noisier." We examine alternative error variances corresponding to different empirical specifications in equations (25) and (26). The simulation results are only moderately affected and, as such, we present only those corresponding to the integrated model specification, which provides a more conservative estimated of our estimated prediction accuracy.

B.3: Shyam-Sunder and Myers (1999) Model

For the estimation of the Shyam-Sunder and Myers (1999) model (equation (13)), we require the change in debt, change in equity and total financing deficits implied by each sequence of financing decisions. The pecking order is ambiguous on how to make this translation, as it depends on the nature of adjustment costs and value of future financial slack. Consider the case where a firm's desired investment is \$150 and they have internal funds of \$100 and additional debt capacity of \$100. Under the pecking order, ignoring dynamic considerations and transactions costs, we would expect the firm to fund the first \$100 of investment with internal funds and the next \$50 with new debt. However, given a likely desire to minimize transactions costs and preserve future financial slack, it may be more desirable to fund the entire \$150 with new debt. This latter case is consistent with the empirical evidence in Stafford (2001) that cash balances tend to increase when firms make large investments and with the fact that dual debt and equity issuances are rare in our sample relative to pure equity issuances.

We therefore calculate ΔD, ΔE and $FinDef$ in two manners. In both methods, if the financing decision is to use internal funds, $\Delta D = \Delta E = 0$. In the first approach, if the financing decision is a debt issuance then ΔD equals the difference between the simulated investment and cash threshold (C^*) and $\Delta E = 0$. If the financing decision is an equity issuance then ΔE is equal to the difference between investment and the debt threshold (D^*) and ΔD is equal to ($D^* - C^*$). In the second approach, which allows for the impact of transaction costs and valuable financial slack, if the financing decision is a debt issuance then ΔD is set equal to investment and $\Delta E = 0$. If the financing decisions is a debt issuance then ΔE is set equal to investment and $\Delta D = 0$. In both cases, $FinDef = \Delta D + \Delta E$, consistent with the accounting identity. Since both cases have little effect on the estimation results, we focus on those obtained using the second decision rule, which are presented in Table 1.

For the issuance decisions generated from the random model, we note that there is no relation between the financing choice and the size of investment relative to available cash and debt capacity. This results in cases where, for example, investment is less than available cash, but the firm issues debt. Therefore, we cannot use the first approach for calculating ΔD and ΔE for the random model simulation and rely only on the second approach. When the Shyam-Sunder and Myers regression is estimated using the data generated according to the pecking order, however, we obtain similar results from each approach for calculating ΔD and ΔE. Therefore, we do not believe that this assumption is a serious limitation.

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Figure 1

Empirical Implications of the Modified Pecking Order

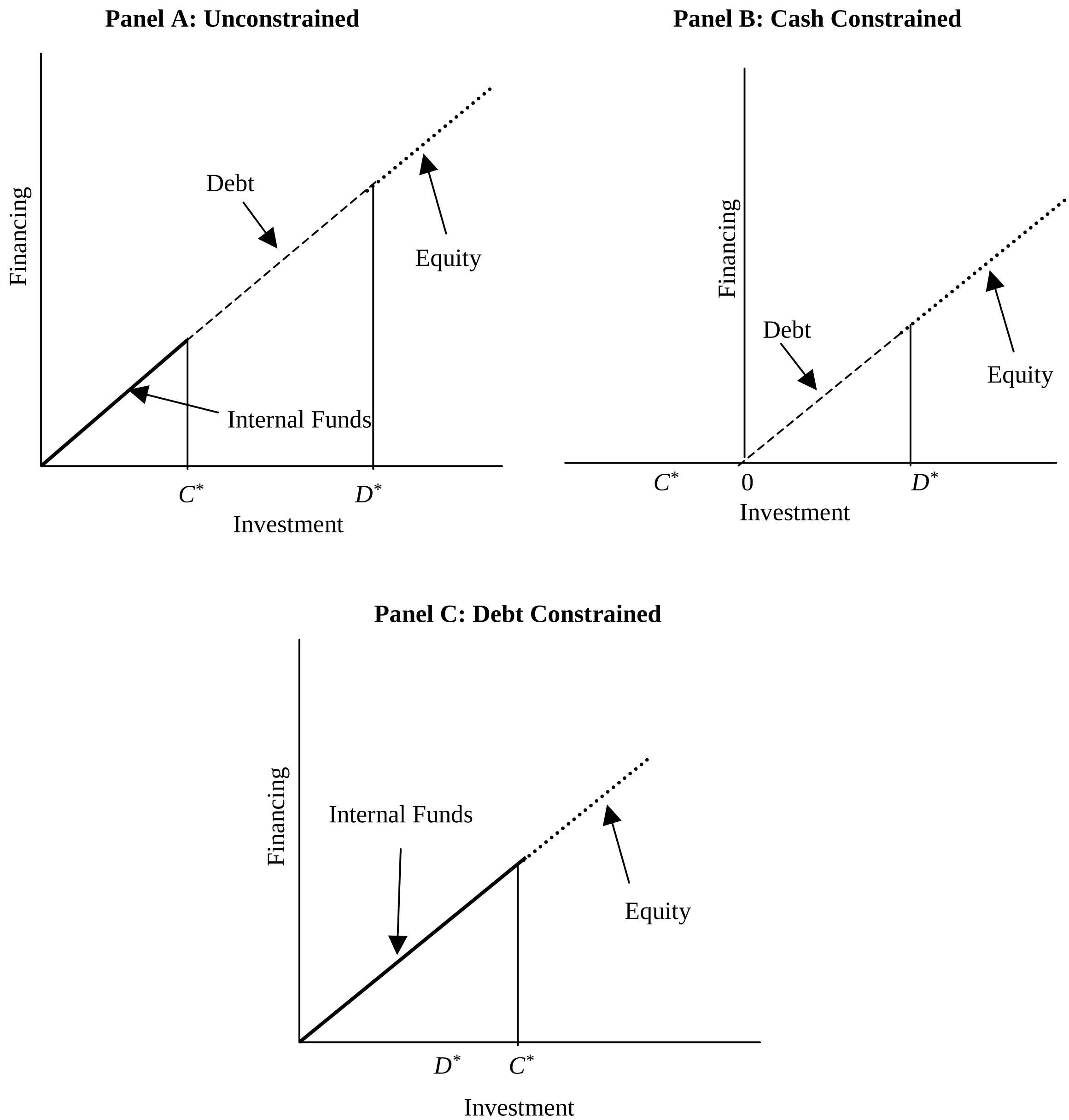

Table 1
Model Simulation Results

The model and simulation experiment are described in Appendix B. Panel A presents the prediction accuracy of the empirical pecking order model for eleven sets of simulated financing decisions that vary in the degree to which they adhere to the pecking order's financing hierarchy. For example, the column marked 50% corresponds to a simulated series of financing decisions in which half are generated according to the pecking order decision rule and half are generated according to a random decision rule. The pecking order decision rule dictates that internal funds are used if investment is less than internal resources and external funds are used otherwise. If external funds are used then debt is used first, followed by equity if investment is sufficiently large. The random decision rule randomly allocates internal-external and debt-equity decisions such that the ratios of these two sets of decisions match those found in the data. Appendix C discusses the details of the simulation experiment in detail. Thus, for the 50% column, 66% (67.1%) of simulated internal (external) financing decisions and 38.2% (50.4%) of the simulated debt (equity) decisions are accurately predicted by the model. The "Average Correct" row presents an equal weighted average of the corresponding two financing decisions. The "Improvement" row presents the increased prediction accuracy of the model over a naive predictor that randomly guessed between debt and equity with equal probability. Thus, for the 50% column, 67.1% of the external issuances are accurately classified suggesting that a naive classification rule would get half (33.5%) of the debt and equity issuances correct. Since the model got 44.3% correct, this corresponds to an improvement of approximately 10.7%. Panel B presents coefficient estimates and R-squares of the Shyam-Sunder and Myers (1999) regression, using the same sets of simulated data. The regression is:

$$\Delta Debt_t = \alpha + \beta \text{Financial Deficit}_t + \varepsilon_t,$$

where

$$\text{Financial Deficit}_{it} = Dividends_{it} + Investment_{it} + \Delta WorkingCapital_{it} - CashFlow_t.$$

Panel A: Prediction Accuracy

	Percent of Firms Following Pecking Order										
Simulated Decision	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
Internal Finance	49.9%	54.2%	56.4%	60.1%	63.9%	66.0%	70.0%	74.7%	77.6%	80.9%	85.4%
External Issuance	50.3%	53.5%	56.8%	60.2%	64.8%	67.1%	71.1%	75.9%	79.5%	83.1%	86.3%
Average Correct	50.1%	53.8%	56.6%	60.2%	64.4%	66.5%	70.6%	75.3%	78.5%	82.0%	85.8%
Debt Issuance	39.8%	24.3%	23.8%	29.1%	34.8%	38.2%	40.6%	46.9%	49.4%	53.9%	59.8%
Equity Issuance	12.3%	32.9%	40.8%	41.2%	46.8%	50.4%	55.8%	59.9%	65.0%	67.4%	70.8%
Average Correct	26.0%	28.6%	32.3%	35.1%	40.8%	44.3%	48.2%	53.4%	57.2%	60.6%	65.3%
Improvement	0.9%	1.9%	3.9%	5.0%	8.4%	10.7%	12.7%	15.4%	17.5%	19.1%	22.1%

Panel B: Shyam-Sunder and Myers Regression Coefficient Estimates

	Percent of Firms Following Pecking Order										
	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
$\hat{\beta}$	0.72	0.70	0.72	0.71	0.71	0.71	0.69	0.70	0.69	0.69	0.68
R^2	0.69	0.66	0.69	0.68	0.67	0.66	0.65	0.65	0.64	0.64	0.62

Table 2
Distribution of the Magnitude of Debt and Equity Issuances

The sample comes from the annual Compustat files during the period 1971-2001. Debt issuance size is computed using the balance sheet change in total debt (long term plus short term) from year $t-1$ to t relative to total assets in year $t-1$. Equity issuance size is comes from the statement of cash flows issuance of common and preferred stock during period t, divided by total assets in year $t-1$. The table presents the density and distribution of each type of issuance.

Issuance Size	Debt	Cumulative Debt	Equity	Cumulative Equity
$[0, 0.01)$	12.7%	12.7%	51.1%	51.1%
$[0.01, 0.02)$	9.8%	22.4%	12.5%	63.6%
$[0.02, 0.03)$	8.0%	30.5%	6.2%	69.8%
$[0.03, 0.04)$	7.3%	37.7%	4.0%	73.8%
$[0.04, 0.05)$	6.1%	43.8%	2.8%	76.6%
$[0.05, 0.07)$	10.8%	54.6%	3.7%	80.4%
$[0.07, 0.10)$	11.7%	66.3%	3.8%	84.1%
$[.10, \infty)$	33.7%	100.0%	15.9%	100.0%

Table 3

Financing Decisions and Firm Characteristics

The sample comes from the annual Compustat files during the period 1971-2001. Debt issuances are defined as a change in total debt (long term plus short term) from year $t-1$ to t divided by total assets in year $t-1$ in excess of 5%. Equity issuances are defined for year t as sale of common and preferred stock net of purchase of common and preferred stock in excess of 5% of total assets at the end of the previous fiscal year. All variables, except for size and age, are scaled by book assets. *Current Inv.* is defined as the sum of capital expenditures, increase in investments, acquisitions, and other use of funds, less sale of PPE and sale of investment; *Liquid Assets* is defined as the sum of cash and marketable securities, inventories, and accounts receivable; *Current Cash Flow* for year t is defined as the average cash flow growth rate over years t-3 to t-1, applied to the actual year t-1 cash flow; *Market-to-Book* is defined as the ratio of total assets minus book equity plus market equity to total assets; *Book Leverage* is defined as the sum of short term and long term debt divided by the book value of assets; *Firm Size* is the natural logarithm of book assets; *Anticipated Investment* and *Anticipated Cash Flow* for year t are the sum of the realized values for years t+1 and t+2 of Investment and Cash Flow (defined as cash flow after interest and taxes net of dividends), respectively; *Tangible Assets* is defined as net property, plant and equipment; *Cash Flow Volatility* is defined as the standard deviation of earnings before interest and taxes, and is based on (up to) the previous 10 years of data for a given firm-year observation; *Firm Age* is defined as the number of years since a given firm first appeared on Compustat.

Panel A: Full Sample

Financing Decision	% of Obs.	Current Inv.	Cash Balance	Current Cash Flow	Market-to-Book	Book Leverage	Firm Size	Anticipated Inv	Anticipated Cash Flow	Tangible Assets	Cash Flow Volatility	Firm Age
Internal	66.20%	0.06	0.06	0.09	1.09	0.22	5.17	0.16	0.2	0.28	0.06	15
Debt	24.60%	0.14	0.04	0.11	1.2	0.23	5.14	0.2	0.22	0.3	0.06	14
Equity	6.10%	0.1	0.06	0.09	1.52	0.27	4.33	0.27	0.21	0.26	0.09	10
Dual	3.10%	0.27	0.05	0.11	1.52	0.26	4.66	0.37	0.27	0.3	0.08	9

Panel B: Balanced Random Sample

Financing Decision	% of Obs.	Current Inv.	Cash Balance	Current Cash Flow	Market-to-Book	Book Leverage	Firm Size	Anticipated Inv	Anticipated Cash Flow	Tangible Assets	Cash Flow Volatility	Firm Age
Internal	50.00%	0.06	0.07	0.09	1.09	0.22	5.17	0.16	0.19	0.28	0.06	15
Debt	25.00%	0.14	0.04	0.11	1.21	0.23	5.14	0.21	0.22	0.30	0.06	14
Equity	16.69%	0.10	0.06	0.09	1.52	0.27	4.33	0.27	0.21	0.26	0.09	10
Dual	8.31%	0.27	0.05	0.11	1.52	0.26	4.66	0.37	0.27	0.30	0.08	9

Table 4
Model Prediction Accuracy Using Observed Financing Decisions

The sample comes from the annual Compustat files during the period 1971-2001. Panels A, B, and C present the prediction accuracy results for three different specifications of our empirical model. Panel A presents the results for the pecking order specification in equations (9) through (12). Panel B presents the results for the tradeoff specification in equations (9), (10), (15), and (16). Panel C presents the results for the integrated specification in that introduces alternative considerations into the pecking order framework by specifying the cash target as in equation (17) and the difference in the cash target and maximum debt capacity as in equation (18). For example, the results in Panel A suggest that the pecking order correctly classifies 71.58% (72.21%) of the observed internal (external) financing decisions and 38.08% (47.19%) of the debt (equity) decisions. However, the pecking order incorrectly classifies 27.58% (28%) of the debt (equity) issuances as internal funds. The "Average Correct" row presents an equal weighted average of the correct classifications. The "Sample Adherence" row presents the fraction of firms in the sample adhering to the particular model (pecking order, tradeoff, integrated), as suggested by the simulation results in Table 1. The "Improvement" row in the debt-equity decision shows the model's improvement in prediction accuracy relative to a naive estimator that would, on average, get half of the accurately identified external issuances correct. For example, in the pecking order model, 72.2% of external issuances are correctly classified, implying that 36.1% of debt-equity decisions will be correctly classified by any naive estimator. Since the model accurately identified 42.64% of the debt-equity issuances, this is an improvement of 6.5% which, according to our simulation results in Table 1, corresponds to approximately 34% of the sample exhibiting pecking order financing behavior. The two numbers in brackets correspond to a 95% bootstrap confidence interval.

Panel A: Pecking Order

	Predicted Financing Decision	
Observed Decision	Internal	External
Internal	71.58%	28.42%
External	27.79%	72.21%
Average Correct [95% CI]	71.89%	[70.58%, 72.93%]
Sample Adherence	62%	

	Predicted Financing Decision		
Observed Decision	Internal	Debt	Equity
Debt	27.58%	38.08%	34.34%
Equity	28.00%	24.80%	47.19%
Average Correct	42.64%		
Improvement [95% CI]	6.53%	[5.33%, 7.59%]	
Sample Adherence	34%		

Panel B: Tradeoff Theory

	Predicted Financing Decision	
Observed Decision	Internal	External
Internal	68.54%	31.46%
External	25.98%	74.02%
Average Correct [95% CI]	71.28%	[70.26%, 72.15%]
Sample Adherence	61%	

	Predicted Financing Decision		
Observed Decision	Internal	Debt	Equity
Debt	23.63%	47.77%	28.60%
Equity	28.33%	33.44%	38.23%
Average Correct	43.00%		
Improvement [95% CI]	5.99%	[5.04%, 7.21%]	
Sample Adherence	32%		

Panel C: Integrated Model

	Predicted Financing Decision	
Observed Decision	Internal	External
Internal	80.85%	19.15%
External	29.41%	70.59%
Average Correct [95% CI]	75.72%	[74.79%, 76.42%]
Sample Adherence	71%	

	Predicted Financing Decision		
Observed Decision	Internal	Debt	Equity
Debt	24.69%	57.62%	17.69%
Equity	18.31%	33.19%	48.50%
Average Correct	53.06%		
Improvement [95% CI]	16.21%	[15.04%, 17.09%]	
Sample Adherence	73%		

Table 5
Comparison of Equity Issuers and Private Borrowers

The table presents a comparison of firm characteristics for two samples of firms: (1) borrowers in the private debt market and (2) Equity issuers identified by our empirical model as violating the pecking order's financing hierarchy ("Equity Violators"). Private lender data come from an August, 2002 extract of the Dealscan database, marketed by Loan Pricing Corporation (LPC), which consists of dollar denominated private loans made by bank (e.g., commercial and investment) and non-bank (e.g., insurance companies and pension funds) lenders to U.S. corporations during the period 1987-2001. *Market Leverage* is defined as the sum of short term and long term debt divided by the sum of short term, long term debt, and market equity. *Profitability* is the ratio of EBITDA to total assets. *Maturity Structure* is the ratio of long term debt to the sum of short term and long term debt. *Financing Deficit* is the sum of common dividends plus capital expenditures plus the change in net working capital minus cash flow all divided by total assets. *Firm Size* is the market value of equity in millions of year 2000 dollars. *Z-Score* is defined as the sum of 3.3 times earnings before interest and taxes plus sales plus 1.4 times retained earnings plus 1.2 times working capital divided by total assets. *Interest Coverage Ratio* is the ratio of EBITDA to Interest Expense. *Current Ratio* is the ratio of current assets to current liabilities. *Quick Ratio* is the sum of cash and receivables divided by current liabilities. Other variables are as defined in Table 3. The t-stat tests the null hypothesis that the sample means are equal and uses standard errors adjusted for clustering at the firm level.

	Private Debt Firms				Equity Violators		Difference in Means
Variable	25^{th}-Percentile	Median	75^{th}-Percentile	Mean	Median	Mean	t-stat
Book Leverage	0.14	0.30	0.46	0.33	0.12	0.12	44.51
Market Leverage	0.09	0.25	0.46	0.30	0.06	0.09	37.69
Profitability	0.08	0.13	0.18	0.09	0.09	0.03	3.94
Maturity Structure	0.60	0.86	0.96	0.73	0.57	0.53	11.63
Market-to-Book	1.06	1.38	1.98	1.85	1.96	2.57	-8.24
Financing Def.	-0.02	0.02	0.15	0.77	0.04	0.13	2.21
Current Investment	0.03	0.05	0.10	0.08	0.05	0.07	2.46
Firm Size	47.68	178.07	794.66	1971.58	58.59	368.40	13.74
Cash Flow Vol.	0.04	0.06	0.10	0.09	0.11	0.19	-6.94
Z-Score	0.91	1.80	2.62	1.52	1.31	0.67	5.88
Tangible Assets	0.14	0.27	0.48	0.33	0.20	0.27	5.86
Current Ratio	1.16	1.70	2.45	2.16	1.93	2.49	-3.09
Interest Coverage Ratio	2.08	4.75	10.29	31.44	5.84	7.92	1.53

Table 6
Actual and Estimated Promised Yields for Borrowers and Equity Issuers

Private lender data come from an August, 2002 extract of the Dealscan database, marketed by Loan Pricing Corporation (LPC), which consists of dollar denominated private loans made by bank (e.g., commercial and investment) and non-bank (e.g., insurance companies and pension funds) lenders to U.S. corporations during the period 1987-2001. Corresponding firm characteristics come from the annual Compustat database during the period 1987-2001. Panel A presents the estimated coefficients of a linear regression of the promised yield of a loan (measured in basis points above the 6-month LIBOR) on various covariates defined in previous tables, which are defined in the previous tables. Test statistics (t-stat) are adjusted for clustering at the firm level and dummy variables corresponding to year and industry (Fama and French 38) are suppressed. Panel B presents descriptive statistics of the loan yield distribution for our sample of Private Borrowers, Equity Violators, Equity Non-Violators, and all Equity Issuers. Equity Violators are those equity issuances identified by our empirical model as violating the financing hierarchy. Equity Non-Violators are those equity issuances identified by our empirical model as not violating the financing hierarchy.

Panel A: Estimates of Loan Yield Determinants

Variable	Estimate	t-stat
Intercept	412.50	19.53
Book Leverage	94.82	8.02
Size	-37.19	-31.48
Tangibility	-23.33	-1.89
Profitability	-125.16	-4.82
Cash Flow Volatility	94.05	3.76
Log(Market-to-Book)	8.07	1.77
Long Term / Total Debt	-17.08	-2.40
Z-Score	-6.70	-3.39
Investment	25.49	0.76
Adjusted R^2	45%	

Panel B: Loan Yield Distributions

Sample	25^{th}-Percentile	Median	75^{th}-Percentile	Mean
All Borrowers	100.00	225.00	300.00	218.90
Equity Issuers	183.39	255.07	328.19	261.65
Equity Non-Violators	183.50	260.21	340.55	266.58
Equity Violators	183.39	250.27	314.94	252.42

Table 7

Cash Target and Maximum Debt Estimated Determinants

The sample comes from the annual Compustat files during the period 1971-2001. The table presents coefficient estimates and t-statistics (t-stat) adjusted for clustering at the firm level of the partially observed bivariate probit:

$$External_{it} = \begin{cases} 1 & Inv_{it} > C^*_{it} \\ 0 & \text{otherwise} \end{cases}$$

$$Equity_{it} = \begin{cases} 1 & Inv_{it} > D^*_{it} \\ 0 & C^*_{it} \leq Inv_{it} < D^*_{it} \end{cases}$$

where $External_{it} = 1(0)$ identifies an external (internal) financing decision, $Equity_{it} = 1(0)$ identifies an equity (debt) issuance, Inv_{it} is investment, and C^*_{it} and D^*_{it} are functions of the cash target and maximum debt, respectively. In turn, the cash target and maximum debt are functions of covariates and parameters β and γ, respectively. Subscripts i and t correspond to firms and years. *PO* is defined as $Investment - CashFlow - CashBalance$ in the External decision equation and as $Investment - CashFlow - CashBalance + Debt$ in the Equity decision equation, where all variables are normalized by book assets. *Dividend Payer* is a dummy variable equal to 1 if a firm paid a positive dividend in year t; *Z-score* is defined as the sum of 3.3 times earnings before interest and taxes plus sales plus 1.4 times retained earnings plus 1.2 times working capital divided by book assets; *R & D* is research and development expense as a percent of sales; *RDD* is a binary variable equal to one if R & D is missing and zero otherwise. *Net Working Capital* is defined as Current Assets excluding cash minus Current Liabilities excluding short term debt. *Stock Return* is defined last periods annual stock return. *MTR* is Graham's (1996) before-financing marginal tax rate. The remaining variable definitions are as defined above in Table 3.

	External Decision		Equity Decision	
Variable	Estimated Coefficients (β)	t-stat	Estimated Coefficients (γ)	t-stat
Constant	-0.518	-6.76	-0.814	-6.31
PO	3.915	57.41	2.222	57.41
Firm Size	-0.028	-4.58	-0.011	-1.06
Future Investment	0.342	12.17	0.143	4.45
Future Cash Flow	-0.341	-7.74	0.035	0.61
Cash Flow Volatility	0.307	2.03	1.293	6.08
Dividend Payer	-0.093	-4.39	-0.132	-3.88
Z-score	0.043	4.24	-0.096	-6.47
R&D / Sales	0.808	4.15	1.423	4.1
RDD	0.060	2.69	-0.109	-2.86
Market-to-Book	0.211	17.71	0.233	14.32
Net Working Capital	-0.380	-6.02	-0.792	-7.42
Book Leverage	-0.194	-3.30		
Tangible Assets			-0.775	-8.99
Firm Age			-0.008	-5.31
Stock Return			0.684	9.31
MTR			-0.241	-2.31

Table 8

Impact of Additional Explanatory Variables on Prediction Accuracy

The sample comes from the annual Compustat files during the period 1971-2001. Prediction accuracy results are shown for several different model specifications differing in terms of the included variables in the cash and debt threshold specifications. All model specifications are estimated on the sample of observations, which requires nonmissing data for all variables used in the Integrated specification described in the text. Additionally, all specifications specify the internal-external decision as in equations (9) and (10), to ease the comparison of accuracy rates for debt and equity issuances across specifications. The first column corresponds to the pecking order specification (equations (9) through (12)). The second column includes proxies for taxes (Graham's (1996) before-financing marginal tax rate, net operating loss carryforwards) and bankruptcy costs (Altman's Z-score, Tangible Assets). The third column includes proxies for investment opportunities (future investment, market-to-book) and equity mispricing (stock returns). The fourth column includes proxies for investment opportunities unrelated to security mispricing (future investment). The final column contains all the variables used in the integrated specification discussed in the body of the text. For example, in the pecking order specification, the model accurately identifies 71.12% of internal decisions, 73.50% of external decisions, 39.39% of debt decisions, and 47.8% of equity decisions. The "Average Correct" row presents an equal weighted average of the correct classifications. The "Sample Adherence" row presents the fraction of firms in the sample adhering to the particular model (pecking order, tradeoff, integrated), as suggested by the simulation results in Table 1. The "Improvement" row in the debt-equity decision shows the model's improvement in prediction accuracy relative to a naive estimator that would, on average, get half of the accurately identified external issuances correct. For example, in the pecking order model, 72.31% of external issuances are correctly classified, implying that 36.15% of debt-equity decisions will be correctly classified by any naive estimator. Since the model accurately identified 43.6% of the debt-equity issuances, this is an improvement of 6.85% which, according to our simulation results in Table 1, corresponds to approximately 35% of the sample exhibiting pecking order financing behavior.

	Strict Pecking Order	Tax and Bankruptcy	Investment Opps/ Mispricing	Non-Mispricing Investment Opps	Integrated Model
% Correctly Predicted					
Internal Finance	71.12%	70.86%	70.89%	70.93%	70.51%
External Issuance	73.50%	73.64%	73.62%	73.62%	73.69%
Average Correct	72.31%	72.25%	72.25%	72.28%	72.10%
Sample Adherence	63.00%	63.00%	63.00%	63.00%	63.00%
Debt Issuance	39.39%	51.40%	52.52%	50.56%	57.62%
Equity Issuance	47.80%	45.05%	47.10%	45.79%	48.50%
Average Correct	43.60%	48.22%	49.81%	48.18%	53.06%
Improvement	6.85%	11.40%	13.00%	11.37%	16.21%
Sample Adherence	35.00%	53.00%	61.00%	53.00%	73.00%

Table 9
Model Prediction Accuracy By Measures of Information Asymmetry

The sample comes from the annual Compustat, SDC Platinum and Dealscan files during the period 1971-2001 and I/B/E/S summary history files from 1976-2001. Panels A and B present the average prediction accuracy for debt and equity issuances of the estimated bivariate probit model discussed in the text, for the pecking order and integrated model specifications, respectively. Predictions are based on the restricted model estimation. "Hot" and "cold" periods are defined using a variant of that found Bayless and Chaplinsky (1996), which enables us to use our entire sample. That is, we rank each year according to the total net issuance volume scaled by the total market value of equity in the sample. We then define hot years to be those in the upper quartile, based on one of these rankings, and cold years to be those in the bottom quartile. *Analyst Coverage* is a binary variable equal to 1 if a firm is covered in the I/B/E/S summary history files for a given year. *Forecast Dispersion* is the standard deviation of the one-year ahead EPS forecast for the first month in each fiscal year. *Pub/Priv*is a designation for issuances identified as either public or private debt or equity issuances by matching issuances identified using our Compustat sample (see text for details) with the SDC Platinum and Dealscan databases. See Table 3 for other variable definitions.

Panel A: Pecking Order Model Specification

Asymmetric Information	Hot/Cold Periods	Firm Age	Asset Tangibility	Analyst Coverage	Forecast Dispersion	Pub/Priv
High	38.40%	36.90%	33.90%	37.80%	35.10%	43.00%
Med		35.40%	37.55%		38.45%	
Low	39.35%	40.70%	42.65%	37.70%	39.80%	38.95%

Panel B: Integrated Model Specification

Asymmetric Information	Hot/Cold Periods	Firm Age	Asset Tangibility	Analyst Coverage	Forecast Dispersion	Pub/Priv
High	46.80%	48.35%	49.20%	50.10%	46.20%	53.15%
Med		49.35%	50.45%		48.95%	
Low	48.05%	45.85%	49.80%	49.10%	50.00%	54.75%

Table 10

Model Prediction Accuracy for Alternative Variable Definitions and Model Specifications

The sample comes from the annual Compustat files during the period 1971-2001. Prediction accuracy are shown for the integrated model specification. Column (1) repeats the results from panel C of Table 4. In column (2), the definition of investment is broadened to include advertising expense and research and development expenditure. In columns (3) and (4), debt issuance is calculated using total and long-term net debt issuance from Compustat statement of cash flows data, respectively. In columns (5) and (6), the percent of assets cutoff for defining an issuance is reduced to 3% and 1%, respectively. In column (7), squared and cubed terms of all the independent (see table IV) are included in the cash target and maximum debt specifications. Column (8) adds additional explanatory variables to the specification in column (7), as discussed in the text. Numbers reported next to each financing decision are the percent of those actual decisions correctly predicted by the model. The "Average Correct" row presents an equal weighted average of the correct classifications. The "Sample Adherence" row presents the fraction of firms in the sample adhering to the particular model (pecking order, tradeoff, integrated), as suggested by the simulation results in Table 1. The "Improvement" row in the debt-equity decision shows the model's improvement in prediction accuracy relative to a naive estimator that would, on average, get half of the accurately identified external issuances correct. For example, the integrated model accurately predicts 80.9% of internal financings, 70.6% of external financings, 42.7% of debt issuances, and 56.5% of equity issuances. The internal-external (debt-equity) average prediction accuracy of 75.7% (49.6%) translates into 71% (65%) of the sample firms adhering to the model's decision rules. The 14.3% Improvement shows the model's improvement over a naive estimator that would correctly classify half of the accurately classified external issuances. Thus, the improvement is 49.6% - 70.6%/2 = 14.3$. The Sample Adherence is obtained from the simulations results in Table 1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Actual Decision	Integrated Model	Expanded Investment	SCF Total DebtIss	SCF LT Debt Iss	3% cutoff	1% cutoff	Polynomial	Polynomial + Add'l Vars
Internal Finance	80.9%	80.6%	79.0%	82.3%	79.4%	75.4%	80.2%	80.0%
External Issuance	70.6%	71.0%	69.2%	71.8%	68.9%	66.9%	70.4%	71.6%
Average Correct	75.7%	75.8%	74.1%	77.0%	74.1%	71.1%	75.3%	75.8%
Sample Adherence	71%	71%	67%	75%	67%	61%	70%	71%
Debt Issuance	42.7%	42.4%	44.3%	44.4%	42.8%	42.6%	41.9%	45.5%
Equity Issuance	56.5%	57.6%	55.7%	54.3%	55.1%	51.3%	58.1%	57.8%
Average Correct	49.6%	50.0%	50.0%	49.4%	48.9%	46.9%	50.0%	51.7%
Improvement	14.3%	14.5%	15.4%	13.5%	14.5%	13.5%	14.8%	15.9%
Sample Adherence	65%	66%	69%	62%	66%	62%	67%	72%