Target Behavior and Financing: How Conclusive is the Evidence?*

Xin Chang
Department of Finance
Faculty of Economics and Commerce
University of Melbourne

Sudipto Dasgupta*
Department of Finance
Hong Kong University of Science and Technology

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ABSTRACT

The notion that firms have a debt ratio target and that this is a primary determinant of financing behavior is influential in finance. Yet, how definitive is the available evidence? We examine this question by benchmarking the dynamics of actual debt ratios and the pattern of financing after major leverage-changing events against what is observed in samples generated through simulations where no target behavior is assumed. We find that the collective evidence that has been interpreted as indicative of target behavior is much weaker than is generally recognized. Specifically, the simulated data show similar reversal of the debt ratio and patterns of debt and equity issuance after major leverage-changing events as in the actual data. We attribute the former to a mechanical reversal that exists on average, even with random financing, if the debt ratios are above or below a cut-off, and the latter to persistence of the financing deficit around major issuance activities. Some of the evidence in the actual data, however, can only be replicated if the simulation samples are modified to accommodate a specific type of “market timing” behavior. On the whole, our results indicate that there is not much to be learnt from the behavior of the debt ratios as to firms’ motives for different types of financing. While models of issuance or repurchase that address the debt versus equity choice are in principle better, our simulations raise some concerns about the interpretation of existing results.

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* Corresponding author. Department of Finance, Hong Kong University of Science and Technology, Clear Water Bay, Kowloon, Hong Kong. E-mail: dasgupta@ust.hk. Tel: 852-2358-7685. Fax: 852-2358-1749.
1. Introduction

A traditional view in finance is that firms have debt ratio targets. For example, the notion of the weighted average cost of capital – taught to generations of finance students and recommended as the discount rate in capital budgeting - presupposes the existence of “target capital structure” weights. Tradeoff models that stress various costs and benefits of debt imply the existence of an optimal debt ratio, and it is assumed that firms make financing choices that minimize the cost of deviation from this optimum. In this paper, we evaluate the evidence in favor of the view that firms do have debt ratio targets. More specifically, we ask whether the available evidence could be consistent with financing behavior that does not assume the existence of any target at all. We find that a bulk of the evidence that has been interpreted as indicative of target behavior can be readily replicated if the choice of the security to be issued is dictated by the resolution of a state variable that has no relationship to either a firm’s current or any optimal debt ratio – such as even the outcome of a coin toss. Some residual evidence does point to the existence of a preferred debt ratio for firms; however, the collective evidence is much weaker than is generally recognized.

Our results by no means contradict the existence of debt ratio targets – nor do we try to establish any specific alternatives to target behavior. While our results imply that the available evidence is consistent with alternative theories of financing, including even indifference, we do not try to discriminate between theories. In this, we differ from some other approaches that specifically question tradeoff theory by proposing alternatives. For example, the Pecking Order Hypothesis (henceforth, the POH) posits that firms do not have debt ratio targets. Firms’ managers do optimally choose a financing that maximizes the payoff to the firm’s existing shareholders – however, the POH maintains that such behavior does not amount to firms targeting a specific debt ratio (see Myers (1984), Myers and Majluf (1984), Shyam-Sunder and Myers (1999)). More recently, two other theories have emerged that question the existence of debt ratio targets. Baker and Wurgler (2002) argue that firms “time” their security issues to take advantage of favorable market conditions, and that the effect of such issuance activity on the debt ratio is quite persistent – suggesting that returning to an optimal debt ratio is not a first-order concern for firms. Welch (2004) argues that the dynamics of the debt ratio is largely determined by stock returns. Firms are not inert or passive – their issuance activity does explain a significant proportion of the variability of the debt ratio. However, the primary objective of such activity does not seem to be to adjust back to a target.
Our methodology is similar to one that was first adopted by Shyam-Sunder and Myers (1999), but, surprisingly, has been ignored by the subsequent literature. For a sample of firms from Compustat from 1971 to 2004 obtained by imposing the requirement of at least twenty years of continuous data, we generate a new series of debt ratios under alternative assumptions about financing behavior. Importantly, the financing deficit, or equivalently, the amount of external capital that is raised, is assumed to be the same as in the actual data in every firm-year for all but one of our samples, so that the sum of net debt and equity issued or net debt and equity repurchased is the same as in the actual data. The simulated data differ from the actual data only in one respect – the amount of debt and shareholder equity on the balance sheet every year.

We track the evolution of the debt and equity under the assumption that firms choose the type of security to be issued (if the actual deficit is positive) or repurchased (if the actual deficit is negative) randomly. Only debt or equity is issued or repurchased in a given year. In one of our samples, the choice of the security to be issued or repurchased is determined essentially by a coin toss. In another sample, the choice is determined randomly in accordance with the empirical probability of debt or equity issuance or repurchases (conditional on the deficit being positive or negative, respectively) in the actual data across all firm years. A third sample is selected by relaxing the assumption that the deficit is the same as in the actual data. Here, the deficit (scaled by the book value of assets) is also randomly drawn, simultaneously with the change in retained earnings scaled by the book value of assets as well as the return on assets, in such a way as to preserve the means and standard deviations and the sample correlations that exist in the actual data. However, since each draw is an independent draw from the same distribution, we break any serial correlation and remove any firm-specific component that exists in the actual time series. For this particular sample, the actual financing choice (the issue or repurchase of debt or equity equal in magnitude to the deficit) is determined by a coin toss. A fourth sample keeps the assumption of random financing with one exception: when the firm’s stock returns are especially good or bad, a specific kind of “timing behavior” is assumed.

Why do we choose random financing as a benchmark? The actual financing choices of firms are likely to be determined by the realization of certain state variables that are observed by the firm insiders but are unobserved (or only imperfectly observed) by researchers. Thus, the

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1 In the actual data, conditional on the deficit being positive, the probability of a debt issue is about 0.75; conditional on the deficit being negative, the probability of a debt repurchase is around 0.65.
2 Existing literature also does not offer much guidance as to the determinants of the debt-equity choice. For example, a recent paper by Leary and Roberts (2005b) shows that even a careful and elaborate modeling of issuance decisions has only about 50% accuracy.
probability of debt or equity issuances or repurchases will correspond to the probability with which these state variables are jointly realized. As long as the realizations of these state variables are unrelated to the actual debt ratio or the target, our simulations that assume random financing encompass almost any other theories of financing except that of target behavior. The latter would require that the probability of equity issuance is high when the debt ratio is above target, and that of debt issuance is high when the debt ratio is below target. By assuming fixed probabilities of debt and equity issuance, we can be sure that our simulations do not mimic target adjustment behavior. Yet, as we discuss below, the simulated data are able to replicate almost all the results associated with target behavior.

Our main findings are as follows. We first examine whether the evidence usually attributed to “rebalancing” behavior and “reversal” after shocks to the debt ratio can occur in the simulated data as well. We find that existing evidence can be replicated on the simulated data. The explanation for this is quite simple: there is a mechanical reason why average debt ratios that are below a cut-off would increase and those that are above a cut-off would decrease even with random financing. Suppose the deficit is positive and firms choose debt or equity issues with equal probability. Then it is easy to check that if the debt ratios are below 0.5, then the average debt ratio will increase; if the debt ratios are above 0.5, then the average debt ratio will decrease. Since firms that make major equity (debt) issues are likely to have a larger proportion of firms with debt ratios below (above) 0.5 after the issuance than non-issuers, the average debt ratio for the issuers will increase (decrease) relative to non-issuers subsequently. Chen and Zhao (2005a) and Baker (2004) have made related points about mechanical mean reversion.

When we compare the debt and equity issuance behavior of the date 0 issuers and non-issuers, or those that experience shocks to equity prices (henceforth “equity shocks”) and those that do not, the evidence is even more revealing. We find that date 0 debt or equity issuers subsequently issue both more debt and more equity than date 0 non-issuers – not only in the actual sample but also for the simulated samples in which the deficit is as in the actual data, but the financing is random. We show that this is due to a higher proportion of positive deficits among date 0 issuers than date 0 non-issuers immediately after date 0 – a consequence of serial

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3 If firms issue debt with probability $p$ and equity with probability $1-p$, then the average debt ratio will increase (decrease) if the initial debt ratio is below (above) $p$.

4 If the deficit is negative and firms buy back debt and equity with equal probability, then the debt ratio will decrease (increase) if the initial debt ratio is below (above) 0.5. However, positive deficits are twice as common in the actual data as negative deficits. Thus, the effects associated with positive deficits dominate.

5 Chen and Zhao (2005a) show that when the book debt ratio is close to 1 (0), the change in the debt ratio must necessarily be primarily determined by change in book equity (book debt). As a consequence, the debt ratio will mean revert.
correlation in the deficit. Conditional on the deficit being positive, there is in fact little difference in the frequency of issuance of either type of security among date 0 issuers and non-issuers in the actual sample. Overall, the evidence raises serious doubts about any rebalancing behavior in the data. Regression analyses confirm this conclusion.

We next examine whether existing evidence that supports mean reversion of the debt ratio can be reproduced in the simulated data. In regressions similar to Flannery and Rangan (2005), we estimate mean reversion rates in both the actual and simulated data that are comparable to those obtained by these authors. In our simulation samples, the “mean reversion” is obviously mechanical rather than driven by any target-reverting behavior, and is a consequence of fitting a firm-specific mean to a time series that is bounded between zero and one. Therefore, the tests of mean reversion on the actual data do not appear to be especially powerful in ruling out mechanical explanations.

In these regressions, we include the usual firm-specific variables that are considered determinants of the target debt ratio. For the simulated samples, there is no target. Yet, these same variables show statistically significant coefficients in the simulated data. The only exception is the sample in which the deficit is also random. Here, except for profitability, all other variables are insignificant. In our simulations, the evolution of the debt ratio is determined by the financing deficit and random financing. Since the financing choice is random and not affected by firm-specific variables, our results suggest that the latter variables in the simulated data are significant only because they affect the financing deficit. Consistent with this observation, when the deficit is also random, these variables are no longer related to the debt ratio. Generally, variables that are likely to be associated with a higher deficit have positive coefficients in the simulated data, and this is especially the case for the simulated sample in which the probability of debt issuance is as in the actual data, i.e., 75%.

The market-to-book ratio is one of the variables associated with larger positive deficits. This variable stands out because its coefficient is positive in most of the simulated samples but negative in the actual data. We next ask whether the negative effect of the market-to-book ratio in the actual data could be because firms issue equity when market conditions are good. We generate a new sample in which firms are mechanically assumed to “time the market”.

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6 Recall that for this sample, when we randomly draw the deficit (together with return on assets and change in retained earnings), we preserve the means, standard deviations and the correlations between these variables as in the actual data. Profitability is negatively significant even in the sample in which the deficit is random because profitable firms retain more and this increases the book value of equity. Our results therefore suggest that retention policy drives the negative effect of profitability on leverage.

7 This new sample is generated as follows. We assume that the deficit is the same as in the actual data, and the probabilities of issuance or repurchase are conditional on market condition. In “good times”, i.e. when the stock
Remarkably, the coefficient of the market-to-book in this “market timing” sample is negative, and of similar magnitude to the one in the actual data.

The literature has proposed various ways of testing whether or not the effects of market timing behavior on capital structure are persistent. For example, Baker and Wurgler (2002) propose an “external financing deficit-weighted” market-to-book ratio to capture market timing. Kayhan and Titman (2005) show that this measure can be decomposed into two components – the covariance of the financing deficit with the market-to-book ratio scaled by the average deficit, and the average market-to-book ratio. We find that the coefficient of the covariance term (reflecting past market timing) is negative in the actual data. It is much smaller in magnitude (though still negative) in the simulated data when the issuance is random. However, in the simulated “market timing” sample, the negative sign of this coefficient reappears, and is virtually of an identical magnitude to that in the actual data. These results suggest that tests of market-timing do have the power to distinguish between random financing and timing behavior.

Overall, our results show that tests of target behavior based on the debt ratio do not have the power to reject alternative financing behavior. A natural question, therefore, is whether or not tests based on firms’ issuance or repurchase activities support target behavior. Hovakimian (2004) reports that when combined issue and repurchase transactions are removed, there is very little evidence that firms with leverage ratios above (below) an estimated target have a higher likelihood of issuing equity (debt). However, firms with above-target debt ratios do tend to buy back debt more often, which is consistent with target behavior. We find similar results.

When these models of debt-equity choice are applied to the simulated data, some interesting findings emerge. Since our simulations assume that the probabilities of debt or equity issuance (repurchase) conditional on the deficit being positive (negative) are exogenous, neither the deviation of the leverage from an estimated target nor firm characteristics should have any explanatory power in probit models of debt versus equity choice. In a small number of cases (less than 3% of the issuance/repurchase years), however, our simulation exercise calls for an issuance or a repurchase activity contrary to what is dictated by the random outcome. This is necessitated by the need to move away from the boundaries of 1 and 0 when the firm has very small book equity or book debt.8 Remarkably, the effect of this apparently innocuous deviation

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8 The details are given in section 4. None of the results involving debt ratios change when these corner cases are removed.
from the random financing rule is to render the deviation from the target (as well as some firm-specific variables) significant in probit models when applied to our simulated data. However, not surprisingly, when these corner cases are removed, none of these variables are significant any more. Multinomial logit models in which the possibility of issuance and repurchase are jointly modeled, on the other hand, reveal an even more surprising finding. Even when the corner cases are removed, the deviation from the target and most firm characteristics are significant. This is because the deficit is correlated with the leverage ratio and firm characteristics – hence whether or not the firm will issue or repurchase is affected by the latter variables through the deficit. These results suggest that (a) Probit models of debt-equity choice can be extremely sensitive to relatively minor quirks in the data, and (b) results from multinomial logit regressions that model issuance and repurchase decisions simultaneously need to be interpreted with caution.

While our results show that tests of target behavior are mostly inconclusive since they cannot reject alternatives, the notion of a debt ratio target need not be a vacuous one. We do find some support for a preferred debt ratio when we compare the proportion of variation in the debt ratio that can be explained by firm dummies and industry dummies, respectively, in the actual and simulated data. In the actual data, 3-digit industry dummies account for about 29% of the variation that can be explained by firm dummies, but for the simulated data the proportion is only 16%. To the extent that industry characteristics subsume firm characteristics, this suggests that the latter are more relevant for observed capital structure in the actual data than in the simulated data – a finding that is consistent with the notion of an optimal capital structure.

The rest of the paper is organized as follows. Section 2 briefly reviews the existing evidence for and against a debt ratio target. Section 3 describes our actual data sample, simulated data, and four major events related to change in firm leverage. Empirical analysis and results are reported in Section 4. Section 5 concludes the paper.

2. The current evidence for and against a debt ratio target

While the so-called “static” trade-off models assume that the debt ratio is the result of a single-period tradeoff between the tax benefit and bankruptcy cost, dynamic models stress tradeoffs that extend beyond a single period. “Target adjustment models” assume that while firms may not be at the target due to various shocks to the leverage ratio and the presence of adjustment costs, they dynamically adjust to a (possibly time-varying) target. Yet, exactly what evidence do we have that firms do indeed have a target debt ratio?
Some of the strongest evidence comes from the fact that firms seem to “rebalance” after major deviations in the debt ratio – for example, because they made large debt or equity issues to finance projects, or because of shocks to equity returns, which temporarily move them away from their previous (market) debt ratios. Leary and Roberts (2005), Alti (2006), Liu (2005), and Frank and Goyal (2003b) are recent examples of studies that document such rebalancing behavior.

A second source of evidence is from the estimation of target adjustment models of the leverage ratio. Empirical estimation of such models seems to indicate that the leverage ratio exhibits mean reversion. The mean is generally supposed to be a target debt ratio. While studies mostly have estimated the speed of adjustment to be rather slow (for example, Fama and French (2002) find that the adjustment is only about 10% per year), a recent study by Flannery and Rangan (2005) finds that the estimated adjustment speed is faster – of the order of 25% - once the firm-specific means are estimated more precisely using firm fixed effects.

A third source of evidence comes from the fact that the debt ratio appears to be reliably associated with several firm-specific variables, often in a manner consistent with the costs and benefits of debt. For example, the market-to-book ratio is consistently negatively related to the debt ratio. This is viewed as supportive of tradeoff theory, since firms with higher growth opportunities are likely to have higher market-to-book ratios. Such firms are also likely to avoid debt because of either debt overhang problems (Myers, 1977) or the loss of growth opportunities should the firm default.

Fourth, evidence from “natural experiments” provides some support for tradeoff theory. Calomiris and Hubbard (1993) study the undistributed profits tax in the US that was introduced in 1936 but abolished in 1938. These authors find that firms increased their debt ratios after the introduction of the tax, presumably to reduce taxes on retained profits. Givoly, Hayn, Ofer, and Sarig (1992) find that leverage ratios changed around the Tax Reform Act of 1986. Goyal, Lehn, and Racic (2002) study the US defense industry during the period 1980-1995. They find that as growth opportunities in the industry declined due to the end of the cold war, firms increased their leverage significantly. They attribute this to an increase in the target leverage ratio on account of a decline in the growth opportunities.

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9 See Frank and Goyal (2003a) for comprehensive study of factors that are robust across different samples of firm years; Fama and French (2002) and Rajan and Zingales (1995) for a discussion of how the signs of the coefficients of particular variables relate to various theories of capital structure.

10 See Frank and Goyal (2006) for a discussion of the outcome of other natural experiments consistent with tradeoff theory.
Fifth, calibrated dynamic tradeoff models stressing various costs and benefits of debt seem capable of replicating observed regularities in the data – especially the negative relationship between leverage and profitability or mean reversion (Hennessy and Whited (2005) and Strebulaev (2007)). Somewhat similar to our approach, these papers also show that empirical results provided in support of market timing (Baker and Wurgler, 2002) or inertia (Welch, 2004) can be replicated assuming dynamic tradeoff behavior as well. In other words, while showing that dynamic tradeoff behavior is consistent with the data, these models do not reject alternatives to tradeoff theory that might have also generated the data.

A sixth potential support for the existence of debt ratio targets comes from evidence on the time-series persistence of debt ratios. Frank and Goyal (2006) observe remarkable persistence in the aggregate data and in fact argue that such persistence is seemingly at odds with tradeoff theory – since one would expect debt ratios to change as the underlying costs and benefits changed. For example, aggregate debt ratios do not differ much between periods even though the corporate tax rates are quite different. Lemmon, Roberts, and Zender (2006), in a recent paper, document that firm level leverage ratios also show remarkable persistence. The reluctance of firms to move from a preferred debt ratio seems to be an appealing explanation for such behavior – even though such a debt ratio might not be optimal in all time periods. In other words, firms might have a debt ratio target that they stick to, even though a target debt ratio is not necessarily an optimal debt ratio in the tradeoff sense.

Some other evidence, however, is less supportive of tradeoff theory. Perhaps the most important such evidence comes from surveys of corporate CFOs. Graham and Harvey (2001) find that CFOs consider the tax advantage of debt to be only of moderate importance (mean response of 2.07 in a scale of 0 to 4 in increasing order of importance). There is very little evidence that firms directly consider personal taxes (mean response of 0.68 for debt policy and 0.8 for equity policy). The importance of potential costs of financial distress is also surprisingly minor (mean response of 1.24); concern for cash flow volatility when making debt decisions is moderate (2.32). Concern for credit ratings, however, is high (3.14). When directly asked whether their firms have an optimal or target debt ratio, close to 20% responded in the negative, while only 10% said they have a strict debt ratio target. The rest said they have a “flexible” target (37%) or a somewhat tight target range (34%). In addition, a majority of firms do not rebalance (mean response rate of 1.08) in response to equity price movements. Even among firms targeting a debt ratio, few firms state that changes in stock prices affect their debt policy.
This suggests that even among firms stating that they have a target debt ratio, presumably it is the book value debt ratio, and not the market value debt ratio, that is targeted.\footnote{We review the survey evidence in Graham and Harvey (2001) in some detail because others have interpreted the same evidence somewhat differently. Graham and Harvey (2001) themselves summarize their evidence thus (page 12): “Overall, the survey evidence provides moderate support for the trade-off theory.”}

In addition, profitability has consistently been found to be negatively correlated with leverage. This again is seemingly at odds with tradeoff theory – more profitable firms should raise their debt levels to shelter profits from corporate taxes. Higher profitability should also reduce the risk of default and make it possible to increase leverage. Recent dynamic models of capital structure show that if firms do not adjust continuously because of adjustment costs, then a negative relationship between profitability and the market debt ratio could result (Strebulaev (2007) and Tserukevich (2005)). However, empirically, both market and book leverage ratios are negatively correlated with profitability. Other evidence suggested as inconsistent with optimizing behavior is the “debt conservatism puzzle”. Graham (2000) has estimated tax rate functions and concluded that firms – most notably large and profitable firms – are significantly underlevered. However, dynamic tradeoff models (Ju et al. (2005), Hennessy and Whited (2005), Strebulaev (2007)) seem to produce debt ratios that are consistent with what is observed.

3. Data and simulated samples

We examine the dynamics of leverage ratio and financing decisions using both actual and simulated data.

A. Actual data and variables

Our actual data sample, S(Actual Data), consists of firms listed in the Compustat Industrial Annual Files at any point between 1971 and 2004. We obtain data on stock prices and returns from the Center for Research on Security Prices (CRSP) Files. All dollar values are converted into 2000 constant dollars. We exclude financial, insurance, and real estate firms (SIC code 6000-6900), regulated utilities (SIC code 4900-4999), and firms with missing book values of assets.\footnote{We also delete a small number of firms that reported format codes 4, 6 (undefined Compustat code), and 5 (Canadian). As a robustness check, we drop firms involved in large asset sales and significant mergers (identified by Compustat footnote code AB). The results are essentially the same.} Since the focus of this study is on dynamic capital structure, we restrict the sample to firms with at least twenty years of continuous balance sheet items.\footnote{Relaxing and tightening this restriction to ten and thirty-four years have no material impact on our results.} Our requirement for
continuous data follows previous studies of target adjustment models. The final dataset is an unbalanced panel consisting of 35,893 firm-year observations. Firm characteristics, such as market to book asset ratio and profitability, are defined in Appendix A and are winsorized at the 0.5% level at both tails of the distribution to mitigate the impact of outliers or mis-recorded data.

Book leverage is defined as the ratio of book debt to total assets. Book debt is the sum of total liabilities and preferred stock minus deferred taxes and convertible debt. When preferred stock is missing, we replace it with the redemption value of preferred stock. Book equity is then defined as total assets minus book debt. We drop firm-year observations where the book leverage is negative or exceeds one.

We define net equity and net debt issues using balance sheet data. Following the accounting identity that book equity equals balance sheet retained earnings plus paid-in share capital, we define net equity issues (Nei) as the change in book equity (ΔE) minus the change in retained earnings (ΔRE). Net debt issues (Ndi) are then defined as the change in total assets less the change in retained earnings and net equity issues. One key variable of our interest, the financing deficit (Def), is the difference between the change in total assets and the change in retained earnings. This variable is positive (Def > 0) when the firm invests more than it internally generates and by definition, this deficit must be filled by the net issues of debt and/or equity. In contrast, the financing deficit takes a negative value (Def < 0) when the firm internally generates more funds than it invests, thus the resulting financing surplus (or the negative financing deficit) has to be used to repurchased debt and/or equity. In other words, the financing deficit is equal to the sum of the net debt and the net equity issued, and this accounting identity can be written as follows:

\[ Def = \Delta A – \Delta RE = Nei + Ndi \]  

Among others, Jalilvand and Harris (1984), Titman and Wessels (1988), Leary and Roberts (2005a), Fama and French (2002), and Flannery and Rangan (2005) exclude companies for which continuous data are not available. The definition of the leverage ratio follows Fama and French (2002), Baker and Wurgler (2002), and Kayhan and Titman (2005). Our results are robust to alternative definitions of debt – for example, when total debt is defined as the sum of short-term debt and long-term debt. Section 4.F.2 provides details about robustness checks.

As a robustness check, we also define debt and equity issues using the cash flow statements. Following Shyam-Sunder and Myers (1999) and Frank and Goyal (2003b), we define equity issues as the sale of common and preferred stock less the purchase of common and preferred stock. Debt issues are defined as long-term debt issuance minus long-term debt reduction plus changes in current debt. Financing deficit (Def) is then defined as the sum of the change in net working capital (ΔNWC), investments (I) and cash dividends (Div), net of internally generated cash flow (CF). These alternative definitions have little impact on our results. We prefer the measures constructed from balance sheets as they offer more non-missing observations than those defined using cash flow statement data.
Table 1 reports summary statistics for the actual data sample. Roughly 2/3 (67.9%) of firms have positive financing deficits. In positive financing deficit years, roughly 3/4 (75.6%) of deficit is financed with debt issues. In contrast, 65.1% of financing surplus (negative deficit) is used to retire debt.

B. Simulation and Samples

This subsection describes the simulation procedures used to generate our simulated data samples. The evolution of a firm’s book leverage critically hinges upon the new net debt and equity issuances together with the newly retained earnings. In the first two simulated samples, S(Half/Half) and S(Actual Probability), the size of debt issuance and change in equity in any given firm year are determined by the actual financing deficit and the actual retained earnings in the data. For the sample S(Random Deficit), we randomize both the financing deficit and the retained earnings, but preserve the correlation structure that exists in the actual data.

We take the initial book leverage ratio of each firm from Compustat. From the second year onwards, we update leverage according to the financing rule that firms follow.

- **S(Half/Half):** If the financing deficit is positive, we assume that firms decide whether to issue debt or equity by tossing a coin, i.e., there is a 50% chance for equity issuance and a 50% for debt issuance. Similarly, firms are assumed to retire debt or equity with equal probability when the financing deficit is negative.

- **S(Actual Probability):** Here, we assume that conditional on the deficit being positive (negative), the probability of debt and equity issuance (repurchase) corresponds to the empirical frequencies in the overall actual data when dual issues are excluded. The probability of debt issuance is approximately 0.75 (equity issuance 0.25), and the probability of debt repurchase is approximately 0.65 (equity repurchase 0.35).

- **S(Random Deficit):** Here, the deficit scaled by the book value of assets ($Def/A$), change in retained earnings scaled by the book value of assets ($ΔRE/A$), and the return on assets ($EBITDA/A$) are simultaneously and randomly drawn in each firm year in such a way as to preserve the means, standard deviations, as well as the correlations between these variables in the actual data. This procedure breaks any serial correlation and removes any firm-specific component in the time series of the deficit and the change in retained earnings that may exist in the actual data. Firms are assumed to issue (retire) debt or equity with equal probability when the financing deficit is positive (negative).
• S(Market Timing): This sample is derived with one change from the sample S(Half/Half) discussed above. If the firm-specific stock return is above the 75\textsuperscript{th} percentile for the firm, we assume this signifies “good times” for the firm: the firm then issues equity (i.e., with probability 1) if the actual deficit is positive, and repurchases debt if the actual deficit is negative. If the firm-specific stock return is below the 25\textsuperscript{th} percentile, we assume the firm issues debt if the actual deficit is positive, and repurchases equity if the actual deficit is negative.

• S(Low Initial Leverage) and S(High Initial Leverage): In these two samples, we start off every firm with the same initial leverage ratio, which are set at 0.2 and 0.8, respectively. The subsequent financing and leverage ratios are generated in the same way as the sample S(Half/Half).

For each simulated sample, the simulated end-of-period total equity is the sum of the simulated beginning-of-period total equity plus net equity issued and the change in retained earnings. The simulated end-of-period debt is the beginning-of-period simulated debt plus (minus) the new net debt issued (retired).

\section*{C. Book versus market leverage, stock returns, and the market-to-book ratio}

Much of our analysis is in terms of leverage ratios. We focus exclusively on book leverage. There are good reasons for this. A financing mix that differs from the actual data at any point of time will also have implications for subsequent stock returns if other firm characteristics did not change, even if we were to assume that financing has no impact on firm value. Under the assumption that the valuation consequences of departures from the actual financing choice are not of first-order importance, it is straightforward to adjust the stock returns when the financing mix changes. However, our results would be less convincing if we were to rely on a market debt ratio based on these adjusted returns. Therefore, we work in terms of the book debt ratio. Stock returns do not feature in our regressions. However, the market-to-book ratio does, since it is a standard proxy in capital structure regressions. Here, we work with the actual market-to-book ratio. Essentially, we are assuming that the departures from the actual debt ratio are not serious enough to have any material impact on firm value.\footnote{In any case, since our simulated data do not assume the existence of an optimal debt ratio, there is no contradiction. We might as well pretend that the simulated world is one in which the Modigliani and Miller theorem holds.} Since the book
value of assets every period is the same in the simulated and actual data for all but one of our samples, the market-to-book ratio does not have to be adjusted under this assumption.

A second reason for focusing on the book debt ratio is that changes in the book debt ratio reflect what might be called “active rebalancing”, i.e., the effect of debt and equity issuances and repurchases, and retention and payout policy. Changes in the market debt ratio reflect unanticipated changes in the stock price that may not be in the control of management. Survey evidence by Graham and Harvey (2001) finds that “few firms (rating of 0.99) state that changes in the price of equity affect their debt policy.”

D. Why Use Random Financing as a Benchmark?

It is important to point out that our objective in using samples generated under the assumption of random financing as benchmark is not to propose that, in reality, financing is random. Rather, this choice is motivated by the fact that we do not know a great deal about the reasons underlying firms’ financing choices. Actual financing behavior is presumably affected by the resolution of state variables that are observed by firm insiders but unobserved or imperfectly observed by researchers; therefore, modeling financing as random reflects the probabilities with which these state variables are jointly realized. Random financing with fixed probabilities of issuance or repurchase of a particular type of security thus incorporates a wide class of theories of financing, but excludes tradeoff behavior. The latter requires that the probability of equity (debt) issuance (repurchase) is high when the debt ratio is above the target, and the probability of debt (equity) issuance (repurchase) is high when the debt ratio is below the target. By assuming probabilities of debt and equity issuances for our simulations independent of the debt ratio and any assumed target, we are ruling out the possibility that our simulations mimic target behavior.

4. Empirical Tests and Results

All results on simulated samples are based on 500 replications of the particular simulation. When average debt ratios are reported for event year \( t \), we take averages over all 500 simulations in event year \( t \). In regressions, we report the 95% confidence intervals of the parameter estimates from the 500 simulations.
In our simulations, in less than 1% of the cases, we deviate from the issuance or repurchase decision dictated by the outcome of the random draw. There are three reasons for this: (a) when a firm incurs operating losses (negative changes in retained earnings) which may turn total equity next period into a negative number, we force these firms to issue equity to make the total equity next period nonnegative. This situation occurs in 130 cases out of 38,593 observations (0.33% of all firms years and 0.75% of all issue years); (b) when a firm already has a very small amount of debt (or zero), i.e., the firm basically has no debt to repurchase, we force these firms to buy back equity if the deficit is negative to avoid negative leverage ratios. This situation occurs in 143 out of 38,593 observations (0.37% of all firm years and 2.75% of all repurchase years), and (c) when firms have very high leverage ratio (low current value of equity) such that a further equity repurchase will make leverage ratio next period greater than 1, we force the firm to retire debt instead. This situation occurs in 141 cases out of 38,593 observations (0.37% of all firm years, and 2.46% of all repurchase years). All results involving debt ratios reported in the paper include these cases where we possibly deviate from the randomly chosen issue or repurchase decision. However, removing these corner cases has no effect on any of the tests that are based on debt ratios. By contrast, as we will discuss later, they have a significant impact on results of tests that involve issue or repurchase decisions.

A. Do firms rebalance?

A.1 Nonparametric Analysis

Inspired by Leary and Roberts (2005a), we perform nonparametric analysis of the firms’ response to four major corporate finance events related to capital structure changes:

- Large equity issues: A large equity issue occurs if a firm’s net equity issue divided by total assets exceeds 5%.\(^{18}\)
- Large debt issues: A large debt issue occurs if a firm’s net debt issue divided by total assets exceeds 5%.
- Positive equity shocks: A firm is defined to experience a positive equity shock if its annual stock return is one standard deviation above the firm-specific mean return.

\(^{18}\) The same cutoff for large debt/equity issues (5%) is used in many previous studies, including Hovakimian, Opler, and Titman (2001), Hovakimian (2004), Leary and Roberts (2005a), and Chen and Zhao (2005a and 2005b). The alternative cut-off of 1% or 10% makes little difference to any of the results that follow.
Negative equity shocks: A firm is defined to experience a negative equity shock if its annual stock return is one standard deviation below the firm-specific mean return.

Leary and Roberts (2005a) consider the first, third, and fourth of these events to study dynamic rebalancing behavior. Unlike Leary and Roberts (2005a), however, we consider the book leverage ratio rather than the market one. Moreover, to save space, we only report results for the cases of large equity issues and large debt issuances. Results for the remaining two cases are very similar.19

A.1.1 Large equity issues

Figure 1 shows the difference in book leverage between date 0 equity issuers and non-issuers for all four of our samples. The book leverage ratio is lower immediately after the equity issue for the equity issuers compared to the non-issuers for all four samples. However, with the exception of the sample S(Actual Probability) which remains essentially flat, the difference becomes smaller over the next five years, although it does not completely vanish. The lower panel shows the paths separately for the issuers and non-issuers.

The fact that even when the financing is random there is the appearance of rebalancing is surprising at first glance. However, the explanation is quite simple. Suppose that the deficit is a positive amount \(x\), let \(D\) denote the existing level of debt, and \(A\) the existing value of assets (here, \(A\) is in book value terms, but the argument goes through even if \(A\) is in market value terms). The initial debt ratio is \(D/A\). Now suppose that a fraction \(p\) of the firms issues debt, and a fraction \((1-p)\) issues equity, equal in magnitude to \(x\). Assume that the change in retained earnings is \(R\). The new average debt ratio then is

\[
p \frac{D + x}{A + R + x} + (1-p) \frac{D}{A + R + x}.
\]

(2)

It is easily checked that

\[
p \frac{D + x}{A + R + x} + (1-p) \frac{D}{A + R + x} \geq \frac{D}{A} \quad \text{as} \quad p \geq \frac{D}{A} \left(1 + \frac{R}{x}\right).
\]

(3)

Now consider the case in which the deficit is negative. Let \(x\) denote the absolute value of the deficit. In this case, the firm repurchases debt or equity of amount \(x\). Therefore, the average debt ratio one period later is

\[
p \frac{D - x}{A + R - x} + (1-p) \frac{D}{A + R - x}.
\]

(4)

19 These and other results not reported in tables are available on request.
It follows that

\[ p \frac{D-x}{A+R-x} + (1-p) \frac{D}{A+R} - x \geq \frac{D}{A} - \frac{A}{R} (1 - \frac{R}{x}). \tag{5} \]

With the aid of this, it is now easy to understand what is going on in Figure 1. Start with the sample S(Random Deficit) in the South East quadrant of Panel B. In this sample, the deficits in the years following date 0 are randomly drawn, but the distribution from which the deficit is drawn is a normal distribution with mean at 8.4% and a standard deviation of 22.9%, as reported in Table 1, so that the positive deficit cases are likely to outnumber the negative deficit cases by about 80%. Moreover, the mean value of retained earnings scaled by book value of assets is 3.3%. Hence, the dynamics of the average debt ratio is likely to be governed by equation (3). Moreover, in this sample, the firms issue debt and equity if the deficit is positive (repurchase debt and equity if the deficit is negative) with equal probability. Hence, \( p = 0.5 \). The average debt ratio of the firms that issue equity at date 0 immediately after the issuance is about 0.3 (as shown in Panel B of Figure 1), so that it is likely that a large proportion of these firms have debt ratios below 0.5, and therefore the debt ratio will increase in the subsequent years, as implied by equation (3). In contrast, the non-issuers have an average debt ratio of 0.42. Since this is close to 0.5, the dynamics implied by equations (3) is not clear-cut. It is possible that growth of retained earnings (normally distributed with mean change of retained earnings scaled by book value of assets at 3.3%) contributes to the downward drift of the debt ratio for the non-issuers, as implied by (3).

The case of the sample S(Half/Half) in the North-east quadrant of panel B is similar. Here, the only difference is that the deficit is as in the actual data. For sample S(Actual Probability) in the South-west quadrant, the threshold \( p = 0.75 \) exceeds the average initial debt ratios of both the issuers as well as the non-issuers by a significant margin. Hence, both the issuer and non-issuer sub-samples are expected to exhibit increasing debt ratios, which is exactly what we observe. Notice that for this sample, the gap in the initial debt ratio between issuers and non-issuers is much smaller than the other samples, which explains the similar dynamics of the two sub-samples.

What we learn from the dynamics exhibited by the three simulated samples is that even when there is no intent to rebalance, the debt ratios can converge for purely mechanical reasons. Thus, the dynamics evident in the North-west quadrant of panel B for the actual sample cannot be taken as evidence of rebalancing.

Next, we turn to the subsequent issuance activity of the date 0 issuers and non-issuers. In the following discussion, the nature of the financing deficit for the issuer and non-issuer (or
shock and non-shock) groups will play an important role. In Figure 2, we show the fraction of firms having large positive deficits (in panels A, B, and C) and large negative deficits (in Panel D) for the two groups of firms after the four types of shocks to the debt ratio. (A deficit is defined to be large if its absolute value is greater than 5% of total assets.) It is immediate that there is a higher fraction of large positive deficits among equity and debt issuers – who have positive deficits in the year of the issue – than non-issuers, reflecting serial correlation in the deficit. The same is also true for firms experiencing positive equity shocks, who also have mostly large positive deficits in the year of the shock. By contrast, for firms suffering negative equity shocks, there is a higher proportion of large negative deficit firms in the subsequent years than those not experiencing these shocks.

Consider first the subsequent debt issuance activity of date 0 equity issuers (Figure 3). The fraction of debt issuers is higher among date 0 equity issuers than non-issuers in the three samples in which the deficit is the actual deficit. However, for the sample in which the deficit is also random, there is no difference in the issuance activity of the two groups. The latter result is expected since the deficit here is a random draw from the same distribution, so the proportion of positive and negative deficits should be the same for the two groups; moreover, conditional on the deficit being positive, the probability of debt issuance is also mechanically the same. In samples S(Half/Half) and S(Actual Probability), the probability of debt issuance is also mechanically the same for the two groups; nevertheless, a higher proportion of the date 0 equity issuers issue debt. This can only be the case if a higher proportion of date 0 equity issuers have a positive deficit than non-issuers. This is exactly what we observe in Panel A of Figure 2. In fact, the pattern of debt issuance by the two groups is strikingly similar in the actual and the simulated samples in which the true deficit is preserved to the pattern of the deficit in Figure 2.

This suggests that the debt issuance patterns in the actual sample are driven more by the persistence of the deficit than by a major shift in the probability of debt issuance after the date 0 large equity issue. The fraction of date 0 equity issuers that issue debt at date 1 is about 47% (Panel B of Figure 3). The fraction that have positive deficit is 60% (Panel A of Figure 2). Given that the average (normal) probability of debt issuance is 75% in the actual sample, the fraction of debt issuers under normal conditions would be 75% × 60% = 45%. Thus, there is hardly any evidence that date 0 equity issuers significantly step up their debt issuance activity in the next year.

There might be a concern that the serial correlation in the deficit is endogenously generated as a result of firms’ attempts at rebalancing. For example, it is conceivable that the equity issuers issue debt even though their investment plus dividend plus normal working capital...
spending needs are less than available internal funds. If this were the case, the proportion of subsequent *equity* issuers among the date 0 equity issuers would be no higher than that among the date 0 non-issuers. In Figure 4, we find that to the contrary, the fraction of equity issuers in date 1 is 20% higher for the date 0 equity issuers than the non-issuers, and it is higher in all subsequent periods up to date 5. Moreover, the difference is much higher in the actual sample than all other samples. Given that 60% (Panel B of Figure 2) of the date 0 issuers have a large positive deficit in the next period, a 25% average probability of equity issuance for the actual sample implies that 15% of date 0 equity issuers would have issued equity at date 1 under “average” conditions. The actual probability is 30%. Possible reasons for the much higher actual figure of 30% include (but perhaps are not limited to) market timing incentives (equity market conditions are likely to remain good after the large equity issues for the issuers, and they take advantage of this window of opportunity and issue equity again).

A.1.2. Large debt issues

Figures 5-7 present the nonparametric analysis for large debt issues. The general features are similar to the case of large equity issues. In Figure 5, all four samples exhibit a tendency for the debt ratios of the date 0 debt issuers to decline relative to non-issuers. Date 0 debt issuers’ debt ratios tend to fall, while those of non-issuers tend to rise, consistent with equation (3). The tendency for the debt ratios of the date 0 debt issuers to fall is more pronounced for samples S(Half/Half) and S(Random Deficit) in panel B of Figure 5, since the threshold $p$ is lower (50%) for these two cases. Figure 6 shows that, except for the random deficit sample, the fraction of debt issuers is higher among date 0 debt issuers than date 0 non-issuers in the other three samples in the subsequent years, contrary to rebalancing incentives, but consistent with a higher fraction of positive deficit cases among date 0 debt issuers. This latter implication is confirmed in Panel B of Figure 2. In fact, the fraction of date 1 debt issuers among the debt 0 debt issuers is the highest in the actual sample. The fraction of equity issuers in subsequent periods is higher among date 0 debt issuers than date 0 non-issuers in all except the random deficit sample (Figure 7). Assuming no shift in the probability of issuance following a date 0 large debt issuance, the predicted fraction of date 1 equity issuers among the date 0 debt issuers for the actual sample is 13% (= 52% (the fraction of large positive deficit firms at date 1) × 25%); the actual fraction is 17%. Thus, again, there is no evidence of a significant step-up in the probability of equity issuance after the debt issuance, as rebalancing behavior would require.
A.1.3. Positive and Negative equity shocks

Positive equity shocks are considered as shocks to the market debt ratio in Leary and Roberts (2005a) and Welch (2004). However, they can also affect book leverage as some of these firms are likely to take advantage of market conditions and issue equity; profits are also likely to be positively correlated with positive equity shocks and increase retained earnings, thereby lowering the book debt ratio. Consistent with this, we find that book debt ratios fall when firms have positive equity shocks. Similarly, during negative equity shocks, book debt ratios rise. While we do not report these cases in detail, what we observe is very similar to that noted for large equity issues and large debt issues. Debt ratios behave similarly for the actual and simulated samples. Issuance (for positive equity shocks) and repurchase activity (for negative equity shocks) conforms to the pattern of the previous cases, and appears to be largely driven by the serial correlation in the deficit. For positive equity shocks, the actual data shows a much higher proportion of equity issuers among the date 0 shock firms than even the S(Half/Half) sample, which is completely contrary to rebalancing behavior (but consistent with other motives for financing, such as market timing behavior). One notable result is that for negative equity shocks, we do find some evidence of rebalancing behavior. The fraction of firms repurchasing equity is similar for shock and non-shock firms after the shock, although the serial correlation in the deficit (which is predominantly negative for shock firms at date 0) would have suggested higher repurchase activity among the shock firms. The fact that this does not happen suggests that in spite of low equity prices, firms seem to avoid a leverage adjustment that will move them further away from the initial debt ratio.

A.2. Relationship with duration analysis

The strongest evidence in favor of rebalancing behavior in the existing literature comes from Leary and Roberts’ (2005a) duration analysis. Leary and Roberts (2005a), using quarterly data from Compustat, estimate hazard function models to understand the duration between successive debt issues, equity issues, debt retirements, and equity repurchases. Their results are consistent with models of dynamic rebalancing where adjustment is costly, and adjustment costs have a fixed component and are weakly convex in the size of the issue. Specifically, Leary and Roberts (2005a) find that the “hazard” of a debt (equity) issue at any point during a debt (equity) issuance spell is lower if leverage is higher (lower), or if leverage increases (decreases) during
the spell. For debt retirement and equity repurchase spells, similarly, higher (lower) leverage and leverage increasing (decreasing) events during the spells increase the likelihood of debt retirements (equity repurchases).

How does the evidence from our nonparametric analysis discussed in section A.1 (which is similar to the nonparametric analysis that is reported in Leary and Roberts (2005a) and is motivated by their underlying dynamic costly adjustment framework) relate to Leary and Roberts’ duration analysis? We do not attempt to replicate Leary and Roberts’ (2005) results by generating quarterly simulated data. However, our results suggest that it is possible that the evidence of rebalancing that they obtain could also be due to serial correlation in the deficit. Suppose, for example, that we are in a debt issuance spell. If leverage increases during such a spell, that is not due to new debt issues, but rather due to negative shocks to the stock price (Leary and Roberts (2005a) work in terms of the market debt ratio) or buyback of equity, or even possibly negative changes in retained earnings. These events are likely to be associated with poor investment outlook and a possibly negative deficit. If the environment persists, firms are unlikely to have a big demand for external funds immediately afterwards, i.e. they are more likely to have negative rather than positive deficits. The likelihood of a debt issue in such a situation will also be lower.

A.3. Regression analysis

We follow an approach similar to Alti (2006) who examines whether or not firms that time the market subsequently rebalance. Alti (2006) argues that firms that go public in hot issue markets are “market timers”. The size of the issue (IPO proceeds from primary issues as well as total proceeds scaled by book value of assets) is higher in hot markets than in cold markets, and the short run impact of such market timing is to lower the debt ratio of hot market issuers further below the pre-IPO levels than for cold market issuers. He then examines whether or not this difference persists over the next few years, and whether or not there is evidence of reversal of the debt ratio for hot market issuers relative to cold market issuers. He finds that timing effects are not persistent – firms rebalance within three years of the IPO. Consistent with this behavior, he documents that hot market issuers increase their debt ratios more in the first and second years after the IPO than cold market issuers.

Following Alti’s methodology, to examine the persistence of the effects of leverage changing events, we estimate the following regression.
\[
\frac{D}{A} - \frac{D}{A}_{\text{pre-event}} = a_0 + a_{\text{Event}} + a_2(\frac{M}{B})_{t-1} + a_3(\frac{EBITDA}{A})_{t-1} + a_4(\frac{PPE}{A})_{t-1} \\
+ a_6(\frac{R\&D}{S})_{t-1} + a_7(RDD)_{t-1} + a_8(\frac{D}{A})_{\text{pre-event}} + \epsilon_i
\]

The dependent variable is the cumulative change in book leverage \((D/A)\) from its pre-event level to that in \(t\) years after the event. The dummy variable \(\text{Event}\) equals 1 if a corporate leverage-changing event occurred \(t\) years ago and zero otherwise.\(^{20}\) If the firms rebalance in response to leverage changing events, then the coefficient of “Event” should monotonically decreases in absolute value as \(t\) increases. For example, if the event is large equity (debt) issuance, then rebalancing would imply that the coefficient of “Event” would be negative (positive) but becomes weaker over time. Complete rebalancing would imply the coefficient to eventually become insignificant or even change sign.\(^{21}\) To save space, Table 2 presents the results only for large equity issues for the actual sample in Panel A and the sample S(Half/Half) in Panel B.\(^{22}\) For the actual data, we report parameter estimates and t-statistics based on the Fama and MacBeth (1973) approach. Specifically, we estimate Equation (6) for every year and conduct statistical tests on the time-series means of the estimated coefficients. For the simulated samples, we report the 95% confidence intervals of the parameter estimates from 500 replications of the same simulation. Standard panel regressions offer qualitatively similar results.

For large equity issues, the evidence of rebalancing is quite weak in the actual sample – the coefficient of “Event” is negative but declines very slightly from year “Event + 1” to year “Event + 5”. Consistent with the nonparametric analysis, the simulated sample appears to provide even stronger evidence of rebalancing, although by construction, the financing is random. It appears that because of the mechanical relationship implied by equation (3), regression results can suggest that rebalancing is taking place even when there is no underlying target debt ratio and financing is random. The speed of rebalancing observed in the actual data is consistent with random financing.

\(^{20}\) In Alti (2006), the corresponding dummy variable takes a value of 1 if the firm is a hot market issuer, zero otherwise.

\(^{21}\) The control variables are firm characteristics lagged one year, and include the market to book ratio \((M/B)\), profitability \((EBITDA/A)\), firm size \((\text{Size})\) measured as the log value of total assets, tangibility of assets \((PPE/A)\), research and development expense to sales ratio \((R\&D/S)\), the dummy variable RDD that takes the value of one when R&D is missing in Compustat and zero otherwise, and the pre-event leverage ratio. These variables are chosen because they have been shown by prior literature to influence capital structure (See Frank and Goyal (2003a)). Alti (2006) uses an almost identical set of variables. The details of variable definitions are in Appendix A.

\(^{22}\) Results for large debt issues and positive and negative equity shocks for the S(Half/Half) sample and all cases for the other simulated samples are qualitatively similar, and consistent with the nonparametric results discussed above.
We now turn to evidence of reversal in the debt ratio by estimating models of leverage change as in Alti (2006). We estimate the following leverage change regression for each of the two years after the events occur.

\[
\frac{D_t}{A_t} - \frac{D_{t-1}}{A_{t-1}} = b_0 + b_1 \text{Event} + b_2 (M / B)_{t-1} + b_3 (\text{EBITDA} / A)_{t-1} + b_4 \text{Size}_{t-1} + b_5 (\text{PPE} / A)_{t-1} \\
+ b_6 (\text{R} \& \text{D} / S)_{t-1} + b_7 \text{RDD}_{t-1} + b_8 \text{HighLev} + b_9 \text{LowLev} + \epsilon_t
\]  \hspace{1cm} (7)

where \( t = \text{Event} + 1 \) or \( \text{Event} + 2 \). High (low) leverage ratio dummy \( \text{HighLev} \) (\( \text{LowLev} \)) equals to 1 if the lagged leverage ratio is above 0.6 (below 0.4), and zero otherwise. Notice the difference between equations (6) and (7): Equation (6) is about the cumulative change in leverage ratio but (7) is about the year-to-year changes.

In Panel A of Table 3, we first report the results of estimating equation (7) for the actual data. If the high and low leverage dummies are not included, the results indicate that leverage changes that are in the opposite direction to the initial shock are stronger for the date 0 large equity issuers than the non-issuers. However, the magnitude of the coefficient of “Event” becomes much smaller once the high and low leverage dummies are included. In Panel B of the same table, the same tests are replicated for the simulated data S(Half/Half). The appearance of reversal is in fact stronger than in the actual data, but again, the magnitude of the coefficient of “Event” is almost halved if the high and low leverage dummies are included.

Notice that the high leverage dummy has a negative sign and the low leverage dummy has a positive sign for both the actual and the simulated samples, and the coefficients of these dummies are economically large compared to the coefficients of “Event”. This is consistent with equation (3) that high leverage firms will reduce leverage on average and low leverage firms increase leverage on average. The fact that adding these dummies to the regression significantly reduces the coefficient on “Event” (making it insignificant for the actual sample for large equity issues) is consistent with the possibility that the appearance of reversal is also due to this mechanical adjustment of the debt ratio. However, evidently, controlling for these dummies does not remove all mechanical adjustment, since in the simulated sample, “Event” remains significant even after controlling for these dummies.

### B. Mean reversion and target adjustment

Mean reversion of the debt ratio has been regarded as evidence that firms adjust their debt ratios if these get out of line with the target. Fama and French (2002), however, noted that

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23 Altı (2006) defines the high (low) leverage dummy to be 1 if leverage is in the upper 80th (lower 10th) percentile, and zero otherwise. Our results are not changed if we define our dummies with respect to these cut-offs.
the adjustment speed is rather slow – the change in the debt ratio closes only about 10% of the gap per year. Recently, Flannery and Rangan (2005) have argued that the estimated slow speed of adjustment is attributable to imprecise estimates of the target. They find that once fixed firm-effects are included in the regression to accommodate unmodelled factors that may affect the firm-specific means, the speed of adjustment increases to about 20%-25%.

Results in Tables 2 and 3 indicate the possibility of mechanical mean reversion in the data. To examine this possibility more carefully, we estimate the standard target adjustment model:

\[
\frac{D_A}{A}_{i,t} - \frac{D_A}{A}_{i,t-1} = \alpha_1 + \lambda\left[\left(\frac{D_A}{A}_{i,t}\right)^* - \left(\frac{D_A}{A}_{i,t-1}\right)\right] + \epsilon_{i,t}
\]

(8)

where \(\frac{D_A}{A}_{i,t}\) is the leverage ratio at time \(t\) for firm \(i\), and \(\frac{D_A}{A}_{i,t-1}\) is leverage ratio lagged one period. \(\frac{D_A}{A}_{i,t}^*\) denotes the target debt ratio for firm \(i\) at time \(t\), which can be expressed as a function of a set of predetermined (lagged one period) variables \(C\):

\[
\frac{D_A}{A}_{i,t}^* = \alpha_2 + \beta C_{i,t-1}
\]

(9)

By substituting equation (9) into (8), we reduce the target adjustment model to:

\[
\frac{D_A}{A}_{i,t} = \alpha_3 + (1-\lambda)\left(\frac{D_A}{A}_{i,t-1}\right) + \gamma C_{i,t-1} + \epsilon_{i,t}
\]

(10)

where \(\gamma = \lambda \beta\). Using the same set of control variables as in equation (6), we estimate the following target adjustment regression model.

\[
\frac{D_A}{A}_{i,t} = c_0 + \lambda\left(\frac{D_A}{A}_{i,t-1}\right) + c_2(M/B)_{i,t-1} + c_3(EBITDA/A)_{i,t-1} + c_4 Size_{i,t-1} + c_5(PPE/A)_{i,t-1} + c_6(R&D/S)_{i,t-1} + c_7RDD_{i,t-1} + \epsilon_i
\]

(11)

For the actual sample, we estimate this model in a panel setting using firm-fixed effects as in Flannery and Rangan (2005). For the simulated samples, we report the 95% confidence intervals from 500 replications of the simulation. The first four columns of Table 4 report the estimation results for our abovementioned four samples. Notice that the estimated speed of adjustment \(1-\lambda\) is 22.5% in the actual data, 17.54% for S(Half/Half) and S(Actual Probability), and 20.5% for S(Random Deficit). In other words, even for the simulated samples, where financing is random, the method estimates adjustment to a “target” at a speed comparable to what we estimate for the actual data. We hypothesize that anytime a firm-specific mean is fitted to a time series that is

bounded within an interval, “mean reversion” will be observed with respect to this fitted mean. Panel regression with firm fixed effects does a better job of fitting a firm-specific mean; it is not surprising that a higher speed of mean reversion is also obtained. However, this is purely mechanical, since mean reversion of comparable speed is observed even in the simulated data where no target-reverting behavior is assumed. Shyam-Sunder and Myers (1999) and Leary and Roberts (2005a) make a similar point.

Notice that except for the sample in which the deficit is random, most of the firm-specific variables are significant in the actual and the simulated samples. The significance of firm-specific variables is usually taken as evidence that the firm’s optimal or target debt ratio is related to firm characteristics. Our results show that even when a firm has no target, firm characteristics can affect the mean debt ratio.

The understand why, it is useful to consider the sample S(Random Deficit), the estimation for which appears in column 4. Except for profitability, all other firm-specific variables are insignificant. Since the difference between this sample and the other simulated samples is that the latter are based on the actual deficit, it appears that the firm-specific variables affect the debt ratio because they are related to the actual deficit. It also appears that for the sample S(Actual Probability), variables that are likely to be associated with a higher deficit generally result in a higher debt ratio. This is plausible because in this sample, the probability of debt issues significantly exceeds that of equity issues.

Even though there is no apparent target for the simulated samples, since we start off the simulations at the initial debt ratio of the firms in the actual sample, it is conceivable that this initial debt ratio is a target debt ratio that is related to firm characteristics. Since firm characteristics are persistent, it is possible that even in the simulated samples, debt ratios stay close to some target reflected in the initial debt ratio. To see if this could explain the significance of the firm-specific variables, we look at two more samples, S(Low Initial Leverage) and S(High Initial Leverage) (please see Section 3.B). The estimation results are reported in columns 5 and 6 of Tables 4. The firm characteristics remain significant. Thus, it is unlikely that the firm characteristics are related to the initial leverage – a proxy for the firm’s target.

C. Profitability, the Market-to-Book Ratio, and Market Timing

C.1 Profitability
Two explanatory variables in leverage regressions that have received the most attention in the literature are profitability (EBITDA/A) and the market-to-book ratio (M/B). In most studies, the coefficient of profitability is negative. Some see this as inconsistent with tradeoff theory, since more profitable firms should have more reason to take advantage of the interest tax shield and increase leverage; more profitable firms are also likely to have greater debt capacity. A negative sign on profitability also seems to be consistent with the implications of the POH, which claims that external financing primarily takes the form of debt financing, so more internal funds should result in less debt issuance and hence lower debt ratios. However, Frank and Goyal (2004) and others have argued that this negative relationship arises because profitability is a proxy for growth opportunities not completely reflected in the market-to-book ratio, which is an imprecise measure of Tobin’s Q. Hence, a negative relationship is in fact consistent with the tradeoff theory implication that firms with higher growth opportunities should have less debt. Frank and Goyal (2004) and others have also argued that the negative relationship can be driven by firm’s retention policy which is affected by taxes and other imperfections. Because of these imperfections, profits are retained, and enter the balance sheet as changes in retained earnings. As a result, a negative relationship between profitability and the debt ratio is induced. Dynamic models suggest that because of infrequent adjustment, firms do not issue debt immediately when they experience positive shocks to profitability; hence, the correlation between profits and market values can generate a negative relationship between market leverage and profitability (Strebulaev (2007)).

In the results reported in the first 6 columns of Table 4, the coefficient of profitability is consistently negative. Since firms in our simulated samples are not guided by tradeoff or pecking order behavior, it does not appear that either of these theories explains the negative relationship. The very comparable coefficients for the actual data and the simulated samples in Table 4 indicate that the correlation between profitability and the change in retained earnings is primarily responsible for the negative coefficient of profitability (recall that, in the random deficit sample, the actual correlations, means and standard deviations for the deficit scaled by assets, EBITDA/A, and change in retained earnings scaled by assets is preserved, and profitability is the only significant variable in the regression). Thus theories stressing retention policy are most likely responsible for the negative relationship in the actual data.

C.2 The market-to-book ratio

25 However, see Tserlukevich (2005) for an explanation that does not depend on adjustment costs.
One noticeable difference between the results in column (1) and columns (2)-(5) of Table 4 is the sign of the coefficient of the market-to-book ratio. The negative sign of this coefficient in the actual data has been noted in a number of studies and is supposed to be consistent with the tradeoff theory notion that firms with more growth opportunities are likely to have lower debt (however, see Chen and Zhao (2006) for a different result and interpretation). The sign of this variable in the simulated samples in columns (2)-(5) of Table 4, however, is either zero or significantly positive. We noted earlier that as long as debt ratios are below a cut-off, debt ratios will increase, on average, for firms that are more likely to have positive rather than negative deficits. Moreover, this cut-off is increasing in the probability of a debt issue. Firms with higher market-to-book are likely to invest more and have positive deficits in the actual data; further, in the samples S(Actual Probability), the probability of debt issuance is higher than that of equity issuance, whereas in the S(Low Initial Leverage), all firms start off with a very low initial leverage. Hence, a positive sign for the market-to-book ratio in these two simulated samples is consistent with our argument. However, since the actual sample reveals a negative coefficient for the market-to-book ratio, should we then reject random financing in favor of target adjustment?

To see if the negative sign of market-to-book could be generated by other types of financing behavior, we consider the “market timing” sample S(Market Timing) described in Section 3.B. The regression results for this sample are reported in the last columns of Table 4. Remarkably, the market-to-book now becomes negative, and in fact has a much larger coefficient than for the actual data in Table 4. This suggests that a negative coefficient for the market-to-book ratio is consistent with non-target behavior.

To rule out other channels through which the market to book ratio affects leverage, we follow Baker and Wurgler (2002) and decompose the change in book leverage as follows:

\[
\frac{D_t}{A_t} - \frac{D_t}{A_{t-1}} = -\left[\frac{E_t}{A_t} - \frac{E_{t-1}}{A_{t-1}}\right] = -\left(\frac{\text{Neti}}{A_t} - \frac{\Delta RE_t}{A_t} - \left(\frac{1}{A_t} - \frac{1}{A_{t-1}}\right)\right]
\]

In contrast, for the sample S(High Initial Leverage), the initial leverage of firms is above the probability of debt issuance. Hence firms with positive deficits, on average, will reduce leverage ratio, while those with negative deficits will increase leverage. Presumably, this explains why the sign of the market-to-book is negative for this sample.

Note that the coefficient of profitability also increases dramatically compared to column 3. This is consistent with positive correlation between profitability and stock returns in the actual data: if stock returns are typically high when profitability is high and the firm issues equity, then the effect of profitability on the debt ratio is likely to be more negative.
As the decomposition illustrates, the change in leverage ratio results from new equity issues, change in retained earnings, and the growth in total assets.\(^{28}\) We regress each of these three components of change in book leverage on the market-to-book ratio and other control variables (the same set as in equation (11)). The results are reported in Table 5. For the regression reported in each panel, the net effect of the market-to-book on the change in the debt ratio is obtained by adding the coefficient of the market-to-book in the three columns. For example, for the first panel, S(Actual Data), the net effect is -0.003. Of the three samples, the coefficient of the market-to-book on net equity issues is the highest in magnitude for the market timing sample - its difference with the corresponding coefficient in the S(Haf/Half) sample being -0.007. Notice that this is slightly larger in magnitude than the overall effect of the market-to-book in the market timing sample. The coefficient on asset growth and the change in retained earnings are almost identical for all three samples (asset growth is also more sensitive to the market-to-book in the market timing sample, since it includes equity issues). Thus, it is clear that the negative effect of the market-to-book in the market timing sample compared to the S(Half/Half) sample is due to the greater sensitivity of equity issues to this variable. In other words, our results demonstrate that timing behaviour can generate a negative coefficient for the market-to-book ratio in leverage regressions that works through the equity issuance channel.

C.3 **Firm-Specific Variables and Debt Ratios: A Summing Up**

The change in the sign of the market-to-book ratio highlights why it is misleading to interpret signs of the coefficients of firm-specific variables as either consistent or inconsistent with particular theories about desired debt ratios. In Section 4.B, we noted that for the sample S(Actual Probability), variables that are likely to be positively associated with a bigger financing deficit (or higher likelihood of positive deficits) are also likely to have a positive relationship with the debt ratio in a standard debt ratio regression. A higher value of a particular variable may cause the *deficit* to be larger (or more likely to be positive), and if firms in general have an incentive to issue and repurchase debt more often than equity (e.g. for transactions cost reasons), then this variable will have a positive impact on the debt ratio. However, a higher value of this same variable may be relevant for the debt versus equity choice and perhaps tilt the firm towards equity issuance, and thus contribute to a lower debt ratio.

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\(^{28}\) The growth in total assets is driven by the combination of new equity issues, new debt issues, and newly retained earnings.
C.4 Firms’ histories and market timing

Whether or not market timing behavior has a persistent effect on observed capital structure is a controversial issue in the literature. Baker and Wurgler (2002) show that a “past external finance-weighted” market-to-book ratio (an average past market-to-book ratio weighted by past financing deficits) has a negative effect on current debt ratios. The idea behind this measure is that if firms had issued equity in the past to finance the deficit when the market-to-book was high, then this measure should be negatively related to today’s debt ratio if the firms do not rebalance quickly.

Baker and Wurgler’s (2002) (BW hereafter) results – and the interpretation of these results - have been questioned. Leary and Roberts (2005a) show that the persistent effect of the BW variable is consistent with dynamic rebalancing in the presence of adjustment costs – and the persistence decreases in samples in which adjustment costs are expected to be lower. However, their nonparametric analysis suggests that the BW variable reflects the historical average market-to-book ratio (a proxy for growth opportunities) rather than market timing. Kayhan and Titman (2005) (KT hereafter) make a similar point. They propose a decomposition of BW’s measure into a term that reflects the covariance between the past market-to-book and the financing deficit, and a term that reflects the past (unweighted) average market to book. They show that the latter term mainly drives Baker and Wurgler’s results. Liu (2005) takes a related point of view and argues that the past market-to-book matters because leverage adjusts slowly to changes in the market-to-book ratio on account of adjustment costs.  

Our market timing simulation sample S(Market Timing) provides an ideal way to test the power of various measures to identify market timing behavior and its persistence. We consider a recent refinement of the market timing measure of Baker and Wurgler (2002) suggested by Kayhan and Titman (2005). Baker and Wurgler (2002) introduced the “external finance weighted-average” market-to-book ratio, defined as follows:

\[ BWMB_s = \frac{\sum_{x=0}^{t-1} \frac{Def_s}{\sum_{r=0}^{s} Def_r} M / B_s}{t} \]

where \( Def_s \) denotes the financing deficit, or equivalently, external financing at time \( s \) and the summations are taken starting at the first year firms enter our sample. Kayhan and Titman (2005)

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29 Hovakimian (2006) also makes the point that BW variable captures future growth potential rather than market timing.
propose a decomposition of the BW timing measure that incorporates the average past market-to-book ratio (a measure of growth opportunities) and the covariance between issuance activity and the market-to-book (a measure of timing activity). They show that

\[ BWMB = \frac{\text{cov}(\text{Def}, M/B)}{\text{Def}} + \frac{\overline{M/B}}{\overline{M/B}} = KTCov + KTMB \]

where \( \text{Def} \) and \( \overline{M/B} \) denote, respectively, the past average deficit and average market-to-book ratio. As the decomposition illustrates, only the first term \( (KTCov) \) captures Baker and Wurgler’s timing intuition.\(^{30}\) If firms time their equity issuance and the timing effects on capital structure are not immediately rebalanced away, we would expect this variable to have a negative effect on changes in capital structure. The second term \( (KTMB) \) is simply the historical average market-to-book which proxies for investment opportunities.\(^{31}\)

We estimate the following equation for the actual sample, the sample S(Half/Half), and the market timing sample

\[ \left( \frac{D}{A} \right)_t = d_0 + d_1(M/B)_{t-1} + d_2(EBITDA/A)_{t-1} + d_3\text{Size}_{t-1} + d_4(PPE/A)_{t-1} \\
+ d_5(R\&D/S)_{t-1} + d_6\text{RDD}_{t-1} + d_7\text{KTMB}_{t-1} + d_8\text{KTCov}_{t-1} + \frac{1}{\text{Def}} + \epsilon_t \]  

(13)

Notice that we control for the inverse of the average financing deficit, since the negative effect of \( KTCov \) could be driven by the denominator.\(^{32}\) The results are reported in Panel A of Table 6. In the actual data, both KT variables are negative and significant.\(^{33}\) In contrast, in the sample S(Half/Half), both KT variables have much smaller, though still negative, coefficients – the coefficient of \( KTCov \) is one seventh of that for the actual sample. In the market timing sample, both KT variables have significantly negative coefficients. In particular, the coefficient of the \( KTCov \) variable is almost the same as that in the actual sample.

The fact that the market timing variable \( KTCov \) has a much weaker effect in a sample where no timing behavior is present, but reappears much stronger when mechanical timing

\(^{30}\) Appendix B derives the decomposition in greater detail.

\(^{31}\) Note that our two terms \( (KTCov \) and \( KTMB \)) are slightly different from Kayhan and Titman’s (2005) yearly timing and long-term timing measures. Kayhan and Titman’s measures are not deflated by average past external financing.

\(^{32}\) We thank Laura Liu for pointing this out.

\(^{33}\) This contrasts with the results of Kayhan and Titman (2005), where the \( KTCov \) variable is much less significant. We attribute this difference in our results to the fact that our variables are scaled by the average financing deficit. Note also that the coefficient of \( PPE/A \) is negative and significant in the actual data. This is not a typographical error. Frank and Goyal (2003a) also document that tangibility has a negative coefficient in similar regressions. The coefficient they report is -0.041 and t-statistic is -7.9.
behavior is introduced but there is no rebalancing, suggests that this variable does indeed capture the persistent effect of timing. The fact that it has almost an identical coefficient in the actual data is consistent with our earlier result that there does not appear to be an extent of rebalancing in the actual data that washes away the effects of market timing quickly.

More puzzling, however, is why the KTMB variable has a fairly strong effect in the sample S(Half/Half). In this sample, there is neither supposed to be any timing behavior, nor any target behavior, so neither of the usual suspects for a negative effect is present. However, notice that the market-to-book (M/B) itself has a positive coefficient of comparable magnitude. The simultaneous presence of the M/B and the KTMB, and the high correlation between these two variables, makes the coefficient difficult to interpret.

While the M/B also has a positive coefficient for the actual data, here the difference in magnitude between the coefficients of M/B and KTMB is more substantial. A negative coefficient of KTMB in the actual sample is consistent with the idea that it might contain information relevant for a future target (Kayhan and Titman (2005)), that it might reflect lagged adjustment (Liu (2005)), or that it captures market timing activity not accounted for by KTCov. 34
Notice, however, that the lagged debt ratio should be a sufficient statistic for any past financing activity; it is also a sufficient statistic for a past target. 35 Therefore, any variable that affects the current debt ratio through either of these two channels should no longer be significant in the regression if the lagged debt ratio is controlled for. On the other hand, if it is a proxy for the current or future target, then it should remain significant even when the lagged debt ratio is controlled for.

In Panel B of Table 6, we modify our empirical specification in (13) to include a one-period lagged debt ratio. The regression results reveal that both KTMB and KTCov have negligible impact in both simulated samples (in fact, the sign flips), which is consistent with our expectation. Since no target is presupposed for these samples, KTMB should not play any role – especially if the lagged debt ratio is controlled for to allow for the possibility that KTCov does not completely account for all timing activity. Further, the lagged debt ratio should also

34 Recall that our earlier results suggest that the negative sign of M/B in the actual data could reflect market timing. KTCov may not completely capture market timing, among other reasons, because it excludes negative deficit years. If firms are buying back shares when market values are low, this would also induce a negative relationship between the market-to-book and debt ratios not captured by KTCov. Baker (2004), in his discussion of Kayhan and Titman (2005)'s paper, has also made the point that the level of the market-to-book may contain relevant information about timing incentives that the covariance term does not capture.
35 To see this, notice that the target adjustment model can be written as: $(D/A)_t = \lambda(D/A)_{t-1} + (1-\lambda)(D/A)_{t-2}$. Hence, any variable that affects the past target $(D/A)_{t-1}$ affects the current debt ratio if $1 > \lambda > 0$, but is subsumed in the lagged debt ratio $(D/A)_{t-1}$ if the latter is included as a control variable.
subsume all timing activity in the sample S(Market Timing). More significantly, the $KTMB$ is insignificant in the actual sample as well. Since the only reason why the average market-to-book might affect the current debt ratio once the lagged debt ratio is controlled for is through its possible effect on the *current or future* target, the specific version of the target adjustment model which argues that the past average market-to-book ratio contains information about current or future targets fails this test.\(^{36}\)

D. Industry effects

If firm characteristics really determine an optimal debt ratio, then to the extent that firms in the same industry are likely to share some common characteristics, industry factors should explain a higher proportion of the variation in the debt ratio in the actual sample than in any of the simulated samples.

In Table 7, we present the results of an ANOVA Analysis where for the three samples S(Actual Data), S(Half/Half), and S(Random Deficit), we report the R-squares from a regression using firm dummies only (Column I), using 3-Digit-SIC-Industry dummies only (column II), and the ratio of the R-square of the latter to the former. For the random sample, industry dummies explain 16.1% of the variation explained by firm dummies. Using this as the benchmark, we notice that the sample S(Half/Half) shows no improvement in this regard, indicating perhaps that there is not much industry level clustering of the financing deficit. However, for the actual data, industry dummies explain 29.1% of the variation – a considerable improvement. Although we cannot rule out alternative explanations as to why firms in the same industry should have more similar debt ratios (such as benchmarking or herding), Table 7 presents one set of results which are more favorable for the existence of a target debt ratio than mechanical financing. Unfortunately, this is the one of the few pieces of evidence we can find in support of a debt ratio target.\(^{37}\)

E. Debt-Equity Issuance and Repurchase Regressions

\(^{36}\) The $KTCov$ variable is significant in the actual data, contrary to our expectation. However, it is only significant at the 5% level and its magnitude is $1/16^{th}$ of that when the lagged leverage is not included. By contrast, the coefficient of profitability is reduced by $4/5$, and that of Size by $7/8$.

\(^{37}\) In an interesting paper, Lemmon, Roberts and Zender (2006) show that debt ratios are remarkably persistent over time. In particular, past debt ratios have strong explanatory power even after an interval of 20 years. While they do not suggest this interpretation, this persistence might appear as *prima facie* evidence of a debt ratio target. Remarkably, the debt ratios in all our simulation samples except the S(Random deficit) sample show similar persistence. In an earlier version of the paper, we explored this issue further. Our results showed that the time series structure of the deficit contributes to the cross-sectional dispersion of debt ratios and its persistence.
Target behavior implies that the probability of debt and equity issuance or repurchase should be related in a particular way to the firm’s debt ratio and the debt ratio target. In particular, if the firm’s debt ratio is above an estimated target, then the firm should be more likely to issue equity as opposed to debt or repurchase debt as opposed to equity, than if the debt ratio is below target. Since our simulation samples are generated under the assumption that conditional on the deficit being positive (negative), the firms have a fixed probability of issuing debt (repurchasing debt), the issuance/repurchase decisions in the simulated samples should have no such characteristic. Nor should the issuance/repurchase decisions in the simulated samples be related to any firm characteristics, whereas in the actual data, variables such as the market-to-book ratio (reflecting equity market conditions) or profitability (reflecting the need for tax shields) could affect issuance or repurchase decisions. Hence, probit models of the debt versus equity choice would seem to be an ideal way to distinguish target behavior from random financing.

Hovakimian (2004) does a very careful study of firms’ issuance and repurchase decisions. He finds that when combined issue and repurchase transactions are taken out, the deviation from target does not have a significant effect on the choice between pure debt and equity issues. There is somewhat stronger evidence on repurchases, but this mostly comes from debt repurchases by highly levered firms. There is no evidence that debt issuers are underlevered. Equity issuers are underlevered rather than overlevered prior to issuance of equity, and issuance of equity increases rather than decreases the deviation from a target. Finally, firms repurchasing equity are underlevered, but the repurchases have a negligible effect on the deviation from the target.

Our findings are similar. We do not find any strong evidence that firms issue debt or equity to move towards an estimated target capital structure. There is stronger evidence that firms reduce debt when they have excess leverage. This is the strongest evidence we can find in support of tradeoff behavior. However, we find several surprising results when we apply standard methodology to the actual and the simulated data. These results raise several methodological and robustness issues about existing tests and their interpretation. We discuss these below.

First, in Table 8, Panel A, we document summary statistics about debt and equity issuance and repurchase and the financing deficit across five leverage deviation groups in the actual data. “Low” refers to the group of firms in the lowest quintile according to the deviation from the target leverage ratio and “High” refers to those with the highest deviation. Deviation
(DevTgt) is defined as the leverage ratio lagged one period less the target leverage ratio, i.e. 

\[ \text{DevTgt}_{i,t} = \left( \frac{D}{A} \right)_{i,t-1} - \left( \frac{D}{A} \right)_{i,t} \]

The target leverage, \( \left( \frac{D}{A} \right)_{i,t} \), is the predicted value of the following cross-sectional leverage regression:

\[
\left( \frac{D}{A} \right)_{i,t} = e_0 + e_1(M/B)_{i,t-1} + e_2(EBITDA/A)_{i,t-1} + e_3\text{Size}_{i,t-1} + e_4(PPE/A)_{i,t-1} \\
+ e_5(R&D/S)_{i,t-1} + e_6\text{RDE}_{i,t-1} + e_7\text{IND} + e_{i,t}
\] (14)

where IND are the 3-digit-SIC-Industry dummies. Notice that the percentage of times (i.e. percentage of all firm years in a given leverage group) that debt is issued actually increases from the lowest to the highest deviation groups. Interestingly, the percentage of times equity is issued also increases. The proportion of equity to debt issuance increases from 36% for the lowest group to 46% in the highest, but the pattern is non-monotonic: the lowest percentage is for group 2 and then group 3.

We then estimate the following probit model similar to those used by Hovakimian, Opler, and Titman (2001) and Hovakimian (2004) to examine the relation between debt-equity choice and the deviation from target leverage ratio:

\[
P(\text{DEchoice}_{i,t} = 1) = F(f_0 + f_1\text{DevTgt}_{i,t} + f_2(M/B)_{i,t-1} + f_3(EBITDA/A)_{i,t-1} + f_4\text{Size}_{i,t-1} \\
+ f_5(PPE/A)_{i,t-1} + f_6(R&D/S)_{i,t-1} + f_7\text{RDE}_{i,t-1} + f_8(Def/A)_{i,t-1})
\] (15)

where \( P \) represents the probability of debt being chosen. \( \text{DEchoice} \) takes a value of one if conditional on issuance (repurchase), debt is issued (repurchased), and zero if equity is issued (repurchased). \(^{39}\) \( F \) denotes the normal cumulative distribution function. Apart from the previously used pre-determined (one-period lagged) control variables, the deficit to asset ratio \( (\text{Def}/A) \) lagged one period is also included to control for the size of financing deficit.

We first estimate equation (15) using deviation group dummies constructed for the five abovementioned leverage deviation groups. Deviation group 3 dummy is excluded to avoid perfect multicollinearity. Not surprisingly, Panel A of Table 9 confirms the non-monotonic pattern in Panel A of Table 8. Hence, relative to firms close to their target, both firms that are overlevered and underlevered are less likely to issue debt than equity. However, when we include a continuous variable (DevTgt) corresponding to the deviation from the target, the

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\(^{38}\) To ensure that our results are not sensitive to the definition of the target leverage ratio, we experimented using the three-digit SIC industry median leverage, firm-specific mean leverage or past three year moving average as Jalilvand and Harris (1984). Our results are essentially the same under all alternative definitions of the target leverage.

\(^{39}\) It is important to reiterate that only issuance or repurchases that exceed 5% of the book value of assets are considered in the probit regressions. The firm is assumed to be inactive in issuance or repurchase otherwise. This is the standard practice in the literature (see, for example, Hovakimian (2004)).
variable is negative and significant in the issuance regression. Though the sign of the continuous variable is consistent with tradeoff theory, the underlying non-linearity is not. We will return to the continuous variable again below.

For repurchases, the data shows a very pronounced tendency for debt repurchases to increase monotonically across the leverage groups. The relative frequency of equity to debt repurchases decreases from 117% to 14% from the least levered to the most levered firms (Panel A of Table 8). Dummy variables representing the groups (as well as a continuous deviation from the target variable) pick up this monotonic pattern, which is consistent with target behavior (Panel A of Table 9).

We now turn to the simulated data. We focus on the sample S(Half/Half) in Panel B of Table 9. Since our simulations assume that the probabilities of debt or equity issuance (repurchase) conditional on the deficit being positive (negative) are exogenous, neither the deviation of the leverage from an estimated target nor firm characteristics should have any explanatory power in probit models of debt versus equity choice. Surprisingly, however, the continuous deviation from target variable is significant, as are some firm-specific variables. We investigate this further, and generate summary statistics on the simulation sample similar to those reported in Panel A of Table 8. These are reported in panel B of the table. We find that the relative frequency of equity to debt issuance is not unity in all leverage groups: it is 118% in the group with the highest deviation. What accounts for this discrepancy? Recall that in a small number of cases (less than 3% of all issue and repurchase years) we deviate from random financing when the debt ratio is near the corner (i.e., close to 0 or 1). Especially when the debt ratio is close to 1 and the firm has low book equity and negative retained earnings, we force an equity issuance even though the random outcome is debt issuance. Since these cases are concentrated in the highest leverage deviation group, we see a higher frequency of equity issuance than debt issuance. However, even such an apparently innocuous deviation from the random outcome can have a major impact on probit models, as seen in Panel B of Table 9. The deviation from the target in continuous form is significant and negative. However, the explanatory power is coming entirely from the highest leverage deviation group, which is the only group dummy that is significant. Since it is mainly the negative retained earnings firms for which the deviation from random financing occurs, it is not surprising to find that profitability is highly significant.40

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40 Note that this deviation from the random outcome corresponds to the type (a) corner case that we discussed at the beginning of Section 4. The regression of debt-equity repurchase decision (Panel B of Table 9) generates similar results. The coefficients of the lowest and the highest deviation group dummies are significant and have signs...
These results show that probit models of debt-equity choice can be highly fragile and sensitive to quirks of the data. However, a bigger problem arises if one uses multinomial models that simultaneously model issuance and repurchase decisions. To illustrate the nature of the problem, we work with a sample in which the corner cases are all removed, so that there is no deviation from the random outcome.\footnote{We simply drop a firm if any point is reached where a “coin toss” could potentially cause any of the corner problems discussed at the beginning of Section 4.} Reassuringly, for this sample, probit models of the type discussed in the previous paragraphs do not result in any significant coefficients for the explanatory variables, which is consistent with the fact that conditional on the deficit being positive (negative), the probability of debt issuance (repurchase) is fixed. However, multinomial logit models which try to simultaneously model debt and equity issuance and repurchase decisions are not conditioned on the deficit being positive or negative. Therefore, factors that are correlated with the size of the deficit will affect the probability of issuance or repurchase of a particular security. The problem is exacerbated by the fact that not only the sign, but also the size of the deficit matters – since only issue or repurchase decisions that exceed 5% of total assets in absolute value are typically considered as issuance or repurchase activity.

Table 10 shows the results of a multinomial regression for both actual and the simulated data (S(Half/Half) sample). Five categories of transactions are considered: (1) no transaction (i.e., transaction size below 5% of book value of assets in absolute value) (2) equity issue (3) debt issue (4) equity repurchase and (5) debt retirement.\footnote{We do not consider dual issues, dual repurchases, case of equity issuance combined with debt reduction , and debt issuance combined with equity repurchases as independent categories, following Hovakimian (2004) and Chen and Zhao (2006). These cases do not occur very often in the actual data, and of course, not at all in the simulated data.} We use the first category as the base category, i.e. probabilities are estimated for the other choices relative to this category, and assume financing decisions can be described as

\[
P_{i,t,k} = \frac{e^{\gamma_k \times \text{DevTgt} + g_k \times X_{i,t-1}}}{1 + \sum_{k=2,3,4,5} e^{\gamma_j \times \text{DevTgt} + g_j \times X_{i,t-1}}} (16)
\]

where \(P_{i,t,k}\) denotes the probability of a firm-year falling into the \(k\)th financing category \((k = 2,3,4,5)\). \(\text{DevTgt}\) is the deviation from target. \(X\) is the same set of control variables as in equation (15).

In the actual data, firms with high debt ratio deviation repurchase less equity and more debt. This is consistent with target behavior. However, they issue both more debt and more equity (effect of the latter is significant at 10% level), which is inconsistent with target behavior. These results are very similar to those in Hovakimian (2004). In the simulated data, remarkably,
many variables are significant, even though the corner cases have been removed for this sample. In fact, the regressions look remarkably similar to those on the actual data, with the notable exception that firms with high leverage deviation are more likely to repurchase equity (relative to no transaction).

The results for the simulation sample can be explained. Since “no transactions” is the base category, variables that are correlated with a higher absolute size of the deficit will have positive significant effects in the regressions. Variables that are associated with a higher positive sign of the deficit will have similar, and positive, coefficients in the debt and equity issuance regressions. Variables that are associated with a higher negative deficit will have similar, and positive, signs in both repurchase regressions. This is exactly what we observe, almost without any exception. In particular, the deviation from target variable has a significant positive coefficient in all cases. Summary statistics for this case (reported in Panel B of Table 8) reveals that firms in the highest leverage deviation group have both a higher proportion of positive deficits and negative deficits (exceeding 5% of book value of assets in absolute value) than the lowest deviation group.

For the actual sample, we also observe a similar feature in the debt and equity issue regressions. Most variables have similar signs in these two regressions. This confirms our earlier finding that issuance activity is largely affected by the size of the deficit. In the repurchase regressions, we see some departures from this pattern. For example, the market-to-book ratio has a positive effect on equity repurchase, but is insignificant in debt retirement regression; profitability has an insignificant effect on equity repurchases but affects the probability of debt repurchases negatively. Hovakimian (2004) also notes similar results for repurchases. Overall, our findings suggest that we need to interpret the results of multinomial logit regressions with caution because of the confounding effect of variables on the deficit.

F. Robustness checks

F.1 Endogeneity of financing deficit

The financing deficit is undoubtedly an endogenous choice variable of the firms – but does this endogeneity explain why mechanical financing can generate a behavior of the debt ratio that is similar to what is observed? In other words, could it be the case that firms choose their deficits in such a way that, even with mechanical financing, they would essentially be following target behavior? We think this is quite unlikely.
First, notice that in our non-parametric analysis, we observed that when firms make large equity or debt issues, they often subsequently issue the same kind of security more actively. If the persistently large deficit were generated endogenously as a result of a desire to issue the opposite type of security in large quantity, we would not expect this result. In fact, our results showed that the issuance activity subsequent to major debt and equity issues at best reflected the result of a higher proportion of positive deficits among the issuing firms with no change in the probability of debt and equity issuance compared to an average year.

To address the issue of endogeneity more thoroughly, we replicated our analysis by generating a time series of the predicted deficit in a variety of ways, and recreated the simulated samples on the basis of these predicted deficits. Our results were similar to those obtained with the actual deficits. For brevity, we do not report these results but they are available upon request.

F.2 Alternative definitions of leverage ratios and financing

Following Fama and French (2002), Baker and Wurgler (2002), and Kayhan and Titman (2005), we use the total liabilities to assets ratio to as the measure of leverage. Total liabilities include account payables that relate to the operations of the firm and arguably bear little resemblance to other forms of debt. To ensure our results are not driven by the inclusion of these current liabilities, we repeated our analysis with the total debt to assets ratio, where total debt is defined as the sum of short-term debt and long-term debt. In addition, we calculated net debt (equity) issues from cash flow statements rather than using balance sheet items. Specifically, net debt issues are defined as long-term debt issuance minus long-term debt reduction; and net equity issues are the sale of common and preferred stock minus the repurchase of common and preferred stock. These alternative definitions of leverage ratios and financing have no material impact on our results but significantly reduce the number of observations for empirical analysis.

5. Conclusions

We show that a variety of evidence about the debt ratio and financing behavior – notably rebalancing, mean reversion, a negative coefficient for the market-to-book ratio in leverage regressions, and persistence – that have been associated with the “targeting” of an optimal debt

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43 In one of the robustness checks, we predict the financing deficit by running a cross-sectional regression of the actual financing deficit on the log of total assets, sales growth, and the change in net PPE to assets ratio.
ratio can be replicated in simulated data even when no target is assumed. The key to understanding why existing evidence can be replicated by simulated data is the financing deficit: its time series properties, its relationship with firm-specific variables, and of course, how it is financed. Our results show that most of what we know about the debt ratio can be explained by the first two features of the deficit even if we make neutral assumptions about how it is financed. How the deficit is financed, however, is at the heart of theories of financing behavior.

The strongest evidence of target behavior we can find comes from repurchase behavior: (a) highly levered firms retire more debt, and (b) firms with poor stock returns and negative retained earnings retire more debt instead of buying back equity. Moreover, industry fixed effects explain a larger proportion of the variation explained by fixed firm-effects in the actual data than in the simulated data. Thus, the collective evidence in favor of a target debt ratio is by no means overwhelming.

Put differently, our results suggest that there is not a great deal to be learnt about firms’ motives for seeking alternative forms of financing from studying debt ratios. Identifying these motives is likely to prove a major challenge for empirical research in corporate finance. Even rebalancing behavior – the idea that debt and equity issuance decisions are determined by deviation from a target debt ratio - does not seem to be strong in the actual data. There is some evidence in existing literature that market conditions affect issuance. However, even fairly elaborate models of financing have only about a 50% success rate in predicting debt and equity issues. In so far as firms’ motives for financing are concerned, it appears that we may well be reaching the limit of what can be explained in terms of variables that are available from large scale databases such as Compustat and CRSP.
References


Myers, Stewart C. and Nicholas S. Majluf, 1984, Corporate financing and investment decisions when firms have information that investors do not have, *Journal of Financial Economics* 13, 187-221.


Figure 1: Book leverage following a large equity issuance

Actual data are collected from *Industrial Compustat* and *CRSP* for the years 1971 to 2004. Section 3 discusses how the simulated data are generated. For each dataset each year, large equity issuers (non-issuers) are identified if firms’ net equity issues divided by total assets is higher (lower) than 5%. Both equity issuers and non-issuers are then followed over the next five event years. Book leverage is tracked at each point in time. The average book leverage is then computed across event times over the entire sample period for both equity issuers and non-issuers, respectively. Date 0 corresponds to the end of the issue period. Each simulated sample is generated 500 times, and the average leverage ratio in each event year over 500 simulations is presented. Panel A reports the differences in book leverage between equity issuers and non-issuers for actual and simulated data. Panel B presents the book leverage of equity issuers and non-issuers separately.

Panel A: Difference in book leverage between equity issuers and non-issuers

Panel B: Book leverage of equity issuers and non-issuers
Figure 2: Financing deficit following leverage changing events (Actual Data)
Data are collected from Industrial Compustat and CRSP for the years 1971 to 2004. Each year, large equity/debt issuer (non-issuers) are identified if firms’ net equity/debt issues divided by total assets is higher (lower) than 5%. A firm is defined to experience a positive (negative) equity shock if its actual annual stock return is one standard deviation above (below) the firm-specific mean return. Firms are then followed over the next five event years. Financing deficit is equal to the change in total assets minus the newly retained earnings. A deficit is defined to be large if its absolute value is greater than 5% of total assets. We track the fraction of firms having large financing deficit at each point in time. The average is then computed across event times over the entire sample period. Date 1 corresponds to the end of the first period after large security issuances or equity shocks.

Panel A: Fraction of firms having large positive financing deficits after large equity issues

Panel B: Fraction of firms having large positive financing deficits after large debt issues

Panel C: Fraction of firms having large positive financing deficits after positive equity shocks

Panel D: Fraction of firms having large negative financing deficits after negative equity shocks
Figure 3: Large debt issuances following a large equity issuance

Actual data are collected from *Industrial Compustat* and *CRSP* for the years 1971 to 2004. Section 3 discusses how the simulated data are generated. For each dataset each year, large equity issuers (non-issuers) are identified if firms’ net equity issues divided by total assets is higher (lower) than 5%. Both equity issuers and non-issuers are then followed over the next five event years. Subsequent debt issuances are tracked at each point in time. The fraction of firms making large debt issues (net debt issued exceeds 5% of total assets) is then computed across event times over the entire sample period for both date 0 equity issuers and non-issuers, respectively. Date 1 corresponds to the first year-end following the equity issue year. Each simulated sample is generated 500 times, and the reported average fraction in each event year is taken over 500 simulations. Panel A reports the difference in the fraction of firms making large subsequent debt issues between date 0 equity issuers and non-issuers for actual and simulated data. Panel B presents the fractions for date 0 equity issuers and non-issuers separately.

Panel A: Difference in the fraction of firms making large subsequent debt issues between equity issuers and non-issuers

Panel B: Fraction of equity issuers (non-issuers) that make large subsequent debt issues

<table>
<thead>
<tr>
<th>S(Actual Data)</th>
<th>S(Half/Half)</th>
<th>S(Actual Probability)</th>
<th>S(Random Deficit)</th>
</tr>
</thead>
</table>

45
Figure 4: Large equity issuances following a large equity issuance

Actual data are collected from *Industrial Compustat* and *CRSP* for the years 1971 to 2004. Section 3 discusses how the simulated data are generated. For each dataset each year, large equity issuers (non-issuers) are identified if firms’ net equity issues divided by total assets is higher (lower) than 5%. Both equity issuers and non-issuers are then followed over the next five event years. Subsequent equity issuances are tracked at each point in time. The fraction of firms making large equity issues (net equity issued exceeds 5% of total assets) is then computed across event times over the entire sample period for both date 0 equity issuers and non-issuers, respectively. Date 1 corresponds to the first year-end following the equity issue year. Each simulated sample is generated 500 times, and the reported average fraction in each event year is taken over 500 simulations. Panel A reports the difference in the fraction of firms making large subsequent equity issues between date 0 equity issuers and non-issuers for actual and simulated data. Panel B presents the fractions for date 0 equity issuers and non-issuers separately.

Panel A: Difference in the fraction of firms making large subsequent equity issues between equity issuers and non-issuers

Panel B: Fraction of equity issuers and non-issuers that make large subsequent equity issues

S(Actual Data)
S(Half/Half)
S(Actual Probability)
S(Random Deficit)
**Figure 5: Book leverage following a large debt issuance**

Actual data are collected from *Industrial Compustat* and *CRSP* for the years 1971 to 2004. Section 3 discusses how the simulated data are generated. For each dataset each year, large debt issuers (non-issuers) are identified if firms’ net debt issues divided by total assets is higher (lower) than 5%. Both debt issuers and non-issuers are then followed over the next five event years. Book leverage is tracked at each point in time. The average book leverage is then computed across event times over the entire sample period for both debt issuers and non-issuers, respectively. Date 0 corresponds to the end of the issue period. Each simulated sample is generated 500 times, and the average leverage ratio in each event year over 500 simulations is presented. Panel A reports the difference in book leverage between date 0 debt issuers and non-issuers for actual and simulated data. Panel B presents the book leverage of date 0 debt issuers and non-issuers separately.

Panel A: Difference in book leverage between debt issuers and non-issuers

Panel B: Book leverage of debt issuers and non-issuers
Figure 6: Large debt issuances following a large debt issuance

Actual data are collected from Industrial Compustat and CRSP for the years 1971 to 2004. For each dataset each year, large debt issuers (non-issuers) are identified if firms’ net debt issues divided by total assets is higher (lower) than 5%. Both debt issuers and non-issuers are then followed over the next five event years. Subsequent debt issuances are tracked at each point in time. The fraction of firms making large debt issues (net debt issued exceeds 5% of total assets) is then computed across event times over the entire sample period for both date 0 debt issuers and non-issuers, respectively. Date 1 corresponds to the first year-end following the debt issue year. Each simulated sample is generated 500 times, and the reported average fraction in each event year is taken over 500 simulations. Panel A reports the difference in the fraction of firms making large subsequent debt issues between date 0 debt issuers and non-issuers for actual and simulated data. Panel B presents the fractions for date 0 debt issuers and non-issuers separately.

Panel A: Difference in the fraction of firms making large subsequent debt issues between debt issuers and non-issuers

Panel B: Fraction of debt issuers and non-issuers making large subsequent debt issues

S(Actual Data)  S(Half/Half)
S(Actual Probability)  S(Random Deficit)
Figure 7: Large equity issuances following a large debt issuance
Actual data are collected from Industrial Compustat and CRSP for the years 1971 to 2004. Section 3 discusses how the simulated data are generated. For each dataset each year, large debt issuers (non-issuers) are identified if firms’ net equity issues divided by total assets is higher (lower) than 5%. Both debt issuers and non-issuers are then followed over the next five event years. Subsequent equity issuances are tracked at each point in time. The fraction of firms making large equity issues (net equity issued exceeds 5% of total assets) is then computed across event times over the entire sample period for both date 0 debt issuers and non-issuers, respectively. Date 1 corresponds to the first year-end following the debt issue year. Each simulated sample is generated 500 times, and the reported average fraction in each event year is taken over 500 simulations. Panel A reports the difference in the fraction of firms making large subsequent equity issues between date 0 debt issuers and non-issuers for actual and simulated data. Panel B presents the fractions for date 0 debt issuers and non-issuers separately.

Panel A: Difference in the fraction of firms making large subsequent equity issues between debt issuers and non-issuers

Panel B: Fraction of debt issuers and non-issuers that making large subsequent equity issues

S(Actual Data)  S(Half/Half)
S(Actual Probability)  S(Random Deficit)
Table 1: Summary Statistics (Actual Data)

Actual data are collected from *Industrial Compustat* and *CRSP* for the years 1971 to 2004. Total assets \((A)\) is Compustat item number 6. Book Leverage \((D/A)\) is defined as total debt divided by total assets. Total debt is equal to total liabilities plus preferred stock minus deferred taxes and convertible debt. Market-to-book ratio \((M/B)\) is defined as \((\text{market value of equity + total debt}) / \text{total assets}\). Market value of equity is defined as the number of shares outstanding multiplied by closing stock price at the end of the fiscal year. Return on assets \((EBITDA/A)\) is the income before depreciation and amortization divided by book value of assets. Tangibility \((PPE/A)\) is the net PPE to asset ratio. R&D/S is the research and development expenses divided by net sales. Net equity issues \((Nei)\) are equal to the difference between the change in total equity minus the change in retained earnings. Net debt issues \((Ndi)\) are defined as the change in total assets minus the change in total equity. Financing deficit \((Def)\) equals the sum of net equity issued and net debt issued. Dollar figures are in millions.

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Median</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Assets ((A))</td>
<td>2,629</td>
<td>200</td>
<td>13,696</td>
</tr>
<tr>
<td>Book Leverage ((D/A))</td>
<td>0.448</td>
<td>0.451</td>
<td>0.186</td>
</tr>
<tr>
<td>Market-to-book Ratio ((M/B))</td>
<td>1.527</td>
<td>1.230</td>
<td>0.993</td>
</tr>
<tr>
<td>Return on Assets ((EBITDA/A))</td>
<td>0.142</td>
<td>0.144</td>
<td>0.099</td>
</tr>
<tr>
<td>Tangibility ((PPE/A))</td>
<td>0.335</td>
<td>0.296</td>
<td>0.201</td>
</tr>
<tr>
<td>R&amp;D to Sales Ratio ((R&amp;D/S))</td>
<td>0.024</td>
<td>0.001</td>
<td>0.052</td>
</tr>
<tr>
<td>Deficit to Assets Ratio ((Def/A))</td>
<td>0.084</td>
<td>0.038</td>
<td>0.229</td>
</tr>
<tr>
<td>Newly Retained Earnings to Assets Ratio ((ARE/A))</td>
<td>0.033</td>
<td>0.037</td>
<td>0.092</td>
</tr>
<tr>
<td>Percentage of firms having positive financing deficit ((Def &gt; 0))</td>
<td>67.9%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Percentage of firms having large positive financing deficit ((Def /A &gt; 5%))</td>
<td>44.9%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Percentage of firms having large negative financing deficit ((Def /A &lt; -5%))</td>
<td>14.8%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Median percentage of financing deficit financed with debt in positive financing deficit years</td>
<td></td>
<td></td>
<td>75.6%</td>
</tr>
<tr>
<td>Median percentage of financing deficit used for debt reduction in negative financing deficit years</td>
<td></td>
<td></td>
<td>65.1%</td>
</tr>
<tr>
<td>Firm years</td>
<td>38,593</td>
<td></td>
<td></td>
</tr>
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Table 2: Persistence of the impact of large equity issuances on capital structure

Actual data are collected from *Industrial Compustat* and *CRSP* for the years 1971 to 2004. Section 3 discusses how the simulated data for the sample S(Half/Half) are generated. For each dataset each year, large equity issues are identified if firms’ net equity issued divided by total assets is higher than 5%. The regression model is as follows:

\[
(D/A)_t - (D/A)_{pre-event} = a_0 + a_1 Event + a_2 (M/B)_{t-1} + a_3 (EBITDA/A)_{t-1} + a_4 Size_{t-1} + a_5 (PPE/A)_{t-1} \\
+ a_6 (R & D / S)_{t-1} + a_7 RDD_{t-1} + a_8 (D/A)_{pre-event} + \epsilon_t
\]

The dummy variable *Event* equals 1 if a large equity issue occurred *t* years ago and zero otherwise. The dependent variable is the cumulative change in book leverage \((D/A)\) from the pre-event year to *t* years after the event occurs. The control variables are firm characteristics that are lagged one year and defined in Appendix A. The constant term is included in the regression but not reported. The reported coefficients for S(Actual Data) are estimated using Fama and MacBeth (1973) approach. t- statistics are in parentheses. Coefficients significant at the 10%, 5%, and 1% levels are respectively marked with *, **, and ***. For S(Half/Half), the reported parameter estimates are the average coefficients obtained from 500 replications of the simulation. 95% confidence intervals are included in square brackets.

<table>
<thead>
<tr>
<th>t</th>
<th>Panel A: S(Actual Data)</th>
<th>Panel B: S(Half/Half)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Event+1</td>
<td>Event+3</td>
</tr>
<tr>
<td>Event</td>
<td>-0.035***</td>
<td>-0.032***</td>
</tr>
<tr>
<td></td>
<td>(-13.1)</td>
<td>(-12.3)</td>
</tr>
<tr>
<td>M/B</td>
<td>-0.001</td>
<td>-0.001</td>
</tr>
<tr>
<td></td>
<td>(-0.6)</td>
<td>(-0.4)</td>
</tr>
<tr>
<td>EBITDA/A</td>
<td>-0.097***</td>
<td>-0.343***</td>
</tr>
<tr>
<td></td>
<td>(-10.1)</td>
<td>(-21.4)</td>
</tr>
<tr>
<td>Size</td>
<td>0.003***</td>
<td>0.012***</td>
</tr>
<tr>
<td></td>
<td>(6.7)</td>
<td>(11.9)</td>
</tr>
<tr>
<td>PPE/A</td>
<td>0.004</td>
<td>0.015***</td>
</tr>
<tr>
<td></td>
<td>(1.2)</td>
<td>(3.2)</td>
</tr>
<tr>
<td>R&amp;D/S</td>
<td>-0.028*</td>
<td>-0.187***</td>
</tr>
<tr>
<td></td>
<td>(-1.9)</td>
<td>(-8.2)</td>
</tr>
<tr>
<td>RDD</td>
<td>0.001</td>
<td>-0.005</td>
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<tr>
<td></td>
<td>(1.4)</td>
<td>(-3.1)</td>
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<tr>
<td>(D/A)_{pre-event}</td>
<td>-0.109***</td>
<td>-0.279***</td>
</tr>
<tr>
<td></td>
<td>(-27.6)</td>
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<td>R²</td>
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<tr>
<td>N</td>
<td>38,593</td>
<td>35,573</td>
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Table 3: Reversal of the impact of large equity issuances on capital structure

Actual data are collected from Industrial Compustat and CRSP for the years 1971 to 2004. Section 3 discusses how the simulated data for the sample S(Half/Half) are generated. Large equity issues are identified if firms’ net equity issued divided by total assets is higher than 5%. The regression model is:

\[(D/A)_{t} - (D/A)_{t-1} = b_0 + b_1 Event + b_2 (M/B)_{t-1} + b_3 (EBITDA/A)_{t-1} + b_4 Size_{t-1} + b_5 (PPE/A)_{t-1} + b_6 (R&D/S)_{t-1} + b_7 RDD_{t-1} + b_8 HighLev + b_9 LowLev + \epsilon_i\]

The dummy variable Event equals 1 if a large equity issue occurred \(t\) years ago and zero otherwise. The dependent variable is the change in book leverage \((D/A)\). High (low) leverage ratio dummy \(HighLev (LowLev)\) equals to 1 if the lagged leverage ratio is above 0.6 (below 0.4) and zero otherwise. The control variables are firm characteristics that are lagged one year and defined in Appendix A. The constant term is included in the regression but not reported. The reported coefficients for S(Actual Data) are estimated using Fama and MacBeth (1973) approach. T-statistics are in parentheses. Coefficients significant at the 10%, 5%, and 1% levels are respectively marked with *, **, and ***. For S(Half/Half), the reported parameter estimates are the average coefficients obtained from 500 replications of the simulation. 95% confidence intervals are included in square brackets.

<table>
<thead>
<tr>
<th>(t)</th>
<th>Panel A: S(Actual Data)</th>
<th>Panel B: S(Half/Half)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Event+1</td>
<td>Event+2</td>
</tr>
<tr>
<td>Event</td>
<td>0.003***</td>
<td>0.002</td>
</tr>
<tr>
<td></td>
<td>(2.7)</td>
<td>(1.2)</td>
</tr>
<tr>
<td>M/B</td>
<td>-0.001</td>
<td>-0.001</td>
</tr>
<tr>
<td></td>
<td>(-0.9)</td>
<td>(-0.8)</td>
</tr>
<tr>
<td>EBITDA/A</td>
<td>-0.044***</td>
<td>-0.043***</td>
</tr>
<tr>
<td></td>
<td>(-4.2)</td>
<td>(-4.1)</td>
</tr>
<tr>
<td>Size</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>(0.7)</td>
<td>(0.9)</td>
</tr>
<tr>
<td>PPE/A</td>
<td>0.005</td>
<td>0.005</td>
</tr>
<tr>
<td></td>
<td>(1.4)</td>
<td>(1.5)</td>
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<td>R&amp;D/S</td>
<td>0.035***</td>
<td>0.039**</td>
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<tr>
<td></td>
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<td>(2.3)</td>
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<tr>
<td>RDD</td>
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<td>-0.000</td>
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<tr>
<td></td>
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</tr>
<tr>
<td>HighLev</td>
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<td>-0.022***</td>
</tr>
<tr>
<td>LowLev</td>
<td>0.026***</td>
<td>0.026***</td>
</tr>
<tr>
<td>(R^2)</td>
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<td>0.01</td>
</tr>
<tr>
<td>(N)</td>
<td>38,593</td>
<td>37,083</td>
</tr>
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</table>
Table 4: Target adjustment model with firm fixed effects

Actual data are collected from *Industrial Compustat* and *CRSP* for the years 1971 to 2004. Section 3 discusses how the simulated data are generated. The regression model is written as follows.

\[
(D/A)_t = c_0 + \lambda(D/A)_{t-1} + c_2(M/B)_{t-1} + c_3(EBITDA/A)_{t-1} + c_4 \text{Size}_{t-1} + c_5(PPE/S)_{t-1} + c_6(R & D/A)_{t-1} + c_7 \text{RDD}_{t-1} + \varepsilon_t
\]

The dependent variable is the book leverage \((D/A)\). The control variables are firm characteristics that are lagged one year and defined in Appendix A. The constant term is included in regressions but not reported. For S(Actual Data), the regression is estimated with firm fixed effects. \(t\)-statistics are in parentheses. Coefficients significant at the 10%, 5%, and 1% levels are respectively marked with *, **, and ***. For simulated samples, the reported parameter estimates are the average coefficients obtained from 500 replications of the simulation. 95% confidence intervals are included in square brackets.

<table>
<thead>
<tr>
<th>Samples</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>S(Actual Data)</td>
<td>S(Half/Half)</td>
<td>S(Actual Probability)</td>
<td>S(Random Deficit)</td>
<td>S(Low Initial Leverage)</td>
<td>S(High Initial Leverage)</td>
<td>S(Market Timing)</td>
</tr>
<tr>
<td>((D/A)_{t-1})</td>
<td>0.775***</td>
<td>0.826</td>
<td>0.826</td>
<td>0.795</td>
<td>0.832</td>
<td>0.825</td>
<td>0.816</td>
</tr>
<tr>
<td></td>
<td>(231.2)</td>
<td>[0.818,0.833]</td>
<td>[0.819,0.833]</td>
<td>[0.788,0.802]</td>
<td>[0.825,0.839]</td>
<td>[0.819,0.832]</td>
<td>[0.809,0.822]</td>
</tr>
<tr>
<td>(M/B)</td>
<td>-0.002***</td>
<td>0.001</td>
<td>0.0025</td>
<td>-0.0005</td>
<td>0.004</td>
<td>0.003</td>
<td>0.012</td>
</tr>
<tr>
<td></td>
<td>(-3.1)</td>
<td>[-0.000,0.002]</td>
<td>[0.001,0.004]</td>
<td>[-0.002,0.001]</td>
<td>[0.002,0.006]</td>
<td>[-0.005,-0.002]</td>
<td>[-0.013,-0.011]</td>
</tr>
<tr>
<td>(EBITDA/A)</td>
<td>-0.128***</td>
<td>-0.123</td>
<td>-0.142</td>
<td>-0.153</td>
<td>-0.115</td>
<td>-0.154</td>
<td>-0.193</td>
</tr>
<tr>
<td></td>
<td>(-22.0)</td>
<td>[-0.141,-0.107]</td>
<td>[-0.156,-0.128]</td>
<td>[-0.166,-0.141]</td>
<td>[-0.130,-0.101]</td>
<td>[-0.167,-0.141]</td>
<td>[-0.206,-0.182]</td>
</tr>
<tr>
<td>(Size)</td>
<td>0.004**</td>
<td>0.001</td>
<td>0.002</td>
<td>-0.001</td>
<td>0.003</td>
<td>0.002</td>
<td>0.003</td>
</tr>
<tr>
<td></td>
<td>(8.6)</td>
<td>[-0.001,0.003]</td>
<td>[0.001,0.0003]</td>
<td>[-0.003,0.001]</td>
<td>[0.002,0.004]</td>
<td>[0.001,0.003]</td>
<td>[0.002,0.004]</td>
</tr>
<tr>
<td>(PPE/A)</td>
<td>0.011**</td>
<td>0.023</td>
<td>0.029</td>
<td>0.001</td>
<td>0.002</td>
<td>0.032</td>
<td>0.034</td>
</tr>
<tr>
<td></td>
<td>(2.3)</td>
<td>[0.009,0.037]</td>
<td>[0.018,0.042]</td>
<td>[-0.015,0.017]</td>
<td>[0.008,0.032]</td>
<td>[0.020,0.043]</td>
<td>[0.023,0.044]</td>
</tr>
<tr>
<td>(R &amp; D/S)</td>
<td>-0.018</td>
<td>0.057</td>
<td>0.058</td>
<td>-0.001</td>
<td>0.077</td>
<td>0.051</td>
<td>0.061</td>
</tr>
<tr>
<td></td>
<td>(-1.1)</td>
<td>[0.004,0.117]</td>
<td>[0.007,0.109]</td>
<td>[-0.053,0.051]</td>
<td>[0.025,0.129]</td>
<td>[0.001,0.100]</td>
<td>[0.016,0.105]</td>
</tr>
<tr>
<td>(RDD)</td>
<td>0.001</td>
<td>-0.001</td>
<td>0.001</td>
<td>-0.001</td>
<td>0.003</td>
<td>-0.001</td>
<td>-0.000</td>
</tr>
<tr>
<td></td>
<td>(0.5)</td>
<td>[-0.006,0.004]</td>
<td>[-0.002,0.004]</td>
<td>[-0.006,0.004]</td>
<td>[-0.000,0.006]</td>
<td>[-0.004,0.002]</td>
<td>[-0.002,0.002]</td>
</tr>
<tr>
<td>(R^2)</td>
<td>0.82</td>
<td>0.84</td>
<td>0.85</td>
<td>0.76</td>
<td>0.83</td>
<td>0.83</td>
<td>0.82</td>
</tr>
<tr>
<td>(N)</td>
<td>38,593</td>
<td>38,593</td>
<td>38,593</td>
<td>38,593</td>
<td>38,593</td>
<td>38,593</td>
<td>38,593</td>
</tr>
</tbody>
</table>
Table 5: Effects of market-to-book on capital structure

Actual data are collected from *Industrial Compustat* and *CRSP* for the years 1971 to 2004. Section 3 discusses how the simulated data are generated. The dependent variables are the three components of the change in book leverage (D/A). The control variables are firm characteristics that are lagged one year and defined in Appendix A. The constant term is included in the regression but not reported. For S(Actual Data), the regressions are estimated using Fama and MacBeth (1973) approach. *t*-statistics are in parentheses. Coefficients significant at the 10%, 5%, and 1% levels are respectively marked with *, **, and ***. For simulated samples, the reported parameter estimates are the average coefficients obtained from 500 replications of the simulation. 95% confidence intervals are included in square brackets.

<table>
<thead>
<tr>
<th></th>
<th>S(Actual Data)</th>
<th></th>
<th>S(Half/Half)</th>
<th></th>
<th>S(Market Timing)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(-\frac{\text{Net}}{\text{A}}), (-\frac{\text{RE}}{\text{A}}), (-\frac{E_{\text{..}}(\frac{1}{\text{A}})}{\text{A}})</td>
<td></td>
<td>(-\frac{\text{Net}}{\text{A}}), (-\frac{\text{RE}}{\text{A}}), (-\frac{E_{\text{..}}(\frac{1}{\text{A}})}{\text{A}})</td>
<td></td>
<td>(-\frac{\text{Net}}{\text{A}}), (-\frac{\text{RE}}{\text{A}}), (-\frac{E_{\text{..}}(\frac{1}{\text{A}})}{\text{A}})</td>
</tr>
<tr>
<td>(D/A)t-1</td>
<td>-0.040*** -0.010** -0.056***</td>
<td></td>
<td>-0.046 0.006 -0.033</td>
<td></td>
<td>-0.057 0.0005 -0.036</td>
</tr>
<tr>
<td>M/B</td>
<td>-0.019*** 0.001 0.017***</td>
<td></td>
<td>-0.017 -0.001 0.018</td>
<td></td>
<td>-0.024 -0.001 0.019</td>
</tr>
<tr>
<td>EBITDA/A</td>
<td>0.084*** -0.419*** 0.254***</td>
<td></td>
<td>-0.002 0.057 -0.049</td>
<td></td>
<td>0.028 0.283 0.015</td>
</tr>
<tr>
<td>Size</td>
<td>0.004*** 0.001 -0.001</td>
<td></td>
<td>0.0018 0.0005 0.001</td>
<td></td>
<td>0.003 0.0006 -0.002</td>
</tr>
<tr>
<td>PPE/A</td>
<td>-0.028*** 0.032*** -0.001</td>
<td></td>
<td>-0.026 0.032 0.004</td>
<td></td>
<td>0.002 0.032 0.002</td>
</tr>
<tr>
<td>R&amp;D/S</td>
<td>-0.176*** 0.138** -0.043</td>
<td></td>
<td>-0.128 0.151 0.019</td>
<td></td>
<td>-0.081 0.014 -0.002</td>
</tr>
<tr>
<td>RDD</td>
<td>-0.004*** 0.004*** -0.001</td>
<td></td>
<td>-0.004 0.003 0.001</td>
<td></td>
<td>-0.004 0.004 0.001</td>
</tr>
<tr>
<td>R²</td>
<td>0.10 0.18 0.13</td>
<td></td>
<td>0.05 0.18 0.11</td>
<td></td>
<td>0.06 0.18 0.12</td>
</tr>
<tr>
<td>N</td>
<td>38,593 38,593 38,593</td>
<td></td>
<td>38,593 38,593 38,593</td>
<td></td>
<td>38,593 38,593 38,593</td>
</tr>
</tbody>
</table>
Table 6: Market timing and capital structure

Actual data are collected from *Industrial Compustat* and *CRSP* for the years 1971 to 2004. Section 3 describes how the simulated samples are generated. The regression model is written as follows.

\[
\frac{D}{A}_t = d_0 + d_1 \frac{M}{B}_{t-1} + d_2 \frac{EBITDA}{A}_{t-1} + d_3 \text{Size}_{t-1} + d_4 \frac{PPE}{A}_{t-1} + d_5 \frac{R \& D}{S}_{t-1} + d_6 \text{RDD}_{t-1} + d_7 \text{KTMB}_{t-1} + d_8 \text{KTCov}_{t-1} + d_9 \frac{1}{\text{Def}} + \epsilon_t
\]

The dependent variable is the book leverage \(D/A\). The control variables are firm characteristics that are lagged one year and defined in Appendix A. The constant term is included in the regression but not reported. The reported coefficients for \(S(\text{Actual Data})\) are estimated using Fama and MacBeth (1973) approach. t- statistics are in parentheses. Coefficients significant at the 10%, 5%, and 1% levels are respectively marked with *, **, and ***. For simulated samples, the reported parameter estimates are the average coefficients obtained from 500 replications of the simulation. 95% confidence intervals are included in square brackets.

<table>
<thead>
<tr>
<th>Samples</th>
<th>Panel A: Without lagged leverage ratio</th>
<th>Panel B: With lagged leverage ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>(M/B)</td>
<td>0.017***</td>
<td>0.020</td>
</tr>
<tr>
<td></td>
<td>(4.1)</td>
<td>[0.013,0.027]</td>
</tr>
<tr>
<td>(EBITDA/A)</td>
<td>-0.477***</td>
<td>-0.670</td>
</tr>
<tr>
<td></td>
<td>(-15.8)</td>
<td>[-0.741,-0.598]</td>
</tr>
<tr>
<td>(Size)</td>
<td>0.026***</td>
<td>0.001</td>
</tr>
<tr>
<td></td>
<td>(18.2)</td>
<td>[-0.003,0.005]</td>
</tr>
<tr>
<td>(PPE/A)</td>
<td>-0.035***</td>
<td>0.043</td>
</tr>
<tr>
<td></td>
<td>(-10.5)</td>
<td>[0.007,0.077]</td>
</tr>
<tr>
<td>(R&amp;D/S)</td>
<td>-0.534***</td>
<td>0.082</td>
</tr>
<tr>
<td></td>
<td>(-16.7)</td>
<td>[-0.077,0.241]</td>
</tr>
<tr>
<td>(RDD)</td>
<td>-0.003</td>
<td>0.015</td>
</tr>
<tr>
<td></td>
<td>(-0.4)</td>
<td>[0.000,0.030]</td>
</tr>
<tr>
<td>(KTMB)</td>
<td>-0.056***</td>
<td>-0.044</td>
</tr>
<tr>
<td></td>
<td>(-27.6)</td>
<td>[-0.057,-0.032]</td>
</tr>
<tr>
<td>(KTCov)</td>
<td>-0.066***</td>
<td>-0.009</td>
</tr>
<tr>
<td></td>
<td>(-14.5)</td>
<td>[-0.031,0.013]</td>
</tr>
<tr>
<td>(1/\text{Def})</td>
<td>-0.019***</td>
<td>-0.038</td>
</tr>
<tr>
<td></td>
<td>(-8.4)</td>
<td>[-0.049,-0.026]</td>
</tr>
<tr>
<td>(D/A)_{t-1}</td>
<td>0.885***</td>
<td>0.925</td>
</tr>
<tr>
<td></td>
<td>(201.5)</td>
<td>[0.921,0.929]</td>
</tr>
<tr>
<td>(R^2/N)</td>
<td>0.25 / 32,532</td>
<td>0.11 / 32,532</td>
</tr>
</tbody>
</table>
Table 7: ANOVA Analysis: Fixed firm and industry effects

Actual data are collected from *Industrial Compustat* and *CRSP* for the years 1971 to 2004. Section 3 describes how the simulated samples are generated. The table presents a variance decomposition of book leverage (D/A) for the actual data and simulation samples. Column I and II report the adjusted R-squares for the fixed firm effects and 3-digit SIC industry effects model, respectively. The last column reports the ratio of the latter to the former. For simulated samples, the reported R-squares are the average obtained from 500 replications of the simulation.

<table>
<thead>
<tr>
<th>Samples</th>
<th>(I) Fixed Firm Effects</th>
<th>(II) 3-Digit SIC Industry Effects</th>
<th>(II)/(I)</th>
</tr>
</thead>
<tbody>
<tr>
<td>S(Actual Data)</td>
<td>0.55</td>
<td>0.16</td>
<td>29.1%</td>
</tr>
<tr>
<td>S (Half/Half)</td>
<td>0.50</td>
<td>0.09</td>
<td>18.0%</td>
</tr>
<tr>
<td>S (Random Deficit)</td>
<td>0.31</td>
<td>0.05</td>
<td>16.1%</td>
</tr>
</tbody>
</table>
Table 8: Summary statistics of debt-equity choice across leverage deviation groups

Actual data are collected from *Industrial Compustat* and *CRSP* for the years 1971 to 2004. Section 3 describes how the simulated samples S(Half/Half) is generated. The table presents the summary statistics of debt-equity choice and the financing deficit across five leverage deviation groups for both the actual data and S(Half/Half). “Low” refers to the group of firms in the lowest quintile according to the deviation from the target leverage ratio and “High” refers to those with the highest deviation. Deviation ($DevTgt$) is defined as the leverage ratio lagged one period less the target leverage ratio, $D/A$, which is the predicted value of the following leverage regression:

$$(D/A)_{t-1} = e_0 + e_1(M/B)_{t-1} + e_2(EBITDA/A)_{t-1} + e_3(Size)_{t-1} + e_4(PPE/A)_{t-1} + e_5(R & D/S)_{t-1} + e_6(RDD)_{t-1} + e_7 IND + e_{it}$$

where $IND$ are the three-digit SIC industry dummies. Debt (equity) issues/repurchases are identified if firms’ net debt (equity) issued/repurchased divided by total assets is greater than 5%. The relative issue (repurchase) frequency is defined as the percentage of times that equity is issued (repurchased) divided by the percentage of times that debt is issued (repurchased). For S(Half/Half), the reported statistics are the averages obtained from 500 replications of the simulation.

<table>
<thead>
<tr>
<th>Deviation Groups</th>
<th>Panel A: S(Actual Data)</th>
<th>Panel B: S(Half/Half)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1 2 3 4 5 (High)</td>
<td>1 2 3 4 5 (High)</td>
</tr>
<tr>
<td>Mean Deviation from Target ($DevTgt$)</td>
<td>-0.21 -0.08 -0.00 0.07 0.22</td>
<td>-0.27 -0.11 -0.01 0.09 0.36</td>
</tr>
<tr>
<td>Lagged leverage ratio ($D/A)_{t-1}$</td>
<td>0.22 0.35 0.44 0.53 0.67</td>
<td>0.12 0.24 0.34 0.46 0.69</td>
</tr>
<tr>
<td>Percentage of firms having large positive financing deficit ($Def/A &gt; 5%$)</td>
<td>40% 45% 46% 45% 42%</td>
<td>37% 43% 46% 48% 45%</td>
</tr>
<tr>
<td>Percentage of firms having large negative financing deficit ($Def/A &lt; -5%$)</td>
<td>10% 10% 12% 17% 24%</td>
<td>17% 13% 12% 14% 20%</td>
</tr>
<tr>
<td>Percentage of times that debt is issued ($P_{Di}$)</td>
<td>33% 40% 42% 39% 37%</td>
<td>19% 21% 23% 24% 22%</td>
</tr>
<tr>
<td>Percentage of times that equity is issued ($P_{Ei}$)</td>
<td>12% 11% 13% 14% 17%</td>
<td>19% 21% 23% 24% 26%</td>
</tr>
<tr>
<td>Relative frequency of equity to debt issuance ($P_{Ei} / P_{Di}$)</td>
<td>36% 28% 31% 36% 46%</td>
<td>100% 100% 100% 100% 118%</td>
</tr>
<tr>
<td>Percentage of times that debt is repurchased ($P_{DR}$)</td>
<td>6% 9% 13% 18% 28%</td>
<td>6% 6% 6% 7% 14%</td>
</tr>
<tr>
<td>Percentage of times that equity is repurchased ($P_{ER}$)</td>
<td>7% 5% 4% 3% 4%</td>
<td>11% 6% 6% 7% 9%</td>
</tr>
<tr>
<td>Relative frequency of equity to debt repurchase ($P_{ER} / P_{DR}$)</td>
<td>117% 56% 31% 17% 14%</td>
<td>183% 100% 100% 100% 64%</td>
</tr>
</tbody>
</table>
Table 9: Deviation from target and debt-equity choices

Actual data are collected from Industrial Compustat and CRSP for the years 1971 to 2004. Section 3 describes how the simulated samples S(Half/Half) is generated. The following probit model is estimated for all issue years and repurchases years, respectively:

\[ P(\text{DeChoice}_t = 1) = F(\beta_0 + \beta_1\text{DevTgt}_{t-1} + \beta_2(M / B)_{t-1} + \beta_3(\text{EBITDA} / A)_{t-1} + \beta_4(\text{PPE} / A)_{t-1} + \beta_5(\text{R} & \text{D} / S)_{t-1} + \beta_6(\text{RDD})_{t-1} + \beta_7(\text{Def} / A)_{t-1}). \]

The dependent variable, \( \text{DeChoice} \), takes a value of one if conditional on issuance (repurchase), debt is issued (repurchased), and zero if equity is issued (repurchased). Deviation (\( \text{DevTgt} \)) is defined as the leverage ratio lagged one period less the estimated target leverage ratio. \( F \) denotes the normal cumulative distribution function. \( \text{Def/A} \) is the deficit to asset ratio. Deviation group dummies are constructed for five leverage deviation groups defined in Table 8. Group 3 dummy is not included in the regression to avoid perfect multicollinearity. For S(Actual Data), z-statistics are in parentheses and coefficients significant at the 10%, 5%, and 1% levels are respectively marked with *, **, and ***. For the simulated samples, the reported parameter estimates are the average coefficients obtained from 500 replications of the simulation. 95% confidence intervals are included in square brackets.

<table>
<thead>
<tr>
<th>Samples</th>
<th>Panel A: S(Actual Data)</th>
<th>Panel B: S(Half/Half)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Issuance</td>
<td>Repurchase</td>
</tr>
<tr>
<td>Deviation from Target (( \text{DevTgt} ))</td>
<td>-0.604***</td>
<td>3.648***</td>
</tr>
<tr>
<td>Deviation Dummy 1 (Low)</td>
<td>-0.146*** (-5.2)</td>
<td>-1.054*** (22.5)</td>
</tr>
<tr>
<td>Deviation Dummy 2</td>
<td>0.052</td>
<td>-0.369*** (-6.4)</td>
</tr>
<tr>
<td>Deviation Dummy 4</td>
<td>-0.172*** (-6.9)</td>
<td>0.322*** (5.6)</td>
</tr>
<tr>
<td>Deviation Dummy 5 (High)</td>
<td>-0.324*** (-9.3)</td>
<td>0.565***</td>
</tr>
<tr>
<td>( M/B )</td>
<td>-0.163*** (-9.8)</td>
<td>-0.238*** (-8.8)</td>
</tr>
<tr>
<td>( \text{EBITDA} / A )</td>
<td>0.798***</td>
<td>0.944***</td>
</tr>
<tr>
<td>Size</td>
<td>0.061</td>
<td>0.064***</td>
</tr>
<tr>
<td>( \text{PPE}/A )</td>
<td>-0.494***</td>
<td>-0.484***</td>
</tr>
<tr>
<td>( \text{R} &amp; \text{D}/S )</td>
<td>-2.664***</td>
<td>-2.558***</td>
</tr>
<tr>
<td>RDD</td>
<td>-0.135*** (-7.7)</td>
<td>-0.141*** (-8.0)</td>
</tr>
<tr>
<td>( \text{Def}/A )</td>
<td>-0.118***</td>
<td>-0.123***</td>
</tr>
<tr>
<td>Pseudo R2</td>
<td>0.06</td>
<td>0.06</td>
</tr>
<tr>
<td>Observations</td>
<td>14,372</td>
<td>14,372</td>
</tr>
</tbody>
</table>

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Table 10: Multinomial logistic regression (with corner cases removed from simulated data).

Actual data are collected from Industrial Compustat and CRSP for the years 1971 to 2004. Section 3 describes how the simulated samples S(Half/Half) is generated. In simulation, we drop firms if any point is reached where a “coin toss” could potentially cause the issuance or repurchase decision to deviation from that dictated by the outcome of the random draw. The table presents the results of a multinomial regression for both the actual data and S(Half/Half) sample. Five categories of transactions are considered: (1) no transaction (i.e., transaction size below 5% of book value of assets) (2) equity issue (3) debt issue (4) equity repurchase and (5) debt reduction. Debt (equity) issues/repurchases are identified if firms’ net debt (equity) issued/repurchased divided by total assets is greater than 5%. The first category is used as the base category, i.e. probabilities are estimated for the other choices relative to this category, and assume financing decisions can be described as

\[ P_{i,t,k} = \frac{e^{y_i^{i,t} \cdot \text{DevTgt}_{i,t} + g_k \cdot X_{i,t-1}}}{1 + \sum_{k=2,3,4,5} e^{y_i^{i,t} \cdot \text{DevTgt}_{i,t} + g_k \cdot X_{i,t-1}}} \]

where \( P_{i,t,k} \) denotes the probability of a firm-year falling into the \( k \)th financing category \((k = 2,3,4,5)\). \( \text{DevTgt} \) is the deviation from target. \( X \) is the same set of control variables as included in Table 9. For S(Actual Data), z-statistics are in parentheses and coefficients significant at the 10%, 5%, and 1% levels are respectively marked with *, **, and ***. For simulated samples, the reported parameter estimates are the average coefficients obtained from 500 replications of the simulation. 95% confidence intervals are included in square brackets.

<table>
<thead>
<tr>
<th>Samples</th>
<th>Panel A: S(Actual Data)</th>
<th>Panel B: S(Half/Half)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Equity Issue</td>
<td>Debt Issue</td>
</tr>
<tr>
<td>Deviation from Target (DevTgt)</td>
<td>0.451*</td>
<td>1.624***</td>
</tr>
<tr>
<td>M/B</td>
<td>0.408***</td>
<td>0.205***</td>
</tr>
<tr>
<td>EBITDA /A</td>
<td>0.024</td>
<td>-0.032</td>
</tr>
<tr>
<td>Size</td>
<td>-0.113***</td>
<td>-0.036***</td>
</tr>
<tr>
<td>PPE /A</td>
<td>0.720***</td>
<td>-0.234***</td>
</tr>
<tr>
<td>R&amp;D /S</td>
<td>2.953***</td>
<td>-1.079***</td>
</tr>
<tr>
<td>RDD</td>
<td>0.266***</td>
<td>0.047</td>
</tr>
<tr>
<td>Def /A</td>
<td>0.534***</td>
<td>0.477***</td>
</tr>
<tr>
<td>Pseudo R2</td>
<td>0.05</td>
<td>0.02</td>
</tr>
<tr>
<td>Observations</td>
<td>38,593</td>
<td>37,083</td>
</tr>
</tbody>
</table>
Appendix A: Variables Definitions

<table>
<thead>
<tr>
<th>Variables</th>
<th>Definitions</th>
</tr>
</thead>
<tbody>
<tr>
<td>4Size</td>
<td>Log of total Assets (6)</td>
</tr>
<tr>
<td>Total Equity</td>
<td>Total Assets (6) – total liabilities (181) – preferred stock (10) +</td>
</tr>
<tr>
<td></td>
<td>deferred taxes (35) + convertible bonds (79)</td>
</tr>
<tr>
<td>Book Leverage (D/A)</td>
<td>(Total assets (6) – total equity) / total assets (6)</td>
</tr>
<tr>
<td>Net Equity Issues (Nei)</td>
<td>Δtotal equity – Δ retained earnings (36)</td>
</tr>
<tr>
<td>Net Debt Issues (Ndi)</td>
<td>Δtotal assets (6) – Δretained earnings (36) – Nei</td>
</tr>
<tr>
<td>Financing Deficit (Def)</td>
<td>Net equity issues (Nei) + net debt issues (Ndi)</td>
</tr>
<tr>
<td>Market value of equity</td>
<td>Number of shares outstanding × fiscal year end share price</td>
</tr>
<tr>
<td></td>
<td>(obtained from CRSP)</td>
</tr>
<tr>
<td>Market-to-book (M/B)</td>
<td>(Total assets (6) + market value of equity – total equity)/total assets</td>
</tr>
<tr>
<td>Profitability (EBITDA/A)</td>
<td>Operating income before depreciation (13) / total assets (6)</td>
</tr>
<tr>
<td>Tangibility (PPE/A)</td>
<td>Net PPE (8)/total assets (6)</td>
</tr>
<tr>
<td>R&amp;D/S</td>
<td>R&amp;D expenses (46) / net sales (12)</td>
</tr>
<tr>
<td>R&amp;D Dummy (RDD)</td>
<td>1 if R&amp;D is missing, and zero otherwise.</td>
</tr>
</tbody>
</table>
Appendix B: Decomposition of Baker and Wurgler’s (2002) timing measure

Let Def denote financing deficit, or equivalently, the amount of external financing raised. Then

\[ BWMB_t = \sum_{r=0}^{t-1} \frac{Def_r \times M / B_r}{EF_r} \]

\[ \Rightarrow BWMB_t \times \sum_{r=0}^{t-1} Def_r = \sum_{r=0}^{t-1} Def_r \times M / B_r \]

scaling both sides by t,

\[ BWMB_t \times Def = \left( \sum_{r=0}^{t-1} Def_r \times M / B_r \right) / t \]

\[ = \left( \sum_{r=0}^{t-1} Def_r \times M / B_r \right) / t - \overline{Def} \times \overline{M / B} + \overline{Def} \times \overline{M / B} \]

\[ = Cov(Def, M / B) + \overline{Def} \times \overline{M / B} \]

Thus, \[ BWMB_t = \frac{Cov(Def, M / B)}{Def} \times \overline{M / B} = KTCOV_t + KTMB_t \]

where, \[ KTCOV_t = \frac{Cov(Def, M / B)}{Def} \] and \[ KTMB = \overline{M / B} \]

As the decomposition illustrates, \( BWMB \) is simply the sum of \( KTCOV \) and \( KTMB \). \( KTCOV \) is the covariance between the external financing and the market-to-book ratio, at t, scaled by the average external financing. To the extent that the market-to-book ratio proxies for equity mispricing, it is \( KTCOV \) that really captures the timing intuition of BW. \( KTMB \) is merely the average market-to-book ratio, which arguably proxies for investment opportunities.