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Corporate Leverage and the Dynamics of Its Components

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Abstract

We investigate the dynamics of observed and target leverage ratios and deviations from the targets. The cross-sectional persistence in leverage ratios is driven by persistent targets, whereas time-series variation is driven by transitory deviations from targets. Consistent with dynamic trade-off theories, persistence is higher when the costs of deviating from targets are lower and when the adjustment costs are higher. Deviations are less persistent for firms that are over-levered and firms that are smaller, younger, or more focused or that have lower credit ratings. In recessions, excess leverage is less persistent for larger firms and is more persistent for smaller firms.

I. Introduction

A fundamental question in corporate finance is how corporate leverage ratios evolve and whether and how this process is affected by firms setting capital structure targets. Dynamic trade-off models of capital structure suggest that, in the presence of adjustment costs, firms may set relatively stable targets but tolerate deviations from these targets as long as leverage ratios stay within their target zones. Such behavior is expected to affect the time-series dynamics of leverage and the variations of these dynamics across firms. To assess the extent to which and how leverage dynamics are driven by such behavior, this article investigates the dynamics of corporate leverage ratios and its elements, target leverage ratios and deviations from targets. We find that the observed cross-sectional persistence in leverage ratios is primarily due to persistence in leverage targets, whereas their time series variation is largely driven by transitory deviations from target leverage.

Several empirical studies have addressed the issue of variations in leverage ratios, reaching somewhat contradictory conclusions. Lemmon, Roberts, and

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Zender (2008) document significant persistence in leverage ratios over time. Using portfolios of firms sorted on leverage ratios, they show that leverage cross sections are relatively stable over time horizons of up to 20 years and conclude that time-invariant, firm-specific factors are the primary determinants of corporate capital structure policies.

DeAngelo and Roll (2015) acknowledge the evidence of stability of debt ratios developed by prior literature but also document substantial variation in firm-level leverage ratios over time. To assess the stability of corporate capital structures, they examine the explanatory power of leverage cross sections for future leverage cross sections at various horizons. They find that, while leverage cross sections are relatively stable in the short to medium run, they are very different in the long run, as the differences grow over time. This leads them to conclude that the empirical relevance of leverage targeting behavior is not a settled question.

The persistence in leverage documented in previous studies could be driven by firms setting stable capital structure targets with relatively narrow target zones. If so, we should find that the deviations from the target are less persistent than the observed leverage ratios, which, in turn, are less persistent than the targets. Alternatively, persistence in leverage could be caused by wide target zones and enduring deviations from capital structure targets if the costs of large deviations are lower than the costs of adjustments to target. Persistence is also compatible with Miller's (1977) neutral-mutation view if firms have no targets and leverage ratios evolve due to arrival of random shocks over time. If firms do not have target leverage ratios or rarely adjust to targets, the persistence in deviations from estimated "targets" should be similar to the persistence in observed leverage ratios.

The variability of leverage documented by DeAngelo and Roll (2015) may be driven by the possibility that firms' capital structure targets change frequently. If so, estimated targets should demonstrate low persistence, similar to the deviations from target and the observed leverage ratios. Leverage variability may also be driven by transitory deviations from desired leverage targets if firms have low tolerance for deviations and offset them relatively quickly.

To explain the observed persistence of leverage cross sections over time, DeAngelo and Roll (2015) conduct simulations under various assumptions regarding target dynamics (time-invariant vs. time-varying mean-reverting targets) and regarding targeting behavior (no adjustment, continuous adjustment vs. adjustment when crossing target zone boundaries, and slow vs. fast adjustments to target). Comparing the observed and simulated persistence of leverage at various horizons, they conclude that the observed patterns are inconsistent with nontargeting behavior and are most consistent with either quick adjustments to targets that vary a lot over time, or slow adjustments to stationary or moderately varying targets.

The current article adopts DeAngelo and Roll's (2015) approach to exploring the dynamics of corporate leverage using cross-sectional regressions of leverage on its lags and extends their methodology by applying it to estimated components of leverage ratios: target leverage and deviation from target leverage. Specifically, we estimate the targets using the regression approach standard in the literature, which we modify in two ways. First, we estimate target leverage regressions over rolling 5-year windows to allow for more variation of targets over the long run.

Second, to avoid any in-sample bias, the regression parameters are estimated in years $t-1$ through $t-5$ and used to predict out-of-sample targets for year t. We then separately estimate and compare the levels of persistence of the estimated targets, deviations from targets, and observed leverage ratios. Our goal is to explain the contribution of each component's dynamics to the time-series and cross-sectional variation in leverage ratios and make inferences about the empirical relevance of dynamic trade-off models of capital structure.

Our results indicate that the observed cross-sectional persistence in leverage ratios is due to persistence in leverage targets, whereas their variation over time is largely driven by transitory deviations from target leverage. In particular, consistent with Lemmon et al. (2008) and DeAngelo and Roll (2015), firms in our sample exhibit substantial persistence in leverage, with the R^2 from the regression of leverage on its 3-year lag of 0.510. Further, the estimated target debt ratios are even more persistent and explain a significant portion of the cross-sectional variation in observed leverage ratios. For comparison, the R^2 from the regression of target leverage on its 3-year lag is 0.776. In contrast, deviations from target leverage are significantly less persistent, with the R^2 from a regression of deviation from target leverage on its 3-year lag equal to 0.003, and, hence, are responsible for most of the time variation in leverage ratios.

Our empirical estimates fall between the parameters of the two simulated time-varying target (TVT) models that DeAngelo and Roll (2015) identify as most closely matching the data. Our target estimates are less time varying than their best-fit TVT model are more time varying than their second-best model. The range of target debt ratios for a median firm over the first 20 years of its life is 0.225 in our sample versus 0.336 for their best-fit TVT model and 0.152 for their second-best TVT model. In addition, our persistence estimates imply slower adjustment when compared to the best-fit TVT model (implied speed of adjustment (SOA) of 0.4 at 1-year horizon for our estimated targets versus SOA of 0.8 for their best-fit TVT model), but faster adjustment vis-à-vis their second-best TVT model (SOA of 0.2).

We further explore the variations in the persistence of deviations from target leverage by deviation characteristics, firm characteristics, and time periods to test the hypothesis that deviations are more likely to endure when the costs of adjustments outweigh the costs of being under- or over-levered. Since most leverage adjustments require some sort of financing, oftentimes external, the costs of adjustment may vary depending on a firm's capacity to obtain capital. For this reason, financially constrained firms may exhibit more persistent deviations from target, especially during recessions or monetary contractions. Deviations are also more likely to endure for firms whose values as a function of leverage are relatively flat (i.e., those with lower costs of excessively high or low leverage). We show that such firms are likely to tolerate larger deviations from the target, given the adjustment costs.

We find that positive deviations are less persistent than negative deviations and that larger deviations are even less persistent, consistent with the notion that the costs of deviating from the target increase with the size of the deviation. We also find that firms that are smaller, younger, or more focused and that have no or low credit ratings tend to show lower persistence in their deviations from target. These differences tend to be more significant for over-levered firms.

Since firms with such characteristics are more likely to be financially constrained, these findings do not support the hypothesis that variations in leverage persistence are driven primarily by variations in costs of adjustment to target leverage.[1] Instead, they imply that firms are more likely to offset their deviations from target when the costs of deviating from target leverage are higher. Specifically, the expected costs of financial distress are likely to rise faster for over-levered firms that are smaller, younger, or more focused or that have lower ratings. Therefore, we would expect such firms to have a stronger impetus to deleverage and hence exhibit lower persistence of deviations from target.

We also find evidence of the importance of adjustment costs. Specifically, we find that small, over-levered firms exhibit more persistent deviations in recessions compared to nonrecession years, whereas large over-levered firms have less persistence in recessions than in nonrecession years. These results are consistent with the hypothesis that financial constraints impede leverage adjustments for small, over-levered firms. In contrast, large firms enjoy financial flexibility that allows them to reduce their excess leverage in recessions when the costs of such excess leverage are likely higher. Last, we find that deviations are less persistent in years with corporate financing transactions than in years without such transactions, which is consistent with our assumption that persistence reflects the extent to which firms are able to actively rebalance their capital structures.

The current article contributes to the existing literature in a number of ways. First, our approach to estimating the persistence of leverage components allows us to identify the sources of observed variation and stability in leverage ratios documented by previous studies. In particular, we show that the observed cross-sectional stability is mostly driven by persistent targets and the time-series variability is mostly driven by transitory deviations. Further, the straightforward methodological extension of DeAngelo and Roll's (2015) approach to examine the persistence of deviations from target leverage presents itself as an alternative to the partial adjustment framework used in prior studies to analyze leverage dynamics. In addition, our finding that the persistence of deviations from target is virtually 0 for an average firm at a 3-year horizon is among the strongest empirical findings in favor of dynamic trade-off theories in the literature. Finally, our findings on cross-sectional variation in persistence provide evidence that both transaction costs and the opportunity cost (value reduction) of operating with suboptimal leverage affect adjustments to target, whereas the primary focus of prior studies was on variation in adjustment costs.

The article proceeds as follows: Section II describes the regression model used to study the dynamics of leverage and its components. Section III describes the estimation of target leverage and deviations from targets. Section IV describes

[1]Hadlock and Pierce (2010) find that firm size and age are strong predictors of financial constraints. Focusing on the 2007–2009 financial crisis, Kuppuswamy and Villalonga (2016) show that diversification helps alleviate financial constraints. Faulkender and Petersen (2006) show that, because of their lack of access to public debt markets, unrated firms borrow less than their rated counterparts. Boot, Milbourn, and Schmeits (2006) argue that credit ratings serve as a coordination mechanism and affect investors' decisions to supply capital.

the sample and data. Section V examines the persistence of leverage, target leverage, and deviations from target leverage. Section VI compares the performance of our empirical estimates of target leverage to alternative measures. Section VII links the variations in deviation persistence across firms with different characteristics and across the business cycle to variations in costs of leverage adjustments and costs of having suboptimal leverage. Section VIII concludes.

II. Model of Corporate Leverage Dynamics

A number of theoretical papers on capital structure dynamics (see, e.g., Fischer, Heinkel, and Zechner (1989)) imply that the composition of observed leverage ratios can be described as follows:

$$\text{(1)} \qquad \text{LEV}_{it} = \text{LEV}^*_{it} + \varepsilon_{it},$$

where LEV^*_{it} denotes the target leverage ratio of firm i in year t and ε_{it} represents the deviation from the target. In this setting, firms may experience shocks that induce them to deviate from their target debt ratios. If these shocks are quickly offset, then the deviations from the target, ε_{it}, will not persist and will be uncorrelated in the time series. However, if adjustment costs prevent firms from fully offsetting the shocks within the same period, the deviations from the target, ε_{it}, will be serially autocorrelated:

$$\text{(2)} \qquad \varepsilon_{it} = \phi\varepsilon_{it-1} + \omega_{it},$$

where ϕ is the coefficient of autocorrelation and ω_{it} represents independently identically distributed (IID) random shocks. Our empirical analysis uses the structure implied by reduced form equations (1) and (2) to examine the dynamics of leverage ratios, and our primary tests are based on the significance of autocorrelation in equation (2). Theoretically, target leverage is determined by the trade-offs between the costs and benefits of leverage. Because many of the theoretical factors that affect this trade-off (e.g., tax advantages of debt and bankruptcy costs) likely do not change much from year to year, we expect target leverage, LEV^*_{it}, to be more persistent than observed leverage ratios, LEV_{it}. Further, if firms have strong incentives to be at the target and if the adjustment costs are not prohibitively large, then firms should rebalance and offset their deviations from target, ε_{it}, relatively quickly. Such deviations should be less persistent than observed leverage ratios.[2]

We should note that this approach is related to the partial adjustment model (PAM) used in a number of earlier studies (see, e.g., Shyam-Sunder and Myers (1999), Flannery and Rangan (2006)). However, it is also different from and complements PAM in several important ways. Similar to our approach, PAM can be motivated by starting with equation (1) and transforming it into an equation of a

[2]Because target leverage is not observable, our conclusions about the importance of the target depend on our ability to generate a good proxy for target leverage. As in other studies of the impact of target leverage, our assumption is that errors in measuring target leverage will weaken the evidence of rebalancing toward the target. In this article, that means that the persistence of deviations from target leverage will not be significantly lower than the persistence of observed leverage if the measurement errors are large.

change in the leverage ratio, as follows:

$$(3) \qquad \mathrm{LEV}_{it} - \mathrm{LEV}_{it-1} = \mathrm{LEV}^*_{it} - \mathrm{LEV}_{it-1} + \varepsilon_{it}.$$

According to equation (3), the change in leverage would consist of a full adjustment from previous observed leverage, LEV_{it-1}, to current target, LEV^*_{it}, plus a random shock, ε_{it}. Using the argument that adjustment costs may prevent a full adjustment, equation (3) is then modified to allow incomplete adjustment, resulting in the following partial adjustment regression model:

$$(4) \qquad \mathrm{LEV}_{it} - \mathrm{LEV}_{it-1} = \lambda(\mathrm{LEV}^*_{it} - \mathrm{LEV}_{it-1}) + \varepsilon_{it},$$

where λ is interpreted as the SOA to target leverage and, as it turns out, equations (2) and (4) are identical if $\phi = 1 - \lambda$ and firm-specific target leverage does not change over time.[3]

While PAM is a legitimate method to analyze capital structure and has been used to develop important insights, a number of factors motivate us to analyze the dynamics of leverage ratios in this article based on equation (2) rather than PAM equation (4). First, testing for persistence in deviations from target leverage using equation (2) is consistent with the focus on persistence of leverage ratios in Lemmon et al. (2008) and DeAngelo and Roll (2015).

Second, SOA is a very specific concept that makes economic sense only if firms behave as assumed by the partial adjustment model, without significant deviations. Certain plausible corporate behaviors that are broadly consistent with dynamic trade-off models can generate "SOAs" that are void of economic meaning. For example, consider a firm that has a target leverage zone within which it does not actively adjust its capital structure due to adjustment costs. Suppose the firm has investment opportunities that require external capital. When these opportunities arise, the firm may make corporate financing choices that allow it to stay within the target zone without trying to adjust to a specific notional target level within that zone. Such a firm may sometimes appear to "partially adjust" toward the notional target level but, at other times, may "over-adjust" and end up on the other side of the target level or move away from the target level but stay within the target zone.

Such "adjustments" are not rare in the data. In our sample, more than 15% of changes in leverage "overshoot" the target (i.e., the change in leverage is larger than the deviation from the target). About half of changes in leverage are away from the target, with more than 20% of firms more than doubling their distance from the target.[4] "Speed of adjustment" is not a very meaningful descriptor of this type of corporate financing behavior and can lead to false conclusions as to which firms are more concerned about "adjusting to target" and which are not.[5]

[3]Noting from equation (1) that $\varepsilon_{it} = \mathrm{LEV}_{it} - \mathrm{LEV}^*_{it}$ and rearranging equation (2), we obtain $\mathrm{LEV}_{it} - \mathrm{LEV}_{it-1} = (1-\phi)(\mathrm{LEV}^*_{it} - \mathrm{LEV}_{it-1}) + \phi(\mathrm{LEV}^*_{it} - \mathrm{LEV}^*_{it-1}) + \omega_{it}$. With $\phi = 1 - \lambda$ and constant firm-specific target leverage, this is identical to equation (4).

[4]In many such cases, both the deviations and the changes in leverage are small. However, even when we drop relatively small deviations, those smaller than 0.05 in absolute value (about half of the deviations in our sample), more than 7% of changes in leverage still "overshoot" the target and more than half of the changes are away from the target.

[5]See Hovakimian and Li (2012) for a detailed discussion of this issue.

For example, a certain subsample that contains disproportionately many instances of "overshooting" will have a higher estimated "SOA," which may lead to an incorrect conclusion that firms in that subsample adjust faster to their targets.

Third, as noted by Chang and Dasgupta (2009) PAMs may be biased toward generating significant SOAs due to "mechanical" mean reversion induced by leverage being constrained between values of 0 and 1. Fourth, studies that focus on SOA are mainly engaged with the assessment and comparisons of the magnitude of SOA rather than the statistical significance of it being different from 0 or 1, as these differences are always found to be significant. Hence, the primary conclusion is typically whether the SOA estimate is considered to be large or small.[6] In contrast, equation (2) not only allows us to test whether there is statistically significant persistence in deviations from target year over year but can also be easily modified to directly test the importance of leverage targeting with a null hypothesis that deviations from target lack persistence at various horizons n.

Failure to reject this hypothesis at horizon n does not imply that the firm is at its target debt ratio at time t but rather implies that the deviation from target at time t is unrelated to the initial deviation at time $t-n$. In that sense, the null hypothesis that deviations from target are not persistent at horizon n is explicitly less ambitious than the hypothesis that firms fully adjust to target in n periods. However, it is more interesting empirically as both a rejection and a failure to reject are realistic possibilities.

III. Estimating the Target and Deviation from Target Components

Our empirical analysis proceeds in several steps. In the first stage, we separate observed leverage ratios (LEV_{it}) into target leverage (LEV^*_{it}) and deviation from target (DEV_{it}) components. To do that, first, we estimate 5-year rolling leverage regressions based on the following model and then use the parameter estimates to calculate out-of-sample leverage targets:

$$(5)\quad \text{LEV}_{it} = \beta_{0i} + \beta_1 \times \text{MARKET\_TO\_BOOK}_{it} + \beta_2 \times \text{TANGIBILITY}_{it} + \beta_3 \times \text{RD}_{it} + \beta_4 \times \text{RDD}_{it} + \beta_5 \times \text{EXP}_{it} + \beta_6 \times \text{SIZE}_{it} + \varepsilon_{it}.$$

In equation (5), for each firm i in year t, LEV is calculated as the sum of short-term debt (Compustat item DLC) and long-term debt (DLTT) divided by the book value of assets (AT). MARKET_TO_BOOK is the ratio of market value of assets over book value of assets, TANGIBILITY is the ratio of fixed capital (PPENT) over total assets, RD is the ratio of research and development (R&D) expenses (XRD) over sales (SALE), EXP is the ratio of selling and administrative expenses (XSGA) over sales, and SIZE is the natural log of Consumer Price Index (CPI)-adjusted sales.[7] Since many firms without R&D do not report R&D at all,

[6]For example, Flannery and Rangan ((2006), p. 471) state in their introduction that the "typical firm converges toward its long-run target at a rate of more than 30% per year. This adjustment speed is roughly three times faster than many existing estimates in the literature, and affords targeting behavior an empirically important effect on firms' observed capital structures."

[7]Market value of assets is (total assets − book equity + market equity). Book equity is the book value of stockholders' equity, plus balance sheet deferred taxes and investment tax credit (TXDITC),

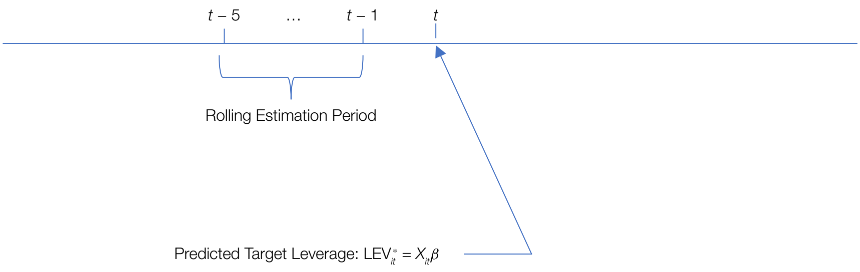
we replace missing values of R&D with zeroes and include an indicator variable, RDD, for such observations in regression (5) and following tests.

The explanatory variables are borrowed from Hovakimian, Opler, and Titman (2001) and are proxy variables for the determinants of optimal capital structure outlined by the trade-off theory. Specifically, firms with high growth opportunities (high market-to-book ratio) are expected to have low target leverage ratios to avoid debt overhang (Myers (1977)). Firms with high tangibility are likely to have relatively low bankruptcy costs due to the collateral value of tangible assets and, therefore, high target debt ratios (Titman and Wessels (1988)). Firms with unique assets and products (high R&D expenses and high selling expenses) are likely to have high costs of financial distress and, therefore, low leverage targets (Titman (1984)).[8] Large firms may have high leverage targets because they tend to have less volatile cash flows and are less likely to become financially distressed (Rajan and Zingales (1995)). We estimate regression model (5) with fixed firm effects (β_{oi}) to account for omitted time-invariant determinants of target leverage.

For each firm-year, LEV^*_{it} is calculated as an out-of-sample predicted value based on the parameter estimates obtained from panel regression (5), estimated over the previous 5 years, $t-1$ through $t-5$.[9] Figure 1 illustrates the timing convention that we follow. The rolling 5-year regression approach allows us to incorporate fixed firm effects that vary over time, something that was found to be important in DeAngelo and Roll (2015). Predicting target leverage out of sample gives us more confidence that any evidence of importance of target leverage in

FIGURE 1
Target Leverage Estimation

Figure 1 presents the timing convention for ordinary least squares (OLS) regressions of leverage on a set of firm characteristics to estimate target leverage ratios. Time-varying target leverage ratios in year t are calculated as the out-of-sample predicted values based on the parameter estimates obtained from rolling fixed-firm-effects regression (5), estimated over the previous 5 years, ($t-1$ through $t-5$). The sample firms are from Compustat. Leverage targets are estimated for 1971 to 2015. The first estimation period starts in 1966.



if available, minus the book value of preferred stock. To estimate the book value of preferred stock, we use the redemption (PSTKRV), liquidation (PSTKL), or par value (PSTK), in that order, depending on availability. Stockholders' equity is SEQ, if it is available. If not, we measure stockholders' equity as the book value of common equity (CEQ) plus the par value of preferred stock, or the book value of assets minus total liabilities (LT).

[8]R&D has also been used as a proxy for growth opportunities.

[9]For each LEV^*_{it}, we require a minimum of 2 observations per firm during the applicable estimation period.

subsequent tests reflects the underlying economics of firm behavior rather than the mechanics of target estimation.[10] Using the estimated LEV_{it}^*, we calculate deviations from target leverage for each firm-year as:

$$\text{DEV}_{it} = \text{LEV}_{it} - \text{LEV}_{it}^*. \tag{6}$$

Based on equation (6), firms with positive deviations are considered over-levered and those with negative values are considered under-levered.

IV. Sample and Variables

We construct the initial sample by drawing all firms that have records in Annual Compustat between 1966 and 2015. We exclude firms in financial services industries (Standard Industrial Classification (SIC) codes 6000–6999) and firms with values of total assets or sales of less than \$1 million. We retain only observations with nonmissing values of variables of interest from Compustat.[11] To limit the influence of data errors and outliers, all ratio variables except leverage are trimmed at the top 1% of the sample distribution. Ratio variables that take on negative values are also trimmed at the bottom 1% of the sample distribution. Leverage is trimmed from above at the value of 1.

Since we use 5 years of data to estimate target leverage, the data from 1966–1970 are only used in estimating leverage targets for 1971–1975 and the final sample used in our analyses actually spans the period between 1971 and 2015. Our final sample includes 125,536 firm-years. Table 1 reports the descriptive statistics for firm characteristics that have been used in prior studies as determinants of target leverage as well as the summary statistics for leverage, estimated targets

TABLE 1

Descriptive Statistics of Target Leverage Determinants

Table 1 presents descriptive statistics of target leverage determinants. The sample firms in Table 1 are from Compustat, and the sample period spans from 1971 to 2015. Leverage ratio is the sum of short- and long-term debt divided by the book value of assets. Market-to-book is the ratio of market value of equity and book value of debt over the book value of assets. Tangibility is the proportion of fixed assets in total assets. R&D is the ratio of research and development (R&D) expense over sales. The R&D indicator equals 1 if a missing value of R&D expense has been set to 0, and 0 otherwise. Selling expenses are scaled by sales. Size is the natural logarithm of CPI-adjusted sales. Time-varying target leverage ratios are calculated as the predicted values based on the parameter estimates obtained from rolling fixed effects regression (5) estimated over the previous 5 years. Deviations from targets are calculated as the difference between observed leverage and estimated target leverage.

Firm Characteristics	Mean	Median	Std. Dev.	No. of Obs.
Market-to-book	1.541	1.225	1.020	125,536
Tangibility	0.295	0.248	0.212	125,536
R&D	0.033	0.000	0.077	125,536
R&D indicator	0.664	1.000	0.472	125,536
Selling expenses	0.263	0.215	0.203	125,536
Size	4.877	4.823	1.981	125,536
Leverage	0.241	0.219	0.197	125,536
Target leverage	0.238	0.219	0.175	125,536
Deviation from target leverage	0.003	−0.005	0.117	125,536

[10] In Section VI, we examine whether and how our main results change using several alternative estimates of target leverage.

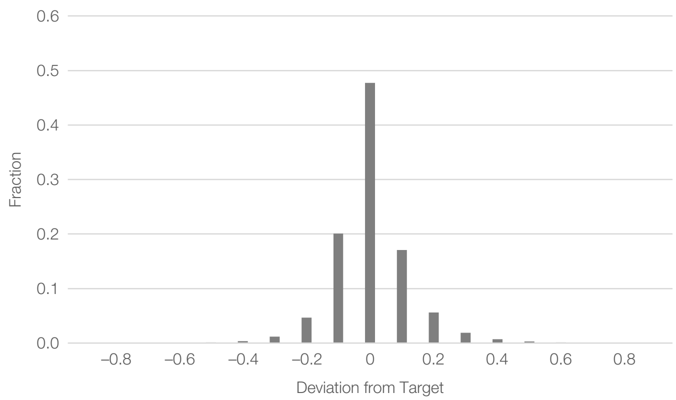
[11] As discussed earlier in Section III, we retain firms with missing R&D expenses and replace missing values of R&D with zeroes.

of leverage, and deviations from estimated targets. As expected with regression-based estimates, the mean target leverage ratios are not substantially different from observed leverage ratios. The medians of target and observed leverage ratios are also close, and the mean and median deviations are close to 0.[12] Figure 2 presents a histogram of deviations from target leverage: 48% of sample deviations are between −0.05 and 0.05 and 90% of the sample deviations are between −0.17 and 0.20.[13]

FIGURE 2

Histogram of Deviations from Target Leverage

Figure 2 presents the distribution of deviations from estimated target leverage. Leverage ratio is calculated as the sum of short- and long-term debt divided by the book value of assets and is restricted to the values of 0 from below and 1 from above. Time-varying target leverage ratios are calculated as the predicted values based on the parameter estimates obtained from rolling fixed effects regression (5), estimated over the previous 5 years and is restricted to the values of 0 from below and 1 from above. Deviations from targets are calculated as the difference between observed leverage and estimated target leverage. The sample firms are from Compustat. Leverage targets and deviations from targets are estimated for 1971 to 2015.



V. Persistence of Leverage, Target Leverage, and Deviation from Target Leverage

The persistence in cross sections of leverage ratios documented in DeAngelo and Roll (2015) could be driven by firms setting stable capital structure targets with relatively low adjustment costs and, hence, narrow target zones. In this case, the persistence of LEV_{it} in equation (1) would be primarily driven by persistence in LEV^*_{it}. If our procedure in Section III is sufficiently successful in generating good estimates for these targets, then we should find that firms tend to offset their accumulated deviations and the deviations, ε_{it}, should not persist for long periods of time.

[12]Had the targets been estimated using a single regression on a full sample, the mean deviation from target would be exactly 0. Given that we estimate the targets using rolling 5-year regressions and predict the targets out of estimation sample, the mean deviations are not exactly 0 but are economically trivial.

[13]For comparison, the mean and the median leverage ratios are 0.241 and 0.219, respectively, and the deviations from target range from −0.90 to 0.99.

Alternatively, leverage persistence could be caused by large adjustment costs and, hence, enduring deviations from capital structure targets. Some level of persistence is also consistent with Miller's (1977) neutral-mutation view, which suggests that firms have no targets and leverage ratios evolve randomly over time. In these two cases, the persistence of LEV_{it} in equation (1) would be primarily driven by persistence in ε_{it}, and we would observe deviations, ε_{it}, that persist for long periods of time. In this section, we test these alternative hypotheses.

Specifically, we use the approach of DeAngelo and Roll (2015), to estimate the persistence of leverage ratios, estimated leverage targets, and deviations from targets. The persistence of leverage ratios is estimated based on a regression model between a current level and a lagged level of LEV_{it}, starting with the 1st lag and moving backward for n lags, 1 year at a time:

$$\text{(7)} \qquad \text{LEV}_{it} = \beta_0 + \beta_1 \times \text{LEV}_{it-n} + \varepsilon_{it.}$$

We estimate equation (7) for each of the n consecutively lagged values of LEV_{it}. Estimates of β_1 reflect the statistical significance as well as the economic magnitude of persistence in leverage ratios. The R^2 reflect the extent to which the cross-sectional variation in leverage in year t is explained by the cross-sectional variation of leverage in year $t-n$. Note that because the standard deviations of LEV_{it} and its lags are similar in magnitude, the β_1 coefficient estimates are roughly equal to the correlations between LEV_{it} and its lags. The estimation results for the first 3 lags are presented in Panel A of Table 2.

The results show significant tenacity of observed leverage. Specifically, the persistence in leverage ratios declines gradually, as we increase the distance between current and lagged values of leverage, but stays both economically and statistically highly significant after 3 years. The coefficient estimate for the 1st lag is 0.897 and declines to 0.740 for the 3rd lag, and the R^2 is 0.768 for the 1st lag and declines to R^2 of 0.510 for the 3rd lag. Such a degree of persistence is consistent with the findings of Lemmon et al. (2008) and DeAngelo and Roll (2015).

Next, we estimate the persistence of deviations from leverage targets using a regression model between a current level and a lagged level of DEV_{it}, starting with the 1st lag and moving backward for n lags, 1 year at a time:

$$\text{(8)} \qquad \text{DEV}_{it} = \beta_0 + \beta_1 \times \text{DEV}_{it-n} + \varepsilon_{it}.$$

The estimation results for the first 3 lags are presented in Panel B of Table 2 and show that the deviations from target leverage are much less enduring than the leverage ratios, which were studied in Lemmon et al. (2008) and DeAngelo and Roll (2015). Specifically, the coefficient on the 1st lag is 0.600, declines by more than 50% to 0.297 on the 2nd lag and becomes economically trivial at 0.058 on the 3rd lag. Likewise, the R^2, which is 0.330 with the 1st lag, drastically declines to 0.078 with the 2nd lag and becomes 0.003 with the 3rd lag. Thus, the cross-sectional variation in deviations from leverage targets has no relation to the cross-sectional variation in deviations 3 years down the road. These results are consistent with the dynamic models of capital structure suggesting that firms offset deviations from target leverage within an economically short time frame.

Finally, we estimate the persistence of leverage target using a similar regression model between a current level and a lagged level of $\text{LEV}_{it}{}^*$:

$$\text{(9)} \qquad \text{LEV}_{it}^* \quad = \quad \beta_0 + \beta_1 \times \text{LEV}_{it-n}^* + \varepsilon_{it}.$$

The results presented in Panel C of Table 2 show that the persistence for target leverage is even stronger than the persistence of observed leverage. Specifically, the coefficient of the 1st lag is close to 1 at 0.975 and declines to 0.879 for the 3rd lag. However, some of this persistence, as well as its decline with the number of lags, could be hard-wired. Because the leverage targets are estimated using 5-year rolling regressions, targets that are less than 5 years apart are estimated using some of the same data. The estimated fixed effects, in particular, could generate hard-wired correlation between leverage targets in nearby years that will be falling as the overlap is reduced. That said, targets that are at least 5 years apart are estimated using completely different 5-year subsamples with no hard-wired correlation present. To show the persistence between target leverage ratios with no hard-wired correlation, in Panel C we present persistence regressions up to the fifth lag. The results show that even at the fifth lag, there is high persistence in target with a coefficient estimate of 0.754 and an R^2 of 0.568. In addition, as we show later in Figure 4, persistence of target leverage declines smoothly across lags, with no observable discontinuity.

To illustrate the similarities and the differences between our findings and the findings in the two important precursor studies, we summarize our results in two figures. Figure 3 is similar to Figure 1A in Lemmon et al. (2008). Specifically, every year, we sort all firms into four portfolios based on their leverage ratios and track the average leverage ratios of these portfolios over time, presented in

TABLE 2

Persistence of Leverage, Deviations from Target Leverage, and Target Leverage

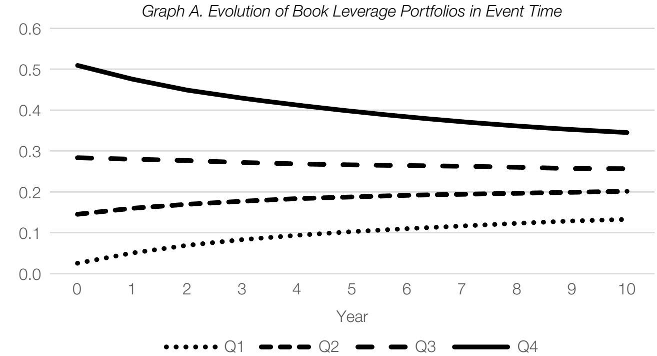
Table 2 presents the coefficients of ordinary least squares (OLS) regressions of leverage, deviations from estimated target leverage, and target leverage on their nth lagged values based, respectively, on the following equations: $\text{LEV}_{it} = \beta_0 + \beta_1 \times \text{LEV}_{it-n} + \varepsilon_{it}$ (Panel A), $\text{DEV}_{it} = \beta_0 + \beta_1 \times \text{DEV}_{it-n} + \varepsilon_{it}$ (Panel B), and $\text{LEV}_{it}^* = \beta_0 + \beta_1 \times \text{LEV}_{it-n}^* + \varepsilon_{it}$ (Panel C). Leverage ratio is calculated as the sum of short- and long-term debt divided by the book value of assets. Time-varying target leverage ratios are calculated as the predicted values based on the parameter estimates obtained from rolling fixed effects regression (5) estimated over the previous 5 years. Deviations from targets are calculated as the difference between observed leverage and estimated target leverage. The sample firms are from Compustat, and the sample period spans from 1971 to 2015. The t-statistics reflect standard errors adjusted for heteroscedasticity and firm-level clustering. Values significantly different from 0 at the 5% and 1% levels are marked * and **, respectively.

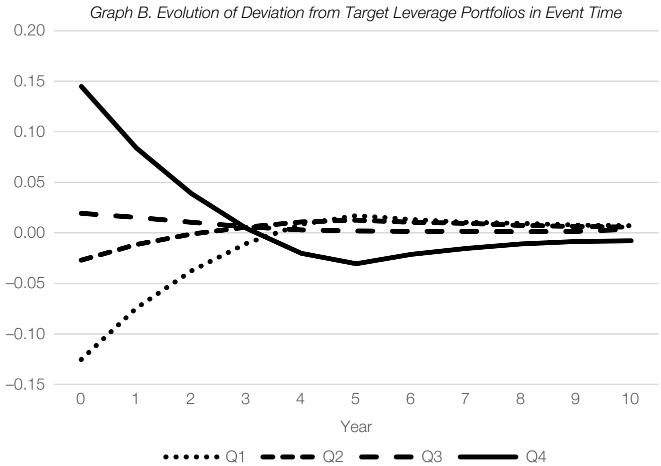
	Coeff.	t-Statistic	R^2	No. of Obs.
Panel A. Leverage				
$(t-1)$	0.897**	440.1	0.768	112,281
$(t-2)$	0.812**	236.8	0.617	100,731
$(t-3)$	0.740**	159.5	0.510	91,210
Panel B. Deviation				
$(t-1)$	0.600**	157.6	0.330	112,281
$(t-2)$	0.297**	64.3	0.078	100,731
$(t-3)$	0.058**	10.8	0.003	91,210
Panel C. Target Leverage				
$(t-1)$	0.975**	1,133.6	0.952	112,281
$(t-2)$	0.933**	512.2	0.872	100,731
$(t-3)$	0.879**	303.2	0.776	91,210
$(t-4)$	0.818**	199.8	0.670	82,983
$(t-5)$	0.754**	141.4	0.568	75,601

FIGURE 3

Portfolios of Average Book Leverage Ratios and Average Deviations from Book Leverage Targets in Event Time

Figure 3 presents the average leverage (Graph A) and the average deviation from estimated target leverage for four portfolios in event time (Graph B). Year 0 is the portfolio formation year. Portfolios are formed every fiscal year and their compositions are held constant, besides firms that dropped out, for 10 years. Leverage and deviation portfolios are formed independently of each other, based on the quartiles of their respective distributions in the year of portfolio formation. Q1 (Q4) is the portfolio with the lowest (highest) leverage (Graph A) or deviation from target leverage (Graph B). Leverage ratio is calculated as the sum of short- and long-term debt divided by the book value of assets. Time-varying target leverage ratios are calculated as the predicted values based on the parameter estimates obtained from rolling fixed effects regression (5) estimated over the previous 5 years. Deviations from targets are calculated as the difference between observed leverage and estimated target leverage. The sample firms are from Compustat, and the sample period spans from 1971 to 2015.





Graph A of Figure 3. Similarly, we sort firms into four portfolios based on their deviations from target leverage ratios and track the average deviations from target of these portfolios over time, presented in Graph B. Consistent with Lemmon et al., the leverage ratios of the cross-sectional portfolios in Graph A are very persistent over time. In contrast, deviations from target leverage ratios in Graph B are not nearly as persistent, and the differences between portfolio deviations disappear after 2–3 years.

Table 2 presents the persistence results only for the first few lags. In Figure 4, we plot the R^2 as a function of the n years separating the leverage ratios

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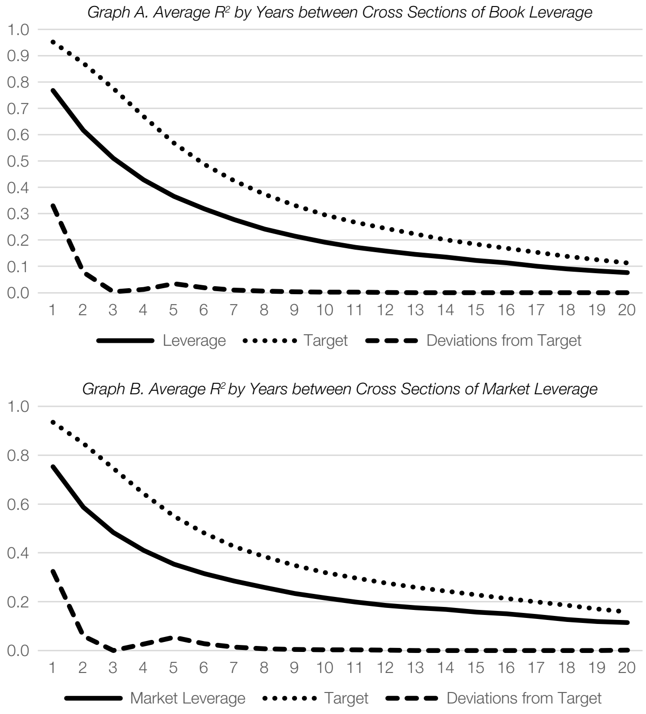
FIGURE 4
Stability in the Cross Sections of Leverage, Target Leverage, and Deviation from Target Leverage

Figure 4 summarizes the R^2 from regressions of leverage ratios in year t on leverage ratios in year $t-n$ as well as similar regressions of target leverage ratios and deviations from target leverage ratios on their lags. The horizontal axis presents the number of years between the current level of leverage, estimated leverage target or deviation from target, and the respective lag. Leverage ratio is calculated as the sum of short- and long-term debt divided by the book value of assets (Graph A) or the market value of assets (Graph B). Market value of assets is calculated as book value of assets minus the book value of equity and plus the market value of equity. Time-varying target leverage ratios are calculated as the predicted values based on the parameter estimates obtained from rolling fixed effects regression (5) estimated over the previous 5 years. Deviations from target are calculated as the difference between observed leverage and estimated target leverage. The sample firms are from Compustat, and the sample period spans from 1971 to 2015.



in regression model (7). This is represented by the middle, solid line in Graph A of Figure 4, which is similar to Figure 3B in DeAngelo and Roll (2015).[14] Similarly, we plot the R^2 from regressions of deviations from target leverage ratios in year t on deviations from targets in year $t-n$ (regression model (8)) as a function of the n years separating these ratios. This is represented by the lower, dashed line in Graph A. The upper, dotted line in Graph A plots the R^2 from regressions of target leverage ratios in year t on target ratios in year $t-n$. Consistent with DeAngelo and Roll, the R^2 of leverage ratio regressions start at a high level (0.768) and then slowly but steadily decline with the number of years separating the leverage cross

[14]Throughout the article, we report the results for book leverage ratios. The results for market leverage ratios are similar, as demonstrated by Graph B of Figure 4. Market leverage is defined as the book value of short- and long-term debt over market value of assets. Market value of assets was defined previously in footnote 7.

sections. In contrast, the R^2 of deviations from target leverage ratios start at a much lower level of 0.330 and quickly decline to effectively 0 by year 3, whereas the regressions of target leverage ratios on their lags (Graph B) exhibit the highest levels of persistence at all lags.

Overall, the results in this section imply that the persistence in observed leverage ratios is primarily due to the persistence in leverage targets, which are more stable and change more slowly over time compared to leverage ratios (the R^2 at 3-year horizon is 0.776 for target leverage vs. 0.510 for leverage). In contrast, the variability in leverage ratios is largely driven by deviations from targets, which are more transitory and are offset within 2–3 years, an economically short period of time. The finding that the persistence of deviations from target virtually disappears at a 3-year horizon offers strong empirical support to leverage targeting behavior implied by dynamic trade-off theories in the literature.

VI. Alternative Targets

Target debt ratios are unobservable and, hence, have to be estimated. The target estimates used in the current article are based on fixed-firm-effects regressions, which is the standard approach in the literature. However, our approach is different from the typical approach in prior literature in that we estimate the target debt ratio for year t using the parameter estimates from 5-year rolling regressions (years $t-1$ through $t-5$) and the firm characteristics in year t. Thus, both the regression parameter estimates, including the firm fixed effects, and the firm characteristics change every year, potentially making our target estimates more time varying than is typical in prior literature.

There is a disagreement in the prior literature on the importance of time variation of leverage determinants. Lemmon et al. (2008) argue that most of the variation in debt ratios is due to unobserved time-invariant factors. In contrast, DeAngelo and Roll (2015) show that interactions of firm fixed effects with decade indicators substantially improve the explanatory power of their regressions and conclude that allowing for firm-specific time-series variation in leverage is important. Whether this firm-specific time-series variation comes from variation in targets or deviations from targets remains an open question. DeAngelo and Roll's top two simulated models assume highly time-varying targets with fast adjustment or, alternatively, slowly varying targets with persistent deviations. These two models generate the best matches with the empirical time-series profile of R^2 from regressions of leverage on its lags.

In this section, we compare the performance of our target estimates with a target that is less time-varying and another one that is time-invariant and examine how our results on persistence of deviations from target change if different types of target estimates are used. First, we assess how much of the variation in observed leverage ratios is explained by different time-varying and time-invariant targets by estimating pooled ordinary least squares (OLS) regressions of observed leverage ratios on these targets. The results for our rolling target estimates are reported in the first row of Panel A in Table 3. At 0.654, the R^2 can be considered fairly high, which supports the notion that firms tend to set targets for their leverage and suggests that these could be reasonable estimates of the actual targets.

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TABLE 3
Regressions of Leverage on Estimated Targets

Table 3 presents the coefficients of ordinary least squares (OLS) regressions of leverage ratios on alternative estimates of leverage targets. Leverage ratio is calculated as the sum of short- and long-term debt divided by the book value of assets. Rolling time-varying target leverage ratios are calculated as the predicted values based on the parameter estimates obtained from rolling fixed effects regression (5) estimated over the previous 5 years. The full-sample target is estimated as the fitted value of fixed-firm-effects regression (5) estimated once on the full sample. Initial time-invariant target leverage is the firm's first nonmissing value of the rolling time-varying target leverage in its time series. The sample firms are from Compustat, and the sample period spans from 1971 to 2015. The t-statistics reflect standard errors adjusted for heteroscedasticity and firm-level clustering. Values significantly different from 0 at the 5% and 1% levels are marked * and **, respectively.

	Coeff.	t-Statistic	R^2	No. of Obs.
Panel A. All Observations				
Time-Varying Targets				
Rolling fixed effects regressions	0.911**	331.7	0.654	125,536
Full-sample fixed-firm-effects regression	1.000**	1,392.7	0.659	125,536
Time-Invariant Target				
Initial target from rolling fixed effects regressions	0.585**	64.0	0.280	125,536
Panel B. 20-Year Survivors Only				
Time-Varying Targets				
Rolling fixed effects regressions	0.895**	221.1	0.656	55,539
Full-sample fixed-firm-effects regression	1.000**	529.1	0.515	55,539
Time-Invariant Target				
Initial target from rolling fixed effects regressions	0.424**	25.2	0.157	55,539

For comparison, the second row of results is for a similar regression on targets obtained by estimating model 5 as a single fixed-firm-effects regression on the full sample as opposed to 5-year rolling regressions. The R^2 of 0.659 is almost identical to that in the first row.[15]

At first glance, the similarity of the R^2 in rows 1 and 2 in Panel A of Table 3 may appear to contradict DeAngelo and Roll (2015), who argue that allowing firm fixed effects to change over time is important. The target leverage in the first row is estimated using rolling 5-year regressions and, hence, allows for firm effects to be fixed over each 5-year estimation period but vary across 5-year periods. In the regression presented in the second row, firm effects are fixed over the whole sample period. The sample in these regressions, however, is dominated by firms with relatively short time series. Allowing firm effects to change across 5-year periods does not make much difference for such firms.

To highlight the difference between firm effects that are fixed over rolling 5-year periods and those that are fixed over the entire sample period, we repeat the analysis on the subsample of firms with at least 20 years in their time series and report the results in Panel B of Table 3. The R^2 of 0.656 for the rolling target model in the first row of Panel B is almost identical to the R^2 from the corresponding regression in the first row of Panel A. More importantly, however, the R^2 of 0.515 for the full-sample fixed-firm-effects regression in the second row of Panel B is now substantially lower compared to the R^2 obtained with the rolling target model. This suggests that, in terms of their ability to explain observed debt ratios,

[15]Note that because the full-sample fixed effects regression that generated the target was estimated on the same exact sample, we are effectively running a regression on its own fitted value. Hence, the coefficient estimate on the target is exactly 1 and the R^2 is equal to the overall R^2 of the original fixed effects regression.

our rolling regression target estimates outperform full-sample fixed effects target estimates.

In full-sample fixed effects regressions reported in the second rows of Panels A and B in Table 3, the target leverage is estimated in sample, using all observations in the sample firms' time series. We also compare our 5-year rolling targets with a time-invariant out-of-sample target set equal to the initial 5-year rolling target leverage estimated for the first year of each firm's time series. Thus, for each firm, the time-varying and time-invariant targets are the same in the first year of the time series, but the time-invariant target remains constant, whereas the time-varying one changes as rolling 5-year regressions generate new estimates for every year. Our use of the initial target estimates as firm-specific time-invariant targets throughout our sample period is motivated by the evidence in prior literature that pooled regressions of leverage ratios on firms' initial leverage ratios recorded in Compustat generate R^2 of about 0.15 in the sample of firms that survive at least 20 years (Lemmon et al. (2008)).

The third rows of Panels A and B in Table 3 report the results of regressions of leverage on the time-invariant out-of-sample initial target. Panel A reports the results for the full sample. The results show that the R^2 from the time-invariant initial target is 0.280, which is substantially lower than the R^2 of 0.654 obtained from the time-varying target in the first row. Panel B reports the results for 20-year survivors only. Once again, the R^2 from the time-invariant initial target (0.157) is much lower than the R^2 of 0.656 obtained from the time-varying target in the first row of Panel B.

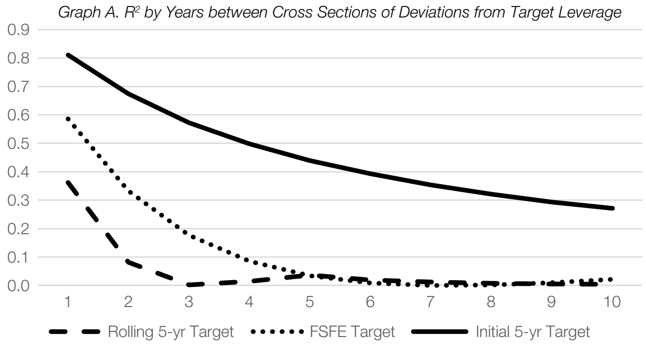
The comparison of these targets based on how well they explain observed leverage ratios comes with an important caveat: It is not necessarily true that a better target estimate always generates higher R^2 in regressions of observed leverage on target leverage. As represented by equation (1), observed leverage can be thought of as a sum of target leverage and deviation from target. If deviations from targets are random with respect to firm characteristics, then firm characteristics and fixed effects will explain only the targets and higher R^2 will imply better estimated targets. However, if deviations are not random but are related to firm characteristics, then the independent variables in the regression may explain deviations from target leverage. This is possible if, for example, shocks to leverage or costs of adjusting leverage to target and, hence, the magnitudes of corresponding deviations are related to firm characteristics. In such a case, higher R^2 may identify regression models that are better in explaining these deviations rather than in explaining the targets.

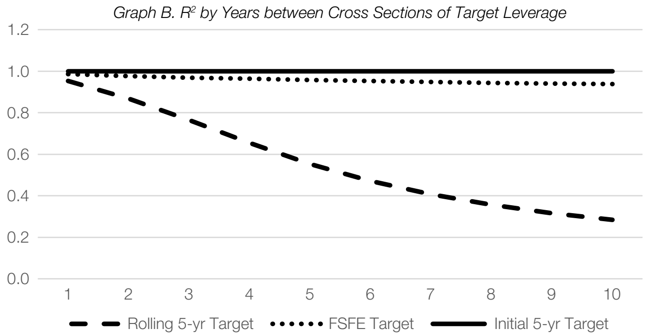
As an alternative way to compare the performance of various targets, we compare the persistence of deviations from different estimates of target at various horizons. The idea here is that the closer the estimated target is to the actual unobserved target, the stronger the evidence that firms offset their deviations from targets should be. In other words, better target estimates should produce less persistent deviations from targets. In Figure 5, we summarize the persistence of deviations from the three described measures of target (Graph A) as well as the persistence of the targets themselves (Graph B) at horizons of 1–10 years. The regressions that generate the numbers for Figure 5 are estimated on a subsample

FIGURE 5

Stability of Cross Sections of Time-Varying and Time-Invariant Leverage Targets and Deviations from Those Targets

Figure 5 summarizes the R^2 from regressions of target leverage ratios and deviations from targets in year t on their lagged values in year $t-n$. The horizontal axis presents the number of years between the current level of leverage or deviation and the respective lag. Leverage ratio is calculated as the sum of short- and long-term debt divided by the book value of assets. Rolling 5-year target leverage ratios are calculated as the predicted values based on the parameter estimates obtained from rolling fixed effects regression (5) estimated over the previous 5 years. Full sample fixed effects (FSFE) target leverage ratios are calculated as the predicted values based on the parameter estimates obtained from regression (5) estimated once on the full sample with fixed firm effects. The initial time-invariant target leverage is the firm's first nonmissing value of the 5-year rolling time-varying target leverage in its time series. Deviation from target is calculated as the difference between observed leverage and estimated target leverage. The sample firms are those with at least 20 years of data in Compustat, and the sample period spans from 1971 to 2015.





of firms with at least 20 years of data, since the difference between time-invariant and time-varying targets is not very meaningful for firms with short time series.

The dashed line in Graph A of Figure 5 presents the R^2 of regression (8), of deviations from the target generated using 5-year rolling regressions based on specification 5. These targets change over time for several reasons. First, firm characteristics used to predict these targets change over time. Second, because we use rolling 5-year regressions, the coefficient estimates used to predict these targets change over time. Third, because we use rolling 5-year regressions, the 5-year fixed effects also change over time. Finally, since the targets are estimated from rolling regressions, changes in sample composition over time will generate variation in estimated targets.

The dotted line presents the R^2 using deviations from targets based on the same regression (5) but estimated only once on the full sample with fixed firm effects. These targets also change over time, but only because firm characteristics used to predict these targets change over time. Unlike targets used to obtain the dashed line, the coefficient estimates and the fixed firm effects are constant throughout the sample period, so the target is likely less time varying. The solid line presents the R^2 of regression of deviations from the time-invariant initial targets set equal to the initial rolling 5-year target leverage estimate for the first year of each firm's time series and kept constant for all subsequent years.

As Graph A in Figure 5 shows, at short horizons (1–4 years), the time-varying targets based on rolling 5-year regressions (dashed line) produce the least persistent deviations from target leverage. Full-sample fixed-firm-effects targets (dotted line) produce levels of persistence that are noticeably higher than those based on rolling targets at horizons of 1–4 years but are also trivial at horizons of 5–10 years. The highest levels of persistence are produced by the initial 5-year regression targets that are fixed for the whole time series of the firm (solid line). Even at 10-year horizon, the R^2 for deviations from these targets is 0.271. Indeed, these deviations are even more persistent than the leverage ratios themselves (R^2 of 0.188 at 10 years), which suggests that the initial time-invariant targets are not a good target proxy.

Because the time-invariant target does not change over time for any given firm, its persistence is represented by the solid horizontal line at the value of 1 in Graph B of Figure 5. The dotted line in Graph B represents the persistence of full-sample fixed effects target estimates. Although these estimates vary over time due to variation in firm characteristics, they are also extremely persistent because the fixed effects component and the coefficient estimates used to generate the target do not change over time. The R^2 of the regression of these targets on their 10-year lags is 0.94. By contrast, the 5-year rolling targets demonstrate substantially lower level of persistence (dashed line in Graph B).

Overall, the results in this section show that, while persistent, our target estimates are substantially more time varying than the estimates from the full-sample fixed effects regression, which is the typical choice in the literature. Second, our target estimates explain a larger fraction of variation in observed leverage ratios than the full-sample fixed-effects estimates or the time-invariant measures of target. Third, deviations from estimated leverage targets are less persistent than the leverage ratios, which are in turn less persistent than the targets in two of the three considered models. This indicates that our findings on the persistence of leverage ratios, targets, and deviations relative to each other are robust and informative. Finally, even though our approach produces the least persistent target estimates, it also produces the least persistent deviations from target, implying that our estimates are closer to unobserved leverage targets that firms actually care about.

VII. Variations in Persistence of Deviations

While our results in the previous sections indicate that deviations from target leverage are, on average, rather short-lived, there may be variations in how fast firms offset these deviations. Dynamic trade-off models (e.g., Fischer et al. (1989)) imply that adjustments to targets are more likely when adjustment costs are lower, other things equal. However, firms may also differ in the value gains

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associated with moving toward target leverage. Holding adjustment costs constant, then, leverage adjustments are also more likely when a firm's market value is more sensitive to its leverage.

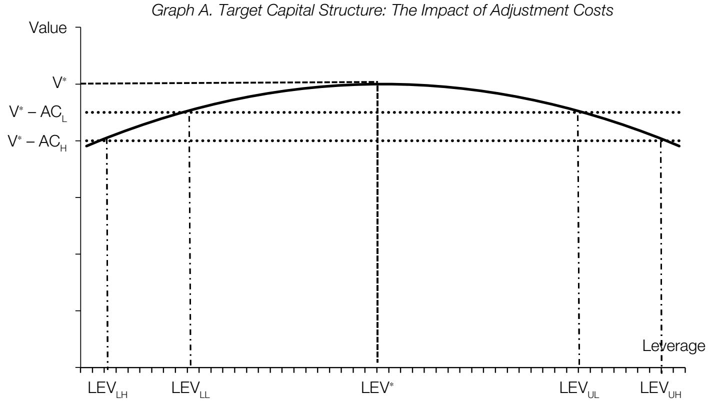
Figure 6 summarizes these ideas. Graph A demonstrates how the likelihood of adjustment to target leverage is affected by the cost of adjustment. In the absence of imperfections, the firm will always adjust its leverage to its target level (LEV*) in response to shocks that create deviations from the target, to maximize its value (V*). However, if the firm faces fixed costs of adjusting leverage, it will only do so when the benefits from adjustment exceed the costs. For example, with a low adjustment cost of AC_L, debt ratio will be allowed to fluctuate within the target zone defined by the lower boundary, LEV_{LL}, and the upper boundary,

FIGURE 6

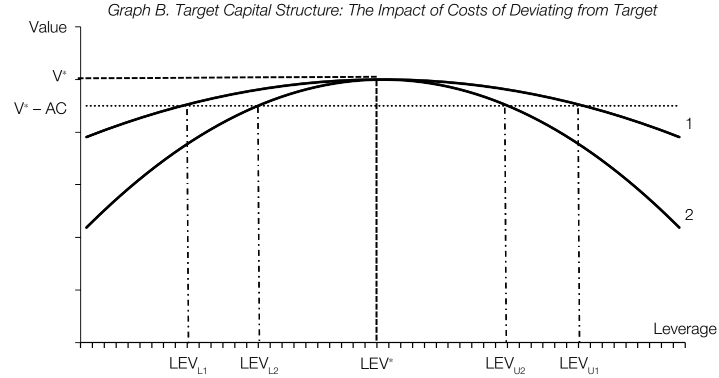
Target Leverage: The Impact of Adjustment Costs and Costs of Deviating from Target

Figure 6 demonstrates the impact of adjustment costs (Graph A) and the costs of deviating from target (Graph B) on leverage targeting behavior. LEV* is the target leverage and V* is the firm value at target leverage. In Graph A, AC_L represents a low level of adjustment costs and AC_H represents high adjustment costs. LEV_{LL} (LEV_{UL}) is the lower (upper) boundary of the target leverage zone that triggers adjustment under low adjustment costs (AC_L). LEV_{LH} (LEV_{UH}) is the lower (upper) boundary of target leverage zone that triggers adjustment under high adjustment costs (AC_H). Graph B presents value functions for firms 1 and 2. AC is the adjustment cost, same for both firms. LEV_{L1} (LEV_{U1}) is the lower (upper) boundary of target leverage zone that triggers adjustment for firm 1. LEV_{L2} (LEV_{U2}) is the lower (upper) boundary of target leverage zone that triggers adjustment for firm 2.

Graph A. Target Capital Structure: The Impact of Adjustment Costs



Graph B. Target Capital Structure: The Impact of Costs of Deviating from Target



LEV_{UL}, since within these boundaries the cost of adjustment to LEV^* exceeds the value increase to V^*. Active adjustment to LEV^* will occur when leverage crosses LEV_{LL} or LEV_{UL}. At a higher adjustment cost of AC_{H}, the target range of debt ratios is wider, ranging from LEV_{LH} to LEV_{UH}. Thus, other things equal, active adjustment is less likely to occur. This is the standard result of dynamic trade-off models, such as that in Fischer et al. (1989).

Graph B of Figure 6 demonstrates the impact of the shape of the value function on the likelihood of adjustment. Consider firms 1 and 2, whose values change with leverage, as shown in Graph B. The firms have the same optimal leverage, LEV^*, where their values are maximized at V^*. At any other level of leverage, the slope of the value function of firm 1 is smaller in absolute value than the slope of firm 2. In other words, the marginal benefits of adjusting to LEV^* are smaller for firm 1 relative to firm 2. Both firms face the same fixed cost (AC) of adjusting their leverage. As in Graph A, each firm ends up with its own target range of debt ratios. Importantly, since the value function of firm 1 is flatter than the value function of firm 2, the target range for firm 1 (LEV_{L1} to LEV_{U1} in Graph B) is wider than the target range for firm 2 (LEV_{L2} to LEV_{U2} in Graph B). Thus, other things equal, firms with higher marginal benefits of being at the target will have narrower target leverage zones and will be more likely to actively adjust leverage than firms with lower marginal benefits.

In the following analysis, we examine variations in deviation persistence based on deviation characteristics, firm characteristics, and macroeconomic conditions that are likely to affect the costs of adjustment to target leverage and/or the benefits of being at target leverage. Based on the previous discussion, we expect that lower adjustment costs and higher benefits of being at the target, LEV^*, should be associated with lower persistence of the deviations from target debt ratios.

A. Persistence of Deviations by Deviation Characteristics

When deciding whether to offset deviations from target leverage, firms may treat leverage excess and leverage deficit differently. Likewise, deviations that are large may be treated differently compared to those that are relatively minor. In this subsection, we test whether the persistence of deviations from estimated targets varies depending on the sign and magnitude of the deviations.

1. Positive versus Negative Deviations

The persistence of positive and negative deviations from target may be different for two reasons. First, the marginal effect of debt on firm value around the target debt ratio may not be symmetrical. If, for example, one extra dollar of debt beyond LEV^* results in a significantly higher value loss than one less dollar below LEV^*, then, other things equal, over-levered firms may be more likely than under-levered firms to offset their deviations from target, and vice versa.

Second, reductions and increases in leverage require firms to undertake different types of corporate financing transactions, such as issuing equity versus issuing debt or repurchasing equity versus retiring debt. Depending on the required type of action, the costs of adjusting leverage up or down could be different. This could make firms more likely to undertake transactions in one direction than the

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other, which could lead to different levels of deviation persistence for over- and under-levered firms.

In Table 4, we re-estimate regression model (8) separately for the subsamples with negative (under-levered) and positive (over-levered) lagged deviations on the right side. Relative to the dependent variable, which is the current deviation, the independent variable is lagged by 1 period in the first row, 2 periods in the second row, and 3 periods in the third row of each panel. The first 3 columns of estimates are for under-levered firms, the next 3 columns are for over-levered firms, and the last column reports p-values for the test of equality of the coefficient estimates for under-levered and over-levered firms. The results show that the deviations from target are significantly less persistent for over-levered firms at all 3 lags. As discussed previously, this could be either because the costs of adjusting leverage down are lower than the costs of adjusting it up or because the costs of being over-levered exceed the costs of being under-levered. Our analysis later in the article sheds more light on this issue.

TABLE 4

Persistence of Negative versus Positive Deviations from the Target

Table 4 presents the coefficients of ordinary least squares (OLS) regressions of deviations from estimated target leverage on their lagged values. Leverage ratio is calculated as the sum of short- and long-term debt divided by the book value of assets. Time-varying target leverage ratios are calculated as the predicted values based on the parameter estimates obtained from rolling fixed effects regression (5) estimated over the previous 5 years. Deviations from targets are calculated as the difference between observed leverage and estimated target leverage. Over-levered (under-levered) firms are defined as those with positive (negative) deviations from the target in year $t-n$. The sample firms are from Compustat, and the sample period spans from 1971 to 2015. The t-statistics reflect standard errors adjusted for heteroscedasticity and firm-level clustering. Values significantly different from 0 at the 5% and 1% levels are marked * and **, respectively.

	Under-Levered			Over-Levered			
	Coeff.	t-Stat.	R^2	Coeff.	t-Stat.	R^2	p-Value of Difference
Deviation ($t-1$)	0.637**	85.9	0.222	0.562**	70.8	0.181	0.000
Deviation ($t-2$)	0.369**	41.2	0.063	0.253**	25.8	0.031	0.000
Deviation ($t-3$)	0.158**	16.6	0.011	0.002	0.2	0.000	0.000

2. Large Deviations

Dynamic trade-off models of capital structure with fixed adjustment costs imply that firms have target debt zones within which they do not adjust to target. Leverage adjustments are triggered when the deviations from the targets cross the boundaries of these zones. Although target boundaries are unobservable, firms are more likely to be crossing them when estimated deviations are larger. Thus, holding boundaries constant, larger deviations are likely to be less persistent. However, boundaries are likely to vary across firms and time. As a result, we are likely to observe larger deviations for firms with wider target zones, in which case larger deviations may not be necessarily less persistent.

In Table 5, we re-estimate regression model (8) with two additional variables on the right side, an indicator for large lagged deviation and the interaction of the indicator with lagged deviation. We consider a deviation to be large if it is 1 sample standard deviation above or below 0. The results are reported separately for under-levered (Panel A) and over-levered (Panel B) firms. In each panel, the independent variable is the deviation from target lagged by 1 year in the first row, 2 years in the second row, and 3 years in the third row. The results show that larger

TABLE 5

Persistence of Large Deviations from the Target

Table 5 presents the coefficients of ordinary least squares (OLS) regressions of deviations from estimated target leverage on their lagged values. Leverage ratio is calculated as the sum of short- and long-term debt divided by the book value of assets. Time-varying target leverage ratios are calculated as the predicted values based on the parameter estimates obtained from rolling fixed effects regression (5) estimated over the previous 5 years. Deviations from targets are calculated as the difference between observed leverage and estimated target leverage. A deviation from the target is defined as large positive (over-levered) or large negative (under-levered) if it is 1 sample standard deviation above or below 0, respectively. The sample firms are from Compustat, and the sample period spans from 1971 to 2015. The intercepts and the "large" indicator coefficient estimates are not reported. The t-statistics reflect standard errors adjusted for heteroscedasticity and firm-level clustering. Values significantly different from 0 at the 5% and 1% levels are marked * and **, respectively.

	$n=1$		$n=2$		$n=3$	
	Coeff.	t-Stat.	Coeff.	t-Stat.	Coeff.	t-Stat.
Under-Levered						
Deviation($t-n$)	0.647**	53.9	0.376**	23.8	0.172**	9.5
Deviation($t-n$) × large	−0.074**	−3.0	−0.051	−1.8	−0.031	−1.1
R^2	0.222		0.063		0.011	
No of obs.	60,731		55,149		50,394	
Over-Levered						
Deviation($t-n$)	0.614**	41.5	0.274**	14.1	0.005	0.2
Deviation($t-n$) × large	−0.130**	−5.4	−0.057	−1.9	0.001	0.0
R^2	0.183		0.031		0.000	
No. of obs.	48,456		42,888		38,438	

deviations are significantly less persistent at 1-year horizon, but the differences are insignificant at 2- and 3-year horizons.

In Table 6, we supplement the analysis in Table 5 by examining the average time-series dynamics of deviations from target 3 years before and 3 years after the large deviations are observed. Columns 1–2 present the results for large negative deviations. Columns 3–4 present the results for large positive deviations. For each case, the first column shows the average deviations from target and the second column shows the average differences between current-year deviations and year 0 deviations, with their statistical significance.

First, note that the average "large" deviation is fairly large. In year 0, the average large negative deviation is −0.195 and the average large positive deviation is 0.213. Second, the comparison of the average values in the time series shows

TABLE 6

Time Series of Average Deviations from Target Around Large Deviations

Table 6 presents the time series of mean deviations (DEV_t) from target leverage ratios from 3 years before and 3 years after a large positive or negative deviation is observed in year 0. Leverage ratio is calculated as the sum of short- and long-term debt divided by the book value of assets. Time-varying target leverage ratios are calculated as the predicted values based on the parameter estimates obtained from rolling fixed effects regression (5) estimated over the previous 5 years. Deviations from targets are calculated as the difference between observed leverage and estimated target leverage. A deviation from the target is defined as large positive (over-levered) or large negative (under-levered) if it is 1 sample standard deviation above or below 0, respectively. The sample firms are from Compustat, and the sample period spans from 1971 to 2015. The t-statistics reflect standard errors adjusted for heteroscedasticity and firm-level clustering. Values significantly different from 0 at the 5% and 1% levels are marked * and **, respectively.

	Large Negative Deviation at $t=0$		Large Positive Deviation at $t=0$	
Time (t)	DEV_t	$DEV_t - DEV_0$	DEV_t	$DEV_t - DEV_0$
−3	−0.005	0.186**	0.013	−0.199**
−2	−0.057**	0.134**	0.052**	−0.159**
−1	−0.117**	0.076**	0.115**	−0.097**
0	−0.195**		0.213**	
1	−0.121**	0.073**	0.123**	−0.080**
2	−0.064**	0.128**	0.057**	−0.143**
3	−0.021	0.172**	0.004	−0.194**

that, in each of the 6 years around year 0, the absolute deviations are significantly smaller than the deviations in year 0. This result holds for both large negative and large positive deviations. Third, the average deviations in years −3 and +3 relative to the year of the large deviation are economically trivial and statistically insignificant, consistent with the hypothesis that firms quickly offset large deviations from the target.

These results are further confirmed in Graphs A–C of Figure 7, which show that distributions of large negative deviations (Graph A) change substantially 1 year (Graph B) and 2 years (Graph C) later. The figures demonstrate how a truncated distribution of large negative deviations (Graph A) becomes fairly symmetric and visually similar to the unconditional distribution of deviations 2 years down the road. Similar patterns are observed in Graphs D–F for large positive deviations.

Finally, to test whether the decline in deviations is due to active rebalancing, we sort all firms into quartiles based on their deviations from the target and then examine the corporate financing activities the following year. Specifically, Table 7 presents the average values of the deviations from the target for each quartile along with the average values of net equity issued and net change in debt.[16] The results show that the amounts of net debt and net equity issued are significantly different across the 4 quartiles. Further, compared to highly under-levered firms (quartile 1), highly over-levered firms (quartile 4) have significantly higher net equity issuance and significantly lower net change in debt. All differences are statistically significant at the 1% level and are consistent with rebalancing toward the target. The differences between the middle two portfolios (quartiles 2 and 3) are smaller in magnitude than the differences between quartiles 1 and 4, consistent with the idea that active efforts to offset the deviations from target intensify when the deviations become large and leverage ratios fall outside the target zone.

TABLE 7

Corporate Financing Activity across Portfolios Sorted on Deviation from Target Leverage

In Table 7, we sort sample observations into quartiles based on the values of deviations from target leverage and report the average deviations from target and the average frequencies of corporate financing activities next year. Leverage ratio is calculated as the sum of short- and long-term debt divided by the book value of assets. Time-varying target leverage ratios are calculated as the predicted values based on the parameter estimates obtained from rolling fixed effects regression (5) estimated over the previous 5 years. Deviations from targets are calculated as the difference between observed leverage and estimated target leverage. Net equity issuance is defined as the change in book value of equity minus change in retained earnings, scaled by the beginning book value of assets. Net change in debt is defined as the change in the sum of short- and long-term debt scaled by the beginning book value of assets. The sample firms are from Compustat, and the sample period spans from 1971 to 2015.

Quartile	Deviation from Target (t)	Net Equity Issuance ($t+1$)	Net Change in Debt ($t+1$)
1	−0.125	0.043	0.044
2	−0.027	0.031	0.028
3	0.018	0.035	0.020
4	0.139	0.049	0.002
p-value for Q4 – Q1		0.000	0.000
p-value for differences across 4 quartiles		0.000	0.000

[16]Net equity issued is measured as the change in book value of equity (BE) minus change in retained earnings (RE), scaled by the beginning value of total assets. Net change in debt is measured as the change in the sum of long-term (DLTT) and short-term (DLC) debt, scaled by the beginning value of total assets.

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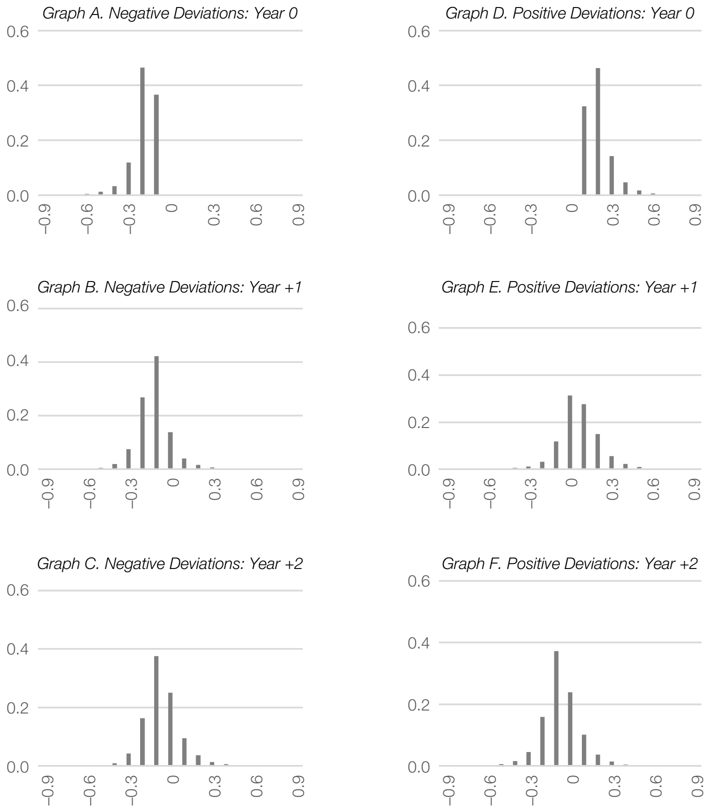
FIGURE 7

Distribution of Deviations from Target Leverage: Highly Under-Levered Firms

Figure 7 presents the distributions of deviations from target leverage ratios in years 0 (Graphs A and D), +1 (Graphs B and E), and +2 (Graphs C and F) for firms with large negative (Graphs A, B, and C) or large positive (Graphs D, E, and F) deviations in year 0. Leverage ratio is calculated as the sum of short- and long-term debt divided by the book value of assets and is restricted to the values of 0 from below and 1 from above. Time-varying target leverage ratios are calculated as the predicted values based on the parameter estimates obtained from rolling fixed effects regression (5) estimated over the previous 5 years and are restricted to the values of 0 from below and 1 from above. Deviations from targets are calculated as the difference between observed leverage and estimated target leverage. A deviation from the target is defined as large negative (highly under-levered cases) if it is 1 sample standard deviation or more below 0. A deviation from the target is defined as large positive (highly over-levered cases) if it is 1 sample standard deviation or more above 0. The sample firms are from Compustat, and the sample period spans from 1971 to 2015.



One exception to the overall pattern is the unusually high net equity issuance among the most under-levered firms (Quartile 1). We have two points to make related to this. First, it is not surprising that the pattern of debt and equity issuance in Table 7 correlates more strongly with adjustment toward the target for over-levered firms (quartiles 3 and 4) than for under-levered firms (quartiles 1 and 2). This is consistent with our findings in Tables 4 and 5 that deviations from target are much less persistent for over-levered firms. Second, firms issue and repurchase their securities for variety of reasons. Equity issuances in particular tend to be timed to periods when the issuers' stock prices are high (see, e.g., Baker and Wurgler (2002)). It is plausible that quartile 1 may include disproportionately many firms that have performed well and ended up with both low leverage and high stock prices.

Overall, the results in this subsection imply that, due to active rebalancing toward the target, large deviations from target are not very persistent, consistent with dynamic trade-off theories. In addition, the finding that our estimates of deviations from target leverage have predictive power about the direction of future changes in capital structure increases our confidence in our estimates of target leverage.

B. Persistence of Deviations by Firm Characteristics

In this subsection, we examine variations in deviation persistence based on firm size, age, credit rating, and diversification status. These characteristics could reflect differences in adjustment costs across firms. Specifically, firms that are larger, more mature, and diversified and enjoy higher credit ratings are likely to have lower adjustment costs because they have easier access to financing (see Hadlock and Pierce (2010), Kuppuswamy and Villalonga (2016), Faulkender and Petersen (2006), and Boot et al. (2006), among others). We also examine deviation persistence in recession versus nonrecession periods. The differences in persistence across the business cycle could reflect differences in adjustment costs since firms are likely to be more financially constrained and incur higher adjustment costs in recessions than in nonrecession periods.[17]

The firm characteristics described previously may also reflect costs of deviating from their target leverage ratios. Specifically, larger firms, more mature firms, and diversified firms have less volatile cash flows. Firms with less volatile cash flows and firms with higher ratings are likely to have lower probability and, hence, lower expected costs of financial distress. Therefore, we would expect positive deviations from target debt ratios to exhibit higher persistence for such firms. Similarly, the expected costs of financial distress should be lower in nonrecession as opposed to recession periods, leading to lower persistence of positive deviations from target in recessions.[18]

In terms of benefits of debt, larger firms, more mature firms, diversified firms, and firms with higher ratings are likely to have less volatile taxable income and, hence, higher expected tax shields (Hovakimian et al. (2001)). Similarly, agency costs of managerial discretion (Jensen (1986)) are likely to be higher at such firms and, hence, the agency cost reducing benefits of debt are also likely to be higher. Both of these considerations suggest that we should expect negative deviations from target debt ratios to exhibit lower persistence for such firms.

On the other hand, larger, more mature, and diversified firms are likely to be more sophisticated, have more resources, and, as a result, be able to reduce their taxes by other means. Similarly, because there is likely to be less information asymmetry between outside investors and managers of such firms, the signaling benefits of debt (Ross (1977)) are likely to be lower. Both of these considerations

[17]Bernanke and Blinder (1988) and Bernanke, Gertler, and Gilchrist (1996) show that financial constraints significantly tighten during recessions due to erosion of corporate balance sheets and decline in supply of financing.

[18]Both default rates and credit spreads tend to increase in recessions (Chen (2010)).

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suggest that we should expect negative deviations from target debt ratios to exhibit higher persistence for such firms.

Given our earlier finding that the deviations are more persistent for under-levered firms than for over-levered firms, the cross-sectional analysis is conducted for over- and under-levered firms separately. Table 8 summarizes the findings on variations of deviation persistence across firms and across the business cycle.

TABLE 8

Variations in Persistence of Deviations

Table 8 presents the coefficients and R^2 from ordinary least squares (OLS) regressions of deviations from estimated target leverage on their lagged values. Leverage ratio is calculated as the sum of short- and long-term debt divided by the book value of assets. Time-varying target leverage ratios are calculated as the predicted values based on the parameter estimates obtained from rolling fixed effects regression (5) estimated over the previous 5 years. Deviations from targets are calculated as the difference between observed leverage and estimated target leverage. Over-levered (under-levered) firms are defined as those with positive (negative) deviations from the target in year $t-1$. Size is the natural logarithm of CPI-adjusted sales. Financing transactions are defined as the instances when net equity issued or net change in debt exceeds in absolute value 5% of pretransaction book value of assets. The sample firms are from Compustat, and the sample period spans from 1971 to 2015. The t-statistics reflect standard errors adjusted for heteroscedasticity and firm-level clustering. Values significantly different from 0 at the 5% and 1% levels are marked * and **, respectively.

	Under-Levered			Over-Levered			
	Coeff.	t-Stat.	R^2	Coeff.	t-Stat.	R^2	p-Value of Diff.
Panel A. Persistence of Deviations by Firm Size							
Smallest	0.639**	50.7	0.236	0.522**	30.4	0.144	0.000
2	0.623**	40.7	0.209	0.586**	38.6	0.190	0.079
3	0.655**	46.6	0.228	0.579**	38.8	0.200	0.000
Largest	0.642**	32.5	0.206	0.567**	36.3	0.194	0.003
p-value for differences across all size groups	0.509			0.030			
Panel B. Persistence of Deviations by Firm Age							
Youngest	0.609**	34.2	0.199	0.541**	33.8	0.164	0.004
2	0.664**	52.6	0.246	0.598**	40.0	0.218	0.001
3	0.674**	59.1	0.251	0.611**	42.7	0.223	0.001
Oldest	0.673**	56.9	0.249	0.597**	42.0	0.240	0.000
p-value for differences across all age groups	0.012			0.008			
Panel C. Persistence of Deviations by Diversification Status							
Single-segment	0.631**	56.5	0.227	0.527**	44.8	0.150	0.000
Multi-segment	0.653**	64.3	0.217	0.594**	49.7	0.217	0.000
p-value for differences	0.167			0.000			
Panel D. Persistence of Deviations by Credit Rating							
Unrated	0.638**	70.7	0.224	0.543**	49.2	0.163	0.000
CCC+ and lower	0.291*	2.0	0.075	0.022	0.1	0.000	0.195
B and BB	0.736**	29.7	0.248	0.612**	32.6	0.230	0.000
BBB− and higher	0.691**	29.4	0.217	0.617**	37.4	0.241	0.011
p-value for differences across all rating groups	0.000			0.000			
Panel E. Persistence of Deviations by Size and Business Cycle							
Smallest and nonrecession	0.646**	45.7	0.232	0.503**	26.2	0.136	0.000
Smallest and recession	0.616**	20.8	0.253	0.589**	16.1	0.171	0.573
Largest and nonrecession	0.636**	28.0	0.202	0.593**	37.1	0.205	0.120
Largest and recession	0.672**	19.5	0.223	0.491**	10.6	0.163	0.003
p-value for differences across all size/business cycle groups	0.650			0.002			
Panel F. Persistence of Deviations by Financing Status							
No financing transaction	0.740**	188.3	0.660	0.815**	111.3	0.594	0.000
Financing transaction	0.609**	48.8	0.149	0.508**	49.9	0.129	0.000
p-value for differences	0.000			0.000			

1. Firm Size, Age, and Diversification

To assess the effect of firm size on the persistence of deviations from target, we re-estimate regression model (8) for subsamples of firms sorted into size quartiles. Panel A of Table 8 presents the estimated coefficients on lagged deviation and the R^2 for all regressions from smallest firms (row 1) to largest (row 4). Columns 1–3 present the results for under-levered firms and columns 4–6 present the results for over-levered firms. The results for the under-levered firms show similar persistence levels across the four size groups and no significant differences in the coefficients on lagged deviations. For over-levered firms, we observe that the smallest firms tend to have the least persistent deviations from the target. In addition, the persistence levels are higher for under-levered firms than for over-levered firms for all size groups, but the difference is the largest for firms in the smallest quartile. Overall, small over-levered firms have the least persistent deviations, despite higher expected adjustment costs.

In Panel B of Table 8, we report the results of estimation of regression model (8) for firms sorted into age quartiles. Among under-levered firms, the persistence of deviations, as reflected in the coefficient estimates for lagged deviation and R^2, is the lowest for the youngest quartile. It is higher and similar across the 3 quartiles with older firms. Similarly, among over-levered firms, the firms in the youngest quartile tend to have the least persistent deviations from the target. Consistent with our previous findings, the persistence levels are higher for under-levered firms than for over-levered firms for all age groups. Overall, younger firms have the least persistent deviations, especially when over-levered.

In Panel C of Table 8, we report the results of estimation of regression model (8) for firms classified by diversification status. Firms that have multiple business segments are classified as diversified. The results show that over-levered single-segment firms have the least persistent deviations (lowest coefficient estimates on lagged deviation and R^2).

The finding that over-levered small, young, focused firms have the least persistent deviations from target is most consistent with the hypothesis that low persistence of deviations in these cases is driven by high costs of remaining over-levered (expected costs of financial distress). The expected costs of financial distress are likely to be higher for such firms due to their typically more uncertain cash flows as well as higher growth opportunities and, hence, a higher likelihood of facing the debt overhang problem.

These findings do not seem consistent with the hypothesis that the persistence of deviations from target for these firms is driven by adjustment costs because small, young, focused firms are typically considered as more financially constrained and are likely to face higher adjustment costs than large, old, or diversified firms. There is a scenario, however, in which adjustment costs could be a factor in the low persistence of leverage for such firms. Given their typically high investment opportunities, which far exceed their internal resources, such firms may frequently need to raise external financing. When raising funds for their investment projects, the incremental cost of choosing the type of financing that would allow them to adjust their leverage to target is likely to be low (Faulkender, Flannery, Hankins, and Smith (2012)).[19]

2. Credit Rating

In Panel D of Table 8, we report the results of estimation of regression model (8) for firms classified based on their credit rating: unrated firms, firms in significant danger of default (CCC+ and lower), speculative-grade firms (B− through BB+), and investment-grade firms (BBB− and higher). The lowest level of persistence is observed for firms in significant danger of default (CCC+ and lower), especially those classified as over-levered, who show 0 persistence within 1 year. This is not surprising as these firms face high probability of default and have the most to gain from deleveraging their capital structure. It is also possible that low-rated firms that are unable to deleverage end up bankrupt and drop out of our sample, which would reduce the estimated persistence. We also observe that over-levered unrated firms show less persistent deviations than those rated speculative (B− or higher) or investment (BBB− or higher) grade. This could be because the expected costs of excess leverage are higher for unrated firms.[20] Alternatively, assuming unrated firms do not issue bonds while all rated firms do, it could be that it is easier (cheaper) to pay down bank debt than to reduce the amount of outstanding bonds. This would be consistent with the hypothesis that persistence of the deviations is affected by adjustment costs.

3. Business Cycle and Firm Size

In Panel E of Table 8, we report the results of estimating regression model (8) across recession and nonrecession periods. We obtain the business cycles information from the National Bureau of Economic Research (NBER) *Business Cycle Expansions and Contractions*. During our sample period, NBER identifies the following periods of economic recessions: Jan. 1980–July 1980, July 1981–Nov. 1982, July 1990–Mar. 1991, Mar. 2001–Nov. 2001, and Dec. 2007–June 2009. We define any fiscal year with at least 1 month that coincides with an NBER recession as a recession year.

The results for under-levered firms show that, while there are slight variations in the coefficient estimates on lagged deviations and the R^2 of the regressions, both large and small firms demonstrate similar persistence levels across the business cycle. For over-levered firms, we observe that the smallest firms tend to exhibit substantially more persistence in deviations from the target in recession years compared to nonrecession years. In contrast, the largest firms tend to exhibit substantially less persistence in deviations from the target in recession years compared to nonrecession years.

The finding that small over-levered firms have more persistent deviations in recessions while large over-levered firms have less persistence in recessions implies that financial constraints impede leverage adjustments for small firms

[19] Indeed, in untabulated results we do observe that small firms and young firms have higher net financing levels than large firms and old firms. However, over-levered young/small firms, which exhibit the lowest persistence in Table 8, have lower overall net financing than under-levered young/small firms.

[20] Faulkender and Petersen (2006) show that unrated firms tend to be smaller, younger, and have higher asset risk relative to rated firms.

whereas large firms enjoy financial flexibility that allows them to reduce their excess leverage in recessions when the costs of such excess leverage could be higher. This finding is consistent with Covas and Den Haan (2011), who find that equity issuance is more procyclical for smaller firms but is countercyclical for very large firms.

C. Financing Transactions

Last, we examine the persistence of deviations from target debt ratios in years when firms undertake at least one of the following corporate financing transactions: equity issue, equity repurchase, debt issue, and debt reduction. As discussed previously, fixed transaction costs may deter firms from adjusting to their leverage targets. However, for a firm undertaking a financing transaction (e.g., to finance an investment project), the financing cost is largely sunk (Faulkender et al. (2012)). As a result, the marginal cost of choosing the type of financing that would allow the firm to offset its deviation from the target should be low.

In Panel F of Table 8, we present the estimation results for regression model (8), separately for years with and without major corporate financing transactions. We follow the prior literature and define major transactions as net debt or net equity issuance or repurchase in excess of 5% of pretransaction firm assets.[21] Consistent with our conjecture, the persistence of deviations from target leverage is substantially lower in years with corporate financing transactions than in years without such transactions. Further, we observe a more significant decline in persistence for over-levered firms, consistent with our prior findings. Specifically, the coefficient on the lagged deviation is 0.815 for firms with no major financing activities and 0.508 for firms with financing activities. Among under-levered firms, these coefficients are 0.740 and 0.609, respectively.

To summarize, our results in this section show that adjustments to targets are more likely when adjustment costs are lower and when a firm's market value is more sensitive to deviations of leverage from target, both consistent with the implications of dynamic trade-off models.

VIII. Conclusion

Our analysis of corporate capital structure dynamics starts with estimating rolling fixed-effects regressions to generate time-varying proxies for leverage targets and separating the observed leverage ratios into estimated targets and deviations from targets. We then replicate DeAngelo and Roll's (2015) results on the persistence of observed leverage ratios and use the same methodology to assess the persistence of estimated targets and deviations from targets.

We find that the estimated target leverage ratios are far more persistent than observed leverage ratios, which in turn are substantially more persistent than estimated deviations from targets. For an average firm, the persistence of deviations from target is virtually 0 at a 3-year horizon. These findings strongly support the

[21]Equity issues are defined as cases in which net equity issued is greater than 5% of pre-issue assets. Equity repurchases are cases when net equity issued is lower than −5% of pre-repurchase assets. Debt issues are defined as cases when net change in debt is greater than 5% of pre-issue assets. Debt repurchases are cases when net change in debt is lower than −5% of pre-repurchase assets.

dynamic rebalancing behavior (Fischer et al. (1989), Leary and Roberts (2005)) and are inconsistent with the view that leverage dynamics are driven by persistent shocks to leverage originating (e.g., in equity markets; Baker and Wurgler (2002), Welch (2004)).

Although our estimated leverage targets are the most persistent component of observed leverage ratios, they are more time varying than the typical leverage target estimates used in prior literature. Further, with their time-varying characteristics, our estimated targets and the deviations from these targets fall within the range of most credible capital structure models identified by DeAngelo and Roll (2015) through simulations.

Our cross-sectional analysis of variations in persistence of deviations based on deviation characteristics, firm characteristics, and the business cycle supports the view that adjustment costs are an important determinant of adjustment behavior (Leary and Roberts (2005), Faulkender et al. (2012)). However, we further find that costs of deviating from target are also significant determinants of the propensity to offset deviations from target and, hence, leverage dynamics. These results are particularly strong when leverage ratios are above the estimated targets indicating that firm value is much more sensitive to changes in leverage when firms are over-levered than when they are under-levered.

Overall, our findings support the notion that firms set time-varying targets and actively engage in adjustments when deviating from these targets with an intensity that varies significantly across firms and across the business cycle. The variations across firms and cycles are consistent with cross-sectional differences in adjustment costs and the value of getting closer to target.

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