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The pecking order, debt capacity, and information asymmetry ☆

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ABSTRACT

We quantify the empirical relevance of the pecking order hypothesis using a novel empirical model and testing strategy that addresses statistical power concerns with previous tests. While the classificatory ability of the pecking order varies significantly depending on whether one interprets the hypothesis in a strict or liberal (e.g., "modified" pecking order) manner, the pecking order is never able to accurately classify more than half of the observed financing decisions. However, when we expand the model to incorporate factors typically attributed to alternative theories, the predictive accuracy of the model increases dramatically—accurately classifying over 80% of the observed debt and equity issuances. Finally, we show that what little pecking order behavior can be found in the data is driven more by incentive conflicts, as opposed to information asymmetry.

1. Introduction

The pecking order hypothesis posited by 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. This prediction has been scrutinized for over two decades by scores of studies attempting to determine whether and when the pecking order accurately describes observed financing behavior; yet, there is little agreement on these issues.

For example, Shyam-Sunder and Myers (1999) conclude that the pecking order is a good descriptor of broad financing patterns; Frank and Goyal (2003) conclude the opposite. Lemmon and Zender (2004) conclude that a "modified" pecking order—which takes into account financial distress costs—is a good descriptor of financing behavior; Fama and French (2005) conclude the opposite. Frank and Goyal (2003) conclude that the pecking order better describes the behavior of large firms, as opposed to small firms; Fama and French (2005) conclude the opposite. Finally, Bharath, Pasquariello, and Wu (2009) argue that firms facing low information asymmetry account for the bulk of the pecking order's failings; Jung, Kim, and Stulz (1996) conclude the opposite.

We argue that this divergence of conclusions is driven primarily by two forces. First, existing testing strategies have been plagued by concerns over statistical power. For example, many studies rely on the financing deficit regressions proposed by Shyam-Sunder and Myers (1999)

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to identify the extent of pecking order behavior; however, Chirinko and Singha (2000) show that this test has no power to discriminate among alternative explanations.[1] Second, the practical irrelevance of a literal interpretation of the pecking order hypothesis—exhaustion of internal funds and no equity issuances—has led researchers to focus on the modified pecking order, which Myers (1984, p. 589) describes as "grossly oversimplified and underqualified." Consequently, empirical implementations have employed a variety of interpretations of the hypothesis, further exacerbating the tension among existing studies.[2]

Our goal is to shed light on this debate by quantifying the empirical relevance of the pecking order and its variants using a novel empirical model and testing strategy that addresses the relevant power concerns. As such, we begin with a simulation experiment showing how our test is able to distinguish between whether 40% or 50%, for example, of observed financing decisions adhere to the pecking order's predictions. Using this empirical framework, we first show that the empirical performance of the pecking order depends crucially on the interpretation of the hypothesis and, consequently, the flexibility provided to the model. Therefore, to avoid drawing conclusions that are governed by a particular interpretation, our empirical strategy begins by examining how the classificatory ability of the pecking order changes as one moves from a more strict to a more liberal interpretation of the hypothesis. Doing so enables us to identify why the pecking order fails or succeeds by isolating the factors necessary to accurately classify observed financing decisions.

For example, our baseline model, or relatively strict interpretation of the pecking order, requires firms to maintain constant cash reservoirs and debt capacities while adhering to the pecking order's financing hierarchy. While not a literal interpretation of the pecking order, it does constrain savings policies and debt capacities to be constant across firms and time. Under this strict interpretation, we estimate that 77% of our sample firms follow the pecking order in choosing between internal and external finance, but only 17% follow the pecking order in choosing between debt and equity.

To incorporate Myers' (1984, p. 589) notion that firms may wish to maintain "reserve borrowing power…to issue safe debt," we relax the constancy assumption on debt capacities by defining them in terms of the leverage ratios of investment-grade rated firms in the same industry-year combination. That is, we assume that firms can issue debt in a given year up to the point where their leverage ratio is equal to that of an average investment-grade rated firm in the same industry and during the same year. Despite this more liberal interpretation of the pecking order, the classificatory accuracy of the model is basically unchanged from our baseline model—fewer than 20% of firms adhere to the pecking order's prediction for debt and equity issuances.

Only when we allow firms' debt capacities, and to a lesser extent their cash reservoirs, to vary with factors typically attributable to alternative theories does the pecking order's predictive ability begin to increase. For instance, when parameterizing debt capacity as a function of both industry and year fixed effects, the pecking order accurately classifies the debt–equity decisions of 48% of our sample firms. Incorporating a broad list of firm characteristics, such as Altman's *Z*-score and the market-to-book ratio, leads to an even larger improvement in the pecking order's performance, accurately classifying the debt–equity decisions of over 80% of our sample firms. The extent to which this success is attributable to the pecking order, tradeoff, or any other theory is ultimately subjective, as the theories and empirical proxies do not allow for a sharp delineation. However, these results illustrate that (1) existing empirical determinants can explain a large majority of financing decisions, and (2) considerations beyond just static adverse selection costs and the ability to issue safe debt appear to play an important role in governing financial policy.

Our second set of analyses reinforces this last point by showing that incentive conflicts (Myers, 2003), not information asymmetry, appear to generate pecking order behavior in the data. In particular, when we split our sample into high and low information asymmetry groups using several proxies suggested by previous research (e.g., Gomes and Phillips, 2005), we find relatively little variation in the propensity to adhere to the pecking order's hierarchy. If anything, firms appear more likely to follow the pecking order's financing hierarchy when information asymmetry is *low*, in contrast to the predictions of Myers and Majluf (1984) and the conclusion of Bharath, Pasquariello, and Wu (2009), but consistent with several theoretical studies (Cooney and Kalay, 1993; Fulghieri and Lukin, 2001; Halov and Heider, 2004; Hennessy and Livdan, 2006) and survey evidence (Graham and Harvey, 2001). Further, even after restricting attention to firms most likely facing severe information asymmetry between managers and investors *and* employing a liberal interpretation of the pecking order, we find that the pecking order is only able to explain at most half of the observed external financing decisions.

In contrast, we find a marked increase in pecking order behavior as the potential for agency conflicts increases. Moving from firms likely facing low agency costs to those facing high agency costs corresponds to an average increase in predictive accuracy of almost 20 percentage points. Thus, the pecking order—be it a strict or liberal interpretation—struggles to identify many observed

[1] Other studies using the Shyam-Sunder and Myers framework include Frank and Goyal (2003), Lemmon and Zender (2004), Brav (2009), Bharath, Pasquariello, and Wu (2009), and Halov and Heider (2004). Similarly, a number of papers (e.g., Titman and Wessels, 1988; Fama and French, 2002) point to the negative correlation between leverage and profitability as supportive evidence of the pecking order; however, Strebulaev (2007) shows that this test has no power to distinguish between alternative explanations, such as one based on a tax-bankruptcy cost tradeoff in the presence of adjustment costs.

[2] For example, Shyam-Sunder and Myers (1999) and Lemmon and Zender (2004) assume that only large firms with investment-grade credit quality are expected to adhere to the financing hierarchy, whereas Fama and French (2005) assume that all firms other than those with negative or abnormally low earnings are expected to adhere to the hierarchy.

financing decisions not only because it disregards as second-order factors that are important for financing decisions, but also because pecking order behavior appears to be driven more by incentive conflicts, as opposed to information asymmetry.

The remainder of the paper proceeds as follows. Section 2 reviews the pecking order hypothesis, and constructs our empirical model and testing strategy. Section 3 describes the simulation experiment and presents the results of a power study comparing our testing strategy with those of previous studies. Section 4 discusses the data and sample selection. Section 5 presents and discusses the primary results. Section 6 concludes.

2. The pecking order hypothesis and empirical model

The intuition behind the pecking order hypothesis is illustrated in Fig. 1. A firm will finance investment with internal resources (e.g., cash and liquid assets) up to the cash threshold $\tilde{C}$, which represents the amount of internal funds available for investment. When the size of current investment exceeds $\tilde{C}$, the firm turns to external finance to fill the financing deficit. Debt finance is applied first and used up to the point $\tilde{D}$, where $(\tilde{D}-\tilde{C})$ represents the amount of debt that a firm can issue without producing excessive leverage (i.e., without becoming financially distressed). Investment needs beyond $\tilde{D}$ require that the firm turn to equity financing. Strictly speaking, the pecking order does not allow for any savings behavior or equity issuances but, practically speaking, the interpretation of the hypothesis provided by Fig. 1 is closer to the spirit of the "modified pecking order" hypothesis described in the last section of Myers and Majluf (1984) and the conclusion of Myers (1984). Thus, Fig. 1 illustrates the traditional financing hierarchy and the dependence of that hierarchy on the thresholds $\tilde{C}$ and $\tilde{D}$.[3]

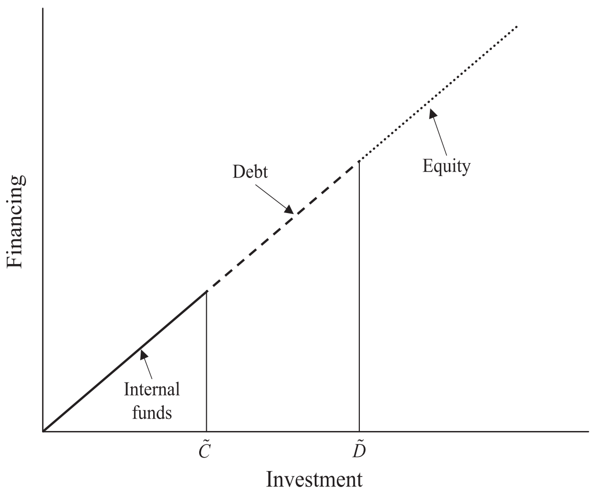

Fig. 1. The financing hierarchy of the pecking order. The figure depicts the relationship between financing choice and the level of investment under the pecking order hypothesis. $\tilde{C}$ represents the amount of internal funds available for investment. $(\tilde{D}-\tilde{C})$ represents the amount of debt that a firm can issue without producing excessive leverage.

Because the pecking order does not give clear guidance on how to define these thresholds, our strategy consists of examining multiple definitions that encompass a spectrum of interpretations of the pecking order ranging from strict to liberal. For example, we define $\tilde{C}$ to be the point at which

$$0 = Investment_{it} - (InternalFunds_{it-1} - (\alpha^C_{it} + \varepsilon_{it})), \tag{1}$$

where i and t index firms and years, ε_{it} is a mean zero random variable, and

$$InternalFunds_{it} = CashBalance_{it-1} + CashFlow_{it} - Divdends_{it} - \Delta WorkingCapital_{it}. \tag{2}$$

The condition in Eq. (1) implies that firms will use internal resources to fund investment up to the point $(\alpha^C_{it}+\varepsilon_{it})$. Thus, an equivalent interpretation of $\tilde{C}$ is the point at which investment equals the internal funds that are available for investment, conditional on any existing cash balances and desire to maintain a particular reservoir of internal funds. Simply put, we allow firms to maintain a cash management policy, whose flexibility is governed by the identifying restrictions imposed on α^C_{it}.

To make things concrete, a literal interpretation of the pecking order would restrict $\alpha^C_{it}=0$, implying that firms exhaust their internal funds to finance investment. Alternatively, a more liberal interpretation of the pecking order might parameterize α^C_{it} to be a function of future investment opportunities so that firms can maintain a reservoir of internal funds for such opportunities. We leave explicit parameterizations for the empirical implementation of the model below.

The pecking order defines the decision between internal and external funds as

$$External_{it} = \begin{cases} 1 & Investment_{it} \geq \tilde{C}_{it}, \\ 0 & \text{otherwise}, \end{cases} \tag{3}$$

where

$$\tilde{C}_{it} = InternalFunds_{it} - (\alpha^C_{it} + \varepsilon_{it}). \tag{4}$$

Eq. (3) corresponds to the first rung of the pecking order, which dictates that investment be financed by external resources ($External_{it}=1$) if internal resources are insufficient to fund investment needs. Otherwise, the firm relies on internal funds to finance investment.

[3] 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 $\tilde{C}$ but less than $\tilde{D}$, or entirely with equity if investment is greater than $\tilde{D}$. Regardless, the empirical implications under this alternative structure are unaffected: firms avoid external capital when investment is less than $\tilde{C}$ and avoid equity capital when investment is less than $\tilde{D}$.

We construct the second threshold in a similar manner, defining $\tilde{D}$ as the point at which

$$Investment_{it} - (InternalFunds_{it} - \alpha_{it}^{C} - \varepsilon_{it}) - (\alpha_{it}^{D} + \eta_{it} - Debt_{it-1}) = 0. \quad (5)$$

The condition in Eq. (5) implies that after exhausting the internal resources that are available for investment (the first parenthetical term), firms will issue debt in excess of their existing debt level, $Debt_{it-1}$, up to the point $(\alpha_{it}^{D} + \eta_{it})$. Thus, $\tilde{D}$ can be interpreted as the sum of $\tilde{C}$ and the amount of debt that a firm can issue conditional on its existing debt level. That is, we allow firms to maintain a debt management or leverage policy.

Again, a strict or liberal interpretation of the pecking order is implemented via the identifying restrictions on α_{it}^{D}. A literal interpretation of the pecking order requires that firms never issue equity, implying that α_{it}^{D} is infinite. A more liberal interpretation might specify α_{it}^{D} as a function of a firm's debt capacity, or their ability to issue "safe debt" according to Myers (1984).

The pecking order defines the decision between debt and equity funds as

$$Equity_{it} = \begin{cases} 1 & Investment_{it} \geq \tilde{D}_{it}, \\ 0 & \tilde{C}_{it} \leq Investment_{it} < \tilde{D}_{it}, \end{cases} \quad (6)$$

where

$$\tilde{D}_{it} = (InternalFunds_{it} - \alpha_{it}^{C} - \varepsilon_{it}) + (\alpha_{it}^{D} + \eta_{it} - Debt_{it-1}).$$

Eq. (6) corresponds to the second rung of the pecking order, which dictates that investment be financed with debt once investment exceeds the available internal resources. Beyond a certain point, $\tilde{D}$, however, firms will turn to equity capital. For estimation purposes, it is more convenient to reparameterize $\tilde{D}_{it}$ as

$$\tilde{D}_{it} = InternalFunds_{it} - Debt_{it-1} - \alpha_{it}^{D'} + \omega_{it}, \quad (7)$$

where $\alpha_{it}^{D'} = \alpha_{it}^{C} - \alpha_{it}^{D}$ and $\omega_{it} = \eta_{it} - \varepsilon_{it}$. Thus, for the remainder of the paper, references to $\tilde{D}_{it}$ refer to the definition in Eq. (7).

Substituting Eq. (4) into Eq. (3) reveals that the decision between internal and external funds is governed by

$$External_{it} = \begin{cases} 1 & y_{1it}^{*} \geq 0, \\ 0 & y_{1it}^{*} < 0, \end{cases} \quad (8)$$

where

$$y_{1it}^{*} = Investment_{it} - InternalFunds_{it} + \alpha_{it}^{C} + \varepsilon_{it}. \quad (9)$$

Substituting Eq. (7) into Eq. (6) reveals that the decision between debt and equity is governed by

$$Equity_{it} = \begin{cases} 1 & y_{2it}^{*} \geq 0, \\ 0 & y_{2it}^{*} < 0, \end{cases} \quad (10)$$

where

$$y_{2it}^{*} = Investment_{it} - InternalFunds_{it} + Debt_{it-1} + \alpha_{it}^{D'} - \omega_{it}. \quad (11)$$

The error terms, ε_{it} and ω_{it}, are assumed to be distributed bivariate standard normal with correlation ρ, so that the model coincides with a censored bivariate probit.

The assumption of unit variances is made for identification purposes and is innocuous as the observable data are governed only by the sign of the latent variables (y_1^*, y_2^*) and not the magnitude. We also assume that the errors are potentially heteroskedastic and correlated within firms (Petersen, 2009), and scale all continuous variables by the book assets of the firm as of the end of the previous fiscal year to control for scale effects and help mitigate heteroskedasticity.[4]

Our test of the pecking order is to quantify the predictive ability of the model in Eqs. (8) through (11). If the observed data are generated according to the pecking order, then the model should accurately identify a relatively large fraction of the observed financing decisions. Further, the model should be able to distinguish among varying degrees of pecking order behavior, as opposed to simply rejecting or failing-to-reject such behavior. The next subsection examines the power of this and previous testing strategies, but before turning to these issues it is important to discuss the exogeneity assumption implicit in our empirical model.

Clearly, the financing deficit is endogenous since it is a function of investment, and to a lesser extent dividends.[5] While this assumption is not unique to our model—all previous empirical tests of the pecking order of which we are aware employ a similar assumption—it is important to understand the potential impact of endogeneity for our results. Using the Myers and Majluf (1984) framework as a guide, the adverse selection problem induces a premium in the cost of external capital and one that is increasing in the information sensitivity of the security. This premium increases the hurdle rate for investments and leads to underinvestment relative to the first-best level. If firms use internal funds, there is no adverse selection premium and therefore no distortion in investment. In other words, the endogeneity issue is not relevant in this case because the financing choice does not affect investment.

If firms use external finance, then there may be an underinvestment distortion but it is not clear that this will taint our inferences. Consider first a firm that uses debt financing. The empirical concern is that the adverse selection premium will reduce observed investment to a level below the available internal funds, which in combination with the debt issuance is in violation of the pecking order. That is, the endogeneity produces empirical evidence against pecking order behavior when, in fact, the firm was behaving in accord with the theory. However, if the adverse selection premium reduces investment below the available internal funds threshold, then there is no reason for the firm to issue debt, thereby

[4] The model specification in Eqs. (9) and (11) imposes the restriction that the slope coefficients on $Investment_{it}$, $InternalFunds_{it}$, and $Debt_{it-1}$ are each equal to one (or negative one). However, unidentifiability of the scale term associated with the errors requires a less restrictive condition: equality of the coefficients in their respective equations—the same restriction found in previous studies of the pecking order (e.g., Helwege and Liang, 1996; Shyam-Sunder and Myers, 1999; Frank and Goyal, 2003; Lemmon and Zender, 2004).

[5] We say lesser extent since fewer than 32% of firms pay dividends and of those firms, dividend volatility is significantly smaller than investment volatility.

incurring the adverse selection cost and wasting debt capacity. Rather, *under the null hypothesis of the pecking order*, a firm would simply use internal funds and, therefore, we should not see this outcome in the data.

Likewise, when a firm uses equity financing, the concern is that the adverse selection premium will reduce observed investment to a level below debt capacity (or available internal funds), which in combination with the equity issuance also produces empirical evidence against pecking order behavior. However, if the adverse selection premium reduces the level of investment so that it may be financed with a cheaper source of funds, then the firm should rationally use that cheaper source according to the pecking order.

3. Simulation experiment and power study

3.1. A simulation experiment

This section provides a heuristic description of our simulation experiment. For details, we refer the reader to Appendix C. We begin by simulating firm-year data for the two thresholds, $\tilde{C}_{it}$ and $\tilde{D}_{it}$. Since $InternalFunds_{it}$ and $Debt_{it-1}$ are observable in our data (discussed below), we draw values of these variables from their empirical distributions.[6] This ensures that later comparisons between simulated and empirical results are not affected by differences in the distributions of the explanatory variables. The error terms, ε_{it} and ω_{it}, are generated according to a bivariate normal distribution; however, using a bivariate lognormal to account for any underlying skew in the data has little effect on our results or inferences.

From the simulated series, we construct two sets of simulated financing decisions denoted "Pecking order" and "Alternative." The former set is generated according to the pecking order decision rule: use internal funds if $Investment_{it} < \tilde{C}_{it}$, use debt if $\tilde{C}_{it} \le Investment_{it} < \tilde{D}_{it}$, and use equity if $Investment_{it} \ge \tilde{D}_{it}$. Since $Investment_{it}$ is also observable, we draw values of this variable from its empirical distribution. The second set of financing decisions is generated by a random decision rule that is independent of the relation among $Investment_{it}$, $\tilde{C}_{it}$, and $\tilde{D}_{it}$. For both sets of simulated decisions, we parameterize the simulation to ensure that the ratios of internal to external and debt to equity decisions are consistent with those observed in the data (see Table 3 for these ratios).

As a brief aside, the Alternative decision rule is not without economic content. For example, in the market timing theory of Baker and Wurgler (2002) and the dynamic tradeoff theory of Fischer, Heinkel, and Zechner (1989), issuance behavior is largely removed from investment demand, dictated instead by equity returns and exogenous shocks to asset values, respectively. While a more realistic representation might be accomplished with the construction of a structural model with endogenous investment, debt, and equity financing, our goal with this simulation experiment is more modest. We merely want to understand whether different empirical tests can distinguish among varying degrees of pecking order behavior observed in the data.

Returning to the mechanics of our simulation, the two sets of financing decisions, pecking order and alternative, 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 intermediate results, we vary the fraction of firms that adhere to the pecking order's decision rule by increments of 10%. This procedure produces 11 sets of financing decisions varying in the degree to which the sample adheres to the pecking order $(0\%, 10\%, \ldots, 100\%)$. Any empirical strategy purporting to test the pecking order should be able to discriminate among these 11 sets of financing decisions. Thus, this criterion forms the basis by which we evaluate our test of the pecking order in the next section.

3.2. The power properties of the model

Panel A of Table 1 presents the predictive accuracy estimates of our model across the 11 sets of simulated financing decisions. These results are obtained by first estimating, for each set of simulated data, Eqs. (8) through (11) via maximum likelihood (see Greene, 2003 for the likelihood function). Using the estimated models, we compute predicted probabilities of issuance decisions, $\hat{Pr}$, which are then mapped into predicted financing decisions as follows. If $\hat{Pr}(y^*_{1it} > 0) > \mu(External_{it})$, then the firm's predicted financing decision is external, where $\mu(External_{it})$ is the empirical likelihood of an external issuance (see Table 3). If $\hat{Pr}(y^*_{1it} > 0) \le \mu(External_{it})$, then the firm's predicted financing decision is internal. Conditional on a predicted external financing, if $\hat{Pr}(y^*_{2it} > 0 | y^*_{1it} > 0) > \mu(Equity_{it})$, then the firm's predicted financing decision is an equity issuance, where $\mu(Equity_{it})$ is the empirical likelihood of an equity (or dual) issuance conditional on an external issuance. If $\hat{Pr}(y^*_{2it} > 0 | y^*_{1it} > 0) \le \mu(Equity_{it})$, then the firm's predicted financing decision is a debt issuance.

We choose the empirical likelihoods as prediction thresholds primarily to address the skewness in the underlying distributions of the financing choice variables *External* and *Equity*. This skewness generates a tendency for the model to predict the more frequent choice very accurately at the expense of the less frequent choice if a 0.50 cutoff is used (see Greene, 2003, Chapter 21). However, the exact choice of thresholds has little impact on our conclusions, which are based more on the theory's ability to characterize financing decisions as a whole, as opposed to its ability to identify one particular decision.[7]

[6] To account for the effect of within-firm error dependence on statistical inferences, for each simulation we draw a bootstrap sample roughly half the size of our empirical sample (see Appendix C for details).

[7] In unreported analysis, we explore the use of alternate thresholds, such as the empirical likelihood of an equity issuance conditional on a *correctly* predicted external financing, or the thresholds that maximize

Table 1
Model simulation results.

The table presents power studies of various testing strategies by estimating alternative models on data simulated to mimic (1) pecking order behavior, and (2) alternative or random financing behavior. The percentages at the top of each panel denote the fraction of observations in each sample that adhere to the pecking order's financing hierarchy, while the remaining fraction adheres to the alternative financing rule (see Appendix C for details). Panel A presents the prediction accuracy of the empirical model in Eqs. (8) through (11). For example, when half of the firms are adhering to the pecking order, 57.6% (67.9%) of simulated internal (external) financing decisions and 37.8% (49.0%) 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 (e.g., predict debt for every observation). Thus, for the 50% column, 67.9% of the external issuances are accurately classified, suggesting that a naive classification rule would accurately classify half (33.9%) of the debt and equity issuances by chance alone. Since the model correctly identifies 43.4%, this corresponds to an improvement of approximately 9.5%. Bootstrap 95% confidence intervals, based on 250 simulations are shown in brackets.

Panel B presents the parameter estimates and R^2's corresponding to the Shyam-Sunder and Myers (1999) empirical model. Panel C presents the parameter estimates and R^2's corresponding to an expanded specification of the Shyam-Sunder and Myers (1999) model that incorporates a squared financing deficit term. Panel D presents the fraction (out of 250 simulations) of statistically significant slope coefficients on the financing deficit variable in a binary logit regression of the decision to use internal funds vs. external funds. Panel E presents the ratio of the estimated financing deficit slope coefficients on debt and equity in a multinomial logit of the choice among internal funds (the omitted category), debt financing, or equity financing. Also presented is the fraction of simulations in which this ratio is significantly different from one, as suggested by a χ^2 test.

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	50.4%	47.3%	49.7%	52.2%	54.9%	57.6%	60.4%	63.3%	66.3%	69.9%	74.0%
External issuance	50.1%	57.7%	60.3%	62.9%	65.4%	67.9%	70.4%	72.8%	75.1%	76.9%	78.0%
Average correct	50.2%	52.5%	55.0%	57.6%	60.2%	62.8%	65.4%	68.0%	70.7%	73.4%	76.0%
95% Confidence interval	[49.5%, 50.8%]	[51.6%, 53.2%]	[54.1%, 55.8%]	[56.7%, 58.3%]	[59.3%, 60.9%]	[62.0%, 63.5%]	[64.6%, 66.1%]	[67.3%, 68.8%]	[70.0%, 71.5%]	[72.6%, 74.0%]	[75.3%, 76.6%]
Debt issuance	26.4%	26.0%	29.4%	32.8%	34.3%	37.8%	41.4%	45.0%	48.6%	51.9%	54.5%
Equity issuance	23.9%	35.2%	38.3%	41.4%	46.0%	49.0%	52.1%	55.0%	57.6%	59.6%	61.4%
Average correct	25.2%	30.6%	33.8%	37.1%	40.1%	43.4%	46.7%	50.0%	53.1%	55.8%	57.9%
95% Confidence interval	[21.7%, 28.8%]	[29.0%, 31.9%]	[32.3%, 35.0%]	[35.7%, 38.5%]	[38.9%, 41.6%]	[42.1%, 44.9%]	[45.3%, 48.3%]	[48.6%, 51.5%]	[51.9%, 54.4%]	[54.3%, 57.1%]	[56.3%, 59.3%]
Improvement	0.1%	1.7%	3.7%	5.7%	7.4%	9.5%	11.6%	13.6%	15.5%	17.3%	18.9%
95% Confidence interval	[−0.8%, 1.1%]	[0.3%, 2.9%]	[2.4%, 4.8%]	[4.6%, 6.9%]	[6.4%, 8.7%]	[8.3%, 10.8%]	[10.3%, 12.9%]	[12.2%, 14.9%]	[14.4%, 16.7%]	[16.1%, 18.5%]	[17.5%, 20.1%]

Panel B: Shyam-Sunder and Myers regression coefficient estimates: $\Delta Debt_t = \alpha + \beta$ Financing Deficit$_t + \varepsilon_t$

	Percent of firms following pecking order										
	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
$\hat{\beta}$	0.69	0.66	0.64	0.61	0.60	0.58	0.56	0.55	0.54	0.53	0.52
R^2	0.66	0.63	0.60	0.58	0.56	0.54	0.53	0.52	0.50	0.49	0.48

Panel C: Shyam-Sunder and Myers Regression Coefficient Estimates (Expanded Specification): $\Delta Debt_t = \alpha + \beta$ Financing Deficit$_t + \gamma$(Financing Deficit$_t)^2 + \varepsilon_t$

	Percent of firms following pecking order										
	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
$\hat{\beta}$	0.694	0.725	0.748	0.766	0.781	0.796	0.808	0.817	0.827	0.836	0.845
$\hat{\gamma}$	−0.002	−0.138	−0.233	−0.306	−0.367	−0.421	−0.465	−0.498	−0.532	−0.562	−0.588
R^2	0.663	0.633	0.612	0.595	0.581	0.570	0.560	0.551	0.544	0.538	0.532

Table 1 (*continued*)

Panel D: Binary logit of choice between internal and external financing as a function of financing deficit

	Percent of firms following pecking order										
	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
Fraction of simulations with statistically significant (5% test size) coefficient on the financing deficit variable	4%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%

Panel E: Multinomial logit of choice between internal, debt, and equity as a function of financing deficit (internal is omitted category)

	Percent of firms following pecking order										
	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
$\frac{\hat{\beta}^{equity}}{\hat{\beta}^{debt}}$	0.35	1.45	1.43	1.41	1.40	1.38	1.36	1.35	1.32	1.30	1.26
Fraction of simulations with statistically significant (5% test size) difference between $\hat{\beta}^{equity}$ and $\hat{\beta}^{debt}$	4%	30%	87%	98%	100%	100%	100%	100%	100%	100%	100%

The classification accuracy of the model for various financing decisions is given in the rows denoted: internal finance, external issuance, debt issuance, and equity issuance. To reduce simulation error, we repeat the process of simulating data, estimating the model, and computing prediction accuracies, 250 times. The resulting prediction accuracies are averaged across the 250 simulations. For example, when 50% of the sample data are generated according to the pecking order's decision rule, the model accurately identifies 57.6% of the internal financings, 67.9% of the external security issuances, 37.8% of the debt issuances, and 49.0% of the equity issuances. The model fit is summarized by the two "average correct" rows, which represent an average of the accuracy rates for internal and external decisions, and debt and equity decisions.

The last row, "improvement," corresponds to the prediction accuracy improvement of the pecking order model over that of a naive predictor, such as one that predicts the same outcome for every decision or that randomly chooses debt or equity. This measure is important in assessing the empirical relevance of the model and highlights several aspects associated with testing the pecking order. First, it illustrates the importance of accounting for the ability of the pecking order to accurately identify the first decision between internal and external funds, which determines the upper bound for accurately predicting debt and equity issuances.[8]

Second, while the Improvement measure enables us to identify the improvement of the model over a naive estimator, it is the combination of this measure with the simulation that enables us to translate the results into a more meaningful economic measure. In particular, though an improvement of 9.5% can be shown to be statistically significant (using bootstrap procedures that we discuss below), the economic significance is difficult to extract. However, by linking this improvement to the simulation results, we can see that a 9.5% improvement over a naive predictor corresponds to half of the sample adhering to the underlying theoretical model. Thus, by measuring the improvement of the pecking order over a naive predictor *and* comparing the improvement to our

(*footnote continued*)
the average percent of issuances correctly classified, which have little effect on the results.

[8] To illustrate, 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 cannot correctly identify any debt or equity issuances because all of the external issuances have been incorrectly identified as internal issuances. In the second case, all of the debt and equity decisions could potentially be accurately classified, though even a naive predictor would correctly predict half of them, on average. Therefore, to appropriately measure the performance of the model, we compare the average prediction accuracy for debt and equity decisions to that of a naive predictor, given the fraction of external decisions correctly predicted. For example, when 50% of the sample firms follow the pecking order, a naive predictor would get half of the accurately classified external issuances ($67.9\%/2 = 33.9\%$) correct, on average. Since the model accurately classifies 43.4% of the debt–equity choices in this case, the improvement is thus, $43.4\% - 33.9\% = 9.5\%$.

simulation results, we can better judge the economic significance of our results.

The results in Panel A of Table 1 lead to the following conclusions. First, the average predictive accuracy of the model increases monotonically with the fraction of firms following the pecking order, ranging from 50.2% to 76.0% for the internal–external decision and from 25.2% to 57.9% 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. Each prediction accuracy rate falls outside of the adjacent 95% bootstrap confidence intervals. Second, we note that even when every firm adheres to the pecking order—the 100% column—the model "only" gets 76.0% and 57.9% of the internal–external and debt–equity decisions correct, respectively. This outcome is due to variation in the error terms, ε_{it} and ω_{it}, which correspond to the econometrician's inability to perfectly measure the thresholds $\tilde{C}$ and $\tilde{D}$. To ensure the robustness of our results, we examine the impact of perturbing the variances of these error terms on the simulations by varying the parameter values over a three-standard-error range around the point estimates (discussed in more detail in Appendix C). None of the alternative values have a significant impact on the results. Thus, by focusing on the ability of the model to accurately classify observed financing decisions, we are able to distinguish among varying degrees of pecking order behavior.

3.3. Comparison with previous approaches

Panels B through E of Table 1 illustrate the power properties of previous approaches, as a means of comparison. For example, many recent studies (e.g., Frank and Goyal, 2003; Lemmon and Zender, 2004; Brav, 2009; Bharath, Pasquariello, and Wu, 2009; Halov and Heider, 2004) test the pecking order's financing hierarchy using the model and testing strategy of Shyam-Sunder and Myers (1999), who specify the change in debt as a linear function of the financing deficit[9]:

$$\Delta Debt_{it} = \alpha + \beta FinDef_{it} + \varepsilon_{it}. \tag{12}$$

The testing strategy proposed by Shyam-Sunder and Myers (1999) focuses on the null hypothesis that $\beta = 1$, so that debt changes dollar-for-dollar with the financing deficit. However, Chirinko and Singha (2000) show that this test 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, and thus, has little power to distinguish pecking order behavior from alternative hypotheses. Consistent with this intuition, Panel B of Table 1 shows that when we estimate Eq. (12) on the simulated data sets described in the previous section, the estimated coefficients and R^2's show a modest decline as the fraction of firms adhering to the pecking order increases from 0% to 100%.

The finding that $\hat{\beta}$ declines as pecking order behavior increases is at first surprising given that the proportion of debt and equity financing decisions is held constant across the samples. However, note that when firms follow a pecking order decision rule, larger investments are more likely to be financed with equity. Thus, for lower levels of *FinDef*, $\Delta Debt_{it} = FinDef_{it}$, but for high values of *FinDef*, $\Delta Debt_{it} = 0$. These high *FinDef* observations pull down the slope of the fitted line. The dampening effect is exacerbated by the skewness in the empirical investment distribution. By contrast, when firms make random financing decisions, the likelihood of an equity or debt issuance is independent of the size of the financing deficit, so the slope of the fitted line reflects the proportion of debt issuances.

Subsequent studies (e.g., Agca and Mazumder, 2004; Lemmon and Zender, 2004) incorporate nonlinear f unctions of the financing deficit into Eq. (12). Panel C of Table 1 shows there is downward trend in the squared financing deficit coefficients as the percent of pecking order firms increases, again a result of higher financing deficits being funded with equity. However, there is little systematic variation in the linear term or the R^2. More importantly, the sign and significance of the estimated coefficients provide little insight into the extent of pecking order behavior. For example, a linear coefficient above 0.7 and a significant negative coefficient on the squared financing deficit are consistent with anywhere from 10% to 100% of firms following the pecking order. Thus, while Lemmon and Zender (2004) appropriately use this nonlinear specification to illustrate the potential role for debt capacity in financing, the larger question of how well the pecking order describes financing decisions cannot be answered any more clearly.

An approach more closely related to that employed in this study is the use of discrete choice models (e.g. Helwege and Liang, 1996), where the choice among financing options is modeled as a function of the financing deficit and perhaps additional control variables. The testing strategy again relies on the sign and significance of the estimated coefficients. For example, in a binary model of the choice between internal and external funds, a positive coefficient on the financing deficit is interpreted as evidence consistent with the pecking order. Similarly, in a multinomial model of the choice among internal funds, debt, and equity, the coefficient on the deficit is expected to be positive for both debt and equity, but larger in magnitude for equity issuances since firms turn to equity only as the financing deficit increases.

Panels D and E present the results of estimating these two discrete choice models using the same simulated data sets and show that tests based on the financing deficit coefficient still have little power to distinguish among varying degrees of pecking order behavior. Panel D identifies the fraction of slope coefficients on the financing deficit (out of 250 simulations) that are statistically significant in a binary logit model of the decision between internal and external funds. The results show that even when only 10% of the firms in the sample are adhering to the pecking order, one obtains a coefficient estimate that is statistically significant at the 5% level.

[9] Shyam-Sunder and Myers (1999) also include the current portion of long-term debt, beyond its role in the change in working capital, when defining the financing deficit *FinDef*.

Panel E presents an analogous finding for a multinomial logit model of the choice among internal funds (the excluded choice), debt financing, and equity financing as a function of the financing deficit. The top row of Panel E presents the ratio of the estimated financing deficit coefficient for the debt equation to that for the equity equation. (We note that both coefficients are positive across all simulations.) First, this ratio is almost always statistically significantly different from one, as suggested by a χ^2 test, as long as at least 20% of the observations are adhering to the pecking order. That is, the coefficient on the equity choice is not only positive but is also statistically larger than that on the debt choice, precisely as the pecking order predicts. Second, the magnitude of the ratio is similar across most of the simulated data sets, suggesting that even an inspection of the magnitude of the ratio would provide little insight into the fraction of firms adhering to the pecking order. Rather, what this ratio conveys is the relative likelihood of issuing equity vs. debt, regardless of the reason why.

Ultimately, the results in this section provide the motivation for our empirical framework by showing that the power concerns raised by Chirinko and Singha (2000) apply quite broadly to existing tests. Additionally, the simulation results in Panel A provide a set of null hypotheses and benchmarks for interpreting our empirical results.

4. Data and summary statistics

4.1. Sample selection

For consistency with previous studies, our data are drawn from the Compustat database over the period 1980–2005.[10] We exclude financial firms (Standard Industrial Classification (SIC) codes 6000-6999) and utilities (SIC codes 4900-4999) to avoid capital structures governed by regulation. In line with previous capital structure studies, we trim the upper and lower 1% of each variable used in the analysis to mitigate the impact of data errors and outliers. The final sample consists of 34,470 firm-year observations, with non-missing data for all of the variables used in our analysis. As noted above, all variables are formally defined in Appendix A.

4.2. Identifying financing decisions

For consistency with the assumptions of the Myers and Majluf (1984) model, our construction of issuance decisions is motivated by a desire to isolate those financing decisions most likely intended to fund investment. To do so, we follow other studies such as Chen and Zhao (2003), Hovakimian (2006), Hovakimian, Opler, and Titman (2001), Korajczyk and Levy (2003), and Leary and Roberts (2005), that identify financing decisions as relative changes in debt and equity above a given size threshold. Specifically, a debt issuance is defined as a net change in total book debt from period $t-1$ to t, normalized by book assets in period $t-1$, in excess of 5%.[11] While there may be instances of misclassification using this scheme, such as when convertible debt is called, several previous studies employing this scheme have shown that their analysis is unaffected by using the Securities Data Company (SDC) new issues database to classify issuances. More importantly, this scheme enables us to include private debt issuances, which represent the most important source of external funds for most firms (Houston and James, 1996).

Table 2
Distribution of the magnitude of equity issuances.

The table presents the density and cumulative distribution of equity issuances. The sample is drawn from the annual Compustat files, excluding financial firms and utilities, during the period 1980–2005, and consists of the 34,470 firm-year observations with non-missing data for all of the variables used in our analysis. Equity (SCF) is defined using the statement of cash flows as the issuance of common and preferred stock, net of repurchases, during period t, divided by total assets in year $t-1$. Equity (SO) is defined for year t as the product of (1) the split-adjusted growth in shares, and (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, divided by assets in year $t-1$.

Issuance size	Equity (SCF)	Cumulative Equity (SCF)	Equity (SO)	Cumulative Equity (SO)
[0,0.01)	61.1%	61.1%	49.6%	49.6%
[0.01,0.02)	11.0%	72.1%	12.1%	61.8%
[0.02,0.03)	4.8%	77.0%	6.0%	67.8%
[0.03,0.04)	2.8%	79.7%	4.0%	71.8%
[0.04,0.05)	2.2%	81.9%	2.8%	74.7%
[0.05,0.07)	2.9%	84.7%	4.0%	78.7%
[0.07,0.10)	2.9%	87.6%	4.0%	82.6%
[.10, ∞)	12.4%	100.0%	17.4%	100.0%

We define equity issuances in two ways. The first uses the statement of cash flows and defines an issuance as the sale of common and preferred stock, net of repurchases, during period t in excess of 5% of book assets in period $t-1$. The second defines an issuance as the product of (1) the split-adjusted growth in shares, and (2) the average of the split-adjusted stock price at the beginning and end of the fiscal year, divided by assets in year $t-1$ and in excess of 5%. We focus on results using the former definition; however, we also present results obtained using the latter definition, as well as results obtained using alternative thresholds (e.g., 1% and 3% of assets) in Appendix B.

Table 2 presents the distribution of net equity issuances as a fraction of book assets. Fama and French (2005) note that "issues of stock to employees via options and grants play a big role in our results on the frequency of equity issues." The results in the table suggest that applying a cutoff of 5% of assets effectively eliminates such issues, which likely account for at least half of the total number of issues (if no cutoff were applied), but arguably fall outside the scope of what the pecking order model was intended to explain.

[10] We start the sample period in 1980 to coincide with the availability of Graham's (1996) simulated marginal tax rates.

[11] 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 Appendix B for robustness checks.

Table 3
Financing decisions and firm characteristics.

The sample is drawn from the annual Compustat files, excluding financial firms and utilities, during the period 1980–2005, and consists of the 34,470 firm-year observations with non-missing data for all of the variables used in our analysis. 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. Internal financing is assumed if no issuance is made. All variables, except for size and age, are scaled by book assets. *Current investment* is defined as the sum of capital expenditures, increase in investments, acquisitions, and other use of funds, less sale of property, plant, and equipment and sale of investment; *Cash balance* is defined as cash and marketable securities; *Current cash flow* for year t is defined as cash flow after interest and taxes net of dividends in year $t-1$; *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 (capital expenditures) 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 ten 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.

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	67.5%	0.06	0.07	0.10	1.18	0.21	4.86	0.15	0.20	0.29	0.07	17.0
Debt	22.6%	0.15	0.04	0.11	1.29	0.23	4.91	0.20	0.23	0.31	0.06	15.0
Equity	7.1%	0.10	0.07	0.09	1.60	0.25	4.23	0.27	0.23	0.27	0.09	10.0
Dual	2.8%	0.26	0.06	0.11	1.60	0.25	4.35	0.35	0.28	0.30	0.08	10.0

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 debt threshold, $\tilde{D}$.

Table 3 presents summary statistics for our data, which are consistent with the aggregate implications of the pecking order. The majority (67%) of financing decisions rely on internal funds, followed by debt (23%), and finally equity. Dual issuances represent a small minority (3%). Also presented for each financing event are average firm characteristics, which are broadly consistent with previous findings (see, for example, Titman and Wessels, 1988; Rajan and Zingales, 1995). Smaller firms, younger firms, and firms with higher leverage, greater cash flow volatility, more growth opportunities, and less asset tangibility rely more heavily on equity financing. Greater current and anticipated future investment results in a greater propensity to turn to external capital markets, both debt and equity. Overall, these results are reassuring in the sense that our sample selection and variable construction enable us to reproduce general results found in previous studies.

5. Results

5.1. Predictive accuracy

In order to measure the ability of the pecking order to explain financing decisions, we estimate Eqs. (8) through (11) via maximum likelihood using the issuance definitions described in the previous section. Panel A of Table 4 presents the predictive accuracies of the various model specifications, which range from a relatively strict (column 1) to a relatively liberal (column 7) interpretation of the pecking order. Panels B and C of Table 4 present, respectively, the corresponding internal–external and debt–equity equation parameter estimates for each model. To ease the discussion, we focus our attention primarily on the results corresponding to the second rung of the pecking order, the debt–equity decision, as the close link between the decision rule for the internal–external decision and the flow-of-funds identity ensures a relatively high prediction accuracy.

Column 1 in Panel A presents the predictive accuracy of a literal interpretation of the pecking order, where firms exhaust internal resources before turning to external financing ($\alpha_{it}^{C}=0$) and firms never issue equity ($\alpha_{it}^{D'}=\infty$). Because this literal interpretation leaves no latitude for savings or leverage policies, there are no parameters to estimate beyond the second moments of the error terms. While this limits our ability to compute sample adherence rates, which are based on both the simulations *and* estimation, we can compute the prediction accuracy rates, which show that 74% of the internal–external decisions and 30% of the debt–equity decisions are accurately classified.

Column 1 also reveals that 39.2% ($100\%-60.8\%$) of the observed debt issuances are in violation of the pecking order because internal funds exceeded investment. The 0% accuracy rate for equity issuances is due to the literal interpretation of the pecking order in which any equity issuance is considered a violation. Consequently, the average accuracy rate for external financing decisions is $(60.8\%+0\%)/2=30.4\%$, which coincides with a 1.2% improvement over a naive estimator—a negligible improvement as we shall see.

Column 2 relaxes the parameter restrictions by allowing firms to conduct independent savings and leverage policies, albeit ones that are a constant fraction of assets across firms and time. That is, we restrict $\alpha_{it}^{C}=\alpha^{C}$ and $\alpha_{it}^{D'}=\alpha^{D'}$, and allow the estimation to identify the optimal (in a maximum likelihood sense) parameter values. Still a relatively strict interpretation of the pecking order, we see that the improvement relative to a naive estimator is 3.1%, only slightly higher than the 1.2% found in column 1. By

Table 4
Parameter estimates and predictive accuracy across model specifications.

The sample is drawn from the annual Compustat files, excluding financial firms and utilities, during the period 1980–2005, and consists of the 34,470 firm-year observations with non-missing data for all of the variables used in our analysis. The table presents the prediction accuracy results (Panel A) and parameter estimates (Panels B and C) for the following censored bivariate probit (Eqs. (8) through (11) in the body of the paper)

$$External_{it} = \begin{cases} 1 & (Investment_{it} - InternalFunds_{it}) + \alpha_C + \varepsilon_{it} \geq 0, \\ 0 & \text{otherwise}, \end{cases}$$

$$Equity_{it} = \begin{cases} 1 & (Investment_{it} - InternalFunds_{it} + Debt_{it-1}) + \alpha_{D'} - \omega_{it} \geq 0, \\ 0 & \text{otherwise}, \end{cases}$$

where all variables are formally defined in Appendix A and scaled by book assets. The variable *PO* in Panels B and C is defined as *Investment* less *Internal funds* in the *External* equation and *Investment* less *Internal funds* plus *Debt* in the *Equity* equation. Standard errors are adjusted for heteroscedasticity and clustering at the firm level. The columns show results for various specifications of α_C and $\alpha_{D'}$. In column 6, the specification for $\alpha_{D'}$ includes those variables used in Rajan and Zingales (1995). Asterisks ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

For example, the results in Panel A column 2 imply that the pecking order correctly classifies 63.5% (75.9%) of the observed internal (external) financing decisions and 56.0% (26.1%) of the debt (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, expanded), as suggested by the simulation results. 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 column 2, 75.9% of external issuances are correctly classified, implying that 38.0% of debt–equity decisions will be correctly classified by a naive estimator. Since the model accurately identified 41.1% of the debt–equity issuances, this is an improvement of 3.1% which, according to our simulation results, corresponds to approximately 17% of the sample exhibiting pecking order financing behavior.

Panel A: Prediction accuracy

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Internal–external (α_C)	0	Constant	Constant	Industry	Year+Industry	Constant	Full integrated
Debt–equity ($\alpha_D - \alpha_C$)	1	Constant	MaxLev	Industry	Year+Industry	Rajan & Zingales	Full integrated
Internal finance	88.9%	63.5%	63.5%	67.6%	68.2%	63.8%	74.0%
External issuance	58.5%	75.9%	75.9%	75.2%	74.8%	75.7%	74.2%
Average correct	73.7%	69.7%	69.7%	71.4%	71.5%	69.8%	74.1%
Sample adherence		77.0%	77.0%	83.0%	84.0%	78.0%	93.0%
Debt issuance	60.8%	56.0%	56.1%	49.5%	52.1%	60.1%	56.7%
Equity issuance	0.0%	26.1%	26.1%	40.9%	41.1%	33.0%	49.1%
Average correct	30.4%	41.1%	41.1%	45.2%	46.6%	46.6%	52.9%
Improvement	1.2%	3.1%	3.2%	7.6%	9.2%	8.7%	15.8%
Sample adherence		17.0%	17.0%	40.0%	48.0%	46.0%	81.0%
Statistical significance (col (n)–col (2))				***	***	***	***
Statistical Significance (col (n)–col ($n-1$))				***	***		***

Panel B: Parameter estimates—Internal–external decision

	(1)		(2)		(3)		(4)		(5)		(6)		(7)	
Internal–external (α_C)	0		Constant		Constant		Industry		Year+Industry		Constant		Full	
Debt–equity ($\alpha_D - \alpha_C$)	1		Constant		MaxLev		Industry		Year+Industry		Rajan & Zingales		Full	
	Coeff.	*t*-stat	Coeff.	*t*-stat	Coeff.	*t*-stat	Coeff.	*t*-stat	Coeff.	*t*-stat	Coeff.	*t*-stat	Coeff.	*t*-stat
Constant (α_C)	0	n.a.	−0.192	−20.26	−0.192	−20.26	−0.109	−4.15	−0.353	−7.58	−0.197	−20.84	−0.626	−8.524
PO	1	n.a.	3.428	37.06	3.428	37.06	3.578	39.53	3.564	39.60	3.407	37.48	3.918	42.22
Firm Size													−0.023	−3.59
Anticipated investment													0.318	5.77
Anticipated cash flow													−0.222	−3.72
Cash flow volatility													0.637	3.67

Dividend payer													−0.133	−5.64
Z-score													0.041	4.34
R&D/sales													0.383	5.81
RDD													0.033	1.35
Market-to-book													0.212	15.94
Net Working capital													−0.632	−8.81
Industry indicators														
Consumer non-durables							−0.255	−6.44	−0.260	−6.53			−0.139	−3.26
Consumer durables							−0.105	−2.11	−0.113	−2.26			0.059	1.15
Manufacturing							−0.255	−7.75	−0.262	−7.89			−0.100	−2.84
Oil, gas and coal							−0.053	−1.07	−0.054	−1.08			−0.098	−2.05
Chemicals and allied prods							−0.309	−5.86	−0.318	−5.99			−0.191	−3.48
Business equipment							0.087	2.36	0.078	2.10			0.079	1.91
Telecom							0.040	0.45	0.051	0.57			0.001	0.01
Wholesale and retail							−0.134	−3.70	−0.140	−3.85			−0.062	−1.61
Healthcare, med equip and drugs							0.287	5.91	0.281	5.75			0.086	1.73

Panel C: Parameter estimates—Debt–equity decision

	(1)		(2)		(3)		(4)		(5)		(6)		(7)	
	Coeff.	*t*-stat	Coeff.	*t*-stat	Coeff.	*t*-stat	Coeff.	*t*-stat	Coeff.	*t*-stat	Coeff.	*t*-stat	Coeff.	*t*-stat
Constant ($\alpha_D - \alpha_C$)	1	n.a.	−1.314	−29.45	−1.366	−15.55	−1.284	−21.47	−1.232	−12.91	−1.349	−26.46	−0.658	−4.49
PO	1	n.a.	0.876	14.05	0.871	13.84	0.972	14.36	0.963	14.22	1.115	19.93	1.016	13.33
Inv Grade Lev					0.135	0.66								
Firm Size											−0.075	−11.41	−0.003	−0.26
Anticipated investment													0.304	7.59
Anticipated cash flow													0.058	1.01
Cash flow volatility													0.852	3.99
Dividend payer													−0.133	−3.79
Z-score													−0.135	−8.44
R&D/sales													0.483	4.03
RDD													−0.122	−3.12
Market-to-book											0.234	17.19	0.173	10.69
Net working capital													−0.369	−3.41
Tangible assets											−0.054	−0.84	−0.268	−2.97
Firm age													−0.010	−6.16
Stock return													0.199	8.69
Marginal tax rate													−0.908	−5.70
Industry leverage													−1.129	−5.10
Profitability											−0.569	−6.75		
Industry indicators														
Consumer non-durables							−0.428	−6.32	−0.429	−6.29			−0.166	−2.40
Consumer durables							−0.259	−3.23	−0.254	−3.15			−0.062	−0.76
Manufacturing							−0.309	−6.14	−0.305	−5.97			−0.132	−2.45
Oil, gas & coal							0.156	2.31	0.157	2.29			0.008	0.11
Chemicals and allied prods							−0.462	−5.39	−0.456	−5.34			−0.306	−3.61
Business equipment							0.367	7.18	0.373	7.21			0.101	1.76
Telecom							0.011	0.10	−0.008	−0.07			−0.211	−1.95
Wholesale & retail							−0.239	−4.57	−0.244	−4.58			0.042	0.76
Healthcare, med equip and drugs							0.519	7.86	0.513	7.69			−0.042	−0.66

comparing this 3.1% improvement to the simulation results in Table 1, we see that this translates into a sample adherence rate of 17%. That is, when 10% of our simulated firms follow the pecking order decision rule, the model's accuracy rate is a 1.7% improvement over a naive predictor. When 20% follow the pecking order, the improvement increases to 3.7%. Using a linear interpolation between these outcomes, a 3.1% improvement corresponds to 17% of the firms adhering to the underlying model. Thus, our results suggest that 83% of the firms in our sample are violating the second rung of the pecking order under this strict interpretation.

Column 3 incorporates Myers' (1984, p. 589) notion that firms may wish to maintain "reserve borrowing power…to issue safe debt" by allowing $\alpha_{it}^{D'}$ to vary across industries and years in accord with the leverage ratio required to maintain an investment-grade rating. That is, we assume that firms can issue debt in a given year up to the point where their leverage ratio would be equal to the 90th percentile of the distribution of leverage ratios of investment-grade rated firms in the same industry and during the same year. Interestingly, there is little change in the predictive accuracy of the model—83% of our sample firms violate the second rung of the pecking order even under this more liberal interpretation of the model.

Columns 4 and 5 incorporate industry and year fixed effects into the specification of both α_{it}^{C} and $\alpha_{it}^{D'}$. Specifically, we define these quantities in column 4 as

$$\alpha_{it}^{C} = \sum_{j=1}^{J} \beta_j I(Industry = j)$$

$$\alpha_{it}^{D'} = \sum_{j=1}^{J} \gamma_j I(Industry = j),$$

and column 5 as

$$\alpha_{it}^{C} = \sum_{j=1}^{J} \beta_j I(Industry = j) + \sum_{t=1}^{T} \delta_t I(year = t)$$

$$\alpha_{it}^{D'} = \sum_{j=1}^{J} \gamma_j I(Industry = j) + \sum_{t=1}^{T} \theta_t I(year = t),$$

where $I(x)$ is an indicator variable, industry is defined by the Fama and French 12-industries, and β_j, γ_j, δ_t, and θ_t are parameters to be estimated. In column 4 we notice a substantial improvement in predictive accuracy—40% of sample firms adhere to the pecking order's second rung. Including year fixed effects with the industry fixed effects, further increases this accuracy to 48%. We verify that these are statistically significant differences, as indicated in the "significance" rows of the table, using bootstrap standard errors.[12] While relaxing the specification in this manner undoubtedly captures elements of Myers' (1984) modified pecking order, the fixed effects also likely capture elements of other theories such as those based on taxes, liquidation costs, product market competition, stakeholder effects, etc. We also note that even with this additional flexibility, the predictive accuracy is consistent with less than half of firms following the underlying model. Therefore, in the last two columns, we explore further the impact of explicitly including other factors that may lie outside the pecking order's purview.

In column 6, we specify firms' debt capacities as a function of four firm characteristics popularized by Rajan and Zingales (1995), but used throughout the empirical capital structure literature (e.g., Baker and Wurgler, 2002; Frank and Goyal, 2003; Lemmon and Zender, 2004). Specifically,

$$\alpha_{it}^{D'} = \beta_1 \ln(Assets_{it}) + \beta_2 \text{Market} - \text{to} - \text{Book}_{it} + \beta_3 Profitability_{it} + \beta_4 Tangibility_{it}.$$

We assume that $\alpha_{it}^{C} = \alpha^{C}$, as in column 2, but note that relaxing this restriction by incorporating year and industry fixed effects or firm characteristics has little affect on the sample adherence rate found for the debt–equity decisions. The sample adherence rate for the debt–equity decision suggests that 46% of firms adhere to the pecking order's hierarchy under this interpretation—close to that found in columns 4 and 5 using year and industry fixed effects.

While multiple interpretations can be placed on the firm characteristics found in this specification, as with the fixed effects in the previous specification, it seems plausible that they capture factors outside a simple static tradeoff between adverse selection costs and financial distress costs. For example, Baker and Wurgler (2002) and Baker, Stein, and Wurgler (2003) suggest that the market-to-book ratio proxies for security mispricing. Likewise, corporate profitability plays a central role in estimating marginal tax rates (Graham, 1996). Nonetheless, even if one does grant full explanatory power to pecking order forces, the model is unable to accurately capture half of the observed debt–equity decisions.

Finally, in column 7, we specify α_{it}^{C} and $\alpha_{it}^{D'}$ to be functions of industry and year fixed effects, as well as a broader list of firm characteristics identified by the empirical literature as being important determinants of corporate capital structure (Frank and Goyal, 2009). (The characteristics are listed in column 7 of Panels B and C, which present the coefficient estimates.) The predictive accuracy of the debt–equity choice increases by 33% from that found in column 5, the model closest in terms of predictive accuracy. Relative to the model in column 3, which allows firms to increase their leverage to that of an investment-grade rated firm in the same industry-year combination, we see a quintupling in predictive accuracy from 17% to 81%. Even the predictive accuracy of the internal–external decision experiences an economically significant improvement relative to previous models. Thus, existing determinants are capable of explaining a large majority of observed financing decisions.

Panels B and C of Table 4 present the corresponding parameter estimates for the internal–external and debt–equity decisions, respectively. We avoid discussing these

[12] The bootstrapping procedure is accomplished by sampling 17,500 observations with replacement, where the sample size corresponds to the effective size of our Compustat sample after accounting for within-firm dependence. (See Appendix C for details.) We then re-estimate the model and compute the predicted financing decisions and corresponding accuracy rates. Repeating this procedure 500 times generates a distribution of accuracy rates, of which we take the standard error.

estimates in detail since the results correspond closely with those found in previous studies of firms' cash management strategies (e.g., Opler, Pinkowitz, Stulz, and Williamson, 1999) and financial policies (e.g., Marsh, 1982; Hovakimian, Opler, and Titman, 2001; Leary and Roberts, 2005). However, we note several features pertaining to our analysis.

First, the parameter estimates from column 2 show that the probability of using external funds and equity financing is positively correlated with the financing deficit as captured by the variable *PO* (the 3.43 and 0.88 figures in Panels B and C, respectively). Second, the negative estimate for α^C seems counterintuitive to the interpretation of this parameter as the mean level of cash holdings for firms, which we know to be strictly positive (e.g., Opler, Pinkowitz, Stulz, and Williamson, 1999). Though, this estimate is more the result of our strict interpretation of the pecking order, which struggles to match the observed financing decisions.[13] Third, our estimate of the correlation between the error terms ε and ω is a highly statistically significant 0.71, suggesting that multinomial specifications relying on the independence of irrelevant alternatives (e.g., multinomial logit) are suspect.[14]

Finally, the variation in predictive accuracy across columns 1 through 7 in Panel A can be traced back to the relative importance of the included variables, many of which are highly statistically significant. For example, in the debt–equity equation (Panel C) anticipated investment and the market-to-book ratio have positive coefficients. This suggests that some firms may issue equity in order to reserve debt capacity for funding future investment opportunities, or to limit the underinvestment problem associated with high leverage. While the first of these explanations can be consistent with a dynamic pecking order, we also find that marginal tax rates, *Z*-score, and industry median leverage have significant negative coefficients, suggesting that tax-bankruptcy tradeoff considerations are relevant factors as well.

While the extent to which the pecking order fails or succeeds clearly depends on one's interpretation of the hypothesis, these results suggest that a fairly liberal interpretation is required to explain even half of the observed financing decisions. While we are reluctant to dismiss the pecking order as empirically irrelevant given the theoretical ambiguity surrounding the hypothesis, two clear conclusions follow from our analysis. First, existing empirical determinants can explain a large majority of financing decisions. Second, factors beyond just static adverse selection costs and the ability to issue safe debt appear to play an important role in governing financial policy.

[13] While we would like to do a similar analysis of the estimate of $\alpha^D = \alpha^C - \alpha^{D'}$, we are unable to calculate it since α^C and $\alpha^{D'}$ are only identified up to (different) scale factors.

[14] In unreported analysis, we note that a likelihood ratio test of the restrictions that the slope coefficients in Eq. (9) are equal and the slope coefficients in Eq. (11) are equal is rejected at all conventional significance levels. This rejection implies that the more restrictive hypothesis assuming that all coefficients are equal is rejected, as well.

5.2. Implied thresholds

As the previous subsection illustrated, the performance of the pecking order depends crucially on the definition of the thresholds defining firms' cash reservoirs and debt capacities. In this subsection, we take an alternative, "model-free" approach to examining the pecking order. Specifically, rather than imposing a particular structure on the key thresholds, α^C_{it} and α^D_{it}, and then asking how well that structure fits, we ask: What thresholds are implied by the data and are those implied thresholds consistent with a modified pecking order?

We do so by recognizing that each observed financing decision places either an upper or lower bound on one of the two thresholds, α^C_{it} or α^D_{it}. For example, in order for an external financing decision (debt or equity) to be consistent with the first rung of the pecking order, it must be the case that investment outstrips the internal funds available for investment, or

$$Investment_{it} - [InternalFunds_{it} - \alpha^C_{it}] > 0,$$

which implies

$$\alpha^C_{it} > InternalFunds_{it} - Investment_{it} \equiv \alpha^{Cmin}_{it}.$$

Observation of *Investment* and *InternalFunds* enables us to quantify this lower bound on firms' savings, which we denote α^{Cmin}_{it}. Thus, any observed external issuance can be justified under the pecking order if the savings requirement of the firm, or equivalently α^C_{it}, exceeds this lower bound.

Likewise, in order for an equity issuance to be consistent with the second rung of the pecking order, it must be the case that investment outstrips both the internal funds and debt capacity available for investment, or

$$Investment_{it} - [InternalFunds_{it} - \alpha^C_{it}] - [\alpha^D_{it} - Debt_{it-1}] > 0,$$

which implies

$$\alpha^D_{it} < Investment_{it} - [InternalFunds_{it} - \alpha^C_{it}] + Debt_{it-1} \equiv \alpha^{Dmax}_{it}. \tag{13}$$

Observation of *Investment*, *InternalFunds*, and *Debt* enables us to quantify this upper bound on firms' debt capacities, which we denote α^{Dmax}_{it}, given an estimate of α^C_{it}. Thus, any observed equity issuance can be justified under the pecking order if debt capacity, or equivalently α^D_{it}, is less than α^{Dmax}_{it}.

These insights suggest that one way to evaluate the empirical relevance of the pecking order is to ask whether the implied values of α^{Cmin}_{it} and α^{Dmax}_{it} appear unreasonably high or low, respectively. In other words, for observed financing decisions to be consistent with the pecking order, are firms required to save an inordinate amount of cash or exhibit an excessively low debt capacity? As in the previous section, we focus our analysis and discussion on the second rung of the pecking order governing the debt–equity choice since this is where the primary tension lies, both theoretically and empirically.

In order to evaluate the implied debt capacities, α^{Dmax}_{it}, we first need an estimate of α^C_{it} corresponding to the portion of current cash holdings that are *not* available for current investment. We choose two simple and conservative estimates: (1) the firm's contemporaneous cash balance, and (2) the median cash balance of firms in the same industry-year combination. The first estimate assumes that *none* of the firm's cash-on-hand is available for investment. The second estimate assumes that the firm targets an industry-year median level of cash, and therefore, only cash balances in excess of that target are available for investment.

We note that these estimates are conservative in that they likely overstate the savings requirements of firms since they assume firms can never tap into their cash balances for investment. However, by overestimating the firms' cash reservoirs, α_{it}^{Cmin}, our implied estimates of α_{it}^{Dmax} will be overstated and, therefore, work in favor of finding that the pecking order provides a reasonable description of observed equity issuances. Simply put, our assumptions are stacking the deck in favor of the pecking order.

The second hurdle in evaluating the implied debt capacities is a benchmark with which to judge their reasonableness. As discussed above, the theory behind the pecking order is unclear on this dimension; however, Myers (1984) and Myers and Majluf (1984) suggest that a firm set its debt capacity to "restrain itself enough to keep the debt safe." And, as before, we interpret this to mean that a firm can issue debt up to the point where its leverage ratio would be in the upper end of the distribution of investment-grade rated firms in the same industry-year combination. Thus, for each equity issuance, we compare the ratio of α_{it}^{Dmax} to total assets, to the 90th percentile leverage ratio of investment-grade rated firms in the same industry-year combination.

Values of this ratio greater than one suggest that issuing debt in place of equity would increase leverage beyond that of an investment-grade rated firm in the same industry-year. In this case, debt capacity may arguably constrain the firm in its ability to issue "safe debt" and, consequently, the equity issuance would appear to be warranted under a modified pecking order story. Values less than one would suggest the opposite, that issuing debt instead of equity would lead to a leverage ratio that would keep the firm's leverage ratio in the investment-grade range. In this case, issuing equity on the basis of limited debt capacity seems less justified.

Panels A and B of Fig. 2 present the cumulative distributions of these ratios for each of the two estimates of α_{it}^{Cmin}. Because the results in both panels are similar, we focus our attention on Panel A, which shows that 40% of observed equity issuances appear to be justified on the grounds that issuing debt may have led to excessively high leverage ratios. However, approximately 60% of equity issuances take place when firms appear to have sufficient debt capacity to fund investment. In fact, the median ratio is 0.85, which implies that in order for the pecking order to explain just half of the equity issues, it must be that leverage ratios 15% *below* those of investment-grade rated firms in the same industry are considered "dangerously high" (Myers, 2001, p. 92). Further, the extent to which firms can use some of their internal capital to finance investment suggests that our estimate may overstate the extent to which debt capacity is, in fact, a binding constraint on firms' abilities to issue debt.

In sum, these results fit nicely with the prediction accuracies found in the previous subsection. Simply put, a modified pecking order in the spirit of the discussion in Myers (1984) and Myers and Majluf (1984) appears to struggle with classifying a large fraction of equity issuances.

5.3. Implied cost of debt capital

In this subsection, we undertake an additional robustness test of our results by testing whether debt capacity concerns (e.g., financial distress) are what drive firms to issue equity in violation of the pecking order. Specifically, we use the prediction results from Model 3 in Table 4—which allows firms' debt capacities to vary across industries and years in accord with the leverage ratios of investment-grade rated firms in the same industry-year combination—to identify whether an equity issuance is or is not in violation of the pecking order's prediction. For those issuances that are in violation ("equity violators"), we examine whether they appear to be driven by debt capacity concerns by comparing them 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 (Denis and Mihov, 2003). 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, 2007).

With this analysis, we can see whether equity issuers are significantly different from private borrowers along the dimensions suggested by the modified pecking order that introduces financial distress costs into the adverse selection framework of Myers and Majluf (1984). Again, we note that this approach is significantly different from that taken by previous studies showing that equity issuances are (are not) correlated with proxies for bankruptcy costs, such as Lemmon and Zender (2004), Helwege and Liang (1996), and Fama and French (2005). Without an ability to accurately identify which issuances adhere to and violate the pecking order, these correlations have little to say about the link between the pecking order and debt capacity considerations.

Our private lender data for this analysis are from an August 2005 extract of the Dealscan database, marketed by Loan Pricing Corporation (LPC). The data consist 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 1987–2003.[15] Borrower

[15] For a complete description of the Dealscan database, see Carey and Hrycray (1999).

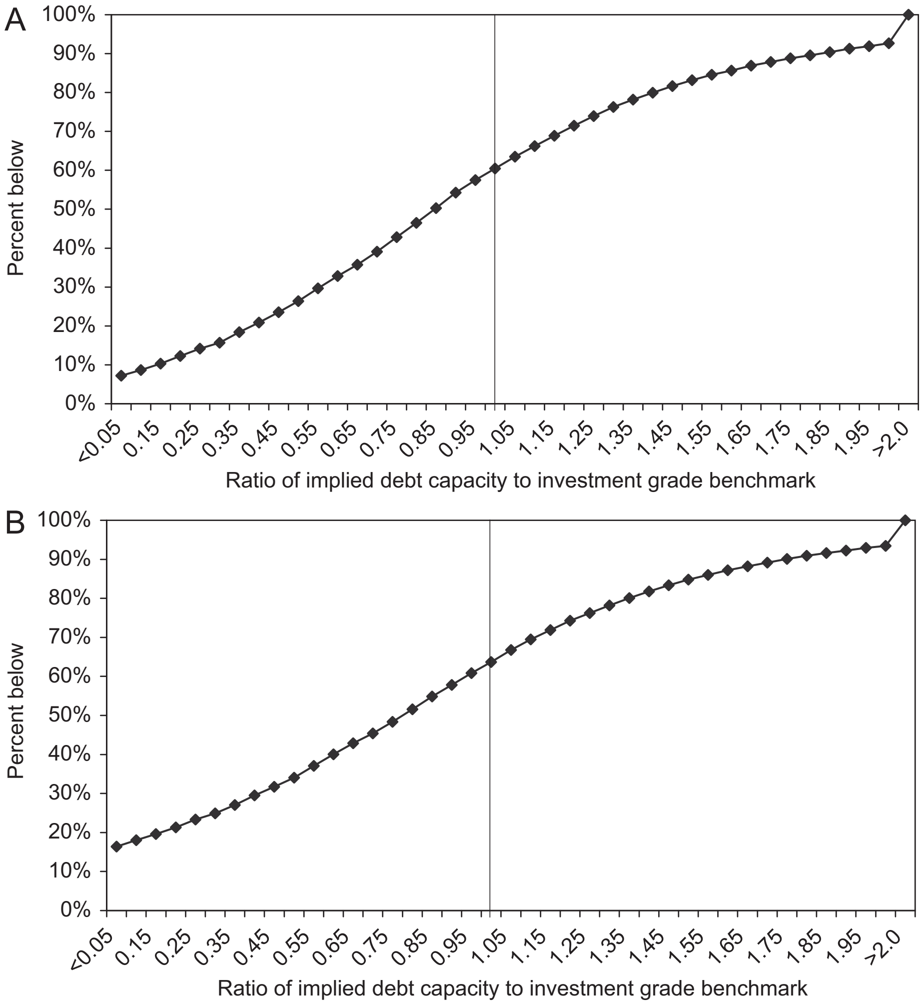

Fig. 2. Cumulative distribution of α_{it}^{Dmax}/ investment grade benchmark. The sample is drawn from the annual Compustat files, excluding financial firms and utilities, during the period 1980–2005, and consists of the 34,470 firm-year observations with non-missing data for all of the variables used in our analysis. The figure shows the cumulative distribution of the ratio of α_{it}^{Dmax} to the 90th percentile leverage ratio of investment-grade rated firms in the same industry-year combination, where industry is defined as the Fama-French 12 industries. For years prior to 1985, when Compustat first reports credit rating data, industries are assigned the median benchmark from the post-1985 period. α_{it}^{Dmax} is computed for each observation in which a firm issues equity as $\alpha_{it}^{Dmax} \equiv Investment_{it} - [InternalFunds_{it} - \alpha_{it}^{C}] + Debt_{it-1}$, as described in Section 5.2. In Panel A, α_{it}^{C} is defined as the firm's contemporaneous cash balance; in Panel B it is defined as the industry median cash balance. Equity issues are defined as proceeds from the sale of common and preferred stock, net of repurchases, in excess of 5% of beginning-of-year book assets.

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 37,764 unique, dollar-denominated loans corresponding to 6,725 non-financial U.S. firms during the period 1987–2003.

Table 5 presents a comparison of the Equity violators' firm characteristics with those of our sample of private borrowers. Because our private borrower data are limited to the time period 1987–2003, 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 mean. The fifth and sixth columns present the median and mean values for the sample of Equity violators. The last column presents t-statistics testing the difference in means between the two samples.[16]

Consistent with the importance of debt capacity concerns, the equity issuers are, on average, smaller (total sales and assets) and less profitable, and have higher cash flow volatility, and lower Z-scores. However, equity issuers also have much lower leverage, a higher current ratio (current assets/current liabilities), similar asset tangibility, and smaller financing deficits. More important than these paired mean and median comparisons, though, is a comparison of the two samples' distributions. In other

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

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 comes from an August, 2005 extract of the Dealscan database, marketed by Loan Pricing Corporation (LPC), which consist 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 1987–2003. *Book leverage* is defined as the sum of short-term and long-term debt divided by the book value of assets; *Market leverage* is defined as the sum of short-term and long-term debt divided by the sum of short-term debt, long-term debt, and market equity. *Profitability* is the ratio of EBITDA to total assets. *Market-to-book* is defined as the ratio of total assets minus book equity plus market equity to total assets; *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. *Current investment* is the ratio of capital expenditures to total assets. *Total assets* is the book value of assets 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. *Tangible assets* is defined as net property, plant and equipment; *Current ratio* is the ratio of current assets to current liabilities. *Loan yield spread* is the all-in spread above the six-month LIBOR obtained from Loan Pricing Corp.'s Dealscan database. For Equity violators, the yield spread is estimated using the empirical model in Bradley and Roberts (2003). Other variables are as defined in Table 3 and Appendix A. The *t*-stat tests the null hypothesis that the sample means are equal and uses standard errors adjusted for dependence at the firm level.

	Private debt firms				Equity violators		Difference in means
Variable	25th-Percentile	Median	75th-Percentile	Mean	Median	Mean	*t*-stat
Book leverage	0.18	0.32	0.47	0.33	0.14	0.19	71.30
Market leverage	0.12	0.30	0.52	0.34	0.09	0.18	65.63
Profitability	0.08	0.12	0.16	0.11	0.09	0.03	47.42
Market-to-book	0.77	1.04	1.56	1.39	1.34	2.04	−34.08
Financing def.	−0.02	0.04	0.19	0.16	0.02	0.14	6.76
Current investment	0.03	0.05	0.09	0.07	0.04	0.06	9.25
Total sales	96.59	369.17	1421.11	2198.04	298.36	1422.94	8.85
Total assets	93.16	363.70	1528.84	2596.41	262.97	1256.27	14.80
Cash flow vol.	0.03	0.06	0.09	0.07	0.10	0.14	−68.09
Z-Score	0.70	1.50	2.31	1.46	1.34	0.52	38.19
Tangible assets	0.15	0.29	0.51	0.34	0.20	0.26	35.38
Current ratio	1.10	1.60	2.31	1.85	2.11	2.73	−48.16
Loan yield spread (bp)	65.00	150.00	275.00	184.21	169.58	182.74	1.06

words, the more relevant question is: What is the overlap in the distributions of both samples? For example, more than half of the Equity violators have market-to-book ratios that fall below the 75th percentile of the borrowers. Thus, while some equity issuers may be facing debt capacity concerns, the majority of our Equity violators do not appear significantly different from their counterparts that turn to the private lending market.

Though suggestive, the above analysis is unconditional. The last row in Table 5 presents a comparison of the distributions of estimated loan yield spreads for our Equity violators (had they turned to the private lending markets) with the actual yield spreads faced by private borrowers. The yield spreads for Equity violators are estimated as a function of firm characteristics, and industry and year fixed effects using the empirical model in Bradley and Roberts (2003).[17] The yield distribution for the sample of bank borrowers has a median (mean) promised yield of 150 (184.21) basis points (bp) above the six-month LIBOR. The median (mean) estimated spread for the Equity violators is 19.6 (−1.5) basis points higher than that of the borrowers. The difference in median spreads, 19.6 basis points, is economically small and the difference in means actually suggests that Equity violators would experience *lower* costs of debt capital than private borrowers, albeit insignificantly lower. Thus, while debt capacity concerns may be important for some potential borrowers, for the majority of equity issuers that violate the pecking order's prediction, the differential cost of capital seems small. Thus, a modified pecking order incorporating debt capacity concerns is unlikely a sufficient explanation for many observed debt and equity financing decisions.

[17] Bradley and Roberts (2003) regress loan yield spreads on book leverage, log assets, the ratio of tangible assets to book assets, the ratio of operating cash flow (EBITDA) to book assets, cash flow volatility, log of the market-to-book ratio, Altman's *Z*-Score, investment, and year fixed effects.

5.4. *What friction generates pecking order behavior?*

While the original motivation for the pecking order comes from the adverse selection model of Myers and Majluf (1984), a number of studies have shown that information asymmetry is neither necessary nor sufficient for a financing hierarchy to arise. For example, transaction costs could generate a pecking order since issuance costs increase as we move from internal funds (no cost) to debt and then to equity (Altinkiliç and Hansen, 2000). Likewise, Myers (2003) illustrates how incentive conflicts, in the sense of Jensen and Meckling (1976), can generate a similar pecking order because the costs of private benefits stay internalized with a debt issuance but are shared with outside shareholders with an equity issuance. Finally, Stiglitz (1973) illustrates how corporate taxes can generate a pecking order of financing in which debt is preferred to equity. As noted by Frank and Goyal (2008), "no one [to date] has tried to distinguish among the alternative possible sources of pecking order behavior."

Interestingly, a number of studies also show that information asymmetry need not result in a preference for debt over equity. Theoretical studies by Cooney and Kalay (1993), Fulghieri and Lukin (2001), Halov and Heider (2004), and Hennessy and Livdan (2006) all show that information asymmetry can lead to financial policies other than a strict preference for debt over equity. In fact, Bolton and Dewatripont (2005) show that even in the Myers and Majluf (1984) framework, the preference ranking can be reversed, with firms preferring to issue equity before debt, under certain parameterizations.

These alternatives motivate us to examine which, if any, underlying frictions are driving pecking order behavior. Our strategy is to first split our sample into high and low friction groups based on various empirical proxies for information asymmetry, corporate taxes, agency conflicts, and transaction costs. We then separately estimate our empirical model on each of the two groups, low and high, in order to compare the predictive accuracies.[18] To minimize the subjectivity of our inferences, we present results from both a strict (constant cash reservoirs and debt capacities, column 2 of Table 4) and a liberal (cash reservoirs and debt capacities that vary with industry and year, column 5 of Table 4) interpretation of the pecking order.

Of course, a limitation of this approach is that the empirical proxies for market imperfections are precisely that—proxies, and often noisy ones at that. Consequently, our stratification scheme, and therefore inferences, may be confounded by other omitted correlated factors. As such, we rely on proxies identified by previous studies focused on specific market imperfections. While the preceding caveat is still relevant, previous research has argued that significant associations between each proxy and its corresponding friction do exist. Additionally, this exercise has descriptive value, insofar as pecking order behavior exhibits systematic variation across different measures.

The predictive accuracies for the debt–equity decision are presented in Table 6. We begin with several proxies for information asymmetry. For example, our first proxy distinguishes between hot (high equity issuance) and cold (low equity issuance) years, as in studies by Korajczyk, Lucas, and McDonald (1990, 1991), Choe, Masulis, and Nanda (1993), and Bayless and Chaplinsky (1996) who investigate time-variation in adverse selection costs on security issuance decisions.[19] This proxy shows little support for information asymmetry playing a role in generating pecking order behavior. Firms appear to adhere to the financing hierarchy only slightly more often in times with high information asymmetry (i.e., cold periods) relative to low information asymmetry (i.e., hot periods) and this difference reverses once we relax the empirical specification to allow cash reservoirs and debt capacities to depend on industry and year fixed effects.

Firms are also slightly more likely to adhere to the financing hierarchy when they are not covered by equity analysts, yet this difference also reverses once we allow for a more flexible model specification. Using analyst forecast dispersion (upper third percentile vs. lower third) as an alternative proxy produces similarly ambiguous results. Further, when we use other proxies for information asymmetry based on firm size, age, and tangible assets, we observed that firms are more likely to adhere to the pecking order when information asymmetry is *low*—a result that is robust to the model specification. Thus, the evidence in favor of information asymmetry generating pecking order behavior is at best ambiguous and not robust to variations in either the proxy or model specification.

Firms facing relatively higher marginal tax rates are slightly more likely to adhere to the pecking order, but only under a strict model specification. Our other proxies for tax burdens—profitability and operating loss carryforwards—reveal similar results.

Our proxies for transaction costs reveal ambiguous evidence that the propensity to adhere to the pecking order increases with issuance costs. Under a strict interpretation of the model, we find that firms facing higher transaction costs for equity issues are actually *less* likely to adhere to the financing hierarchy. Under the more liberal interpretation, however, we see some evidence that pecking order behavior increases as transaction costs rise.[20]

Finally, when we stratify the sample according to agency cost proxies, we see a systematic and robust pattern of high agency cost firms being more likely to adhere to the pecking order. Specifically, large firms, firms with low market-to-book ratios, high cash flow, and low shareholder protection are more likely to follow the pecking order. This result is robust across the different proxies, as well as the different model specifications. Further, the prediction accuracies among high agency cost

[18] In order to ensure an appropriate comparison between empirical and simulation results, we rerun the simulation described in Section 3 and Appendix C for each subsample, matching the distributions of investment, internal funds, and debt as well as the sample proportions of investment decisions to the firm-years in each given subsample. Results are similar if we rely solely on the simulation results in Table 1.

[19] 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 the number of equity issuances scaled by (1) the number of sample firms, or (2) the total net issuance volume scaled by the total market value of equity in the sample. This second measure controls for market value fluctuations. 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). Because all measures yield similar results, we report only those based on the issuance volume rankings.

[20] The issuance costs are computed using the results of Altinkiliç and Hansen (2000), who regress underwriter spreads, separately for debt and equity issues, on the size of the issuance and the size of the issuance relative to the size of the firm (i.e., market capitalization). We use their estimated parameters to estimate the underwriter spreads that would occur for each firm-year observation if the entire investment were financed with debt or equity. We then use two related measures of transaction costs to stratify our sample: the estimated spread for an equity issue, and the difference between the estimated equity and debt spreads.

Table 6
Model prediction accuracy across sample strata.

The sample comes from the annual Compustat and IBES summary history files during the period 1980–2005. The table presents the average prediction accuracy for debt and equity issuances from the empirical model discussed in the text. "Hot" and "Cold" periods are defined using a variant of that used by 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 (low information asymmetry) to be those in the upper quartile, based on this ranking, and cold years (high information asymmetry) to be those in the bottom quartile. *Analyst coverage* is a binary variable equal to 1 if a firm is covered in the IBES summary history files for a given year. High (low) information asymmetry is associated with *Analyst coverage* $=0$ (1). *Forecast dispersion* is the standard deviation of the one-year-ahead EPS forecast for the first month in each fiscal year. High (low) information asymmetry is associated with the upper (lower) third of the distribution. *Firm age* is the number of years the firms has been on Compustat. High (low) information asymmetry is associated with the lower (upper) third of the distribution. *Firm size* is the natural logarithm of book assets. High (low) information asymmetry is associated with the lower (upper) third of the distribution. High (low) agency cost is associated with the upper (lower) third of the distribution. *Tangible assets* is defined as the ratio of net property, plant, and equipment to total assets. *Marginal tax rate* is Graham's (1996) before-financing marginal tax rate, obtained from John Graham's Web site. High (low) taxes is associated with the upper (lower) third of the distribution. For *Operating loss carryforward*, high (low) taxes is associated with the lower (upper) third of the distribution. *Equity spread* is the estimated underwriter spread associated with funding contemporaneous investment with an external equity issue, using the empirical model of Altinkiliç and Hansen (2000). High (low) transaction costs is associated with the upper (lower) third of the distribution. *MA/BA* is defined as the ratio of total assets minus book equity plus market equity to total assets. High (low) agency cost is associated with the lower (upper) third of the distribution. *Hi CF - Low growth op* is an indicator equal to one for firms with above-median profitability and below-median market-to-book ratio (high agency cost), and zero for firms with below-median profitability and above-median market-to-book ratio (low agency cost). *G-Index* is the Gompers et al. (2003) governance index of shareholder rights, obtained from Andrew Metrick's Web site. High (low) agency cost is associated with the upper (lower) third of the distribution.

	Measures of information asymmetry			
	α_C, α_D specification = constant		α_C, α_D specification = year-industry	
	Low info asymm	High info asymm	Low info asymm	High info asymm
Hot/cold periods	11%	12%	57%	40%
Analyst coverage	17%	24%	51%	46%
Forecast dispersion	24%	17%	55%	58%
Firm size	34%	17%	58%	46%
Firm age	30%	11%	59%	43%
Asset tangibility	32%	17%	56%	51%
	Measures of corporate taxes			
	α_C, α_D specification = constant		α_C, α_D specification = year-industry	
	Low tax	High tax	Low tax	High tax
Marginal tax rate	13%	19%	54%	54%
Operating loss carryforward	16%	17%	45%	47%
Profitability	21%	25%	58%	50%
	Measures of transaction costs			
	α_C, α_D specification = constant		α_C, α_D specification = year-industry	
	Low trans cost	High trans cost	Low trans cost	High trans cost
Equity spread	33%	11%	50%	64%
Equity–debt spread	42%	22%	54%	68%
	Measures of agency costs			
	α_C, α_D specification = constant		α_C, α_D specification = year-industry	
	Low agency	High agency	Low agency	High agency
Firm size	17%	34%	46%	58%
MA/BA	28%	35%	51%	60%
Hi CF–Low growth op	11%	36%	52%	56%
G-Index	13%	53%	61%	78%

firms are noticeably higher than any of the other high friction groups. Indeed, based on the *G*-Index, roughly 53% (78%) of high agency cost firms adhere to a strict (modified) pecking order, by far the highest predictive accuracy of any subgroup. Ultimately, these results suggest that observed pecking order behavior is more likely due to incentive conflicts, as opposed to information asymmetry.

We also note that our results with regard to firm size are interesting in relation to the conflicting conclusions of two recent studies. Frank and Goyal (2003) argue that larger firms are more likely to follow the pecking order, based on their finding that β in Eq. (12) is increasing in firm size. This is in contrast to Fama and French's (2005) conclusion that small firms are more likely to adhere to the pecking order, based on their classification scheme. Our results support the conclusions of Frank and Goyal (2003), but for very different reasons. Frank and Goyal's (2003) results imply that small firms issue relatively more equity than large firms. Our results imply that *when* small firms issue equity, they are less apt to be motivated by pecking order considerations (i.e., the relation between investment needs and the availability of internal funds and debt financing) than are larger firms.

6. Conclusion

We provide new evidence on whether and when the pecking order accurately describes financial policy using a novel empirical model and testing strategy that addresses power concerns. A relatively strict interpretation of the hypothesis that limits the variation in firms' savings and debt policies leads to relatively poor performance—fewer than 20% of firms follow the pecking order's predictions concerning debt and equity issuance decisions. However, even after allowing firms' debt capacities to vary in a manner consistent with that of investment-grade rated firms in the same industry, we still find that fewer than 20% of firms follow the pecking order's predictions concerning debt and equity issuance decisions.

Only when we allow firms' debt capacities to vary with variables often attributed to alternative theories (e.g., tradeoff) does the predictive ability of the pecking order improve significantly. Indeed, a model incorporating a broad range of determinants from previous capital structure studies accurately classifies over 80% of the observed debt and equity issuance decisions. This finding is consistent with the conjecture of Fama and French (2005) who suggest treating pecking order and tradeoff models "as stable mates, each having elements of the truth that help explain some aspects of financing decisions." Thus, while the empirical relevance of the pecking order depends crucially on one's interpretation of the hypothesis, our findings show that (1) existing empirical determinants can explain a large majority of financing decisions, and (2) considerations beyond just static adverse selection costs and the ability to issue safe debt appear to play an important role in governing financial policy.

Additionally, we find that incentive conflicts, not information asymmetry, appear to generate pecking order behavior in the data. For firms facing more severe incentive conflicts, we find that even a strict interpretation of the pecking order can explain more than half of the observed debt and equity decisions. Thus, the pecking order appears to struggle with identifying observed financing decisions not only because it disregards as second-order many factors that are important for financing decisions, but also because pecking order behavior appears to be driven more by incentive conflicts, as opposed to information asymmetry.

7. Uncited reference

Frank and Goyal (2008).

Appendix A. Variable definitions

Dividends = data127
Investment
 = data128 + data113 + data129 + data219 − data107 − data109
 (Format code 1,2 & 3)
 = data113 − data109 + data128 − data107 + data129 − data310
 (Format code 7)
Change in Net Working Capital (excluding changes in cash and short-term debt)
 = − (data180 − (data1(t) − data1($t-1$)) − (data34(t) − data34($t-1$))
 (Format code 1)
 = − (data112 − data116) + (data1(t) − data1($t-1$)) − data301
 (Format code 2)
 = data236 + data301 − data274 + (data1(t) − data1($t-1$)) − data301
 (Format code 3)
 = data302 + data303 + data304 + data305 + data307 + data312
 (Format code 7)
Cash Balance = data1
Cash Flow
 = data123 + data125 + data124 + data126 + data106 + data217
 + data213 + data218
 (Format codes 1,2,3(post 1986))
 = data123 + data125 + data124 + data126 + data106 + data217 + data218
 (Format codes 1,2,3(pre 1987))
 = data123 + data125 + data124 + data126 + data106 + data213
 + data217 + data314
 (Format code 7)
Debt = data9 + data34
Firm Size = ln(data6 ∗ Consumer Price Index (CPI) deflator)
Firm Age = number of years since first observation in Compustat
Tangible Assets = data8/data6
Forecast Dispersion = STDEV/abs(MEANEST) of the one-year-ahead earnings per share (EPS)
 forecasts from the Institutional Broker's Estimate System (IBES) database
Analyst Coverage = $I[NUMEST > 0]$ for the one-year-ahead EPS forecasts from the IBES database
Market Leverage = (data9 + data34)/(data9 + data34 + data25 ∗ data199)
Book Leverage = (data9 + data34)/data6
Profitability = data18 + data15 + data16/data6($t-1$)
Book Equity = data6 − data181 − data10(or data56
 if data10 is missing) + data35 + data79
Market − to − Book = (data6 − Book Equity + (data199 ∗ data25))/data6;
Total Sales = data12
Total Assets = data6
Cash Flow Volatility = std dev(Profitability) over years $t-1$ up to $t-10$
Z−Score = [3.3 ∗ (data18 + data15 + data16) + data12 + 1.4 ∗ data36
 + 1.2 ∗ (data4 − data5)]/data6
Current Ratio = data4/data5
Anticipated Investment = $(Investment_{t+1} + Investment_{t+2})/BookAssets_{t-1}$
Anticipated Cash Flow = $(CashFlow_{t+1} + CashFlow_{t+2})/BookAssets_{t-1}$
Dividend Payer = I[data127($t-1$) > 0]
RD/Sales = data46/data12(set to zero if data46 missing)
RDD = $I[RD/Sales = 0]$
Stock Return = (data199/(lagdata199 ∗ (data27/lagdata27))) − 1
Marginal Tax Rate = Before-financing MTR, kindly provided by John Graham (http://faculty.fuqua.duke.edu/jgraham/taxform.html)
Depreciation = data14/Total Assets
Operating Loss Carryforward = data52/data12
Industry Leverage = median(Book Leverage($t-1$)) among firms in the same two-digit SIC group
Selling Expense = data189/data12

Appendix B. Robustness checks

Though we have addressed various robustness concerns throughout the paper, we report the results of several specific tests in Table B1, using as a baseline model in Panel A the constant-only specification (column 1 of Table 4), and in Panel B the Rajan and Zingales (1995) specification (column 6 of Table 4). The second column shows the results when we expand our definition of

Table B1
Model prediction accuracy for alternative variable definitions and model specifications.

The sample is drawn from the annual Compustat files, excluding financial firms and utilities, during the period 1980-2005, and consists of the 34,470 firm-year observations with non-missing data for all of the variables used in our analysis. In Panel A (B), column 1 repeats the results from column 2 (6) 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, equity issuance is defined as the product of (i) the split-adjusted growth in shares, and (ii) the average of the split-adjusted stock price at the beginning and end of the fiscal year in excess of 5% of assets. 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 "Improvement" row in the debt–equity decision shows the model's improvement in prediction accuracy relative to a naive estimator that would, on average, accurately identify half of the external issuances. For example, the baseline model accurately predicts 63.5% of internal financings, 75.9% of external financings, 56.0% of debt issuances, and 26.1% of equity issuances. The internal–external average prediction accuracy of 69.7% translates into 77% of the sample firms adhering to the model's decision rules, based on the simulation results in Table 1. The improvement over a naive estimator is 41.1% −75.9%/2 = 3.1%. This is consistent with 17% of the sample firms adhering to the model's decision rules.

Panel A: Constant-only model

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Actual decision	Baseline model	Expanded investment	SCF Total DebtIss	SCF LT DebtIss	3% Cutoff	1% Cutoff	Equity (SO)
Internal finance	63.5%	67.9%	64.0%	63.9%	61.4%	58.2%	73.6%
External issuance	75.9%	74.9%	77.3%	75.7%	75.0%	72.3%	64.0%
Average correct	69.7%	71.4%	70.7%	69.8%	68.2%	65.2%	68.8%
Sample adherence	77%	84%	81%	78%	72%	61%	74%
Debt issuance	56.0%	47.9%	65.1%	60.6%	60.5%	71.4%	70.6%
Equity issuance	26.1%	32.6%	18.8%	17.8%	19.3%	6.2%	4.8%
Average correct	41.1%	40.3%	41.9%	39.2%	39.9%	38.8%	37.7%
Improvement	3.1%	2.8%	3.3%	1.4%	2.4%	2.7%	5.7%
Sample adherence	17%	15%	18%	7%	13%	14%	30%

Panel B: Year-Industry Model

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Actual decision	Baseline model	Expanded investment	SCF Total DebtIss	SCF LT DebtIss	3% Cutoff	1% Cutoff	Equity (SO)
Internal finance	68.2%	69.3%	69.1%	68.4%	67.1%	66.6%	75.5%
External issuance	74.8%	74.3%	76.0%	74.2%	73.3%	69.5%	60.3%
Average correct	71.5%	71.8%	72.6%	71.3%	70.2%	68.0%	67.9%
Sample adherence	84%	85%	88%	83%	79%	71%	71%
Debt issuance	52.1%	49.7%	57.8%	52.2%	51.6%	51.3%	45.5%
Equity issuance	41.1%	44.0%	35.0%	38.0%	39.3%	35.4%	31.2%
Average correct	46.6%	46.8%	46.4%	45.1%	45.5%	43.3%	38.3%
Improvement	9.2%	9.7%	8.4%	8.0%	8.9%	8.6%	8.2%
Sample adherence	48%	51%	44%	42%	47%	45%	43%

investment to include both advertising and research and development (R & D) expenditures. Many of the small, young firms issuing equity in the 1990s may have been focused on the development of intellectual property (e.g., high-tech and pharmaceutical companies) or on establishing 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 only slightly increases the model's ability to explain firms' internal vs. external financing choices and has little effect on its ability to classify debt vs. equity decisions. Thus, while there may be important investments for some firms beyond those measured by capital expenditures, this consideration does not account for those security 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-term debt from the statement of cash flows. The fourth column uses only long-term debt issuance to identify debt issues. This measure 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. Neither of these changes affect our conclusions.

Columns 5 and 6 present the results of using alternative (1% and 3%) thresholds in our definition of debt and equity issuances. Again, the results are not altered substantially, but the model is less able to classify financing decisions as the threshold is lowered. This finding suggests that either the model is simply better able to identify relatively larger financing decisions, or that those decisions are more likely related to investment financing, insofar as non-investment financing is more prevalent among smaller issuance sizes. Finally, column 7 illustrates the results using Fama and French's (2005) definition of equity issuances based on the change in shares outstanding. This measure of equity issuance includes issuances for the purpose of stock-based mergers that do not generate cash. Using this definition weakens the model's performance on the first rung of the pecking order, as the decision rule for the internal–external decision is now further from the flow of funds identity. Of the external decisions it does accurately predict, the model is able to correctly classify a higher percentage of debt and equity decisions (30%) than in our baseline model. However, our qualitative conclusions regarding the pecking order remain unchanged.

Appendix C. Simulations

C.1. Data simulation

We begin by rewriting Eqs. (8) through (11) in a slightly different form to ease the discussion of the simulation experiment:

$$External_{it} = \begin{cases} 1 & Investment_{it} - C_{it} + \varepsilon_{it} \geq 0, \\ 0 & Investment_{it} - C_{it} + \varepsilon_{it} < 0, \end{cases} \tag{14}$$

$$Equity_{it} = \begin{cases} 1 & Investment_{it} - D_{it} + \omega_{it} \geq 0, \\ 0 & Investment_{it} - D_{it} + \omega_{it} < 0, \end{cases} \tag{15}$$

where

$$C_{it} = InternalFunds_{it} - \alpha_C,$$

$$\begin{aligned} D_{it} &= InternalFunds_{it} - Debt_{it} - \alpha_{D'} \\ &= InternalFunds_{it} - Debt_{it} - (\alpha_C - \alpha_D) \\ &= C_{it} + D'_{it}\ , \end{aligned}$$

and $\omega_{it} = \varepsilon_{it} - \eta_{it}$. To eventually estimate the model, we require simulated data for *Investment*, *C*, *D'*, and the two errors, ε and ω. Using these simulated data, we can construct simulated financing decisions, *External* and *Equity*, using either the Pecking order decision rule or the Alternative decision rule discussed below and in Section 2.

Because *Investment*, *Internal Funds*, and *Debt* are observable, we simply use the values from our empirical sample. This ensures that comparisons between simulated and empirical results are not affected by differences in the distributions of the explanatory variables. We then need only to generate simulated data for the two errors, ε and ω, and the two constants, α_C and α_D.

We assume that the error vector, (ε, ω), has mean zero and covariance matrix

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

The error terms, ε and η (not ω), correspond to variation around the average cash reservoirs and average debt levels maintained by firms, respectively. As such, we proxy for these unobservables with the residuals from the following regressions:

$$\frac{CashBal_{it}}{Assets_{it-1}} = \beta_0 + \varepsilon_{it},$$

$$\frac{Debt_{it}}{Assets_{it-1}} = \beta_1 + \eta_{it}.$$

Because $\omega = \varepsilon - \eta$, we can use the residuals from the above regressions to construct an estimate of ω_{it}. With empirical proxies for both ε and ω, we can estimate the components of the covariance matrix *W*, namely, σ^2_ε, σ^2_ω, and $\sigma_{\varepsilon,\omega}$, with their sample counterparts.[21]

The two unspecified parameters are the constants, α_C and α_D. Because the focus of the pecking order and our study is on financing decisions, we specify these two parameters in a manner to ensure that the means of the simulated financing decisions, *External* and *Equity*, match their empirical counterparts. That is, conditional on the data and other parameter estimates, we choose α_C and $\alpha_{D'}$ such that the ratio of internal to external decisions and debt to equity decisions match what is found in the data (see Table 3). 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.

With the parameterization in place, the simulation begins by independently drawing random pairs from a bivariate normal distribution with zero mean vector and covariance matrix *W*. The simulated errors, ε and ω, are added to the observable components of *C* and *D'* and the constants to obtain $\tilde{C}$ and $\tilde{D}$ required for constructing the financing decisions. The normality assumption is made to coincide with our empirical model, a bivariate probit, and is consistent with previous studies relying on symmetric distributions (i.e., normal or logistic) to model financing decisions (e.g., Marsh, 1982; Mackie-Mason, 1990; Hovakimian, Opler, and Titman, 2001).

With a simulated triplet $(Inv, \tilde{C}, \tilde{D})$, we construct financing decisions using two different decision rules: "pecking order" and "alternative." The former rule is defined by Eqs. (3) and (6) so that internal funds are used if $Inv < \tilde{C}$, otherwise, external funds are used. Conditional on using external funds, debt finance is used if $Inv < \tilde{D}$, otherwise, equity finance is used. The Alternative 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

[21] The variance estimates, σ_ε and σ_η, defined by the two regressions correspond to upper thresholds of the unobserved variation in firms' cash and debt levels (i.e., there is no explained variation beyond the mean). Reducing these estimates only reduces our estimates of pecking order accuracy since the model must identify a greater number of decisions for a given fraction of firms following the pecking order.

(see Table 3). Specifically, the Alternative decision rule is governed by

$$External_{it} = \begin{cases} 1 & \tilde{U}_1 \geq 0.67, \\ 0 & \tilde{U}_1 < 0.67, \end{cases} \tag{16}$$

$$Equity_{it} = \begin{cases} 1 & \tilde{U}_2 \geq 0.70, \\ 0 & \tilde{U}_2 < 0.70, \end{cases} \tag{17}$$

where $\tilde{U}_1$ and $\tilde{U}_2$ are random draws from uniform (0,1) distributions. Thus, the probability of a debt or equity issuance is the same as under the Pecking order rule, but the issuance decision is no longer a function of *Investment*, $\tilde{C}$, or $\tilde{D}'$.

C.2. Model estimation

We simulate 17,500 observations according to each of these two rules. This sample size is chosen to approximate the effective number of observations in our empirical sample after accounting for within-firm dependence.[22] Additionally, we simulate nine samples varying the fraction of the simulated issuance decisions that use the Pecking order decision rule and the Alternative decision rule by increments of 10%. For each of the 11 simulated samples, we estimate the model in Eqs. (8) through (11) via maximum likelihood (Greene, 2003) and we map the predicted probabilities into predicted financing decisions using the mapping outlined in the body of the paper. To reduce simulation error, we repeat the process of simulating data, estimating the model, and computing prediction accuracies, 250 times. The resulting prediction accuracies are averaged across the 250 simulations to produce the results in Table 1.

In order to estimate the financing deficit regression (Eq. (12)) using our simulated data, we compute the change in debt, change in equity, and financing deficit implied by each sequence of simulated financing decisions. Specifically, if the firm uses internal funds, then $\Delta Debt = \Delta Equity = 0$. If the firm uses debt financing, then $\Delta Debt = Investment$ and $\Delta Equity = 0$. If the firm uses equity financing, then $\Delta Debt = 0$ and $\Delta Equity = Investment$. 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. In unreported analysis, 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 similar.

[22] We approximate the effective sample size by first calculating standard errors for our baseline bivariate probit model (column 2 of Table 4) with and without firm-level clustering. The clustered standard errors are approximately 1.4 times larger than the unclustered. This suggests the effective sample size is roughly 51% ($1/1.4^2$) of the actual sample size.

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