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A Multilevel Index of Heterogeneous Short-term and Long-term Debt Dynamics

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A multilevel index of heterogeneous short-term and long-term debt dynamics

Maria Elena Bontempi [a], Laura Bottazzi [b], and Roberto Golinelli [c]

Abstract

We have created a novel index that classifies U.S. public firms by their leverage choice. Our statistical approach to the construction of this index considers the interaction of all firm characteristics and unpredictable events that shapes the observed leverage choices. We have subsequently associated our estimates of the degree and persistence of short-term and long-term debt fluctuations with pecking-order, market-timing, and static and dynamic trade-off theories. Our index reveals that: (i) one-third of firms have a stationary leverage target, (ii) adjustments to targets are faster for short-term debt, and (iii) the persistence of long-term debt ratios is driven by investment constraints and market conditions.

[a] Corresponding author.
Department of Economics, University of Bologna,
Strada Maggiore, 45
40125 Bologna (Italy)
mariaelena.bontempi@unibo.it
https://www.unibo.it/sitoweb/mariaelena.bontempi

[b] Department of Economics, University of Bologna and IGIER-Bocconi, Italy, l.bottazzi@unibo.it and laura.bottazzi@unibocconi.it
[c] Department of Economics, University of Bologna, Italy, roberto.golinelli@unibo.it

1. Introduction

The present study proposes a new index that contributes towards the achievement of a primary goal of research into the dynamic nature of corporate capital structure, namely the identification of sub-samples of firms with homogenous borrowing behaviour from a population of heterogeneous companies. Identifying such sub-samples is of paramount importance, since there are theoretical arguments as to why firms change their debt ratios that are not backed by clear empirical evidence when tested in aggregate samples (Shyam-Sunder and Myers, 1999, and Frank and Goyal, 2008).

A first issue concerning the aforementioned unidentified heterogeneity regards those explanatory variables of corporate debt that can have opposite effects depending on whether corporate capital structure theory envisages the existence, or the absence, of an optimal debt ratio. For example, Danis et al. (2014) distinguish between firms at refinancing points (quarters in which debt issuance exceeds a percentage threshold), and firm-quarters with little or no debt adjustment, and show a positive relation between debt ratio and profitability in the former case, and a negative one in the latter case. It is worth noting that the effect of profitability on debt, estimated over the aggregate, can be either non-significant or biased. Other examples, proposed by the literature (Frank and Goyal, 2003, Lemmon et al., 2008, Antoniou et al., 2008, Chang et al., 2014, and Zhou et al., 2016 to mention just a few), base the identification of the groups of homogeneous companies on specific variables and their thresholds denoting company characteristics, such as size, performance rating, default risk, institutional context, ownership structure and the cost of equity.

A second issue deriving from unidentified heterogeneity regards the speed of adjustment (SOA) driving capital structure dynamics – which may range from zero (no target) to high values (rapid movement towards the target). Although estimated in panel datasets of companies, the SOA is supposed to be unique for all companies/periods, and for this reason its estimate is affected by a poolability bias (Graham and Leary, 2011). As far as we know, very few papers have offered a (partial) account of this question. Elsas and Florysiak (2011) acknowledge the need to avoid estimating a unique SOA parameter in companies facing different adjustment costs, although they introduce a pooled estimator. Frank and Shen (2014) estimate individual target debt ratios using common factors, but again they assume pooled SOAs towards these targets. Leary and Michaely (2011) recognize the importance of considering firm-specific adjustment speeds, albeit in a model explaining dividend smoothing towards a target which is proxied by median dividends.

Our index derives from fully *heterogeneous* dynamic specifications in the SOA that deal with possible non-stationary debt ratios using an approach that simultaneously considers firm-specific characteristics, unpredictable events that shape observed leverage choices, and different debt maturities (long-term and short-term). In other terms, our index is based on between-firm, within-

firm, and maturity-related heterogeneity in the debt ratio behaviour obtained from statistical insights into the poolability of slope parameters, that go well beyond the additive heterogeneity captured by the firm-specific effects used by the empirical literature based on panel data. This is why the index offers several advantages. It has the undoubted advantage of not depending on the evolution of firm-specific attributes measured by variables/thresholds that simultaneously cause, and are affected by, the debt ratio. Hence, it is not subject to the bias from endogenous selection that contributes, in the words of Welch (2012), to the confusion about which variables are endogenous and which are exogenous in quantitative capital structure research.

Additionally, our index is broad enough to consider economic upturns or downturns, business cycles, competitive challenges within the market, and all those other factors affecting a company during its lifetime, that may result in the non-stationarity of its debt ratio. This aspect is quite important in DeAngelo and Roll (2015), who claim that leverage spikes and long drifts suggest there is much yet to be learnt about whether, or in what way, capital structure is stable.

Another innovative aspect of our index is the creation of debt-specific indicators and the comparative assessment of the long- and short-term debt ratios' behaviour. Most empirical literature estimates the behaviour of the total debt ratio, whereas the dynamics of the two components are driven by quite different factors and differ across companies. Custódio et al. (2013) show that corporate long-term debt has decreased in the US over the past three decades, and that this trend is heterogeneous across firms: the shortening of debt maturity was generated by firms with higher information asymmetries (low tangibility and R&D-intensive small firms), and by new firms issuing public equity in the 1980s and 1990s. Short-term debt arguably exposes borrowers to roll-over risk and covenant violations, and thus can exacerbate financial crises as well as credit and liquidity shocks (Benmelech and Dvir, 2013). Choe (1994) finds evidence that expected common stock returns are positively related to the extent of short-term debt financing, possibly because an increase in short-term debt displaces the same amount of long-term debt. The consequent increase in the expected returns on common stocks is possibly due to the transfer of risk from long-term debtholders to shareholders.

As a final advantage, our index confirms the evidence and predictions about zero-leverage firms discussed in Strebulaev and Yang (2013), and in Kieschnick and Moussawi (2018).

We base our findings on U.S. corporations observed over the period 1950-2011, and we use the sub-samples of firms identified by our index to estimate, and comparatively evaluate, the performance of a benchmark dynamic model for both long- and short-term debt ratios. Our benchmark model extends the one in de Jong et al. (2011), which is broadly representative of the standard models used by the empirical corporate finance literature, and offers enough flexibility to be

compatible with different underlying behavioural hypotheses, such as those in Auerbach (1985). The surveys conducted by Graham and Harvey (2001), Brounen et al. (2006), Frank and Goyal (2008), Parsons and Titman (2008), and Graham and Leary (2011), all support our chosen explanatory variables (for a pedagogical point of view, see Miglo, 2012).

The rest of the paper is organized as follows. Section 2 contains a general specification encompassing the linear and nonlinear models proposed by the empirical literature on capital structure. Section 3 presents the two-steps strategy followed in constructing the index. Five heterogeneous Cases on debt dynamics and non-stationarity are estimated and compared with the extant empirical literature on corporate capital structure. The second step is set out in Section 4, where the new index is presented, discussed and used to compare the performance of the benchmark model across clusters of firms with homogeneous borrowing behaviour. Section 5 summarises and discusses our findings, and concludes by outlining further possible developments of our research. The methodological aspects are set out in Appendix A1, while the data and the variables are presented in Appendix A2.

2. The general model nesting the empirical literature on capital structure dynamics

From the seminal works of Myers (1977), Taggart (1977) and Auerbach (1985) to the recent studies by Frank and Shen (2014, 2017) and DeAngelo and Roll (2015), significant empirical research has been (and is still) devoted to assessing whether a firm's debt ratio fluctuates or not around an optimal target, that is, whether its SOA is either significant or zero.

Since Bontempi (2002), SOAs estimates have been interpretable in terms of firms' behaviour. SOAs significantly different from zero imply Trade-Off (TO) behaviour (e.g. Bradley et al., 1984, Jensen and Meckling, 1976, Jensen, 1986, Harris and Raviv, 1991, Hackbarth et al., 2007), indicating that firms have optimal debt ratios which they have established by balancing the advantages and the costs of debt. SOAs close to zero, on the other hand, denote either Pecking-Order (PO) behaviour (Myers and Majluf, 1984, Leary and Roberts, 2010, Lambrecht and Myers, 2012), whereby companies borrow in order to meet the need for investment financing, when internal funds prove insufficient, and/or Market-Timing (MT) behaviour (Baker and Wurgler, 2002, Alti, 2006, Elliott et al., 2007), suggesting that the debt ratio changes in order to 'time the stock market' in the case of those companies issuing equities, when they perceive the market as advantageous. Note that the interpretation of the effects of the control variables changes depending on the underlying theories: going back to the Danis et al. (2014) example given in the Introduction, the theoretical predictions in terms of profitability are: a positive effect on debt ratio under TO, and a negative effect on debt ratio under PO and MT.

Hence, much of the empirical literature on corporate capital structure dynamics may be summarized by the following reduced-form[1] representation of debt ratio changes, ΔL, for a panel of firms $i = 1, 2, ..., N$ observed over a sufficiently lengthy time span $t = 1, 2, ..., T$:[2]

$$\Delta L_{it} = \eta_{it} + \gamma'_{it} X_{it}^{PO/MT} + \alpha_{it}(L_{it-1} - L^*_{it-1}), \qquad \text{with: } L^*_{it} = \beta'_{it} Z_{it}^{TO} \qquad (1)$$

where L and L^* are, respectively, the observed and the optimal debt ratios; $X^{PO/MT}$ is a vector of variables that may affect the short-term dynamics of the debt ratio, as suggested by the PO (for example, the need for investment not funded by retained earnings) and by the MT (for example, the timing of the equity markets); Z^{TO} is a vector of variables identified by the TO as those able to determine the optimal debt ratio (the benefits of borrowing, such as tax savings due to the deductibility of interest paid and to monitoring managers, and the costs of borrowing, such as those associated with default risk and agency costs).[3] The parameters γ, α, and β measure the impact of the PO/MT/TO explanatory variables on the debt ratio. The term η captures any unobservable determinant of change in the debt ratio, and it is included to avoid biases due to the omission of relevant variables.

Alternative specifications proposed by the empirical literature are nested in model (1). Below we highlight the pros and cons of these models, Table 2 of Section 3 will survey the related empirical literature and link it to our methodology.

According to the linear approach (LA), the slope coefficients are assumed to be poolable, while heterogeneity is accounted for by the three components of η: individual effects, μ_i, macroeconomic cross-sectionally correlated time effects, τ_t, and idiosyncratic shocks, ε_{it}.[4] The assumptions in (2), substituted in the general specification (1), lead to model (3):

$$\gamma_{it} = \gamma; \alpha_{it} = \alpha; \beta_{it} = \beta; \eta_{it} = \mu_i + \tau_t + \varepsilon_{it} \qquad (2)$$

$$\Delta L_{it} = \mu_i + \tau_t + \gamma' X_{it}^{PO/MT} + \alpha\left(L_{it-1} - \beta' Z_{it-1}^{TO}\right) + \varepsilon_{it} \qquad (3)$$

Note that the slope parameters γ, α, and β in model (3) are assumed to be fixed across individuals and over time, meaning that all firms are assumed to adjust at the same constant speed α.

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[1] In what follows, we focus on reduced-form approaches, and not on dynamic structural models of capital structure. A powerful paper on structural modelling of capital structure is Korteweg and Lemmon (2013).
[2] As is quite usual in the literature, equation (1) explains borrowing by individual firms as a continuous process of changes in debt ratios, rather than discrete issuances and repurchases. For the latter point of view, see Eckbo and Kisser (2014).
[3] Note that throughout the paper, we make the implicit assumption that capital structure is in fact a choice variable for firms. However, leverage, investment, and pay-out cannot all be choice variables, as one must be the residual. PO and TO assume that pay-out is the residual. In contrast, Lambrecht and Myers (2012, 2017) assume that leverage is the residual in modelling the interaction between borrowing, investment and payout within a dynamic agency model. Whited (1992), and Hennessy and Whited (2007) are other works exploring the interdependence of investment, dividends and debt.
[4] The role of the time dummies is discussed in Appendix A1.3.

The statistical significance of the SOA is generally interpreted as "target adjustment behaviour" or "validity of TO model": a non-zero SOA supports the existence of an optimal debt target, as argued by TO theory. However, not much attention is paid to the fact that SOA point estimates – usually ranging between -0.15 and -0.35 – suggest amazingly slow speeds of adjustment: a SOA pooled estimate equal to -0.25 means that *all* firms in the sample manage to bridge 90% of the gap between actual and target debt within the space of about 8 years.[5]

These unconvincing results led a strand of literature to review model (3). Several papers propose nonlinear approaches (labelled as NLA), whose results have been seen as being more reliable than those of the linear model. The main nonlinear variants of model (3) allow for alternative parameter-shifting mechanisms, ranging from the traditional variables' interactions to maximum likelihood estimates of regime-switching models (with threshold parameters or driven by thresholds of intervention).[6] In symbols, non-linearity implies the replacement of the assumptions (2) in model (1), with the following assumptions (4):

$$\gamma_{it} = \gamma(W_{it}^k); \ \ \alpha_{it} = \alpha(W_{it}^k); \ \ \beta_{it} = \beta(W_{it}^k); \ \ \eta_{it} = \mu_i + \tau_t + \varepsilon_{it} \tag{4}$$

Under this specification, the parameters γ, α, and β are no longer considered fixed over time and across individuals, but they evolve as a function of some $k = 1, ..., K$ determinants W_{it}^k that are either firm- or industry- or macroeconomic-specific. For example, in the simple case of a model with interactions, the SOA is modelled as a linear function of the K drivers in W_{it}^k, i.e. as $\alpha_{it} = \alpha + \sum_{k=1}^{K} \alpha_k W_{it}^k$, where α is the linear SOA of model (3) when $\alpha_k = 0 \ \ \forall k$ (i.e. without SOA shifts). The W_{it}^k determinants are usually related to transaction and adjustment costs.

This NLA literature is, however, based on two assumptions: first, that the TO theory is a valid representation of the data; second, that parameter heterogeneity is solely driven by a few *a priori* known variables in W_{it}^k. This strand of literature still assumes stationarity and parameter poolability, and nonlinear dynamics are introduced at the price of further assumptions regarding the selection of W_{it}^k. As an alternative to interactions, some authors compare the estimation results coming from subsamples of firms, with potentially different adjustment costs. But again, the *ex-ante* selection/definition of subsamples cannot prevent results from being affected by an invalid assumption of SOAs' poolability.

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[5] The misunderstanding in the literature assuming poolability is well represented by quotes such as: "A SOA coefficient estimate of 25% [i.e. α = -0.25 in model (3)] means that it takes the average firm 2.4 years to recover half of the target leverage deviation [...].", Eckbo and Kisser (2014, note 2). The *a priori* assumption of SOA poolability implies that not the *average* firm but *every* firm in the sample reacts so slowly.

[6] DeAngelo and Roll (2015) label the latter as "target zone models".

Although the assumptions of poolability and stationarity could be motivated by the need to deal with a simple and treatable model, several drawbacks emerge. Using thousands of observations to estimate a few pooled parameters can lead to considerable variability and to apparently very precise estimates of γ, α, and β, since small standard errors unavoidably inflate the SOA's statistical significance.[7]

A more serious drawback is that the assumption of poolabity ignores heterogeneity, non-stationarity and their consequences for the estimates. To show the effect of the invalid assumption of homogeneity, let us suppose that PO/MT/TO driving forces have firm-specific parameters, assumed, without any loss of generality, to be constant over time:[8]

$$\gamma_{it} = \gamma_i; \ \alpha_{it} = \alpha_i; \ \beta_{it} = \beta_i; \ \eta_{it} = \mu_i + \tau_t + \varepsilon_{it} \tag{5}$$

By substituting assumptions (5) in equation (1), we obtain the heterogeneous counterpart of model (3):

$$\Delta L_{it} = \mu_i + \tau_t + \gamma_i^{'} X_{it}^{PO/MT} + \alpha_i \left(L_{it-1} - \beta_i^{'} Z_{it-1}^{TO} \right) + \varepsilon_{it} \tag{6}$$

Hence, if assumptions (5) are true, the pooled model (3) becomes:

$$\Delta L_{it} = \mu_i + \tau_t + \gamma' X_{it}^{PO/MT} + \alpha \left(L_{it-1} - \beta' Z_{it-1}^{TO} \right) + \\ \varepsilon_{it} + \left[\delta_i'^{PO/MT} X_{it}^{PO/MT} + \delta_i L_{it-1} - \delta_i \beta' Z_{it-1}^{TO} - (\alpha + \delta_i) \delta_i'^{TO} Z_{it-1}^{TO} \right] \tag{7}$$

where the squared brackets contain the error components due to the neglected heterogeneity.

Regardless of whether linear or nonlinear dynamics are used, the pooled estimates of model (7) remain inconsistent because the explanatory variables in the first row are correlated with the composite error term in the second row. Non-linearity cannot solve the omitted variables bias arising from invalid restrictions of poolability; neither can the use of instrumental variables estimators solve this bias, since any relevant instrument would be inevitably correlated with the error term.[9] The difficulties in finding valid ways of dealing with endogeneity, together with the cumbersome interpretation of many parameter estimates relating to (sometimes ad hoc) explanatory variables, represent critical aspects of pooled estimates. Moreover, the correlation between the debt ratio and the determinants of its target does not necessarily corroborate the validity of TO predictions, as it can

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[7] As outlined by Iliev and Welch (2010, p. 2) "Ironically, the main challenge in this literature could be viewed as not too much, but too little estimation uncertainty".

[8] If the temporal span is long enough, the firm-specific slope parameters can also change over time for a given firm. The assumption of time-invariance will be validated in Appendix A1.6, by estimating the models we propose over recursive and rolling samples.

[9] See Imbs et al. (2005). If we define the heterogeneous parameters of model (6) as: $\gamma_i = \gamma + \delta_i^{PO/MT}$, $\alpha_i = \alpha + \delta_i$, and $\beta_i = \beta + \delta_i^{TO}$ where the deterministic or stochastic δ terms are the distances between pooled and heterogeneous effects, the poolability restrictions can be tested as: $H_0: \delta_i^{PO/MT} = \delta_i = \delta_i^{TO} = 0, \forall i$. Under the null, the expression in the squared brackets of model (7) vanishes, and the specification collapses in model (3).

also be detected with simulated data where the debt ratio is generated independently of any target (see Shyam-Sunder and Myers, 1999, and Chang and Dasgupta, 2009).

As a matter of fact, the empirical findings based on the pooled models cannot provide clear and robust inferences regarding the SOA's measurement, which remains a puzzle if model parameters are heterogeneous.

3. A new methodology: univariate heterogeneous models (the first step)

We propose a new method of representing heterogeneous debt ratio dynamics based on two steps. In this Section, we use the parsimonious univariate representation of each firms' debt ratio dynamics as a way of simultaneously estimating fully *heterogeneous* SOAs and testing for *stationarity*. In the next Section 4, the outcomes of said tests are used to construct a *multilevel index* designed to separate firms on the basis of the capital structure theory they adhere to. We show that our index is capable of grouping companies in clusters characterised by homogeneous borrowing behaviour, whereby pooled models can be estimated.

From a methodological point of view, the firm-by-firm estimates of model (1) represent the application of the new techniques for dynamic panel data models described in Phillips and Moon (2000), and facilitate the study of individual debt ratio behaviour over time. A second advantage of firm-by-firm regressions is that they provide heterogeneous parameter estimates.[10] A third advantage is the possibility of testing firm-by-firm debt non-stationarity and of using the outcomes as the most effective way of classifying the cross-sectional units of a panel.[11] Our unit root approach is also supported from the economic point of view: as DeAngelo and Roll (2015) argue, leverage spikes and long drifts suggest that there is still much to be understood regarding whether, and in what way, capital structure is stable. Bontempi and Golinelli (2012) use panel unit root tests to establish the prevalence of non-stationary debt ratios in the case of Italian firms, and they suggest, as a possible direction for future research, the use of individual unit root tests to better qualify the debt ratio dynamics. From a macroeconomic point of view, Canarella et al. (2014) find that the financial crisis and the Great Recession play a key role in non-rejecting the unit root hypothesis for the debt ratios of ten economic sectors in which publicly traded US companies operate.

Three conditions are required for consistently estimating model (1) in finite samples: parsimonious and flexible representations of individual debt ratio dynamics; assumptions regarding the stationarity of TO/PO/MT determinants in order to define targets and short-term adjustments;

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[10] Heterogeneous estimates are the basic ingredient of the unbiased mean estimator of Pesaran and Smith (1995) and Pesaran et al. (1999).
[11] See also the discussions in Chortareas and Kapetanios (2009) and in Costantini and Lupi (2014).

considerations relative to the minimum time span, T_i, required for each ith company. The discussion of the quantitative and qualitative aspects of the first step is set out in the methodological Appendix A1.

Here we would point out that comparing alternative representations of debt dynamics and the performance of the associated unit root tests over different time spans, is the best way of considering all the models surveyed in Section 2, and of ensuring robustness. In fact, in order to overcome the limitation whereby "one theory alone is unlikely to be able to make sense of all data variation" (Danis et al., 2014, p. 430), and the criticism from Graham and Leary (2011) that debt dynamics are mispecified in the aggregate, we propose five parsimonious representations of debt dynamics, labelled as **Cases**, together with specific unit root tests for each Case:

A1/ADF and **A1**/DF-GLS: stationary TO drivers with linear SOAs;

A2/BvD and **A2**/KSS: stationary TO drivers with nonlinear SOAs;

B1/BT1 and **B1**/BT2: non-stationary TO drivers inducing breaking debt ratio targets;

B2/mean: non-stationary TO drivers with firms adjusting their debt ratios towards average ratios by industry/group;

C1/EG, **C1**/BO-BA and **C1**/JO: non-stationary TO drivers inducing non-stationary debt ratio targets through cointegration.

These five Cases, together with the ten corresponding unit root and cointegration tests, encompass and extend the empirical literature on capital structure dynamics, as shown in part *a* of Table 1; they range from linear SOAs (LA) to nonlinear SOAs (NLA), assume industry-specific targets (LMA) and firm-specific breaks, and end with the cointegration analysis of non-stationary debt ratio targets and their drivers. The overall comparison of the outcomes of all these different tests, and the corresponding SOA estimates, together provide original, robust evidence of the degree of heterogeneity in the target-adjustment dynamics.

Table 1a and 1b here

Overall, our Cases represent a valid specification under both stationary and nonstationary debt ratios, since they distinguish between transient and persistent shocks to debt ratios. Cases **A1-B2** are based on parsimonious, flexible representations of each firms' debt ratio dynamics, that do not need to estimate firm-specific and time-varying targets as functions of many - often unobservable – drivers. Without any loss of generality, we can in fact assume that PO/MT and TO determinants $X_{it}^{PO/MT}$ and Z_{it}^{TO} admit the valid autoregressive Wold representations:

$$a_i(B)X_{it}^{PO/MT} = \varepsilon_{it}^{PO/MT}$$
$$b_i(B)Z_{it}^{TO} = \varepsilon_{it}^{TO} \tag{8}$$

where the heterogeneous inertia characterizing the PO/MT and TO drivers is measured by the $a_i(B)$ and $b_i(B)$ polynomials in the backshift operator B, and by the random shocks $\varepsilon_{it}^{PO/MT}$ and ε_{it}^{TO}. Representations (8) prevent many of the estimation problems discussed in Section 2, and more importantly they allow for various modelling options, depending on the stationary/integrated status of the data generation process of $X_{it}^{PO/MT}$ and Z_{it}^{TO}.

Several studies suggest the stationarity of the PO/MT determinants: Raymar (1991) and Sarkar and Zapatero (2003) introduce theoretical models where earning processes are heterogeneous but mean-reverting; Alti (2006) shows that the impact of market timing on the debt ratio vanishes after two periods, and such limited persistence of MT shocks justifies the stationarity assumption on $a_i(B)$ polynomials in (8). Under stationarity, the Wold representation of the PO/MT drivers is given by $X_{it}^{PO/MT} = \frac{\varepsilon_{it}^{PO/MT}}{[1-a_i(B)]}$, where $X_{it}^{PO/MT}$ is an infinite weighted sum of the past PO/MT shocks $\varepsilon_{it}^{PO/MT}$.[12] Under the stationarity also of the TO drivers, we can substitute the Wold representations (8) into model (1) and assume $\eta_{it} = \mu_i + \varepsilon_{it}$, to obtain:

$$\Delta L_{it} = \mu_i + \alpha_{it} L_{it-1} + e_{it} \tag{9}$$

where the random error $e_{it} = \gamma'_{it}\left(\frac{\varepsilon_{it}^{PO/MT}}{[1-a_i(B)]}\right) - \alpha_{it}\beta'_{it}\left(\frac{\varepsilon_{it}^{TO}}{[1-b_i(B)]}\right) + \varepsilon_{it}$ combines the distributed lags of PO/MT and TO random shocks ($\varepsilon_{it}^{PO/MT}$ and ε_{it}^{TO}) with the idiosyncratic shocks ε_{it} to the debt ratio. Hence, the parsimonious linear model for the debt ratio with heterogeneous SOA parameters α_{it} is the AR(p_i+1) process:

$$\Delta L_{it} = \alpha_{it} L_{it-1} + \mu_i + \sum_{j=1}^{p_i} \lambda_{ij} \Delta L_{it-j} + \nu_{it} \tag{10}$$

where the error terms ν_{it} are white noise errors, unrelated to lagged debt ratios, L_{it-1}, because the possible serial correlation in the errors e_{it} of equation (9) is dealt with, in equation (10), by the parameters λ_{ij} measuring the reduced-form dynamics of PO/MT and TO shocks through the p_i firm-specific lags of the dependent variable.

Of course, an interpretation of all the Cases exists, as given in part *b* of Table 1, and the construction of our index is based on this interpretation (the second step). The benchmark is represented by Case **A1**/ADF, where firm-specific idiosyncratic events have permanent effects on the debt ratios of non-targeting PO/MT companies (in the second column of Table 1b). Companies adopting TO behaviour, target the firm-specific optimal debt ratio, L_i^*, and change their borrowing behaviour so as to bridge the gap between optimal and actual debt ratios over the long term, while

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[12] Under nonstationary PO/MT drivers, the changes in debt ratios would also be nonstationary, and by definition their levels L_{it-1} integrated of order two, I(2), a data feature that has never been witnessed in any company ratios. Furthermore, I(2) levels prevent the insurgence of a relationship between L_{it-1} and Z_{it-1}^{TO}. Thus the target adjustment dynamics largely used in the empirical literature need completely reviewing.

firm-specific events occurring over a short period have only transitory effects (shown in the final column of Table 1b). Case **A1**/ADF recognizes $\alpha_i = 0$ (PO/MT behaviour) in the population when the null hypothesis is not rejected (top-left cell of Table 1b), meaning that the debt ratio of the ith firm does not move toward its firm-specific target, but rather it displays a stochastic trend driven by a sequence of reduced-form shocks v_{it} faced year after year by the company that permanently affect debt ratio levels; of the different components of v_{it}, the PO/MT shocks $\varepsilon_t^{PO/MT}$ measure the need for external funds to finance investment projects (in the PO case), or the outcome of timing the market (in the MT case). Similarly, Case **A1**/ADF recognizes $\alpha_i < 0$ (TO behaviour) in the population when the null hypothesis is rejected (bottom-right cell of Table 1b), meaning that debt ratios and Z_{it}^{TO} are stationary, companies borrow to gradually adjust towards their optimal debt ratios L_i^*, and the random idiosyncratic shocks v_{it} have only transient effects on the firms' financial structure.

There may be situations where the ADF test misinterprets the underlying true behaviour of companies. When $\alpha_i = 0$ in the population and the null is rejected (bottom-left cell of Table 1b), the ADF test suffers from size distortions and tends to over-reject due, for example, to moving average components in the error term of equation (10). Following the suggestion made by Haldrup and Jansson (2006), we prefer Case **A1**/DF-GLS, where we employ the test of Elliott et al. (1996), which has high power and low size distortions and works well in small samples, which is particularly important if we want to avoid the bias towards larger and older companies.[13] Case **A1**/DF-GLS will be the first Case used to construct our multilevel index. When $\alpha_i < 0$ in the population and the null is not rejected (top-right cell of Table 1b), the ADF test lacks power and tends to under-reject due to the presence of specification errors in the equation. Since distinguishing between debt targets that change every period (under the unit root null) and those that never change (under the alternative of constant debt target) can result in a rather rigid distinction, it is more realistic to contrast models where targets either change every period or change only occasionally (once or twice) when large events occur. Hence, we propose non-linear SOA (Case **A2**), non-stationary TO drivers because of breaks/shifts in the target debt ratio (Case **B1**), and other possibilities based either on by-industry averages or on multivariate approaches (Cases **B2** and **C1**). Case **B1** will be the second such Case used to construct our multilevel index. In fact, the failure to reject zero SOAs does not necessarily invalidate the TO theory, but on the contrary could be due to the lack of stationarity of Z_{it}^{TO} determinants. The level of many corporate financial ratios is described as non-stationary by, among others, Ioannidis et al. (2003), and McLeay and Stevenson (2009). Cases **B1**/BT1/BT2 consider the possibility of TO non-stationary determinants leading to changes in the targets through a class of

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[13] The quantitative and qualitative role of T_i in explaining size and power of DF-GLS is assessed in Appendix A1.2 by means of a series of Monte Carlo experiments.

parsimonious univariate breaking target models. This approach can account for the instability of corporate capital structures, as theoretically depicted in DeAngelo and Roll (2015). Furthermore, companies experience economic upturns/downturns and competitive challenges; consequently, they may adjust their debt ratios at heterogeneous speeds and experience breaks and persistent swings in their targets.

After having given reasons for the Cases, we have selected to construct the multilevel index, we would suggest that it is interesting to check the robustness of the results to the other Cases resembling those models proposed by the literature on corporate capital structure. Specifically, Case **A2** deals with possible SOA non-linearity related to the state of the debt ratio: if the SOA is higher when firms are over-levered (that is, their actual debt is above their target debt), then debt peaks may be less persistent than troughs. This asymmetric behaviour could be due to firm-specific adjustment costs (Graham and Leary, 2011), and financial distress costs and debtholder/equityholder agency problems (Titman and Tsyplakov, 2007). Case **A2**/BvD considers two different heterogeneous SOAs, α_i^- and α_i^+, when firms are under- and over-levered in period *t-1*, respectively. Case **A2**/KSS assumes that SOAs are heterogeneous and that they vary over time, increasing as the distance between firms' actual and target debt ratios increases. This Case may be considered as a heterogeneous extension of the non-linear approach adopted by Korteweg and Strebulaev (2012), who developed a stationary and poolable (S,s) model of capital structure with upper and lower refinancing thresholds: when actual debt falls within the thresholds, the firm does not feel the need to modify its capital structure.

Case **B2**/mean is based on the *a priori* assumption that firms target predetermined debt ratios, measured by the averages computed on a given grouping variable *g*.[14] The economic assumption is that the target debt ratio is driven by unmeasured TO determinants proxied by the group-specific averages. As no statistical assumptions are made regarding the features of the data generating process (DGP) of these averages, the stationarity of the average driver L_{gt} is not guaranteed. Hence, this Case is the most prone to awkward outcomes, despite its extensive usage in applied literature starting from Lev (1969).

Finally, Case **C1** is multivariate and considers heterogeneous cointegrated relationships between potentially strongly persistent (i.e. characterized by stochastic trends) actual debt ratio *L* and TO determinants. This Case is discussed in Appendix A1.5 and will be analysed in greater depth in Section 4 by estimating multivariate models using the homogeneous samples identified by our multilevel index.

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[14] The most commonly used measures are the industry-specific averages. Other suggested measures are either the firm's time-series mean of leverage (appropriate in Cases **A1** and **A2** which assume the stationarity of TO drivers), or the leverage ratio predicted by cross-sectional regressions.

3.1. Empirical results from the heterogeneous models

Since the first step is univariate, it exploits the availability of information on debt ratios over time. The data, taken from Compustat, are annual[15] and cover the period 1950-2011.[16] We compare the results from our Cases over seven balanced sub-panels, ranging from the longest (1950-2011) to the shortest (1990-2011) time span. We balance the samples with the aim of maximizing the number of yearly observations T_i for each company, while we balance over seven periods to assess the robustness of our first methodological step to the presence of a selection bias toward the oldest and largest companies.[17] To further avoid the issue of selection bias, in Section 4 (the second step of our methodology) we replicate the unit root tests on an unbalanced panel of 2,612 firms over the 1970-2011 period. Overall, the evidence of strong leverage persistence is robust across time spans. It is important to note that we define the debt ratios (total, long- and short-term) as financial debts divided by total assets, hence committing the "common sin" discussed in Welch (2011)[18] regarding the correct measure of a firm's capital structure. In our defence, this "sin" is a necessary one if we are to achieve comparability with "about half of all recently published papers" (Welch, 2011, p. 2), that is, with the literature surveyed in Section 2 and Table 1a.[19]

3.1.1 - To what extent do debt ratios revert to deterministic targets?

Table 2 summarizes the outcomes of the **A1**-**A2** and **B1**-**B2** Cases under which the univariate and heterogeneous models assume that debt targets are implicit in the deterministic components.[20] Following the suggestion of Pesaran (2012), the overall economic relevance of stationarity is quantified by the shares of firms for which unit-root tests are rejected and actual debt ratios revert to firm-specific targets. The upper panel in Table 2 refers to the short-term debt ratio, the middle panel to the long-term ratio, and the lower panel to the total debt ratio (the sum of the previous two).

Table 2 here

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[15] Details of the sample and the definition of variables are given in Appendix A2. The Stata codes used to create the multilevel index are available on the journal's website.

[16] Interestingly, during this period the use of debt by U.S. companies more than doubled, rising to 35% of total capital. And since 1970, aggregate leverage has remained above 35%, peaking at 47% in 1992; see Graham et al. (2015). The leverage of unregulated U.S. corporations, on the other hand, has decreased markedly since 1992. The greater power of institutional investors partly explains this deleveraging trend; see the insightful paper written by Grennan et al. (2017).

[17] The firms' number increases inversely with the length of the time span, from 50 companies in the case of the longest time span, to 412 companies (possibly smaller and newer) in the case of the shortest time span.

[18] Welch points out that although it is not clear whether non-financial liabilities should be considered as debt, they should never be considered as equity. Yet, the common financial-debt-to-asset ratio (FD/AT) measure of leverage commits this very mistake.

[19] In Subection 4.2 we check the robustness of the first and second steps of our approach to the use of the alternative definitions of debt ratios. See also Appendix A2 for details of the variables' definitions.

[20] Results for Case **C1** are set out in Appendix A1.5.

Our Cases are reported down the columns, and the results relative to different balanced samples along the rows. It is worth remembering that most of the literature implicitly assumes the stationarity of debt ratios. The results shown in Table 2 do not support the statistical evidence of stationarity, as all the shares are significantly below one. As regards total debt ratios, the share of target-reverting firms is constantly well below 40%, regardless of the assumptions underlying the target's definition down the columns. This fact leads to two main broad considerations. Firstly, the econometric methods used in the literature to estimate, and to make inferences regarding, SOAs suffer, at best, from substantial statistical problems, as they are unfit for data which are so persistent over time that they are often non-stationary. Secondly, the clear heterogeneity of behaviours invalidates the poolability assumption usually made in the literature, as the shares in Table 2 are never even close to either zero (all the firms do not revert to a target) or one (all the firms are target reverting with the same SOA).[21]

Therefore, studies that use unbalanced panels with an average T substantially shorter than ours produce results that depend more on cross-section variability, because of the poolability assumption, than on the specific temporal behaviour of each firm. Therefore, they spuriously inflate the evidence of a target adjustment process (TO).

Pooling the different maturities also has drawbacks, as short- and long-term debts are characterized by heterogeneous dynamics. Short-term debt is more prone to target adjustments, especially in periods when firms are over-levered. One possible explanation is that firms face short-term debt rollover risk (He and Xiong (2012)) or they face costly covenant violations. Hence, they prefer to stay close to the target when debt is high, due to their fear of not being able to refinance their short-term debt. Specifically, the share of reverting firms for short-term debt ranges from 50% (in Case **A1**) to 60-70% (in Cases **A2** and **B1**), with stationarity usually requiring only one break.

On the contrary, long-term debt seems to be driven by either non-stationary TO or PO/MT determinants. For example, the matching maturity hypothesis would suggest that long-term debt is more appropriate when financing investments, generally with realization over a period of several years, and that agency costs contribute towards determining an optimal target. On the other hand, firms also need to meet market fluctuations with the issue of long-term bonds; and random shocks to companies' cash flow and/or to the stock market cause persistent shifts in the historical trend of long-term debt ratios. This mixed evidence emerges from the survey conducted by Graham and Harvey (2001). Specifically, the share of reverting firms for long-term debt ranges from 20% (in Case **A1**) to

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[21] We also checked for the robustness of this finding by using the panel unit root tests of Im et al. (2003) and of Pesaran (2007). The unit-root null hypothesis is strongly rejected in all sub-panels. The result whereby only a portion of firms are target-reverting has also been found in Peel et al. (2004) for the UK, Bontempi and Golinelli (2012) for Italy, and Yang et al. (2014) for Taiwan and China. Symmetrically, significant shares of non-reverting firms are supported by the clear rejection of Hadri's (2000) heterogeneous panel stationarity test. Results are available upon request.

25-30% (in Cases **A2** and **B1**).[22] Long-term debt adjusts more quickly when firms are under-levered, and this behaviour supports the debt ratio ratchet effect proposed by Admati et al. (2016), and is compatible with the rebalancing process that follows conversions of convertible bonds, as suggested by Rastad (2016).

Finally, regardless of maturity, the pattern of the industry averages/medians over time cannot drive the targeting behaviour (Case **B2**, in the last two columns of Table 2). This result, in the case of total debt, is in line with Lev (1969)[23], while it is at odds with Frank and Goyal (2009) who claim that in the pooled context, the by-industry median is the most powerful factor in explaining the debt ratio.

3.1.2 - At what speed do debt ratios revert to deterministic targets?

Table 3 reports the averages of the SOAs of reverting and non-reverting firms. As suggested in Pesaran and Smith (1995) and Pesaran et al. (1999), the SOA mean group estimates (MG) for these two distinct groups of firms offer consistent estimates of aggregate SOAs, regardless of whether the individual parameters are poolable or not. Of course, the greater the difference between the two average estimates, the less likely the validity of the poolability assumptions will be.

Table 3 here

The SOA MG estimates of non-target-reverting firms is much lower than those of mean-reverting firms (less than one-third thereof), and this is true for both short- and long-term debt ratios. Interestingly, the average SOAs of non-reverting firms are in line with those obtained from models under the (invalid) assumption of poolability and stationarity. As far as low SOAs estimates are concerned, frictions can play a substantial role in shaping the cost-benefit adjustment (see for example Myers (1984) and Fischer et al. (1989)), although Welch (2004) argues that TO models with transaction costs cannot entirely account for such low SOA estimates, see also Iliev and Welch (2010). On the contrary, the average SOA estimates of mean-reverting firms are in line with those reported in Frank and Shen (2014), who assume time-varying targets as heterogeneous functions of a high number of determinants.

Therefore, we can conclude that under the hypothesis of homogeneous slopes, pooled SOA estimates are biased (i.e. the adjustment process seems slower than it is), and that at the firm-level it is important to consider time-varying, rather than static, debt ratio targets.

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[22] The share of less than 40% in the case of total debt is the result of the fact that long-term debt represents, on average, about 70% of total debt.

[23] On the basis of 245 observations made over the period 1947-1966, Lev (1969) finds that equity to total debt ratios reverts to the by-industry arithmetic mean in very few cases.

Summarising our various different approaches, linear SOA estimates (Case **A1**) are higher, in absolute terms, for short-term debt than for long-term debt, and this is in line with the previous finding of non-stationarity of long-term debt. Short-term debt changes faster than long-term debt because it is probably easier to adjust, or because it is too costly to keep at a level far from the target ratio. When we use sub-panels with shorter time spans, the average SOA for long-term debt also converges towards an estimated figure of -0.7: about 70% of the gap between actual and desired (target) debt ratios is bridged the following year. Long-term debt, rather than short-term debt, is the form of borrowing chosen when optimizing behaviours are adopted (achieving the target when stationary, financing the investment or exploiting favourable market conditions when non-stationary). Consequently, stationary long-term debt is closer to the target level, with a low speed of adjustment because re-adjustment is often unnecessary. Short-term debt is the form of borrowing used to deal with a contingent situation (a sudden need to finance an operation or an investment).

Higher speeds of adjustment are observed when we consider estimates based on asymmetric dynamics or shifts. Case **A2** estimates are summarized in five columns of Table 3: $\hat{\alpha}_i^+$ and $\hat{\alpha}_i^-$ are the average SOA estimates when, respectively, firms are over-levered and under-levered, for those companies that react more when over-levered (under the heading "$+ > -$"), have the same reaction (under the heading "$+ = -$"), and react more when under-levered (under the heading "$+ < -$"). SOA estimates of about -1 show that the gaps are bridged in one year, while SOAs of above -1 (for example -1.2) indicate that the firms are overshooting the target. The overshooting dynamics pushes firms, when over-levered, below the target in less than one year in the case of both types of debt, while the process of adjustment towards the target is quite slow for firms once they are under-levered, especially in the case of long-term debt. The overshooting is even more pronounced, for short-term debt, when firms are under-levered[24]. The preference for being over-levered with shorter debt maturity can account for the higher debt overhang effect of long-term borrowing for immediate investments, as suggested by Diamond and He (2014). When the estimates of $\hat{\alpha}_i^+$ and $\hat{\alpha}_i^-$ are not significantly different, the target-reverting process needs just a single SOA which, as expected, is very close to the one estimated by the linear model. A higher SOA, when firms are over-levered, is to be found in several papers: Byoun (2008) considers pooled SOA parameters for firms above (below) the target and with a financial surplus (deficit); Chang et al. (2014) distinguish companies according to their corporate governance; Warr et al. (2012) estimate a faster pooled-adjustment for the group of firms over-levered and overvalued in the equity market. Dang et al. (2012) find a faster adjustment in firms with large financing imbalances, large investments or low earning volatility;

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[24] We must note that being under-levered is infrequent for short-term debt, while it represents about 40% of cases for long-term debt.

Faulkender et al. (2012) find that large (in absolute value) operating cash flow drives more aggressive changes in the debt ratio in the direction of the target; Baum et al. (2014) provide evidence that risk exerts asymmetric effects on SOAs, even after controlling for financial unbalances in driving actual/target leverage deviations.[25] There are cases where studies disagree, however. For example, Aybar-Arias et al. (2012) find that firms adjust faster when the actual debt is closer to the target, because of lower adjustment costs; whereas according to Drobetz and Wanzenried (2006), firms further away from the optimal capital structure adjust more readily. Several papers also assign a role to the macroeconomic conditions: the SOA is significantly faster when such conditions are good (Drobetz and Wanzenried, 2006, Cook and Tang, 2010, and Halling et al., 2012).[26] Thus compared to our methodology, the identification of *a priori* selected groups of companies with higher SOAs is not an easy task and often leads to conflicting evidence.

When the target is proxied by a shifting process, as in Cases **B1**, the SOAs are in general above -0.80, suggesting that regardless of the term structure of debt, 90% of the adjustment process is accomplished in slightly more than one year.

The SOAs estimated for firms reverting towards industry-level targets, as in Cases **B2**, confirm that when the adjustment process is significant, it is quicker than the one estimated by pooled regressions. Lev (1969) finds that the third quartile (ninth decile) of the SOA estimates distribution is equal to -0.42 (-0.65), with t-statistics equal to -2.30 (-2.94).[27] On the contrary, the lack of reversion in the pooled context is also supported by MacKay and Phillips (2005), who find a very slow-reverting SOA estimate, equal to -0.032, barely statistically significant even though it is a pooled estimate.[28]

3.1.3- Four anecdotal examples produced using our methodology

Our empirical approach delivers single outcomes for every company in the data-set. Table 4 and Figure 1 summarize the key features of, and the results obtained for, four companies drawn from DeAngelo and Roll (2015). Specifically, the second column of Table 4 reports the coefficient of correlation between short-term and long-term debt, while the results of the test, by debt term structure (first long-term and then short-term debt), for Cases **A1**, **A2** and **B1,** are set out in the next six

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[25]In this strand of research, neither financial deficit/surplus nor equity mispricing exert PO/MT effects as explicit explanatory $X_{it}^{PO/MT}$ variables of model (3), but rather they drive the non-linear effects.

[26] The issue of the instability over time of heterogeneous parameters is considered in Appendix A1.6.

[27] When T=20, the 5% critical value of the Dickey-Fuller statistic is -3.0. Hence the share of stationary equity-to-debt ratio firms in the Lev's sample is lower than 10%.

[28] These findings playing down the role of industry determinants in accounting for capital structure are also supported by Kayo and Kimura (2011) who use a statistical multilevel approach: time-level and firm-level determinants account for 78% of leverage, while the rest is left to less relevant industry- and country- determinants. See also Hovakimian et al. (2001).

columns.[29] The four plots in Figure 1 show the time pattern of the long and short-term debt ratios by company, together with their total debt ratio and their market-to-book ratio.

Table 4 and Figure 1 here

According to our taxonomy, Standard Oil of New Jersey (Exxon Mobil) is classified as non-stationary, possibly as a PO firm, in terms of both short-term and long-term debt. As DeAngelo and Roll (2015) indicate, the company incurred substantial new debt in the late 1960s because its investment program had doubled and required more funding than was available by expanding internal cash flows.

Goodyear Tire & Rubber is classified as a stationary TO firm in terms of long-term debt by Cases **A1** and **A2** (with a high SOA when over-levered), and as reverting in relation to short-term debt by Cases **A1**, **A2** (with a higher SOA when under-levered) and **B1** (with one break); the correlation between the two types of debt is negative and very low. The slow adjustment of long-term debt when under-levered, and the adjustment with overshooting when over-levered, can be explained by the fact that this firm used borrowing to repurchase stock and deter a hostile takeover in the eighties.

Allied Chemical (Honeywell) is classified as PO in regard to long-term debt by our taxonomy, and as stationary TO in regard to short-term debt by Cases **A1** and **A2**; there is a negative correlation between short-term and long-term debt. The firm increased its debt ratio at the beginning of 1950 and then deleveraged passively over the following few years, thanks to the growth of its assets, and possibly by financing its activity through internal funds and short-term debt, which was used to cover contingent situations such as a sudden need to finance an operation (DeAngelo and Roll, 2015).

B. F. Goodrich is another company we can classify as PO in regard to long-term debt, and as stationary TO in regard to short-term debt, in all the Cases; the positive correlation between short-term and long-term debt is low. The firm borrowed to fund a $400 million capital expenditure program for the 1966-1970 period, and then deleveraged thanks to a substantial growth in assets.

These few examples should provide an idea of the deliverables of our approach and its usefulness in classifying the most relevant features of the debt ratio of each company using indicators that can be compared within and between firms.

4. A new methodology: a new multilevel index of debt ratio dynamicity (the second step)

We propose a new firm-specific multilevel indicator of the degree of dynamicity in the debt ratio, based on a combination of the outcomes of those heterogeneous tests presented in Section 3.

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[29] The correlation between the two maturities will be analysed in greater depth in Subsection 4.1.

We construct three indexes for total, long-term and short-term debt ratios, respectively. Specifically, each index exploits the insights gained from the combination of the outcomes of the linear heterogeneous model (Case **A1**/DF-GLS) with those of nonlinear-breaking debt target L^* models (Cases **B1**/BT1/BT2). The linear model, we selected was the indicator in Case **A1**/DF-GLS, because the DF-GLS test is better than the ADF test (see Elliott et al, 1996, and Haldrup and Jansson, 2006). Of the nonlinear tests, we chose to use the outcomes of those with one/two breaks in the target leverage (Cases **B1**/BT1/BT2), since they refer to models that explicitly tackle the issue of breaks in the firm-specific time series (a feature that recent literature has paid a lot of attention to; see Danis et al., 2014, and DeAngelo and Roll, 2015).

The values assumed by each index range from 1 to 5 according to the level of dynamicity of each company's debt ratio. In other terms, the order followed by our index increases as companies move away from having an optimal debt ratio. We believe that this setting is reasonable and facilitates interpretation: the number of constraints imposed on the dynamics of model (10) decreases as the index increases, and the number of values assumed by the index is related to the number of mainstream theories on corporate capital structure. The first three values of each indicator (from 1 to 3 in the first column of the upper panel of Table 5) indicate those companies whose debt ratio dynamics are in line with TO theory. The static TO model is suggested by the original framework of Merton (1974) and Leland (1994, 1998). Subsequent developments in TO theory consider the possibility that companies' fundamentals may change, and that the debt target also fluctuates over time accordingly. Therefore, the value of our indicator is 1 for the static TO companies whose target debt ratio L^* is constant over time, while for the dynamic TO companies (whose L^* can change over time) the indicator takes the values 2 and 3.[30] The last two values of the indicator (from 4 to 5 in the first column of the upper panel of Table 5) indicate those companies whose debt does not adjust toward a target, but rather fluctuates over time like a random walk. Therefore, the value of our indicator is 4 for those PO companies whose growth opportunities need to be financed with internal funds, or following PO/MT theory, is 5 when relevant shocks to the cash flow or to the equity return occur.

Table 5 here

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[30] We chose to continue considering the fact that the adjustment process envisaged by the dynamic TO theory can be affected by not just one shock forcing companies some distance from the target in question, but also by more than one such shock. This choice was driven by the desire to keep the index construction process as general as possible; in the case in question, a researcher has companies observed for a very long time so that more than one break is highly probable. Of course, it is possible to combine the one break and two breaks cases into a single value, and this is what we did when assessing the validity of the index using the estimates of the dynamic models for long-and short- term debt ratios in the sub-samples.

Table 5 shows the construction of the index and its distribution. It should be pointed out that in order to be consistent with the empirical literature and to magnify the cross-sectional variability of the panel, this second step uses an unbalanced panel of 2,612 companies covering the period 1970-2011, giving a total of 63,356 observations with an average T_i of about 24 years.[31] The distribution of companies according to the values of the indexes shows a prevalence of PO/MT behaviour in regard to the long-term debt ratio, and is bimodal for the short-term debt ratio, being polarized between dynamic TO behaviour (with only one change in target) and PO/MT behaviour.

The first advantage our index offers is that it utilises statistically sound insights into the poolability of parameters, which enable us to cluster companies in alternative subsamples which are homogeneous in terms of the degree and type of persistence of debt ratio fluctuations, and display a borrowing behaviour that may be accounted for by the theoretical models. Variables denoting firms' characteristics have been used by the literature to identify groups of homogeneous companies; however, these variables are numerous, are sometimes chosen arbitrarily, and are often difficult to measure (variables such as size, industry, ownership, rating, and default/bankruptcy risk). Additionally, we cannot ignore the fact that some companies are affected by unforeseen events that see them shift away from their standard behaviour. Being based on univariate approaches, our index implicitly considers the "final result" of the interaction of all firms' characteristics and unpredictable events, which is the observed debt ratio. Therefore, our index avoids "the confusion in empirical work about what variables are endogenous and what variables are exogenous" (Welch, 2012 p. 132).

As an additional advantage, our index is easy to compute and can be improved by further research; for example, by exploiting the outcomes of asymmetric tests (faster/slower speeds depending on being under/over-levered). Moreover, it can address other important questions such as the role of adjustment costs in accounting for the considerable persistence of debt ratios far from the target, the effects on the adjustment process of going public, and how specific types of debt can be classified under heterogeneous dynamics.

Although our index, being based on univariate approaches, is easy to compute, our method of combining different univariate tests in a single index is indiscriminate with regard to the source of the noise. Just like any other reduced-form statistical approach, our procedure gives more importance to statistical features than to structural aspects. For this reason, in Subsection 4.1 we validate our

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[31] The second step uses several explanatory variables, some of which are only available for the 1970-2011 period, with 1970 the first year usually considered by the empirical literature. To make use of the information available, and to check for robustness, we replicate the first step and follows the second step for the period 1970-2011, so as to exploit the larger cross-sectional dimension of an unbalanced panel. The requirement is that companies remain in the panel for at least 20 consecutive years. To gauge leverage behaviour over long periods, also DeAngelo and Roll (2015) focus on the subset of firms with 20 or more years on Compustat. We also performed the analyses on the balanced subsample of 161 companies over the period 1970-2011, in order to check for the robustness of our results (which are not reported but are available upon request).

index by estimating, in the subsamples identified by the index, a model for each debt ratio as a function of those explanatory variables which the literature suggests as relevant for companies with a similar borrowing behaviour.

The condition to be met in order to construct the index is the same as that to be met in order to perform heterogeneous unit root tests, namely: the availability of a sufficiently long time span T_i. From the economic point of view, this condition means that our index can classify the debt ratio behaviour of active firms that are neither affected by extraordinary operations (such as mergers and acquisitions) nor bankrupt. However, we note that these requirements are commonly used as selection rules also by the extant empirical literature.[32]

4.1 An application of the new index

We compare the results of a benchmark dynamic model (like those broadly used in the corporate finance literature) estimated over the whole sample under the assumption of poolability with the estimates in the sub-samples identified using the univariate outcomes from the Cases presented in Section 3, and in the sub-samples of homogeneous borrowing behaviour identified by our index. In addition, we compare the estimates of the benchmark model for both short- and long-term debt ratios. Running separate regressions on each group and type of debt is helpful to assess the potential usefulness of the index and the magnitude of the bias if pooled parameters for all (or some of) the explanatory variables are, instead, estimated.[33]

The specification of the two equations is:

$$\Delta L_{it}^l = \mu_i^l + \tau_t^l + \phi_c^l \Delta L_{it}^s + \gamma'^l_c X_{it}^{PO/MT} + \alpha_c^l\left(L_{it-1} - \beta'^l_c Z_{it-1}^{TO}\right) + \varepsilon_{it}^l$$

$$\Delta L_{it}^s = \mu_i^s + \tau_t^s + \phi_c^s \Delta L_{it}^l + \gamma'^s_c X_{it}^{PO/MT} + \alpha_c^s\left(L_{it-1} - \beta'^s_c Z_{it-1}^{TO}\right) + \varepsilon_{it}^s \qquad (11)$$

where l and s denote, respectively, the long-term and the short-term debt ratios (labelled as *LDA* and *SDA* in Tables 6 and 7); the ϕ^l and ϕ^s parameters capture the potential substitutability of the two debt maturities in the short run (Auerbach, 1985);[34] c denotes alternative clusters (pooled sample,

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[32] The topics regarding extraordinary operations and failure are of course extremely important but they are not the aim of the present analysis. It is to be stressed again that the requirement of at least 20 consecutive years selects operative surviving firms and not only mature and large firms. Hence it should not be affected by a relevant selection bias.

[33] Hence, our approach differs from the one used by e.g. Danis et al. (2014) who evaluate the role of refinancing on profitability only, while constraining the coefficients on the vector of the other explanatory variables to be equal across groups.

[34] These parameters can account for reduced form effects that are due, for example, to: the simultaneous issue of short-term and long-term debt as per Diamond (1991a), according to whom the share of short-term debt changes to allow good borrowers to receive some of the benefits of the good news they anticipate, without incurring the liquidation risk; the fact that a good track record in regard to monitored borrowing (bank/short-term debt) will allow the borrower to issue debt directly without monitoring (publicly traded bonds/long-term debt), as in Diamond (1991b); the possibility that firms borrow short-term when they feel that short interest rates are lower than long rates, or when they expect long-term interest rates to fall, as evidenced by the survey conducted by Graham and Harvey (2001).

sub-samples identified by the outcomes of Cases **A1**/DF-GLS, **A2**/BvD, **B1**/BT1/BT2, and sub-samples of homogeneous behaviour identified by our indexes).

The $X_{it}^{PO/MT}$ vector includes the following PO/MT explanatory variables (we report the labels in brackets and italics in Tables 6 and 7):[35] free cash flow (*fcf*, cash flow minus capital expenditures and cash dividends), financial slack (*DWC1*), R&D expenses and a dummy equal to one for observations with missing information (*rd_ta* and *rd_dum*), and the interaction of the market-to-book ratio with an index that increases with the rating of long-term and short-term debts (*mbRLDA* and *mbRSDA*). The Z_{it}^{TO} vector includes the following TO explanatory variables: cash dividends (*DIVA*), the relative cost of debt (*rcostd1*), non-debt tax shields and their interaction with positive taxable income (*ndts* and *ndts_lGAIN*), guarantees and intangible assets (*Tang* and *Intan*) and profitability (*ebit_ta*).

It is widely acknowledged that it is not easy to select and measure the variables in *X* and *Z* vectors. Frank and Goyal (2009) provide a list of 25 empirical proxies for the PO/MT/TO theoretical variables after excluding the most strongly correlated measures within the same block of determinants. Lemmon et al. (2008) reinforce the aforesaid point by stressing the difficulty of measuring the wide range of TO determinants using a limited number of relevant variables. The risks of measurement errors and simultaneity bias increase as the model size increases, while few, often weak instruments cannot effectively deal with the inconsistency of pooled estimates (see Gordon, 1985, and Auerbach, 1985). Our benchmark model (11) overcomes these difficulties and is broad enough to capture the essence of the borrowing determinants, since it is an extended version of the specifications proposed by de Jong et al. (2011), and Danis et al. (2014). Except for some variables that are specific to the maturity modelled (e.g. the *mbRLDA* and *mbRSDA* determinants), the use of the same specification across samples and debt maturities aids the comparison of results. Parameter estimates are obtained by using the GMM-LEV estimator (to deal with the issue of possible non-stationarity). To increase the efficiency of the instrumental variables estimator, and to avoid the under-rejection of the Hansen test due to instrument proliferation, our chosen instruments are the principal components extracted from three large subsets of instruments, namely: all the available lags of the two dependent variables; all the available lags of the PO/MT determinants; all the available lags of the TO determinants. Details of this principal component procedure for GMM estimates are set out in Bontempi and Mammi (2015).

Tables 6 and 7 (respectively for long-term and short-term debt ratios) bridge the MG estimates of the SOAs in Table 3 with the GMM estimates of the benchmark models (11) over the whole sample

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[35] Details of the variables' definitions are given in Appendix A2.

(in the first columns of Tables 6 and 7), through nine sub-samples defined on the basis of the outcomes of linear and non-linear unit root tests (cases **A1**/DF-GLS, **B1**/BT1/BT2 and **A2**/BvD), and four sub-samples defined on the basis of our multilevel index.[36]

Tables 6 and 7 here

If we look in general at the differences in the parameter estimates across the columns of Tables 6 and 7, and then focus on the results shown in the last four columns of each table, we note that our multilevel indicator tends to classify the companies in clusters on the basis of their homogeneous behaviour: parameter differences between groups are almost always significant with signs which are in line with the theoretical predictions. The main findings can be summarized by the following six points.

(1) SOA estimates in all the subsamples of mean-reverting companies are always lower (i.e. the speeds of adjustment towards the target are higher) than those of the non-reverting firms (this fact is in line with the MG estimates reported in Table 3);[37]

(2) SOA estimates in the sub-samples of non-reverting companies are always downward biased and, more importantly, spuriously statistically significant, as we know that these companies should have SOA point estimates quite close to (and not significantly different from) zero;

(3) The estimates of the invalidly-pooled SOA parameters over the full sample assume values - as expected – which are often close to the average of the sub-sample estimates;

(4) As far as short-term debt ratios are concerned, the speeds of adjustment are always higher than in long-term debt models, and the free cash flow effect is higher, and more related to PO considerations, than in long-term debt models;

(5) Dividends, non-debt tax shields, guarantees and profitability (which are clearly TO determinants) are more important in explaining long-term debt ratios;

(6) The same estimates in relation to the balanced sub-sample covering the 1970-2011 period, show higher SOAs, the greater short-term substitutability of the two debt maturities, more intense use of free cash flow and of financial slack, and a TO-type role for dividends. Overall, we have a list of results that are consistent with the behaviour of long-standing, quite large companies (details available upon request).

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[36] Given the frequency distribution in Table 5, we group together those companies classified as "2" or "3" by our index, in order to increase the number of observations in the "TO dynamic" sub-sample. The "TO static" sub-sample collects those firms classified as "1" by our index, the "PO" sample those firms classified as "4", and the "MT" sample those firms classified as "5". The values "2" and "3" could be used separately to capture the possibility that whereby companies observed for over a very long time span could be subjected to more than one break.

[37] The results in Frank and Shen (2017) support this finding.

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As far as the measure of the speed of adjustment commented on in points (1) and (2) is concerned, it is worth remembering that SOA estimates of about -0.15 for non-mean-reverting companies imply that the average firm takes more than 14 years to bridge 90% of the gap between target and actual debt ratios: the statistical significance of these low (in absolute terms) point estimates cannot exclude the existence of economically insignificant adjustment processes over time. Conversely, the SOA estimates of about -0.4 for mean-reverting companies suggest that a considerably shorter time (only 4 years) is required to bridge 90% of the gap.

The finding in point (4) establishes that the SOAs of short-term debt ratios are always the highest, as 90% of the gap is usually bridged in less than 3 years.

4.2 Sensitivity analysis

We check the robustness of our findings in three ways. A first set of interesting results follows the question raised in Welch (2011) as to how a firm's capital structure is to be measured (see the analysis in Welch's Table 1 on p. 9), and for this reason we have also constructed the index for other forms of debt ratio: total debt over the book value of capital, total debt over the market value of capital, total liabilities over total assets, and bank debt, bonds and leasing over total assets (the specific definitions are in Appendix A2). The results, set out in Table A2.3 of Appendix A2, can be summarized as follows.

(1) The distribution of financial debt over capital is very close to that of financial debt over assets, and the latter follows a similar pattern to that of total liabilities over assets.

(2) Bank debt resembles short-term debt, and thus it is reasonable to believe that a dynamic TO with a changing target will be the predominant financial behaviour of bank debt; since bank debt is closely held and subject to moral hazard problems between shareholders and debtholders, specific TO variables (such as collateral and profitability) play an important role in limiting the agency problems in Jensen and Meckling (1976). This component of short-term debt could also be the result of a trade-off between borrowers' private information about the future credit rating, and liquidity risk, as explained in Diamond (1991a, 1991b).

(3) Instead, bonds are very similar to long-term debt, and consequently the most noticeable feature of the index distribution for bonds is the predominance of MT behaviour. Given that bonds can be considered public debt (arm's length principle), the variables proxying the role played by information asymmetries (such as the market-to-book ratio and the rating) can help explain debt variations.

(4) Finally, capitalized leasing expenses tend to be bimodal, boasting the highest frequencies of both dynamic TO and MT. This behaviour could be related to the form of leasing contract and

to the provider of the lease (a bank or financial company more oriented towards a broad pool of financial investors). What is more interesting is the distribution of the index for the rental leverage: the classification of the index goes in the direction envisaged by Rampini and Viswanathan (2013), whereby more constrained firms suffering adverse cash-flow shocks, tend to hedge less and lease more. In other words, there is a pecking order, and firms only use lease financing if their internal funds are insufficient.

A second and important consideration concerns the behaviour of our index with regard to "all equity" firms. In our sample, the proportion of zero-levered firms, , varies across the term structure of debt: it is about 12.9%, 8.7% and 7.6%, for short-term, long-term and total debt, respectively. In general, our findings are in line with the figure of 10% reported by Strebulaev and Yang (2013) for the total debt of large public nonfinancial US firms between 1962 and 2009.[38] In the period 1970-2011, the available firm-specific time series show that the spells of zero-leverage are either long-lasting (i) or are occasional (ii). In fact, 25% of zero-leverage firms do not have any long-term (short-term) debt for 64% (50%) of the period in which we observe them, corresponding to a total duration of 15 (12) years. Also, 25% of zero-leverage firms do not have any long-term (short-term) debt over 18% (12.5%) of the period in which we observe them, corresponding to 4 (3) years.[39]

The index classifies cases (i) as either PO/MT or TO dynamic, with the latter prevailing when the duration of zero spells is the longest and the number of spells is the highest: in such cases a series of zeros can be seen as a possible "target" which the firm adheres to. Firms characterized by fewer spells and comparatively shorter zero spells are classified as PO/MT.

The index classifies cases (ii) as either TO static or PO, with a tendency toward PO the shorter the number of spells.[40] Following the indications provided by the index, we assume that consecutive positive stock market shocks or random positive shocks to free cash flow push debt close (or equal) to zero in accordance with PO or PO/MT behaviour. Our assumption is supported by the findings of Strebulaev and Yang (2013): zero-leverage firms are more profitable and have higher cash balances, pay higher dividends and have higher market-to-book ratios. This result is also reassuring in the light of the statistical issues regarding the performance of unit-root tests conducted on bounded series

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[38] Strebulaev and Yang (2013) investigate the zero-leverage puzzle, and Kieschnick and Moussawi (2018) analyse the issue further by considering the role of age and of corporate governance.

[39] On average, the duration of zero spells for zero-leverage firms accounts for 42% of the period (10.6 years) for long-term debt, and 35% of the period (8.7 years) for short-term debt; spells for zero short-term debt last a shorter time and are more frequent than those for zero long-term debt. The fact that the zeros for total debt have an average duration equal to 37% of the period (9 years) reinforces the impression that long-term debt and short-term debt are used alternatively: despite short-term debt accounting on average for 28% of total debt, the pattern of total debt indicates that when a firm resorts to short-term debt, it does not use long-term debt, and vice-versa.

[40] Note that the index cannot classify firms when affected by many lengthy spells (which is relatively more frequent with regard to short-term debt), because in this context nonlinear-breaking debt target L^* models (Cases **B1**/BT1/BT2) cannot be estimated.

affected by zeros. The presence of zero lower bounds, if unaccounted for, could jeopardize the size of the unit root tests, and the null of a unit root could be over-rejected. If that were the case, bounded I(1) processes could be interpreted as stationary I(0), simply because bounds prevent the I(1) process from drifting away from its expected value when it is close to the bounds (Cavaliere and Xu, 2014). Hence, an attenuation effect due to the lowest bound might occur, and the debt ratio could appear more stationary than it really is. Luckily, the index would indicate PO/MT behaviour for zero-leverage firms, thus avoiding the occurrence of the attenuation effect.

A third set of interesting results derives from the analysis of the link between the index and a vector of firm characteristic variables supported by, for example, Frank and Goyal (2003), Byoun (2008), Cook and Tang (2010): firm size, frequently used to capture asymmetric information problems and access to external funds; the ex-ante probability of distress measured by Altman's Z-score (Graham, 1996, 2000); the industry that, according to Frank and Goyal (2004) and Byoun (2008), acts as a proxy for several factors, including intangibility, regulation, stock variance, uniqueness, purchasing manager's sentiment index; having bond ratings and high market-to-book that, according to Byoun (2008), Whited (1992), Faulkender and Petersen (2006) and Lemmon and Zender (2004), indicate low financial constraints due to asymmetric information or growth opportunities as firms with bond ratings can borrow in the public debt markets and have lower adjustment costs than firms without bond ratings.

Since our index indicates the increasing dynamicity of the debt ratio, we test for the ability of different drivers to account for the movement of our indicator from the value of 1 to the value of 5[41], i.e. from a static TO towards a dynamic PO/MT, by using an ordered probit model estimated for both long-term and short-term debt ratios. The main findings are as follows.[42]

(1) For the long-term debt ratio, large firms (>1000 employees) tend to adopt TO behaviour.

(2) For the short-term debt ratio, small firms (<1000 employees) tend to behave according to PO theory. Having a good rating, together with a higher market-to-book ratio, further encourages PO/MT behaviour

(3) The role of non-debt tax shields (*ndts*) is difficult to establish: TO with higher *ndts* are only more likely for the long-term debt ratio and in large firms that have been profitable in the past; this finding is in line with the works of MacKie-Mason (1990) and Graham (2003) on the non-

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[41] For example, the fact that the value 4 represents more dynamic borrowing behaviour than the value 1 provides useful information, even though the degree of dynamicity itself only has an ordinal meaning. We cannot say that the difference between four and one is four times the size of the difference between two and one. However, we can estimate the role played by firms' characteristics in explaining their tendency toward a static TO (negative sign) or toward a fully dynamic PO/MT (positive sign).

[42] Detailed results are available upon request.

neutrality of corporate taxation, and of Jensen (1986) on the role of borrowing in reducing managerial agency costs through the firm's resources freely available to managers.

(4) By combining industries (as defined by the Fama-French 12-industry classification) with R&D intensity, we find evidence supporting the existence of an inverse relationship between intangible investment opportunities and financial leverage indicated by Long and Malitz (1985), and the conflict of interest between lenders and borrowers whereby debt could result in sub-optimal investments in firms with opportunities for innovative projects (Jensen and Meckling, 1976). More specifically, long-term debt is more likely to shift from PO/MT to TO in the case of low-tech firms producing durables and disposing of plentiful collateral. Conversely, the short-term debt ratio of high-tech and service firms is more likely to observe a PO pattern of behaviour. These patterns are consistent with the limited use of transactional debt (corporate bonds) and relational debt (bank loans) by R&D-intensive firms presumed by Wang and Thornhill (2010), and the dynamic agency-based models of Rampini and Viswanathan (2010, 2013), according to which collateralizability and tangibility are key determinants of leverage and of the dynamics of firm financing: an increase in collateral assets – which R&D intangibles are not - allows firms to lever more.

(5) Altman et al. (1977)'s Z-score (measuring failure risk) implies that low-risk firms tend to behave according to TO theory, but only in regard to the long-term debt ratio.[43]

(6) In general, the TO determinants are more effective in driving the long-term debt ratio of firms identified as TO by the index, while the PO determinants are more commonly detected for the short-term debt ratio of firms identified as PO/MT by the index.

5. A discussion of our results

The findings we obtained using a panel of U.S. companies over the period 1950-2011, may be articulated in the following points. Firstly, firms adopt heterogeneous forms of borrowing behaviour: some firms do not pursue an optimal debt ratio policy, while others display different speeds of adjustment towards a debt target. The literature has suggested various firm-specific characteristics as drivers of this heterogeneity, such as adjustment costs, binding constraints and governance feature, to mention just three. We develop a multilevel index which is statistically based without depending on any variable selected *a priori*, and this index groups together homogeneous firms that adopt either static or dynamic TO models at the lower values of the index, and either PO or MT models at the higher values of the index.

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[43] We used different formulae for listed and unlisted companies, and for manufacturing and non-manufacturing firms, according to Altman (2002).

Secondly, each component of total debt - short-term debts and long-term debts- is subject to firm-specific shocks and common shocks, and consequently it may persistently fluctuate over time. When detected, target-adjustment dynamics are not homogeneous across companies, over time, or between types of debt. Our index increases with the persistence of firm-specific and time-specific idiosyncratic shocks, and is also specific to alternative types of debt.

Thirdly, the evidence of non-stationarity for a large share of US firms' debt ratios, may account for the low SOA estimates usually reported in the empirical research, due to the invalid assumption of poolability across firms, periods and debt maturities. This invalid assumption unavoidably biases the estimated parameters of the other explanatory variables included in multivariable regression models used to explain borrowing. More precisely, the incorrect pooling of heterogeneous firms with heterogeneous debts – i.e. with different maturities, adjusting or not-adjusting to targets - explains the statistically significant, but extremely slow, estimated SOAs of actual to target leverage (described as "snail's pace" and "practically no-readjustment", respectively, by Fama and French, 2002, p. 24, and by Welch, 2004, p. 129). Furthermore, unstable pooled SOA estimates, such as those produced by DeAngelo and Roll (2015) and Chang and Dasgupta (2009), result from shares of non-zero and zero SOA firms that vary over time. Finally, debt ratios generated by non-stationary processes make the standard significance tests invalid when assessing the relationships with borrowing determinants, giving rise to the risk of spurious relationships emerging. Our index resolves this problem.

Fourthly, long-term debt is less prone to target adjustment, and is affected by more breaks than short-term debt. When detected, the adjustment to targets is faster for short-term debt than for long-term debt, with overshooting occurring when firms are over-levered in the short maturity and under-levered in the long maturity. Long-term and short-term debt ratios display different speeds of adjustment, which is in keeping with the fact that most short-term debt is bank debt (closely held), while long-term debt is more likely to consist of public bonds (arm's length). These findings clearly contrast with the ubiquitous dynamic adjustment of companies' actual debts towards targets suggested by TO theories. In fact, when we consider the most favourable case of the short-term debt ratio, the share of firms which behave in accordance with TO theories – identified by our index as about 44% - is never even close to the percentages which could support homogeneity in the stationarity TO model of behaviour. This share drops dramatically to about 20% in the case of the long-term debt ratio. Given the prevalence of the latter form of financing in the sample, only about 30% of firms have total debt ratios that revert to their target leverage, irrespective of the way the alternative models proxy the target. Assuming an optimal target for the total debt ratio, past studies have accounted for a form of behaviour that is a mixture of heterogeneous behaviour for short-term and long-term debt ratios.

Fifthly, the persistence of long-term debt ratios depends more on the need to finance future investments or to exploit market conditions, than on the need to achieve a dynamic target, unless profitability and the need to exploit the fiscal advantages of debt are high. In fact, the dynamic trade-off model can account for the behaviour of long-term debt in large, collateralized, profitable companies. On the contrary, short-term debt fluctuates with less persistence because it is often used by small, innovative companies in contingent situations, such as that of an immediate investment requirement. On the other hand, short-term debt is more prone to target adjustments and is affected to a greater degree by rollover risk in non-innovative companies. DeAngelo et al. (2017) discuss the fact that the empirical evidence does not support the financial flexibility hypothesis, according to which firms prefer to avoid permanently high leverage and to maintain unused debt capacity instead. We find evidence of this behaviour more in the case of short-term debt than in that of long-term debt. As a matter of fact, this behaviour implies the existence of a target i.e. a dynamic TO behaviour. This is exactly the main behaviour of short-term debt identified by our new index.

Remarkably, our approach is robust and fits the evidence even when firms do not use debt (see Strebulaev and Yang, 2013, and Kieschnick and Moussawi, 2018). According to our methodology, a debt ratio equal to zero is treated just like any other positive value, and a company's decision to switch from not resorting to debt to using debt is interpreted as a persistent shift within that company.

5.1. Conclusions

Our index can condense between-companies heterogeneity in clusters of borrowing behaviour which are homogenously related to the mainstream theories on corporate capital structure. Simultaneously, our index is able to classify within-companies heterogeneity according to the effects on the debt ratio of the shocks affecting each company. Moreover, our index also considers debt heterogeneity, which is an important aspect previously discussed by Rauh and Sufi (2010). For all of these reasons, we believe that our index can offer several interesting advantages to researchers. These advantages may be both methodological and empirical. As an example of the former, we would like to quote Zhou et al. (2016, JCF) who stated that "Collectively, our findings imply that capital structure targeting is not equally important to all firms. Indeed, we argue that while evidence of the trade-off theory will tend to be obscured in broad samples, it can hold strongly in meaningfully chosen subsamples of firms….". Our index can be used to identify companies strictly adhering to a trade-off model of behaviour. Moreover, the variables that are presumed to drive such a preference for the trade-off approach –Zhou et al. (2016), for example, suggest that firms characterized by the high sensitivity of equity cost to leverage deviation are those behaving in accordance with the trade-off theory – can be easily tested. From an empirical point of view, our index is able to choose groups

where within-group heterogeneity is small, and thus to reduce bias in dynamic panels covering a limited time-span. Hence, our index goes in the direction envisaged, for example, by Hendricks and Smith (2015), who demonstrate that the grouped coefficients estimator can lead to substantial bias reduction compared to pooled GMM dynamic panel estimators. Finally, the order followed by our index, that is, it increases as the existence of an optimal debt ratio is departed from, is reasonable and facilitates interpretation of the results.

The findings of this present study offer a number of new directions for applied research into capital structure. These include increasing the number of TO determinants in a parsimonious context, by utilising the information set of a large number of target components with few common factors.[44] The classification of firms resulting from our index could be used to pool together those companies that are more reactive to the business cycle, or to competitive challenges, or to the adjustment costs of leverage, and to study their behaviour within homogeneous samples, without having recourse to ad hoc assumptions, but testing for them instead. Our index could be utilised to assess the heterogeneous role of institutional investors identified by Grennan et al. (2017), as a mechanism with which to monitor management and reduce agency costs, and encourage TO-type firms to target lower, more efficient optimal leverage ratios. The index could also be constructed for each type, source and priority of every balance-sheet debt instrument presented, as an example, in Rauh and Sufi (2010). Another line of research could be that of linking our index with the main aspects characterizing financial market developments over the last few decades, in order to better understand their relationship with capital structure as explored by Graham et al. (2015). An additional direction could be the empirical exploration of alternative patterns of those debt ratio dynamics resulting from the interaction of macro and micro factors that influence heterogeneous firms' corporate strategies. Recent theoretical papers by Admati et al. (2016), DeMarzo and He (2016), and He and Milbradt (2016), all seem particularly promising in guiding future empirical analyses based on the methodology we have introduced here.

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[44] Frank and Shen (2014) use heterogeneous common factors to construct (but without accounting for the important issues of unit root and heterogeneous dynamics parameters) a broad information set of 146 variables which probably encompasses the unobservable determinants of TO. Their findings reveal a substantial increase in firms' SOA, which is in line with our own findings.

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Table 1a – Cases/tests of/on heterogeneous SOAs and debt ratio dynamics: models and links with the empirical literature on capital structure

Case/test	Restrictions on:	Target leverage	Test equation	Literature
A1/ADF **A1**/DF-GLS	model (10): $\alpha_{it} = \alpha_i$	$L_i^* = \dfrac{\mu_i}{-\alpha_i}$	$\Delta L_{it} = \alpha_i(L_{it-1} - L_i^*) + \sum_{j=1}^{p_i} \lambda_{ij}\Delta L_{it-j} + v_{it}$	(LA)
A2/BvD	model (10) $\alpha_{it} = \alpha_i^+(1 - I_{it}) + \alpha_i^- I_{it}$	L_i^* is estimated	$\Delta L_{it} = [\alpha_i^+(1 - I_{it}) + \alpha_i^- I_{it}](L_{it-1} - L_i^*) + \sum_{j=1}^{p_i} \lambda_{ij}\,\Delta L_{it-j} + v_{it}$	(NLA)
A2/KSS	model (10) $\alpha_{it} = e^{-\theta_i(L_{it-1}-L_i^*)^2} - 1$	$L_i^* = \dfrac{\sum_{t=1}^{N} L_{it}}{N}$	$\Delta L_{it} = \left[e^{-\theta_i(L_{it-1}-L_i^*)^2} - 1\right](L_{it-1} - L_i^*) + \sum_{j=1}^{p_i} \lambda_{ij}\Delta L_{it-j} + v_{it}$	(NLA)
B1/BT1	model (10) $\alpha_{it} = \alpha_i$	$L_{it-1}^* = \dfrac{\delta_{1i}DTB_{1it} + d_{1i}DU_{1it}}{-\alpha_i}$	$\Delta L_{it} = \mu_i + \delta_{1i}DTB_{1it} + d_{1i}DU_{1it} + \alpha_i L_{it-1} + \sum_{j=1}^{p_i} \lambda_{ij}\Delta L_{it-j} + v_{it}$	(NLA)
B1/BT2	model (10) $\alpha_{it} = \alpha_i$	$L_{it-1}^* = \dfrac{\sum_{j=1}^{2} \delta_{ji}DTB_{jit} + d_{ji}DU_{jit}}{-\alpha_i}$	$\Delta L_{it} = \mu_i + \delta_{1i}DTB_{1it} + \delta_{2i}DTB_{2it} + d_{1i}DU_{1it} + d_{2i}DU_{2it} + \alpha_i L_{it-1}$ $+ \sum_{j=1}^{p_i} \lambda_{ij}\Delta L_{it-j} + v_{it}$	(NLA)
B2/mean	model (10) $\alpha_{it} = \alpha_i$	$L_{it}^* = Lgt = \dfrac{\mu_i}{-\alpha_i} + \dfrac{\sum_{i=1}^{N_g} L_{it}}{N_g}$	$\Delta L_{it} = \alpha_i\left(L_{it-1} - \dfrac{\sum_{i=1}^{N_g} L_{it-1}}{N_g}\right) + \mu_i + \Delta L_{gt} + \sum_{j=1}^{p_i} \lambda_{ij}\Delta L_{it-j} + v_{it}$	(LMA)
C1/EG	model (1) $\alpha_{it} = \alpha_i; \beta_{it} = \beta_i$	$L_{it}^* = \dfrac{\mu_i}{-\alpha_i} + \beta_i' Z_{it}^{TO}$	$\Delta L_{it} = \alpha_i(L_{it-1} - \beta_i' Z_{it-1}^{TO}) + \mu_i + \sum_{j=1}^{p_i} \lambda_{ij}\Delta L_{it-j} + v_{it}$	(NLA)
C1/BO-BA	model (1) $\alpha_{it} = \alpha_i; \beta_{it} = -\dfrac{\pi_i}{\alpha_i}$	$L_{it}^* = \dfrac{\mu_i}{-\alpha_i} + (-\alpha_i)^{-1}\pi_i' Z_{it}^{TO}$	$\Delta L_{it} = \alpha_i L_{it-1} + \pi_i' Z_{it-1}^{TO} + \mu_i + \sum_{j=1}^{p_i}\left(\lambda_{ij}\Delta L_{it-j} + \omega_{ij}'\Delta Z_{it-j}^{TO}\right) + v_{it}$	
C1/JO	model (1) $\alpha_{it} = \alpha_i; \beta_{it} = \beta_i$	$L_{it}^* = \dfrac{\mu_i}{-\alpha_i} + \beta_i' Z_{it}^{TO}$	$\Delta X_t = \Lambda_0 + \sum_{k=1}^{p-1}\Lambda_k\Delta X_{t-k} + \Pi X_{t-1} + \Upsilon_t$, where X is the vector of all the variables of the system (L_{it} and Z_{it}^{TO}).	

The reference equation is equation (10), $\Delta L_{it} = \alpha_{it}L_{it-1} + \mu_i + \sum_{j=1}^{p_i}\lambda_{ij}\Delta L_{it-j} + v_{it}$. Case **A1**: stationary TO drivers with linear SOAs towards a constant firm-specific target (**A1**/ADF Dickey and Fuller (1979) and **A1**/DF-GLS Elliott et al. (1996)). Case **A2**: stationary TO drivers with nonlinear SOAs, either asymmetric (**A2**/BvD: Berben and van Dijck (1999), where the Heaviside indicator driving the SOA changes is defined as $I_{it} = 1$ if $L_{it-1} \leq L_i^*$ and $I_{it} = 0$ if $L_{it-1} > L_i^*$ and α_i^- and α_i^+ are, respectively, the heterogeneous SOAs for under- and over-levered companies in period *t-1*) or varying over time and increasing in terms of the distance between actual and target debt ratios (**A2**/KSS: Kapetanios at al. (2003)). Case **B1**: non-stationary TO drivers inducing breaking debt ratio targets (**B1**/BT1 and **B1**/BT2 are, respectively, the one-break and two-breaks in target unit root tests of Perron and Vogelsang (1992) and Clemente et al. (1998), where DTB_{jit} (j =1, 2) is a pulse variable that takes the value 1 if $t = TB_{ji} + 1$ or 0 otherwise - with TB_{1i} being the year of the first break and TB_{2i} that of the second break, and DU_{jit} is a step dummy equal to 1 if $t > TB_{ji}$ or 0 otherwise). Case **B2**/mean: non-stationary TO drivers with firms adjusting their debt ratios towards industry-specific time-varying targets ("mean" denotes a target leverage estimated by the within-group average of the debt ratios of the firms belonging to the industry *g*). Case **C1**: non-stationary TO drivers of non-stationary debt ratio targets through cointegration (**C1**/EG: Engle and Granger (1987) and Stock (1987); **C1**/BO and

C1/BA: Boswijk (1994) and Banerjee et al. (1998), respectively; **C1**/JO: Johansen (1995)). Table A1.1 of Appendix A1 presents the technical details of the procedures we used to estimate and to test all of these Cases.

(LA) Linear approaches are covered by our **A1** cases, which include both heterogeneity and stationarity. Linear models are based on model (3) with the recent econometric practice of first-differencing the model - to get rid of the individual effects - and using either OLS or GMM estimators under the assumptions of data stationarity and slope parameters poolability (see Flannery and Watson Hankins, 2013). Elsas and Florysiak (2011, 2015) introduce a new estimator to account for the fractional nature of the dependent variable, but still assume slope poolability and stationarity of debt ratio. This line of reasoning leads Chen and Zhao (2007) to claim that debt ratios revert to the mean simply because they are ratios (they talk about mechanical mean reversion), and not because they are pushed by TO-like behaviour. Some authors exclude from the sample those debts ratios smaller than 10% and higher than 90% to prevent this issue arising (see e.g. Warr et al. (2012)). Hovakimian and Li (2011) show that models like equation (3) produce results that are severely biased toward the target adjustment, and list several good practices - such as the use of recursive two-step estimation methods and the exclusion of firms characterized by extremely high debt ratios – that may facilitate the estimation of dynamic models with improved power properties. Other published articles based on Compustat data, are: Auerbach (1985), Shyam-Sunder and Myers (1999), Fama and French (2002), Frank and Goyal (2003), Welch (2004), Flannery and Rangan (2006), Hovakimian (2006), Kayan and Titman (2007), Lemmon et al. (2008), Huang and Ritter (2009), de Jong et al. (2011), Fama and French (2012). For the non-US case: Bontempi (2002) for Italy, de Miguel and Pindado (2001) for Spain, Ozkan (2001) and Bevan and Danbolt (2002) for the UK, Gaud et al. (2007) for Europe, Nunkoo and Boateng (2010) for Canada, Guney et al. (2011) for China, Noulas and Genimakis (2011) for Greece, Antao and Bonfim (2012) for Portugal, and Koksal and Orman (2015) for Turkey. Antoniou et al. (2008) compare the results between bank-oriented (France, Germany, Japan) and market-oriented (the USA and the UK) countries.

(NLA) Nonlinear approaches are covered by our **A2**-**B1** cases. Chang and Dasgupta (2009) and Hovakimian and Li (2011) are examples of challenges to the validity of empirical inference based on linear target adjusting models. For example, Leary and Roberts (2005) show that firms' financing behaviour is consistent with the presence of adjustment costs, and companies actively rebalance their debt ratios to stay within an optimal range; in this context, the persistence of leverage shocks (low SOAs) emerging from linear models is more likely to be due to high adjustment costs than to indifference towards the target. A long, albeit non-exhaustive list, includes: Fischer et al. (1989), Gilson (1997), Roberts (2002), de Haas and Peeters (2006), Drobetz and Wanzenried (2006), Titman and Tsyplakov (2007), Byoun (2008), Cook and Tang (2010), DeAngelo et al. (2011), Elsas and Florysiak (2011), Graham and Leary (2011), Aybar-Arias et al. (2012), Dang et al. (2012), Faulkender et al. (2012), Halling et al. (2012), Korteweg and Strebulaev (2012), Warr et al. (2012), Baum et al. (2014), Chang et al. (2014), Danis et al. (2014), Elsas et al. (2014), DeAngelo and Roll (2015), and Zhou et al. (2016). Recently, Pereira-Alves and Ferreira (2011), and Oztekin and Flannery (2012), have used dummy interactions to extend the international comparison (in the linear model context) of Antoniou et al. (2008) and to explore the effect of country-specific institutional determinants.

(LMA) Linear approaches converging towards average debt ratios by group are covered by our **B2** case. In many empirical papers, by-industry debt ratio averages (usually medians) are added to the list of the explanatory variables of the target. Examples include: Lev (1969), Fama and French (2002), Hovakimian et al. (2001), Hovakimian (2006), Flanney and Rangan (2006), Lemmon et al. (2008), and de Jong et al. (2011). The industry median debt ratio is one of the alternative measures utilised by D'Mello and Farhat (2008) to proxy the time-varying optimal (target) debt ratio.

Table 1b – Relations between the Cases/tests of/on heterogeneous SOAs and debt ratio dynamics

		When the theory truly driving corporate behaviour is	
		PO/MT: Companies have SOAs $\alpha_i = 0$	TO: Companies have SOAs $\alpha_i < 0$
A1/ADF null that α_i=0	Not rejected	**A1**/ADF is right, as firms are assumed to behave in accordance with PO/MT theories and do not have a target debt ratio (SOA is zero).	**A1**/ADF is wrong, as it does not reject PO/MT which is false. This failure can be due either to non-constant SOA (non-linearity may be a cause of equation (10) mis-specification, see **Case A2**), or to breaks/shifts in debt ratio levels (see **Case B1**), or to the non-stationarity of the target debt ratio determinants (see **Cases B2, C1**).
	Rejected	**A1**/ADF is wrong, as firms' debt ratios revert towards a fixed target over time. This failure may be due to moving average components in the error term of equation (10), and it can be overcome by the **A1**/DF-GLS Case.	**A1**/ADF is right, as firms are assumed to behave in accordance with TO theory with stationary drivers, which implies that the target debt ratio is constant over time.

The reference equation is equation (10), $\Delta L_{it} = \alpha_{it} L_{it-1} + \mu_i + \sum_{j=1}^{p_i} \lambda_{ij} \Delta L_{it-j} + \nu_{it}$. Case **A1**: stationary TO drivers with linear SOAs; Case **A2**: stationary TO drivers with nonlinear SOAs; Case **B1**: non-stationary TO drivers resulting in breaks from debt ratio targets; Case **B2**: non-stationary TO drivers with firms adjusting their debt ratios towards average ratios by industry/group; Case **C1**: non-stationary TO drivers resulting in non-stationary debt ratio targets through cointegration.

Table 2 - Shares of firms with target reverting debt ratios by term structure and balanced panels

Begin	End	Time span	# of firms	A1 Linear SOAs		A2 Asymmetric SOAs					B1 Breaking target			B2 Industry- time-varying targets	
				ADF	DF-GLS	BvD	+> -	+= -	+< -	KSS	BT	*One break*	*Two breaks*	mean	median
Short-term debt ratios															
1950	2011	62	50	0.440	0.520	0.680	*0.706*	*0.265*	*0.029*	0.480	0.740	*0.649*	*0.351*	0.520	0.440
1960	2011	52	97	0.583	0.567	0.711	*0.623*	*0.333*	*0.043*	0.474	0.773	*0.680*	*0.320*	0.557	0.573
1970	2011	42	161	0.640	0.491	0.733	*0.534*	*0.407*	*0.059*	0.488	0.776	*0.760*	*0.240*	0.590	0.566
1975	2011	37	196	0.631	0.520	0.714	*0.493*	*0.471*	*0.036*	0.523	0.740	*0.752*	*0.248*	0.590	0.577
1980	2011	32	227	0.602	0.520	0.670	*0.526*	*0.461*	*0.013*	0.522	0.731	*0.735*	*0.265*	0.558	0.569
1985	2011	27	290	0.561	0.507	0.641	*0.446*	*0.527*	*0.027*	0.458	0.662	*0.729*	*0.271*	0.552	0.531
1990	2011	22	412	0.542	0.430	0.604	*0.402*	*0.594*	*0.004*	--	0.585	*0.714*	*0.286*	0.549	0.550
Long-term debt ratios															
1950	2011	62	50	0.163	0.160	0.280	*0.286*	*0.214*	*0.500*	0.224	0.320	*0.500*	*0.500*	0.143	0.163
1960	2011	52	97	0.253	0.206	0.402	*0.308*	*0.359*	*0.333*	0.253	0.371	*0.528*	*0.472*	0.211	0.170
1970	2011	42	161	0.233	0.335	0.348	*0.304*	*0.286*	*0.411*	0.297	0.329	*0.642*	*0.358*	0.222	0.237
1975	2011	37	196	0.240	0.306	0.332	*0.200*	*0.415*	*0.385*	0.215	0.342	*0.627*	*0.373*	0.196	0.183
1980	2011	32	227	0.242	0.326	0.317	*0.236*	*0.417*	*0.347*	0.194	0.344	*0.551*	*0.449*	0.246	0.204
1985	2011	27	290	0.256	0.283	0.303	*0.182*	*0.455*	*0.364*	0.187	0.421	*0.574*	*0.426*	0.237	0.241
1990	2011	22	412	0.216	0.250	0.294	*0.223*	*0.479*	*0.298*	--	0.420	*0.497*	*0.503*	0.219	0.220
Total debt ratios															
1950	2011	62	50	0.220	0.160	0.360	*0.500*	*0.222*	*0.278*	0.180	0.300	*0.667*	*0.333*	0.260	0.300
1960	2011	52	97	0.229	0.258	0.392	*0.342*	*0.421*	*0.237*	0.175	0.309	*0.667*	*0.333*	0.198	0.188
1970	2011	42	161	0.306	0.292	0.391	*0.206*	*0.476*	*0.317*	0.231	0.348	*0.554*	*0.446*	0.239	0.196
1975	2011	37	196	0.246	0.276	0.316	*0.258*	*0.452*	*0.290*	0.193	0.337	*0.561*	*0.439*	0.202	0.201
1980	2011	32	227	0.267	0.308	0.335	*0.276*	*0.487*	*0.237*	0.194	0.339	*0.545*	*0.455*	0.232	0.204
1985	2011	27	290	0.254	0.283	0.331	*0.219*	*0.385*	*0.396*	0.184	0.376	*0.532*	*0.468*	0.230	0.191
1990	2011	22	412	0.208	0.252	0.286	*0.254*	*0.466*	*0.280*	--	0.383	*0.437*	*0.563*	0.210	0.224

Short-term is *SDA* = DLC/AT; long-term is *LDA* = DLTT/AT and total is *TDA* = FD/AT (see the definition of the debt ratios by term structure in Appendix A2). **A1**/ADF and **A1**/DF-GLS: unit root tests for linear models of Dickey and Fuller (1979) and Elliott et al. (1996). **A2**/BvD: asymmetric SOAs unit root test of Berben and van Dijk (1999); the columns in Italic report the three shares of target reverting firms with SOAs larger (>), equal (=) or smaller (<) when firms are over (+) or under (-) levered. **A2**/KSS: nonlinear START unit root test of Kapetanios et al. (2003), where "--" stands for not computed statistics because of few observations. **B1**/BT: unit root test around broken targets of Perron and Vogelsang (1992) for one break and Clemente et al. (1998) for two breaks; the columns in Italic report the composition of the target reverting firms by number of breaks. **B2**/mean and **B2**/median: shares of firms reverting to a time-varying target measured as either the mean or the median of the debt ratios by industry.

Table 3 - Average SOA estimates by term structure, balanced panels, and groups of non-reverting and reverting firms.

				MG of non-reverting firms	MG of reverting firms									
					A1 Linear SOAs DF-GLS	**A2** Asymmetric SOAs					**B1** Breaking target		**B2** Industry-time-varying targets	
						+> -		+= -	+< -		One	Two		
Begin	End	Time span	# of Firms			$\hat{\alpha}_i^+$	$\hat{\alpha}_i^-$	$\hat{\alpha}_i$	$\hat{\alpha}_i^+$	$\hat{\alpha}_i^-$	break	breaks	mean	median
Short-term debt ratios														
1950	2011	62	50	-0.194	-0.516	-0.968	-0.138	-0.463	-0.510	-1.746	-0.727	-0.820	-0.479	-0.533
1960	2011	52	97	-0.229	-0.544	-1.067	-0.155	-0.525	-0.436	-1.508	-0.816	-0.845	-0.538	-0.554
1970	2011	42	161	-0.261	-0.638	-1.214	-0.176	-0.607	-0.605	-1.755	-0.851	-0.933	-0.614	-0.637
1975	2011	37	196	-0.272	-0.711	-1.317	-0.193	-0.706	-0.879	-1.914	-0.933	-0.945	-0.672	-0.699
1980	2011	32	227	-0.314	-0.763	-1.377	-0.199	-0.816	-0.623	-1.834	-0.987	-1.039	-0.742	-0.749
1985	2011	27	290	-0.339	-0.827	-1.404	-0.208	-0.848	-0.458	-1.526	-0.995	-1.174	-0.799	-0.824
1990	2011	22	412	-0.391	-0.845	-1.523	-0.192	-0.850	-0.695	-1.974	-1.012	-1.196	-0.858	-0.856
Long-term debt ratios														
1950	2011	62	50	-0.129	-0.323	-0.877	-0.098	-0.324	-0.084	-1.109	-0.590	-0.656	-0.303	-0.295
1960	2011	52	97	-0.160	-0.345	-1.001	-0.125	-0.343	-0.108	-1.403	-0.654	-0.790	-0.348	-0.372
1970	2011	42	161	-0.193	-0.499	-1.130	-0.148	-0.481	-0.142	-1.503	-0.757	-0.800	-0.456	-0.436
1975	2011	37	196	-0.202	-0.539	-1.327	-0.139	-0.544	-0.172	-1.470	-0.811	-0.936	-0.497	-0.490
1980	2011	32	227	-0.222	-0.603	-1.307	-0.136	-0.626	-0.183	-1.593	-0.822	-0.942	-0.558	-0.551
1985	2011	27	290	-0.256	-0.643	-1.393	-0.179	-0.625	-0.230	-1.574	-0.877	-1.142	-0.632	-0.628
1990	2011	22	412	-0.299	-0.701	-1.489	-0.183	-0.624	-0.268	-1.719	-1.008	-1.068	-0.716	-0.712
Total debt ratios														
1950	2011	62	50	-0.121	-0.318	-0.840	-0.081	-0.311	-0.082	-1.157	-0.521	-0.754	-0.301	-0.289
1960	2011	52	97	-0.151	-0.371	-1.090	-0.117	-0.340	-0.106	-1.367	-0.585	-0.738	-0.387	-0.390
1970	2011	42	161	-0.180	-0.441	-1.115	-0.123	-0.426	-0.143	-1.458	-0.753	-0.893	-0.466	-0.459
1975	2011	37	196	-0.206	-0.499	-1.396	-0.109	-0.504	-0.181	-1.582	-0.815	-0.986	-0.522	-0.500
1980	2011	32	227	-0.219	-0.532	-1.420	-0.150	-0.538	-0.190	-1.647	-0.864	-0.974	-0.553	-0.556
1985	2011	27	290	-0.258	-0.595	-1.559	-0.198	-0.560	-0.216	-1.588	-0.859	-1.037	-0.595	-0.621
1990	2011	22	412	-0.292	-0.696	-1.568	-0.220	-0.641	-0.234	-1.700	-1.085	-1.079	-0.711	-0.686

Short-term is *SDA* = DLC/AT; long-term is *LDA* = DLTT/AT and total is *TDA* = FD/AT (see the definition of the debt ratios by term structure in Appendix A2). Mean group ("MG") indicates the averages of firm-specific SOA estimates within either non-reverting or reverting to target groups of firms. The "non-reverting firms" are those for which the null of the **A1**/DF-GLS test is not rejected. Under "reverting firms", "**A1** Linear SOAs" denotes those firms for which the null of the **A1**/DF-GLS test is rejected. "**A2** Asymmetric SOAs" denotes those firms that reject the **A2**/BvD test; these firms are in turn sub-grouped in three shares of target reverting firms with SOAs larger (>), equal (=) or smaller (<) when firms are over (+) or under (-) levered (see the three shares in Italic of Table 2). For the two sub-groups ">" and "< ", two mean-SOAs are reported ($\hat{\alpha}_i^+$ and $\hat{\alpha}_i^-$ when, respectively, firms are over-levered and under-levered), while for the sub-group "=" only one SOA is reported. The average SOA estimates cannot be computed for Case **A2**/KSS as it includes models which are non-linear functions of the actual-target debt ratio gaps; this Case is discussed in Appendix A1.4. "**B1** Breaking target" denotes firms that reject the **B1**/BT1 test for "one" break, and the **B1**/BT2 test for "two" breaks. Finally, "**B2** Industry-time-varying targets" denotes the groups of those firms that revert to "mean" or "median" time-varying target computed at the industry level.

Table 4 - Four anecdotal examples of our methodology.

Company	Short- and long-term debt correlation	Case **A1** Linear Long-term debt	Case **B1** Broken target Long-term debt	Case **A2** Asymmetric Long-term debt	Case **A1** Linear Short-term debt	Case **B1** Broken target Short-term debt	Case **A2** Asymmetric Short-term debt
EXXON MOBIL CORP	0.49	Non-reverting	Non-reverting	Non-reverting	Non-reverting	Non-reverting	Non-reverting
GOODYEAR TIRE &	-0.14	Reverting	Non-reverting	Reverting with higher SOA when over-levered	Reverting	Reverting with 1 break	Reverting with higher SOA when under-levered
HONEYWELL INTERN	-0.34	Non-reverting	Non-reverting	Non-reverting	Reverting	Non-reverting	Reverting with equal SOA
GOODRICH CORP	0.14	Non-reverting	Non-reverting	Non-reverting	Reverting	Reverting with 1 break	Reverting with equal SOA

The four companies analysed here are part of the sample of firms used in DeAngelo and Roll (2015).
Short-term is *SDA* = DLC/AT and long-term is *LDA* = DLTT/AT (see the definition of the debt ratios by term structure in Appendix A2).
Along the columns, the three Cases **A1**, **B1** and **A2** are described in Table 1.

Table 5 – A multilevel index of heterogeneous dynamics classifying firms' borrowing behaviour

Values and meaning	Total debt ratio (*TDA*)		Long-term debt (*LDA*)		Short-term debt (*SDA*)	
		%		%		%
1 - TO static	7,955	12.88	8,070	13.17	5,605	9.57
2 - TO with D* changing	3,777	6.11	4,741	7.74	18,042	30.82
3 - TO with D* even less stable	2,777	4.5	3,092	5.05	4,521	7.72
4 - PO driven by INV/CF	28,832	46.67	25,786	42.1	11,585	19.79
5 - PO/MT driven by stock market	18,436	29.84	19,567	31.94	18,794	32.1
Total	61,777	100	61,256	100	58,547	100

Total debt is *TDA* = FD/AT; long-term debt is *LDA* = DLTT/AT and short-term debt is *SDA* = DLC/AT (see the definition of the debt ratios by term structure in Appendix A2). Value 1 of the index indicates stationarity according to the linear model **A1**/DF-GLS *AND* no breaks according to **B1**/BT1/BT2; Value 2 indicates stationarity according to **A1**/DF-GLS *AND* one break according to **B1**/BT1 (over the sample there are two targets); Value 3 indicates stationarity according to **A1**/DF-GLS *AND* two breaks according to **B1**/BT2 (the target changes twice); Value 4 indicates non-stationarity in linear model (**A1**/DF-GLS does not reject the null) *AND* no breaks according to **B1**/BT1/BT2; Value 5 indicates non-stationarity according to **A1**/DF-GLS *AND* 1 or 2 breaks according to **B1**/BT1/BT2. Note that Values 2 and 3 could be put together to denote in general the dynamic TO behaviour with a target debt ratio non-constant over time. The index is obtained from the combinations described below:

Nonlinear target breaking [B1/BT1/BT2**]**

		I(1)	*I(0) with 1 break*	*I(0) with 2 breaks*
	I(1)	PO, **4**	MT, **5**	
Linear [A1/DF-GLS**]**				
	I(0)	Static TO, **1**	Dynamic TO, **2**	Dynamic TO, **3**

Table 6 – Estimates of the benchmark model for the long-term debt ratio, LDA

	A1/DF-GLS			**B1**/BT1/BT2			**A2**/BvD				**Multilevel index**			
	Whole sample	Non stationary	Stationary	Non stationary	Stationary 1break	Stationary 2breaks	Non stationary	Higher over-lev	Same SOAs	Higher under-lev	TO static	TO dynamic	PO	MT
LDA$_{it-1}$	-0.154***	-0.118***	-0.311***	-0.163***	-0.210***	-0.207***	-0.155***	-0.246***	-0.346***	-0.180***	-0.315***	-0.340***	-0.138***	-0.152***
	(0.0199)	(0.0212)	(0.0311)	(0.0274)	(0.0274)	(0.0332)	(0.0219)	(0.0447)	(0.0381)	(0.0363)	(0.0404)	(0.0379)	(0.0308)	(0.0223)
ΔSDA$_{it}$	-0.312***	-0.348***	-0.394***	-0.461***	-0.297***	-0.462***	-0.309***	-0.402***	-0.391***	-0.633***	-0.541***	-0.333***	-0.439***	-0.311***
	(0.0576)	(0.0738)	(0.0465)	(0.0599)	(0.0733)	(0.0602)	(0.0602)	(0.0581)	(0.0815)	(0.0577)	(0.0485)	(0.0562)	(0.0679)	(0.0885)
fcf$_{it}$	-0.082***	-0.050**	-0.127***	-0.092***	-0.074***	-0.160***	-0.082***	-0.056**	-0.091***	-0.244***	-0.084**	-0.119***	-0.129***	-0.088***
	(0.0211)	(0.0245)	(0.024)	(0.0323)	(0.0218)	(0.0305)	(0.0269)	(0.0240)	(0.0225)	(0.0471)	(0.0363)	(0.0244)	(0.0332)	(0.0255)
DWC1$_{it}$	-0.003	-0.006	-0.01	-0.028	0.057**	-0.004	0.003	-0.006	0.040**	0.066**	-0.030	-0.002	0.004	0.040
	(0.0093)	(0.0249)	(0.0062)	(0.0298)	(0.0222)	(0.0054)	(0.0062)	(0.0133)	(0.0173)	(0.0336)	(0.0287)	(0.0088)	(0.0318)	(0.0264)
rd_ta$_{it}$	-0.024	-0.015	-0.035	-0.036	0.001	-0.108	-0.024	-0.050	-0.022	-0.112	-0.150**	-0.081	0.020	-0.027
	(0.0345)	(0.0280)	(0.0431)	(0.0548)	(0.0224)	(0.0750)	(0.0492)	(0.0516)	(0.0278)	(0.1351)	(0.0610)	(0.0558)	(0.0503)	(0.0314)
rd_dum$_{it}$	-0.001	0.000	-0.001	0.001	-0.001	-0.004	-0.004	0.012**	0.007	0.001	0.003	-0.006	0.000	-0.001
	(0.0022)	(0.0022)	(0.0039)	(0.0027)	(0.0031)	(0.0042)	(0.0027)	(0.0051)	(0.0068)	(0.0052)	(0.0052)	(0.0057)	(0.0031)	(0.0027)
mbRLDA$_{it}$	0.000	-0.002	0.020*	-0.001	0.006	0.003	-0.003	0.006	0.040*	0.000	0.013	0.042*	-0.002	-0.008
	(0.0031)	(0.0031)	(0.0101)	(0.0032)	(0.0099)	(0.0088)	(0.0031)	(0.0099)	(0.0214)	(0.0116)	(0.0125)	(0.0214)	(0.0031)	(0.0060)
DIVA$_{it-1}$	0.232**	0.202**	0.012	0.272**	0.135	-0.205	0.255**	0.150	-0.235	0.330**	-0.064	-0.065	0.244**	0.271**
	(0.1001)	(0.0982)	(0.0849)	(0.1147)	(0.1066)	(0.1924)	(0.1062)	(0.1855)	(0.1457)	(0.1379)	(0.1724)	(0.1007)	(0.1088)	(0.1194)
rcostd1$_{it-1}$	0.004	0.062	-0.053	-0.032	0.016	-0.010	0.022	0.055*	0.074*	-0.013	0.017	-0.041	0.095**	0.024
	(0.0362)	(0.0392)	(0.0492)	(0.0452)	(0.0488)	(0.0508)	(0.0470)	(0.0309)	(0.0414)	(0.0746)	(0.0552)	(0.0451)	(0.0448)	(0.0508)
ndts$_{it-1}$	-0.070	-0.093	0.046	-0.055	-0.083	-0.149*	-0.119	0.111*	-0.089	0.264**	0.307	0.049	-0.106	-0.130*
	(0.0737)	(0.0812)	(0.1240)	(0.1278)	(0.0748)	(0.0907)	(0.1015)	(0.0671)	(0.1522)	(0.1270)	(0.1954)	(0.1516)	(0.1355)	(0.0713)
ndts_lGAIN$_{it-1}$	-0.004	0.068	-0.195**	-0.029	-0.036	0.117	0.022	-0.015	-0.055	-0.244**	-0.301**	-0.165	0.053	0.078
	(0.0515)	(0.0598)	(0.0871)	(0.0941)	(0.0635)	(0.0782)	(0.0693)	(0.0869)	(0.0975)	(0.1196)	(0.1284)	(0.1103)	(0.1057)	(0.0616)
Tang$_{it-1}$	0.049***	0.024*	0.119***	0.038**	0.069***	0.066***	0.054***	-0.009	0.097***	0.024	0.061**	0.125***	0.027	0.040***
	(0.0136)	(0.0139)	(0.0245)	(0.0175)	(0.0196)	(0.0217)	(0.0162)	(0.0273)	(0.0324)	(0.0186)	(0.0292)	(0.0310)	(0.0178)	(0.0157)
ebit_ta$_{it-1}$	0.024**	0.012	0.053***	0.020	0.060***	0.030***	0.011	0.036*	0.064***	0.111***	0.025	0.052***	0.02	0.052**
	(0.0115)	(0.0188)	(0.0130)	(0.0272)	(0.0166)	(0.0115)	(0.0119)	(0.0215)	(0.0159)	(0.0385)	(0.026)	(0.0150)	(0.0294)	(0.0220)
Intan$_{it-1}$	0.045***	0.024**	0.102***	0.038**	0.057***	0.074***	0.053***	0.013	0.075***	0.012	0.052*	0.102***	0.029*	0.049***
	(0.0118)	(0.0123)	(0.0209)	(0.0163)	(0.0166)	(0.0204)	(0.0144)	(0.0264)	(0.0249)	(0.0194)	(0.0311)	(0.0259)	(0.0164)	(0.0143)
Constant	0.015***	0.022***	0.002	0.018**	0.020***	0.027***	0.015**	0.042***	0.018	0.034***	0.026**	0.009	0.026***	0.020***
	(0.0052)	(0.0053)	(0.0085)	(0.0074)	(0.0065)	(0.0089)	(0.0064)	(0.0134)	(0.0110)	(0.0096)	(0.0124)	(0.0107)	(0.0081)	(0.0062)
NT	48588	35856	12732	27586	11624	8470	28170	5834	5978	5440	6733	5635	20853	14459
N	2486	1825	661	1293	656	450	1420	283	334	236	316	313	977	793
Tavg	19.5	19.6	19.3	21.3	17.7	18.8	19.8	20.6	17.9	23.1	21.3	18	21.3	18.2
R^2	0.23	0.21	0.27	0.26	0.23	0.28	0.21	0.22	0.26	0.44	0.27	0.25	0.26	0.22
Hansenp	0.006	0.111	0.200	0.135	0.260	0.507	0.157	0.361	0.559	0.772	0.075	0.339	0.041	0.257

LDA = DLTT/AT and *SDA* = DLC/AT are respectively long- and short-term debt ratios. The PO/MT explanatory variables are (in brackets and Italic their labels are reported): free cash flow (*fcf*, i.e. cash flow minus capital expenditures and cash dividends), financial slack (*DWC1*), R&D expenses and a dummy equal to one for observations with missing information (*rd_ta* and *rd_dum*), market-to-book ratio interacted with an index increasing with the rating of long- and short-term debts (*mbRLDA* and *mbRSDA* in Table 7). The TO explanatory variables are cash dividends (*DIVA*), relative cost of debt (*rcostd1*), non-debt tax shields and their interaction with positive taxable income (*ndts* and *ndts_lGAIN*), guarantees and intangible assets (*Tang* and *Intan*), profitability (*ebit_ta*). The exact definition of

these variables is in Appendix A2 (Δ indicates the first difference). Model parameters estimates are GMM-LEV with principal components as instruments (see Bontempi and Mammi, 2015). *, ** and *** denote significance at 10, 5 and 1%. Standard errors robust to both heteroscedasticity and within-autocorrelation are in brackets. NT is the total number of observations; N is the total number of firms; Tavg is the average of the N individual spans T_i.(i= 1, 2, …, N). R^2 is the squared coefficient of correlation between actual and fitted debt data. Hansenp is the p-value of the Hansen J test of valid moment conditions under the null.

Along the columns, regressions are run over alternative samples, starting from the "Whole sample" in the first column. **A1**/DF-GLS columns report estimates over samples of firms that either do not reject (Non stationary) or reject (Stationary) the null of the Elliott et al. (1996) test. **B1**/BT1/BT2 columns report estimates over samples of firms that do not reject (Non stationary) the null of both the Perron and Vogelsang (1992) *AND* the Clemente et al. (1998) tests, that reject (Stationary 1break) the null of the Perron and Vogelsang (1992) test; the remaining firms are "Stationary 2breaks". **A2**/BvD columns report estimates over samples of firms that do not reject (Non stationary) the null of the Berben and van Dijk (1999) test (BvD), while "Higher over-levered" and "Higher under-levered" collect firms that reject the null of BvD with SOAs that are respectively higher when over-levered and higher when under-levered; "Same SOAs" denotes rejection of the null of BvD with SOAs that are the same for over- or under-levered firms. Finally, "Multilevel index" columns report the estimates over the four sub-samples identified by the indicator described in Table 5.

Table 7 – Estimates of the benchmark model for the short-term debt ratio, SDA

	A1/DF-GLS			B1/BT1/BT2			A2/BvD				Multilevel index			
	Whole sample	Non stationary	Stationary	Non stationary	Stationary 1break	Stationary 2breaks	Non stationary	Higher over-lev	Same SOAs	Higher under-lev	TO static	TO dynamic	PO	MT
SDA_{it-1}	-0.318***	-0.203***	-0.477***	-0.238***	-0.366***	-0.314***	-0.177***	-0.394***	-0.596***	-0.233***	-0.458***	-0.503***	-0.136***	-0.226***
	(0.0245)	(0.0329)	(0.0334)	(0.0385)	(0.0362)	(0.0414)	(0.0244)	(0.0407)	(0.0611)	(0.0579)	(0.0513)	(0.0411)	(0.0288)	(0.0311)
ΔLDA_{it}	-0.296***	-0.303***	-0.278***	-0.322***	-0.272***	-0.434***	-0.366***	-0.248***	-0.292***	-0.361***	-0.245***	-0.304***	-0.433***	-0.308***
	(0.0407)	(0.0460)	(0.0435)	(0.0586)	(0.0415)	(0.0595)	(0.0552)	(0.0492)	(0.0421)	(0.0848)	(0.0566)	(0.0533)	(0.0653)	(0.0488)
fcf_{it}	-0.039	-0.048**	-0.042*	-0.031	-0.035	-0.081**	-0.052	-0.048*	-0.039	-0.162***	-0.025	-0.061**	-0.154***	-0.070***
	(0.0236)	(0.0241)	(0.0256)	(0.0458)	(0.0235)	(0.0384)	(0.0347)	(0.0273)	(0.0259)	(0.0537)	(0.0356)	(0.0264)	(0.0322)	(0.0201)
$DWC1_{it}$	-0.031***	-0.013	-0.026***	-0.024	-0.035	-0.027***	-0.036	-0.005	-0.038***	-0.034	0.005	-0.019	-0.024	-0.011
	(0.0080)	(0.0174)	(0.0085)	(0.0240)	(0.0216)	(0.0095)	(0.0271)	(0.0134)	(0.0068)	(0.0255)	(0.0260)	(0.0126)	(0.0189)	(0.0190)
rd_ta_{it}	0.039	0.02	-0.033	0.059	0.032	0.027	0.091	-0.067*	0.028	-0.621***	0.028	-0.048	-0.015	0.02
	(0.0265)	(0.0297)	(0.0331)	(0.0443)	(0.0570)	(0.0437)	(0.0559)	(0.0362)	(0.0306)	(0.1496)	(0.0399)	(0.0620)	(0.0539)	(0.0361)
rd_dum_{it}	0.004**	0.002	-0.002	0.000	0.004	0.005*	0.000	-0.006**	0.008**	-0.007	-0.002	-0.002	-0.003	0.004
	(0.0019)	(0.0023)	(0.0029)	(0.0030)	(0.003)	(0.0033)	(0.0022)	(0.0026)	(0.0033)	(0.0061)	(0.0054)	(0.0037)	(0.0025)	(0.0027)
$mbRSDA_{it}$	0.004*	0.002	0.004	-0.005*	0.006**	0.010	0.005	-0.001	0.006*	0.011*	-0.011	0.006**	0.000	0.003
	(0.0019)	(0.0022)	(0.0027)	(0.0028)	(0.0024)	(0.0062)	(0.003)	(0.0022)	(0.0036)	(0.0060)	(0.0084)	(0.0027)	(0.0026)	(0.0031)
$DIVA_{it-1}$	-0.017	-0.135	0.019	0.195	0.007	0.157	-0.008	0.224***	0.035	-0.801**	0.009	0.076	0.221	-0.084
	(0.0725)	(0.1032)	(0.0874)	(0.1334)	(0.0638)	(0.1149)	(0.0852)	(0.0831)	(0.1002)	(0.3547)	(0.0661)	(0.0618)	(0.1487)	(0.0801)
$rcostd1_{it-1}$	0.021	0.054**	-0.043	-0.014	-0.004	-0.039	0.090***	-0.031	-0.026	0.164**	-0.050	-0.02	-0.003	0.051*
	(0.0294)	(0.0265)	(0.0444)	(0.0384)	(0.0324)	(0.0388)	(0.0348)	(0.0384)	(0.0429)	(0.0777)	(0.0407)	(0.0474)	(0.0560)	(0.0275)
$ndts_{it-1}$	0.173**	0.114	0.054	-0.132	0.162**	0.119	-0.025	-0.043	0.182**	0.297	-0.033	0.107	-0.270**	0.165
	(0.0764)	(0.1003)	(0.1004)	(0.1035)	(0.0821)	(0.1416)	(0.1224)	(0.0899)	(0.0854)	(0.2230)	(0.0758)	(0.1010)	(0.1197)	(0.1050)
$ndts\_lGAIN_{it-1}$	-0.153***	-0.102	-0.092	-0.015	-0.117**	-0.087	0.000	-0.032	-0.135**	-0.231	-0.09	-0.089	0.125	-0.094
	(0.0533)	(0.0674)	(0.0698)	(0.086)	(0.0551)	(0.1020)	(0.0911)	(0.0657)	(0.0669)	(0.1724)	(0.0722)	(0.0678)	(0.0955)	(0.0771)
$Tang_{it-1}$	-0.018**	-0.016	-0.004	0.009	-0.020*	-0.020	-0.003	0.006	-0.039**	-0.096***	0.008	-0.014	0.013	-0.028**
	(0.0082)	(0.0112)	(0.0111)	(0.0111)	(0.0110)	(0.0141)	(0.0110)	(0.0091)	(0.0151)	(0.0243)	(0.0205)	(0.0118)	(0.0122)	(0.0132)
$ebit\_ta_{it-1}$	0.022*	0.031*	0.003	0.006	0.008	0.011	0.013	-0.018	0.01	0.096***	0.014	-0.003	-0.001	0.045**
	(0.0125)	(0.0173)	(0.0157)	(0.0367)	(0.0198)	(0.0329)	(0.0260)	(0.0167)	(0.0215)	(0.0273)	(0.0430)	(0.0154)	(0.0289)	(0.0206)
$Intan_{it-1}$	-0.008	-0.005	-0.002	-0.002	-0.003	-0.021*	-0.008	0.004	-0.02	-0.018	0.012	-0.009	0.013	-0.006
	(0.0064)	(0.0079)	(0.0094)	(0.0124)	(0.0085)	(0.0122)	(0.0098)	(0.0092)	(0.0125)	(0.0357)	(0.0259)	(0.0098)	(0.0123)	(0.0096)
constant	0.016***	0.017***	0.020***	0.017***	0.014***	0.009	0.013***	0.015***	0.030***	0.076***	0.030**	0.020***	0.014**	0.015**
	(0.0036)	(0.0045)	(0.0051)	(0.0059)	(0.0051)	(0.0066)	(0.0050)	(0.0058)	(0.0065)	(0.0156)	(0.0122)	(0.0054)	(0.0066)	(0.0063)
NT	48588	23899	24689	12407	24589	8443	14432	17434	13721	951	4407	18338	8000	14694
N	2486	1309	1177	696	1148	426	775	807	702	42	234	815	462	759
Tavg	19.5	18.3	21	17.8	21.4	19.8	18.6	21.6	19.5	22.6	18.8	22.5	17.3	19.4
R^2	0.27	0.24	0.33	0.21	0.29	0.33	0.26	0.27	0.38	0.27	0.24	0.34	0.26	0.25
Hansenp	0.774	0.384	0.17	0.812	0.251	0.649	0.313	0.565	0.382	1	0.453	0.066	0.221	0.919

The notes of this table are the same as those in Table 6.

Fig. 1 – Four anecdotal examples
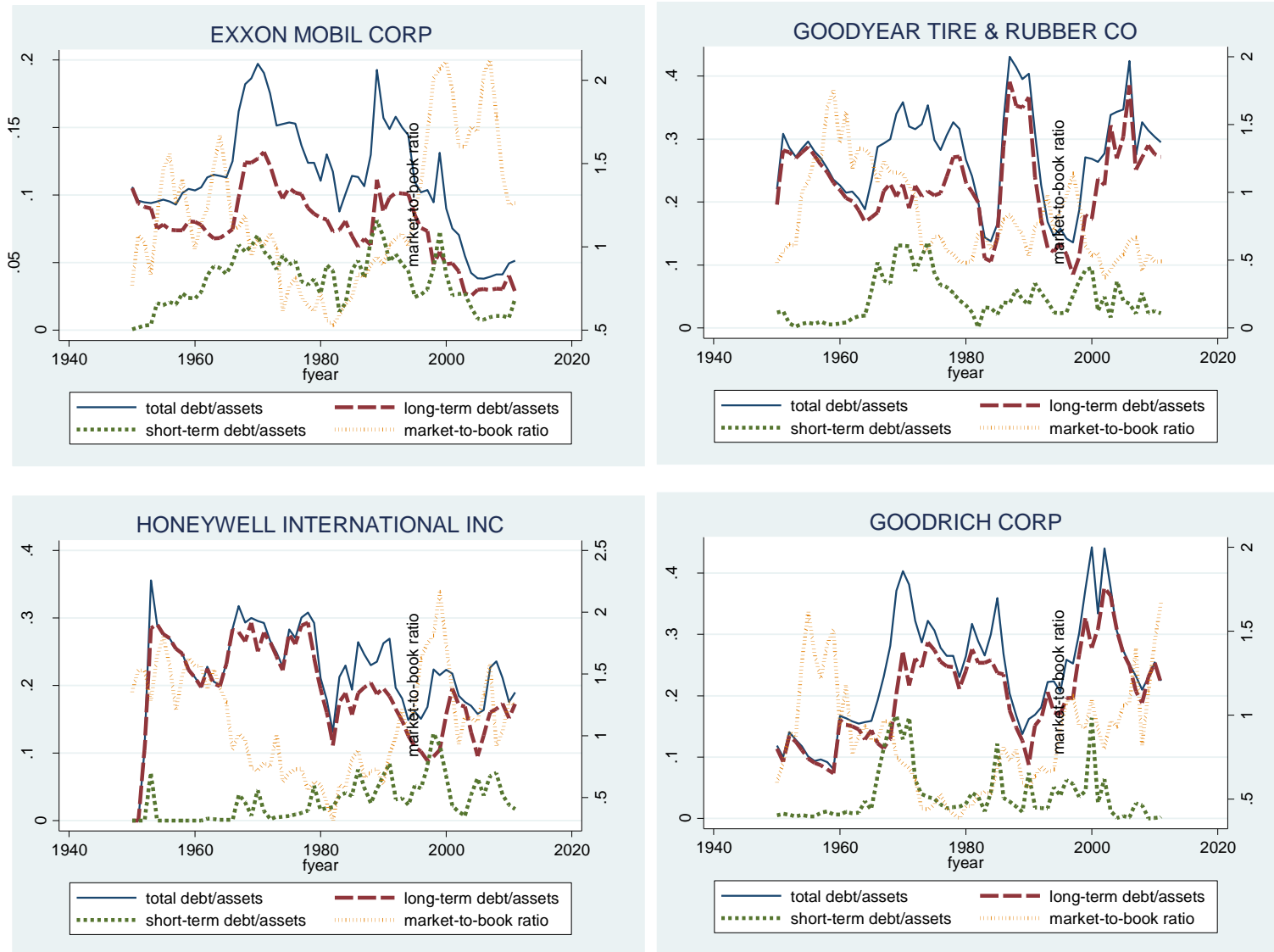
Appendix A1 – The univariate heterogeneous models (the first step): technical aspects and further results

Table A1.1 - Cases/tests on heterogeneous SOAs and debt ratio dynamics: specific settings[45]

Cases/test	Methodology
A1/ADF **A1**/DF-GLS	Inference on α_i parameters is accomplished by using the distribution of the Dickey and Fuller (1979) test, ADF, and the parameters λ_{ij} measure the reduced-form dynamics of PO/MT and TO shocks through p_i firm-specific lags of the dependent variable; the rule for truncating the lags, p_i, are from Ng and Perron (1995, 2001). The ADF has some drawbacks. On one side, the presence of sizeable MA terms (MA roots very close to minus one) may produce the near cancellation of roots and severe size distortions of the testing down procedures to select the appropriate lag order p_i of model (10). On the other side, a long autoregressive process may mitigate the size problems, but it reduces the power of the test. Hence, we prefer the Elliott et al. (1996) test, DF-GLS, based on GLS de-trended data. DF-GLS has excellent size and power properties in assessing the null $\alpha_i = 0$ (see Ng and Perron, 2001, and Haldrup and Jansson, 2006), and it works well also in small samples. Although the ADF over-rejection is mainly due to the structure of the errors in model (10), also the variability over time of the α_i estimates and the presence of breaks at the beginning of the series may induce size distortions. To keep under control the latter two circumstances, we estimated our models over rolling samples, in Appendix A1.6.
A2/BvD	Asymmetric adjustment extensions of the unit root test were introduced by Enders and Granger (1998) and reconsidered in Berben and van Dijk (1999) based on a threshold AR model (TAR) with asymmetric SOA, specifically, two different heterogeneous SOAs, α_i^- and α_i^+, when, respectively, firms are under- and over-levered in period *t-1*. BvD estimates the unobservable target debt ratio by using the sequential conditional least squares; their innovation with respect to Enders and Granger (1998) is that of searching the target which minimizes the residuals variance of the model, rather than estimating the debt target with the sample mean of the actual data. This is because, when the strength of the adjustment towards the attractor L^* is very different under the two regimes, the sample mean is a biased estimator of the target. First, L_i^* is estimated (belonging to the 15% trimmed interval within the minimum and maximum historical value of the actual debt ratios). Second, a statistic F (tabulated by BvD) is used to test for the null hypothesis of non-stationarity, $\alpha_i^-=\alpha_i^+= 0$. If the unit-root null is rejected, we can also test for $\alpha_i^-=\alpha_i^+$ (the two SOAs do not significantly differ) with a standard F statistic.
A2/KSS	Kapetanios et al. (2003) approach: under the alternative, the nonlinear SOA is equal to $\alpha_{it} = e^{-\theta_i(L_{it-1}-L_i^*)^2} - 1$, as that of a stationary exponential smooth transition AR model (ESTAR). The unit root null hypothesis is $\theta_i = 0$ (which corresponds to $\alpha_{it} = 0$), against the alternative $\theta_i > 0$. In the KSS nonlinear target adjustment, SOA is symmetric (as the speed of adjustment depends on the squared distance); differently from BvD, its non-linearity cannot be tested against the linear ADF test equation. The implementation of the KSS test entails computing a first-order Taylor series approximation to the ESTAR model under the null that leads to the ADF-like equation where, however, the lagged and demeaned actual debt ratio regressor, $L_{it-1} - L_i^*$, is substituted by $(L_{it-1} - L_i^*)^3$. The t-statistic of the estimated parameter for the cubic regressor is tabulated by KSS and is used to test for the debt ratio non-stationarity. In the implementation of their procedure when data have nonzero mean, KSS suggest using demeaned data. We estimated the target debt ratio using the sample mean.
B1/BT1/BT2	One- and tow-break unit root tests of Perron and Vogelsang (1992) and Clemente et al. (1998). Breaking/shifting parameter models represent the debts with two fundamentally different types of shocks: the "big shocks" occurring infrequently and affecting debt-levels in a permanent way, and the "regular shocks" occurring every period and not necessarily affecting the debt-levels in a permanent way. When structural breaks are introduced under the alternative, the series share features like unit root series under the null, and it is quite difficult to discriminate between the two hypotheses. As the similarity between the two processes

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[45] In the jargon of Granger and Swanson (1997), all the tests in the Table are exact unit root tests as the theoretical drivers of firm-specific leverages cannot change over time. The case in which firm-specific leverages are generated by stochastic processes that can be stationary for some periods and nonstationary (or even mildly explosive) for others, can be detected by random unit root tests, i.e. AR models with random autoregressive coefficients. This approach is used for modelling bond yields and stock indices (e.g. Leybourne et al., 1996 and discussion in Granger, 2005). Being data intensive, it is more suitable with monthly/quarterly datasets.

increases with the number of breaks, the tests for multiple breaks under the alternative have a decreasing power. Hence, it is better to represent the non-stationary patterns of the debt ratios by few but very relevant k events occurring during the life of the firm, rather than by the existence of unit roots (Perron, 1989). If a limited number of fundamental shocks occurs at time TB_{ji} ($j = 1, 2, \ldots, k$), the debt ratios dynamics can be decomposed in a sequence of transitory PO/MT and TO shocks plus k permanent effects modelled and estimated as deterministic shifts of the target. The target leverage L^* is defined as in the fourth and fifth rows of column three in Table 1, where we test for unit roots against target leverage stationarity with, respectively, one break (BT1, in the fourth row) and two breaks (BT2, in the fifth row). Since the break dates, TB_{ji} ($j = 1, 2$), are unknown, their estimation is implemented as a sequential procedure run over the full sample, with dummy variables for each possible break date: the break date is found where the evidence is the least favourable for the unit root null hypothesis. Given the estimate(s) of the break date(s), if we reject the null $\alpha_i = 0$ of unit roots in the model with either one or two breaks, we find evidence supporting a stationary model with breaking L^*_{it} driven by (not modelled) TO determinants. For example, in the case of one break, the target debt ratio shifts from $L^*_i = \mu_i / -\alpha_i$ up to $L^*_i = (\mu_i + d_{1i}) / -\alpha_i$ at the break date TB_{1i}.

B2/mean	The 12-industry disaggregation used to compute by-industry averages is downloadable from Kenneth French website at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/ftp/Industry_Definitions.zip. To allow for enough data in each cell, the averages are computed over the whole unbalanced panel. In this way, we expect that these averages better represent the by-industry patterns for the US economy (see Table A2.1 of Appendix A2). Results, available upon request, are robust to the use of averages specific to the balanced sub-panels.
C1/EG	Given that cointegration can be tested using alternative approaches (see Gregory et al., 2004, and Gonzalo and Lee, 1998), we use three approach. The first is the cointegration approach due to Engle and Granger (1987), which is based on the direct assessment of the stationarity of deviations $L_{it} - L^*_{it}$ with a Dickey-Fuller type test, where L^*_{it} is proxied by the OLS fit of the static (or "long run" or "cointegration") regression of L_{it} against Z^{TO}_{it}. To prevent the spurious significance that could arise from the use of standard t statistics (Granger and Newbold, 1974), the statistical significance of the parameters β_i is assessed by testing the stationarity of the residuals from the firm-specific static regressions. Under cointegration, the OLS estimator of the static regressions is super-consistent, that means not affected either by Z^{TO}_{it} endogeneity or omitted dynamics (see Stock, 1987). The main drawbacks of the EG approach are two. First, a common factor restriction is imposed to the dynamics of the relationship between debt and TO determinants and, second, the disequilibria $L_{it} - L^*_{it}$ are assumed to feed-back only to the short-run debt changes and not to those of Z^{TO}_{it} (weak exogeneity of Z^{TO}_{it}).
C1/BO-BA	The EG common factor restriction is relaxed by the cointegration approach of Boswijk (1994, BO) and of Banerjee et al. (1998, BA): after the OLS estimate of the dynamic relationship reported in column 4 of Table 2, the BA test is the t-statistic of the null hypothesis $\alpha_i = 0$, whereas the BO test is the Wald F-statistic for the joint null hypothesis $\alpha_i = \gamma_i = 0$. Although apparently quite close to model (3), this test equation introduces heterogeneous SOAs and uses non-standard t and F distributions (tabulated by the authors), which are more appropriate when variables are persistent (see Hall et al., 1992).
C1/JO	The EG and BO-BA assumption of Z^{TO}_{it} weak exogeneity is relaxed by the cointegrated VAR approach of Johansen (1995, JO) which tests for the rank r of the matrix Π of a VAR model parameterized as the vector error correction mechanism (VECM, in column four of Table 2), where r is the number of cointegration relationships among the variables in X. The significance of Z^{TO}_{it} in driving the long run debt target requires that $r > 0$. First, we test for the cointegration rank being zero; under the not rejection of the null the company is classified as non-reverting. If the null is rejected, we impose rank one and jointly test for loading parameters significantly negative in the debt equation and zero in the other equations. If the null is not rejected, we classify the company as non-reverting, while, under the alternative, companies have cointegration rank equal to 1 and TO drivers weakly exogenous. Because of its generality, JO approach lacks parsimony: being VAR-based, it entails a number of parameters to be estimated larger than those of EG/BO-BA, and this can be a severe limitation in our firm-specific heterogeneous context. Moreover, the cointegration rank estimate can be biased (inflated) by the presence of stationary variables in the system that, combined with intercepts, might lead to additional stationary relationships that have nothing to do with the target debt ratio definition. Finally, if the non-stationary variables have a VAR representation with a near-singular covariance matrix, JO tends to find a spurious cointegration.

A1.2 – Quantitative and qualitative aspects of the first step

The minimum time span, T_i, required for each ith company to perform our first step needs both quantitative and qualitative considerations. The quantitative aspect of the first step of our methodology is directly related to the temporal dimension, T_i, available for each company, i. In general, unit root tests may lack power against very persistent dynamic processes, i.e. they may fail to reject the false null when the processes revert very slowly in the long run. Many studies (e.g. Hakkio and Rush, 1991) have shown that more observations on the long run fluctuations increase the power of the tests. "More observations" doesn't literally mean a higher number of observations but longer time spans: a data set of annual data (as in our case) over a given time span leads to tests with higher power than the tests performed on higher frequency observations over a shorter time span (Shiller and Perron, 1985).[46] The drawback of using a long time period to perform unit root tests is that long historical data may be affected by structural changes (Campbell and Perron, 1991), as well as by the risk of survivorship biases because of the selection of oldest and largest firms. Moreover, any given time period, even if long, represents a finite sample in which persistent but stationary processes, behaving similarly to random walks, cannot display the sharp asymptotic differences between unit root and stationary processes (as shown in Blough,1992, Hamilton, 1994, and Stock, 1994). The conclusion is that the best unit root test does not exist; instead, it is better to compare the performance of different unit root tests in alternative finite samples characterized by different temporal spans.

The qualitative aspect of our methodology concerns, more importantly, the "length of the long run", that is the number of periods necessary to the debt ratio to revert to its equilibrium, which depends on the SOA, on the nature of the determinants of the target (the TO variables), and on the short-run fluctuations (the PO/MT variables).[47] For example, consider the debt ratio of the ith and the jth firms, which changes to close the gap with the target. Suppose that the debt ratio of the ith firm is highly persistent (for example with a SOA equal to -0.1), while the debt ratio of the jth firm is less persistent (with a SOA equal to -0.6). Then, a time span T_i of 20 years cannot inform on the long run behaviour of the ith company simply because such a persistence entails a half-life of about 7 years for a debt shock and requires more than 21 years to close 90% of the gap between actual and target debt ratio. Further, such a slow reactivity of the debt ratio contrasts with the existence of a long run target. On the opposite side, the long run of the jth firm is shorter, as the half-life of a debt shock is 9 months and the 90% of the actual-target debt gap is closed in less than 3 years. Therefore, a time span T_j of

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[46] This fact is quite understandable, as "it would be surprising if simple time disaggregation (from years to month, say) helped in the estimation of long run relations", Hendry (1986); see also Lahiri and Mamingi (1995).

[47] The length of the long run also varies across fields. In the field of growth, the long run may be a matter of decades, while in finance it may be a matter of months or even less.

20 years contains enough information to capture the target reverting behaviour of the debt dynamics of the jth firm. The qualitative aspect reinforces the need of using alternative representations of the debt dynamics and unit root tests over alternative time spans.[48]

The quantitative and qualitative role of T_i and SOA on the power and size of unit root tests is discussed by Monte Carlo experiments applied to the DF-GLS test. We select DF-GLS test because of its pivotal role in creating our multilevel index. The DGP used to carry out the experiments is the simple heterogeneous AR(1) model

$$y_{it} = \alpha_i y_{it-1} + \mu_i + v_{it} \tag{A1.1}$$

where the constant term is generated as $\mu_i \sim N(0, \sigma_\mu^2)$ and the shocks are generated as homoskedastic random i.i.d. errors $v_{it} \sim N(0, \sigma_v^2)$. The initial values of y_{it} depend on the sum of their steady-states plus a heterogeneous random disturbance $\omega_i \sim N(0, \sigma_\omega^2)$, i.e. $y_{i1} = \frac{\mu_i}{(1-\alpha_i)} + \omega_i$. The parameters set in the experiments are the autoregressive parameter α_i, and the three variances σ_μ^2, σ_v^2, and σ_ω^2.[49]

By specifying the AR(1) model in the error correction form, we have:

$$\Delta y_{it} = (\alpha_i - 1)\left(y_{it-1} - \frac{\mu_i}{1-\alpha_i}\right) + v_{it} \tag{A1.2}$$

that we used in 10,000 replications of 20 cases obtained from setting six alternative SOAs, from very fast to very slow depending on different values of the α_i parameter in equation (A1.1) ($\alpha_i = 0.2, 0.4, 0.6, 0.8, 0.9,$ and 0.999) over four alternative time spans, from short to long ($T_i = 20, 30, 40,$ and 50). Note that the selected time spans mimic the lengths of our balanced and unbalanced sub-panels.

The power of the DF-GLS test for each (SOA, T_i) pair is reported in Table A1.2 and it is measured as the fraction of replications where DF-GLS p-values are lower than 5%, i.e. the proportions of the right rejection of the false null hypothesis.

Results are clear cut: the biggest power problems (partial inability to reject the false unit root) emerge when the dynamics is very persistent: independently from the time span, SOAs between -0.2

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[48] It could be argued that there is a non-zero probability that the PO/MT-like debt ratio will explode (the firm's solvency condition cannot be met). Nevertheless, from the theoretical point of view, Fama and French (2002) point out that there are certain forces preventing this to happen. Firms that pay dividends can maintain lower debt ratios by lowering pay-outs. Firms which do not pay dividends may need to borrow more to finance investments but, given both current and future borrowing costs, they tend to preserve low-risk debt capacity until positive net cash flows arrive. From the empirical point of view, the conclusion that debt ratios are integrated processes cannot be true in a very strict sense because integrated series are unbounded, while debt ratios are bounded between zero and one. Nevertheless, when sample data suggest that the statistical characteristics of debt ratios are closer to integrated rather than stationary series, it is better to treat these series as if they had stochastic trends; see e.g. Hall et al. (1992). In addition, as noted in Brunello et al. (2000), the relevant issue is not the fact that the variables are bounded from above by 1 and from below by 0, but it is the time needed to reach these limits 0 and 1 which is relevant. In our context, for reasonable values of the variance of debt shock v_{it}, the expected time required for the barriers to be binding is extremely large (of an order of magnitude of about 1,700 years) and, during such a huge temporal interval, the debt ratio is exactly equivalent to an unrestricted random walk.

[49] In all the simulations all the variances are set to one. It is worth noticing that results of DF-GLS tests are broadly the same under alternative settings of the variances. The settings of DF-GLS are the same as those in Table A1.1. The Monte Carlo program is available upon request.

and -0.1 are associated with low power. In the limit, when the SOA is almost zero (equal to -0.0001), the power of DF-GLS is even lower, tending to be close to the size of the test for every time span. This means that the "borrowing behaviours" of "snail-pace" adjusting companies (very slowly adjusting TO) are mostly indistinguishable from those of never-reverting PO/MT firms. Coherently, in these cases the power of DF-GLS vanishes, and extremely slow adjusting behaviours are classified by DF-GLS for what they are in practical terms: non-adjusting behaviours. From Table A1.2 we see, in fact, that companies with very low SOAs have a debt-dynamics that take more than twenty years (in the limit, more than 23,000 years!) to close 90% of the gap between the actual and target debt, measured by $\frac{\mu_i}{(1-\alpha_i)}$.

Table A1.2 – Power function for Monte Carlo experiments [a]

α_i [b]	SOA[c]	Long run[d]	$T_i = 20$	$T_i = 30$	$T_i = 40$	$T_i = 50$
0.2	-0.8	1.4	0.6308	0.8104	0.8881	0.9245
0.4	-0.6	2.5	0.5675	0.7589	0.8726	0.9210
0.6	-0.4	4.5	0.4569	0.6340	0.7934	0.8773
0.8	-0.2	10.3	0.3018	0.3942	0.5261	0.6314
0.9	-0.1	21.9	0.2208	0.2378	0.2966	0.3570
0.9999	-0.0001	23,024	0.1258	0.0980	0.0933	0.0814
1 [e]	0	∞	0.1173	0.1028	0.0879	0.0782

[a] Fraction of replications with p-values < 0.05. [b] See eq. (A1.1). [c] $(\alpha_i - 1)$ parameter in eq. (A1.2).
[d] Number of periods after a shock to close 90% of the gap between the actual y and its steady-state solution, measured by $\frac{\mu_i}{(1-\alpha_i)}$. [e] Proportions of the rejections of the true null using the 5% nominal size.

The last line of Table A1.2 reports the output of the experiments for the size of the test. Here the SOA is set equal to 0 in the simulations, so that equation (A1.2) becomes a random walk under the null of the DF-GLS test. We extracted T_i+100 normally distributed and uncorrelated pseudorandom numbers with standard deviation equal to unity to represent the sequence of shocks added to the initial value of y (set equal to zero). We made 10,000 replications and, for each series, we discarded the first 100 realizations. Using the 5% nominal size, in the last line of Table A1.2 we report the proportions of the rejections of the true null. Results suggest that the actual size of DF-GLS test is a bit higher than the 5% nominal size: DF-GLS slightly over-rejects the null of unit roots when $T_i < 100$ (the actual size reaches the nominal one when T_i is larger than 150). Such over-rejections entail that DF-GLS slightly underestimates the share of the genuine PO/MT companies, a fact *per sé* not much warrying given the very high portion of PO/MT companies estimated in our samples, see the empirical results in Subsection 3.1.

A1.3 - Relating the use of time dummies with the practice of data demeaning

The estimation of a model with time dummies is equivalent to the estimation of the model (without τ_t) where all the variables are demeaned. In this context, "demeaning" means that we measure the dependent variable with $L_{it}^d = L_{it} - \bar{L}_t$ rather than L_{it}, where $\bar{L}_t = \frac{1}{N}\sum_{i=1}^{N} L_{it}$ (N is the number of firms in the panel). The inclusion of time effects τ_t (or demeaning model's variables) under the assumption of stationary variables implies that the disturbance for each firm can be decomposed into common disturbances that are shared by all the members of the panel, and independent idiosyncratic disturbances that are specific to each member. Hence, time dummies are motivated by the need to account for a degree of dependency across individuals due to collectively significant but unobservable effects, such as widespread optimism or pessimism.

To give the intuition with a simple example, let's start from the demeaned univariate model to account for heterogeneity in the linear context:

$$\Delta L_{it}^d = \alpha_i L_{it-1}^d + \mu_i + e_{it} \tag{A1.3}$$

If we substitute the definition of demeaned data, we have:

$$\Delta L_{it} = \alpha_i(L_{it-1} - \bar{L}_{t-1}) + \mu_i + \Delta \bar{L}_t + e_{it} \tag{A1.4}$$

where $\Delta \bar{L}_t$ proxies the shocks common to all N members of the panel and e_{it} embodies all the idiosyncratic shocks. As shown in equation (A1.4), estimating a model with demeaned data assumes an error correction mechanism process of adjustment where individual debt ratios converge to the heterogeneous target $L_{it}^* = \frac{\mu_i}{-\alpha_i} + \bar{L}_t$.

Model (A1.4) can be augmented, as it is possible for the Dickey-Fuller test equation, to fix residuals' autocorrelation. In this case, the dynamic specification (A1.4) is still an error correction mechanism:

$$\Delta L_{it} = \alpha_i(L_{it-1} - L_{it-1}^*) + \sum_{j=1}^{p_i} \lambda_{ij} \Delta L_{it-j} + \sum_{j=0}^{p_i} \lambda_{ij} \Delta \bar{L}_{t-j} + \omega_{it} \tag{A1.4}$$

which corresponds to the Dickey-Fuller equation augmented by the changes in the common driving component $\Delta \bar{L}_{t-j}$.

For a theoretical justification of a slight generalization of model (A1.4), see the cross-sectional augmented Dickey-Fuller (CADF) test of Pesaran (2007), where the common stochastic disturbance is proxied by a single common factor independent on the idiosyncratic disturbances.

A1.4- Deepening non linearity of Case A2

The average SOA estimates cannot be computed for Case **A2**/KSS as it includes models which are non-linear functions of the actual-target debt ratio gaps. Figure A1.1 plots two of these SOA functions for reverting firms over the period 1980-2001 (which correspond to the first and third quartiles of the distribution of θ_i, see Tables 1 and A1.1), estimated for the total debt.

Fig. A1.1 – SOA estimates for total debt under Case A2/KSS over the sample 1980-2011

Actual-target debt gaps
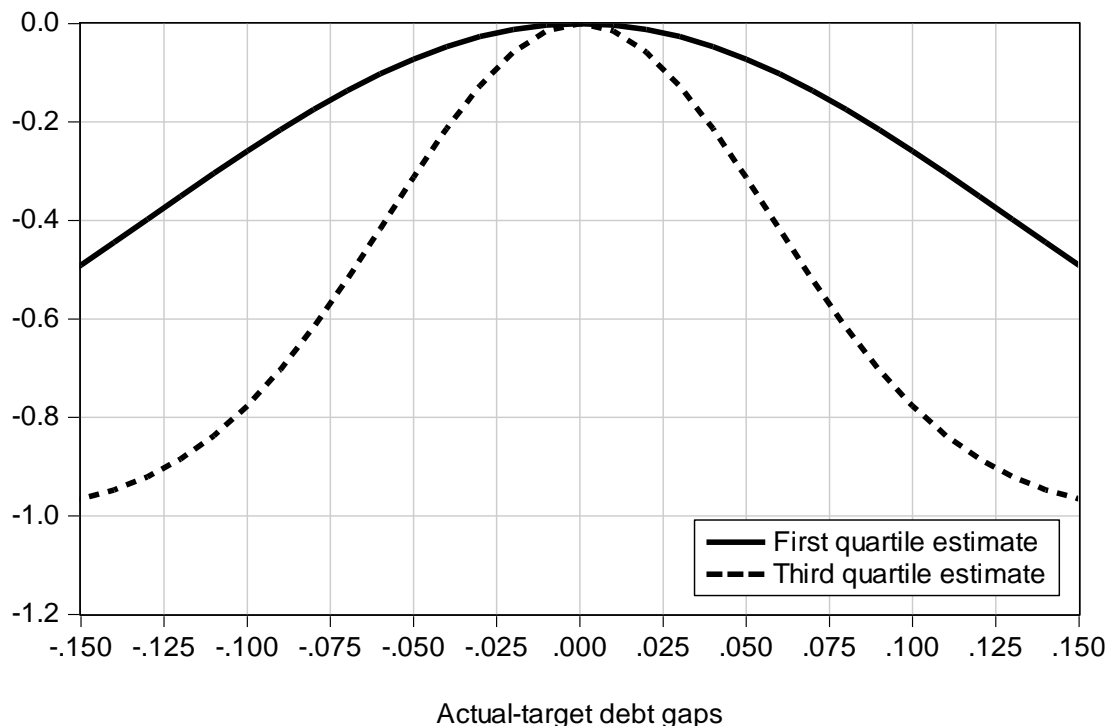
The two SOA estimates for different debt gaps are obtained using the first and third quartile of the distribution of θ_i estimates.

The wide distance between the two depicted patterns suggests that non-linear SOAs are heterogeneous. When the size of the gap is about half of the average total debt ratio (±0.125), the two speeds of adjustment of the firms in the third and first quartile, respectively, range from -0.9 to -0.4, that is, from an adjustment process that closes 90% of the gap in about one year to another one that takes almost five years to close the same gap.

A1.5- Extending the univariate models to targets driven by explicit explanatory variables

Interestingly, if the actual debt ratio L and some TO determinants Z are strongly persistent (i.e. characterized by stochastic trends), the statistical significance of SOAs cannot be assessed by using standard t-statistics but must be tackled in the context of the integration-cointegration properties

through the Granger representation theorem.[50] Under the multivariate Case **C1**, non-stationary TO drivers can induce non-stationary optimal debt targets through heterogeneous cointegrated relationships. In this context, the deviations between the actual debt and its target - driven by valid TO determinants, $L_{it}^* = \beta'_i Z_{it}^{TO}$, can be only transitory, as the non-stationary L_{it} and Z_{it}^{TO} are cointegrated.[51] Under the assumption of stationary PO/MT determinants, debt ratio changes can be explained by a heterogeneous, possibly lag-augmented, the error correction model like

$$\Delta L_{it} = \alpha_{it}\left(L_{it-1} - \beta'_i Z_{it-1}^{TO}\right) + \mu_i + e_{it} \text{, where errors } e_{it} = \gamma'_{it}\left(\frac{\varepsilon_{it}^{PO/MT}}{[1-a_i(B)]}\right) + \varepsilon_{it} \text{combine the distributed}$$

lags of PO/MT shocks $\varepsilon_{it}^{PO/MT}$ with the idiosyncratic debt shocks ε_{it}. Although this model is less parsimonious than the univariate models, it estimates the long-run target without the need of further assumptions, such as the stationarity of Z_{it}^{TO} (as in Cases **A1** and **A2**), or the existence of breaking targets (as in Case **B1**), or the driving effect of industry-wide averages (as in Case **B2**). In Table A1.1 we introduce three different cointegration tests that gradually relax a list of constraints. Case **C1**/EG is the most restrictive, as it imposes a common factor restriction to the dynamics of the relationship between the debt ratio and the TO determinants, and it assumes the weak exogeneity of Z_{it}^{TO}, meaning that the disequilibria $L_{it} - L_{it}^*$ feeds back, in the short run, to the equation for the debt and not to the equations for the variables inside the Z_{it}^{TO} vector. Case **C1**/BO-BA only relaxes the common factor restriction. Finally, Case **C1**/JO also relaxes the assumption of weak exogeneity of Z_{it}^{TO}.

We switch from the univariate cases presented in Subsection 3.1 to the multivariate approach, Case **C1**, by augmenting the heterogeneous specification with the variables belonging to the set of TO determinants Z_{it}^{TO}. As the assumption of heterogeneity is quite expensive in terms of degrees of freedom with finite T time series, we keep the model as much parsimonious as possible. We include in Z_{it}^{TO} only four drivers: (1) Guarantees (*Tang*); (2) Profitability (*ebit_ta*); (3) the relative cost of capital, capturing the fiscal advantage of debt (*rcostd1*); (4) the non-debt tax shields (*ndts*). Details on variables definitions are in the following Appendix A2. To further reduce the number of estimated parameters, the lag order of both single-equation and VAR models is selected by the parsimonious Schwarz's Bayesian information criterion.

Table A1.3 reports, over alternative sub-periods listed along the rows, the shares of firms reverting towards the (cointegrated) target (under the alternative approaches to Case **C1**, along the columns) and the corresponding mean-group (MG) average SOA estimates (for Case **C1**/EG). To

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[50] See Granger and Newbold (1974), and Engle and Granger (1987). Ioannidis et al. (2003) explicitly stress the risk of spurious regressions using very persistent financial ratios.

[51] Case **C1** can represent the leverage dynamics even if Z_{it}^{TO} are stationary. In such circumstance both the actual debt, L_{it}, and its drivers are stationary, their discrepancy is also stationary, and the steady-state level-relationship gives information about the contribution of each single TO component to the time-invariant target leverage.

ensure results' comparability, companies entering each sub-panel are the same used above but now we add a column labelled as "incomplete" containing the share of firms not included in the cointegration estimates because of a lack of data.[52]

Results are quite clear-cut: the advantage of using explicit and potentially non-stationary determinants for debt targets does not trade off the disadvantage of more parameters to be estimated, as the composition of reverting/non-reverting firms is quite close to that detected with the univariate approaches. As in the univariate case, the share of target reverting firms is larger if we focus on short-term debt, and the corresponding average SOA estimates for the reverting companies are broadly in line with those obtained with breaking targets (Case **B1**) in Table 3.[53]

The messages coming from these results are twofold. First, the advantage of modelling the persistence of debt ratios with persistent TO determinants is not much relevant, as it is easily offset by the complexities induced by the multivariate setting. Since it is not easy to find relevant drivers of debt targets, the apparently statistical significance detected by much of the past studies is due more to the poolability assumption rather than to a genuine relevance.[54] Second, the concept of SOA is related to the study of model dynamics, and the deepening of time series methods can be very helpful to improve our knowledge about company financing choices.

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[52] Note that the share of firms with incomplete data slightly grows in shorter T samples, as the related increase in the number of firms is likely to select companies with lacking data.

[53] We find comparable results also by running the heterogeneous panel cointegration tests of Pedroni (1999) and Westerlund (2007). Pedroni test statistics (with and without data demeaning) reject the null of no-cointegration between debt ratios and the four TO explanatory variables because of a significant share of cointegrated firms. Westerlund's test statistics, with bootstrapped standard errors to account for possible cross-section dependence of debt ratio shocks, deliver the same cointegration outcome only for the short-run debt ratio, while the null of no cointegration is never rejected for the long-run debt ratios.

[54] The lack of cointegration - that is of a statistically founded long run relationship between target leverage and some TO variables - can be explained by the well-known difficulty (see among others Lemmon et al. 2008) of measuring the wide range of theoretical TO determinants with few variables.

Table A1.3 - Shares of firms with explicit TO targets, and SOA estimates by groups of reverting firms.

| Begin	End	Time span	# of firms	Incomplete	C1/EG Non-reverting firms	C1/EG Reverting firms	C1/JO	C1/BA	C1/BO	MG estimates of SOAs for C1/EG
Short-term debt ratios										
1950	2011	62	50	0.000	0.400	0.600	0.280	0.580	0.540	-0.657
1960	2011	52	97	0.010	0.396	0.594	0.313	0.542	0.531	-0.705
1970	2011	42	161	0.012	0.422	0.566	0.296	0.497	0.535	-0.815
1975	2011	37	196	0.015	0.410	0.575	0.332	0.492	0.482	-0.903
1980	2011	32	227	0.009	0.449	0.542	0.302	0.449	0.489	-0.976
1985	2011	27	290	0.028	0.497	0.475	0.309	0.426	0.511	-1.048
1990	2011	22	412	0.034	0.614	0.352	0.304	0.402	0.588	-1.228
Long-term debt ratios										
1950	2011	62	50	0.000	0.800	0.200	0.120	0.120	0.140	-0.411
1960	2011	52	97	0.021	0.832	0.147	0.095	0.158	0.211	-0.517
1970	2011	42	161	0.025	0.803	0.172	0.127	0.185	0.293	-0.640
1975	2011	37	196	0.026	0.833	0.141	0.120	0.120	0.272	-0.779
1980	2011	32	227	0.018	0.816	0.166	0.121	0.121	0.300	-0.824
1985	2011	27	290	0.024	0.792	0.184	0.163	0.159	0.357	-0.859
1990	2011	22	412	0.032	0.863	0.105	0.208	0.246	0.524	-1.044
Total debt ratios										
1950	2011	62	50	0.000	0.860	0.140	0.200	0.040	0.220	-0.401
1960	2011	52	97	0.010	0.896	0.094	0.125	0.052	0.208	-0.426
1970	2011	42	161	0.019	0.823	0.158	0.133	0.082	0.304	-0.546
1975	2011	37	196	0.015	0.850	0.135	0.140	0.067	0.254	-0.639
1980	2011	32	227	0.009	0.880	0.111	0.151	0.076	0.284	-0.765
1985	2011	27	290	0.014	0.878	0.108	0.217	0.115	0.360	-0.786
1990	2011	22	412	0.024	0.906	0.070	0.189	0.197	0.550	-1.057

Short-term is *SDA* = DLC/AT; long-term is *LDA* = DLTT/AT and total is *TDA* = FD/AT (see the definition of the debt ratios by term structure in Appendix A2). "**C1**/EG" refers to the test of cointegration of Engle and Granger (1987); "Incomplete" denotes the share of firms for which the **C1**/EG test was not feasible because of a lack of information on the explanatory variables; "Non-reverting firms" are those for which the null of the **C1**/EG test is not rejected; vice-versa, for the "Reverting firms", the null of the **C1**/EG test is rejected. Of course, the sum of these three columns is equal to one. "Reverting with alternative approaches" denotes the shares of those firms for which the null of the other three cointegration test is rejected, namely the Johansen (1995) cointegration rank test (**C1**/JO), and the error-correction cointegration tests of Boswijk (1994) (**C1**/BO) and of Banerjee et al. (1998) (**C1**/BA). Finally, the column "MG estimates of SOAs for **C1**/EG" reports the mean group estimates of the firm-specific SOA estimates within the group of the "Reverting firms" in the light of the **C1**/EG test.

A1.6 - The stability of results over rolling windows

Empirical results in Subsection 3.1 showed that the shares of stationary firms in each sub-sample are significantly higher than zero and lower than one. Therefore, firms are significantly heterogeneous in their adjustment processes of debt ratios towards targets. However, such analyses have been carried out over alternative samples of balanced panels of those firms that always belong to specific sub-periods. In this case, the variability of the results listed along the rows of Tables 2-3 and A1.3 is due to the joint effect of two factors: (*a*) the sample composition variability, because of the increase in the number N of panels' members due to the decrease in the number of years T in which firms have to report no-missing data; (*b*) the time variability, because specific and different events can affect the behaviour of firms over different time sub-periods.

The variability of counts over the alternative balanced samples used in Tables 2-3 and A1.3 is depicted in Figure A1.2 by four straight lines: each line counts N (the number of firms) in the sub-period of time reported in its corresponding label. Conventionally, the horizontal axis reports the first year of the alternative sub-samples. Of course, the information in this axis is also reported in selected rows of the first column ("Begin") of Tables 2-3 and A1.3, and the information in the vertical axis is also reported in the third column ("Time span"), same rows. The sum of the "begin" year plus the labelled T gives the "end" year of each subsample.

Fig. A1.2 - Counts of firms (N) belonging to alternative fixed and rolling sub-samples [a]
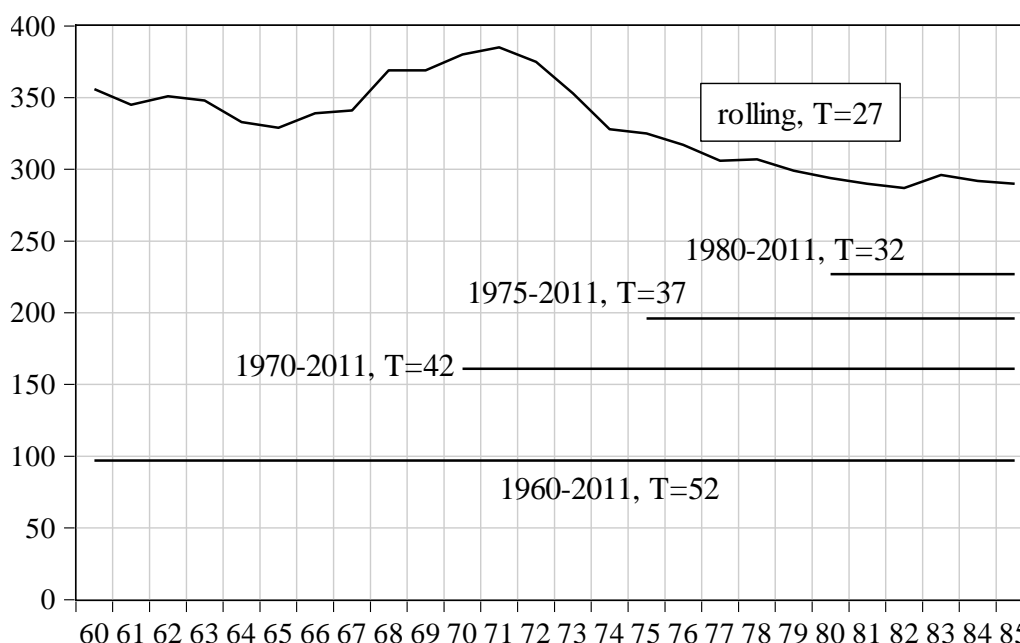
([a]) Conventionally, the x-axis reports the first year (begin) of the alternative the sub-sample periods. Of course, for straight lines the sum of the begin year plus the labelled T gives the end year of each fixed sub-period (always 2011), while the rolling sub-periods are defined form the beginning to 27 years later.

The variability of counts over time is represented by the upper curve in Figure A1.2. Its pattern reports the number of Compustat firms belonging to a sequence of sub-samples with a rolling window of amplitude T=27 years. For example, the observation corresponding to "60" on the horizontal axis measures the number of firms (N=356) always in the sample over the period 1960-1986, and the following observation (N=345) is the number of firms belonging to the 1961-1987 sub-period.

Over the period 1960-2011, 97 firms always belong to all rolling samples above because they have no missing data from 1960 to the end of the whole sample (2011). The balancing of the panel over the 1970-2011 period adds further 64 new firms which entered Compustat from 1961 to 1970 and then never dropped out. The reduction of other 5 years of the sub-sample further increases the balanced 1975-2011 sub-panel of other 35 new firms. The entry of other 31 new firms occurred during the five years from 1976 to 1980, for a total of N=227 firms belonging to the 1980-2011 balanced panel.[55] The story told by the upper curve is quite different, as the time series of counts is the annual balance of the entry of new firms net of those firms which exit (did not survived) each year, plus of course the firms always belonging to the two consecutive rolling subsamples. As a result, the average level of the rolling sample, about 300/350 firms by year, is much larger than that of the balanced samples. In addition, given that the rolling sub-samples analysed in this Section are affected more by events occurring over time rather than by sample composition, the fluctuations in the rolling estimates are more due to models' parameter instability over time.

The four graphs in Figure A1.3 show the shares of reverting firms (upper panel) and the average SOAs (lower panel) over rolling samples of 27 years beginning in the years reported along the x-axes. The left hand-side columns pertain to short-term debt, the right hand-side ones to long-term debt.

The upper panel graphs compare the outcomes in terms of alternative shares of reverting firms for short- and long-term debt. As noted in the previous Subsection 3.1, the shares relative to the short-term debt are markedly higher than those relative to the long-term always in rolling samples. Further, the shares show a slight tendency to increase since mid-1970s, and the asymmetric adjustment and breaking target models deliver shares of short-term debt reverting firms which are higher than those of the other three models, while in the long-term debt case only breaking targets shares seem slightly higher. In both cases, the study of the cointegration relationship between debt and specific determinants does not modify the basic outcomes.

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[55] The latter count N=227 is obtained by summing the number of firms always in the data-set from 1960 to 2011 (97) plus the three changes mentioned in the text (i.e. 64+35+31). Two points are noticeable: (1) the increased number of firms is due to *new* companies in the sample which never drop out in the following years, up to 2011; (2) the rate at which firms enter the sequence of sub-samples is approximately the same, i.e. about 65 new firms every ten years.

The lower panel compares alternative rolling SOA estimates. They all are remarkably stable over time and suggest that debt targeting firms broadly revert to their optimal levels in around one-two years, independently on the maturity of the debt. It is worth stressing again that - in general - the estimates of the average speeds for the target-adjusting firms are again significantly higher than those usually reported in studies assuming poolability.

Fig. A1.3 - Rolling estimates of reverting firms' shares (upper panel) and of average SOAs (lower panel) by debt term structure [a]
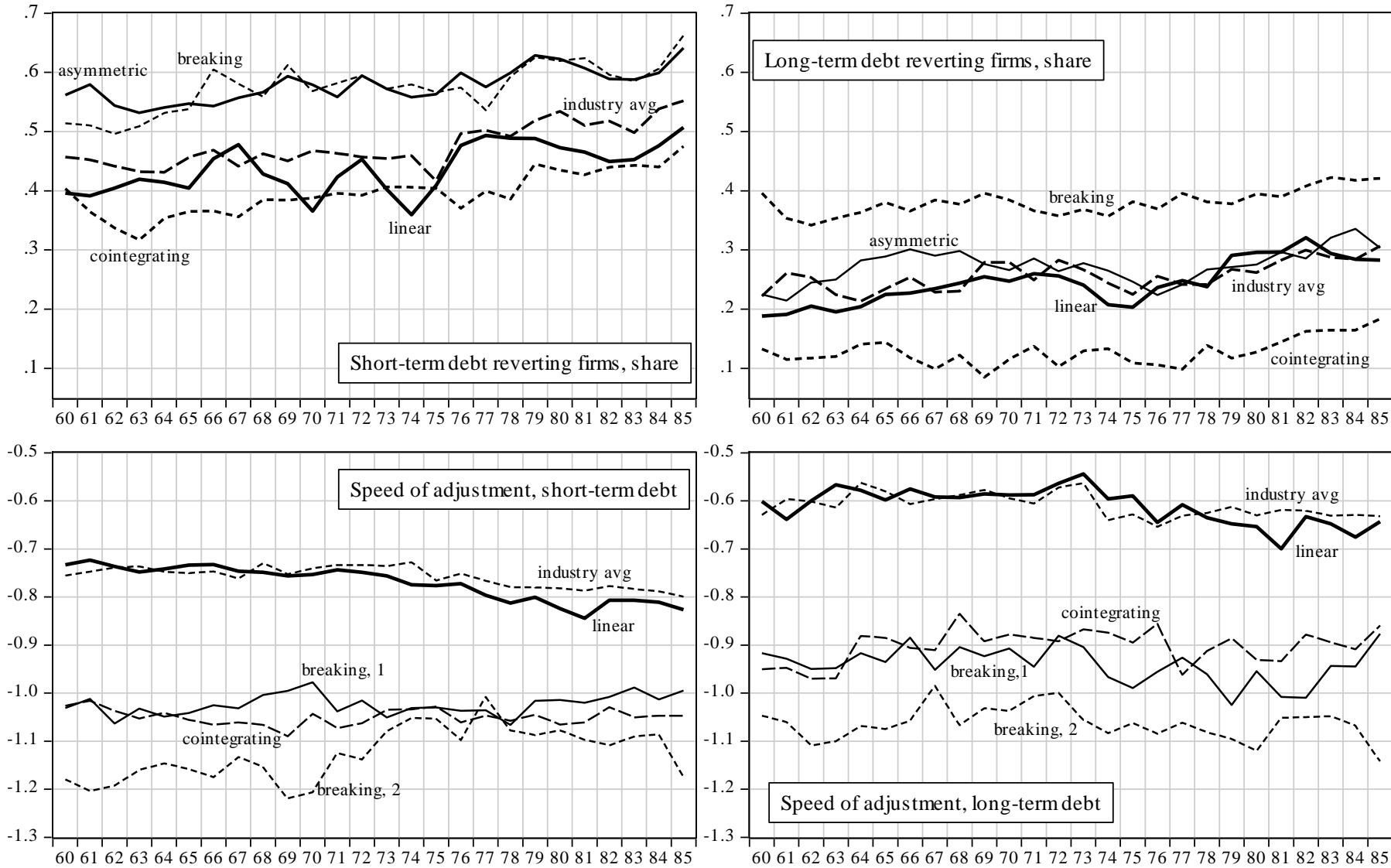
(a) Conventionally, the horizontal axes report the first year of the alternative rolling sub-samples with a 27-years window over which shares and average SOAs are estimated.

Appendix A2 - Data

Selection rules and sub-samples. The sample is drawn from the annual Compustat database covering the period 1950-2011. In order to have consistent measures over time in terms of both data frequency and seasonality, we selected firms with the closing date of the 12-months balance sheets equal to the 31st December, corresponding to 291,880 observations (24,524 firms with average T equal to 11 years).[56] We also imposed the selection rules listed below because they are standard in the empirical analyses on corporate capital structure; hence they are necessary to obtain estimated results comparable with that literature. Specifically, we excluded: firms classified as Financial Services according to the variable Industry Format (9.6% of firms);[57] companies involved in major mergers (Compustat footnote code AB, 1.9% of companies); firms-year observations with missing data on employees and total assets (about 15% of observations), with total debt negative or higher than total assets, with gross tangible and intangible capital stocks higher than total assets, with market value of debt ratio and effective interest rate outside the 1st and 99th percentiles (less than 18% of observations).[58] This set of rules leads to 168,696 observations (15,577 firms with average T equal to 11 years) used to extract the sub-panels of the paper.[59] In Section 3 we used balanced subsamples, from 3,100 observations (50 companies over the longest 1950-2011 period) to the 9,064 observations (412 companies over the shortest 1990-2011 period); the analyses performed in Section 3 have non missing data for financial debt and total assets as the only requirement.[60] In Section 4 the same sample of 168,696 observations is used to extract 63,356 observations (2,612 firms over the 1970-2011 period) with non-missing data for financial debt, for total assets and for the explanatory variables of models (11), and with at least 20 consecutive years.[61] A 20-year time span should be a good compromise between having enough history to consistently perform unit root tests to create our index classifying the companies, and avoiding selection biases towards oldest and largest companies that

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[56] Our date *t* is the fiscal year-end and the calendar date of the fiscal year-end is the Compustat mnemonic DATADATE.
[57] According to the Standard & Poor Compustat Xpressfeed manual "Understanding the data", Industry Format (Compustat indfmt variable) represents company industry format at record level by identifying the basic financial presentation - mainly Financial Services (FS) versus Industrial format (INDL).
[58] Note that the empirical literature usually adds, as a selection rule, the exclusion of regulated firms (SIC codes 4900-4999) and financial firms (SIC codes 6000-6999). These companies represent about the 24% of our 168,696 observations. To avoid unnecessary "ad hoc" selection rules and to be general the most as possible, we computed the index also for regulated and financial firms, and we estimated the dynamic model both with and without these companies; results are robust and available from the authors upon request; the paper reports results including these firms.
[59] The discarded 94,758 observations correspond to 18,720 firms with a very short average T, less than 5 years. We investigated the differences between the firms in and out of the sample obtaining results close to Whited (1992): the excluded companies have a mean TDA (total financial debt to assets) 0.06 percentage points higher than that of included companies (0.24) and are smaller companies (in 2009 out-of-sample firms have on average about 4,700 employees and a book value of equity equal to 1,207.3 million 2009 dollars, while the corresponding figures for the in-sample firms are more than 7,000 workers and 2,190.7 million 2009 dollars; the differences in the book values of capital are not significant).
[60] Financial debts and total assets are available in Compustat since 1950.
[61] Cash flow, dividends paid, non-debt tax shields are examples of explanatory variables which are available since 1971.

would be implied by the use of the balanced sub-panel over the 1970-2011 period (which is composed by 161 companies and 6,762 observations).

Variables' definitions according to Compustat mnemonics.
Most of the definitions are from Frank and Goyal (2003, 2009) and de Jong et al. (2011).

Variable	Description	Definition (Compustat mnemonics)
TDA_{it}	Total book leverage ratio[62]	FD_{it}/AT_{it} where FD = DLTT+DLC is financial debt and AT total assets.
LDA_{it}	Long-term debt ratio	$DLTT_{it}/AT_{it}$ where DLTT is long-term debt exceeding maturity of one year.
SDA_{it}	Short-term debt ratio	DLC_{it}/AT_{it} where DLC is debt in current liabilities, including long-term debt due within one year.
fcf_{it}	Free cash flow is cash flow minus investments and dividends = $cashflow_{it}$ - $inva_{it}$ - $DIVA_{it}$	$cashflow_{it}$ = ICF_{it}/AT_{it}, where ICF is income before extraordinary items (IBC) plus extraordinary items and discontinued operations (XIDOC) plus depreciation and amortization (DPC) plus equity in net loss/ earnings (ESUBC) plus sale of property plant and equipment and investments/gain/loss (SPPIV) plus funds from operations/other item (FOPO) plus exchange rate effect (EXRE) plus deferred taxes (TXDC) and sources of funds/other (FSRCO), according to the cash flow format code (SCF);[63] $inva_{it}$ = INV_{it}/AT_{it} with INV investment in fixed assets, equal to capital expenditures (CAPX) plus acquisitions (AQC) plus increase in investments (IVCH) minus sale of property (SPPE) minus sale of investments (SIV) plus uses of funds/other (FUSEO) minus short-term investments change (IVSTCH) minus investing activities/other (IVACO), according to the cash flow format code (SCF); $DIVA_{it}$ = DV_{it}/AT_{it} where DV is cash dividends.
$DWC1_{it}$	Financial slack	Change in working capital = $\Delta(NWC/AT)_{it}$ where NWC is variation of working capital (WCAPC), cash and equivalents (CHECH), current debt/change (DLCCH), accounts receivable (RECCH), inventory (INVCH), accounts payable and accrued liabilities (APALCH), income taxes/accrued (TXACH), other assets and liabilities (AOLOCH), financing activities (FIAO), according to the cash flow format code (SCF).[64]
rd_ta_{it}	R&D expenses	XRD_{it}/AT_{it} with XRD research and development expense.
rd_dum_{it}		Dummy equal to 1 for rd_ta missing.
$mbRLDA_{it}$	Market-to-book ratio long	$(PRCC_{it} \times CSHO_{it}+DLC_{it}+DLTT_{it})/AT_{it} \times RLC_{it}$

[62] Following Table 1 at p. 9 of Welch (2011), we also used alternative definitions of total debt ratio: LT_{it}/AT_{it} where LT is total liabilities; FD_{it}/BCP_{it} where BCP = FD + BEQ is the book value of capital, with BEQ = SEQ + MIB the book value of equity (SEQ is total stockholder's equity and MIB is minority interests); FD_{it}/MCP_{it} where MCP = FD + MEQ is the market value of capital, with MEQ = PRCC_F × CSHO the market value of equity (PRCC_F fiscal year-end common share price and CSHO number of shares outstanding). We also used: bank debt, proxied by NP_{it}/AT_{it} where NP is notes payable (according to Compustat North America User's Guide, NP comprises items like bank acceptances, bank overdrafts, bank and savings and loans' short-term borrowing, line(s) of credit, note payable to banks and others); bonds, proxied by $(DD_{it}+DN_{it})$ /AT_{it} where DD is debentures (all long-term debentures or bonds which are neither convertible nor subordinated, mortgage bonds) and DN Notes (all notes and debentures/bonds when presented together); leasing, proxied by $DCLO_{it}/AT_{it}$, where DCLO is capitalised lease obligations which includes all items specifically classified as leases or a capitalised lease in the form of a bond; rental leverage computed as in Rampini and Viswanathan (2013), given by 10 times rental expense (Compustat mnemonic XRENT) divided by lease adjusted assets (total assets, AT, plus 10 times rental expense).

[63] The data from 1971 to 1987 is from the "Cash Statement by Sources and Use of funds" (Compustat format codes 1, 2, 3); the structure has funds from operations plus other sources of funds minus uses of working capital equals change in working capital. Beginning in 1988, most firms start reporting "Statement of Cash Flows" (format code 7), structured as income plus indirect operating activities plus investing activities plus financing activities equals change in cash and cash equivalents (Frank and Goyal (2003)).

[64] It captures change in operating working capital + change in cash and cash equivalents + change in current debt; it can also be proxied as $\Delta((ACT-LCT)/AT)_{it}$, with ACT current assets/total and LCT current liabilities/total.

		where PRCC is common share price-close; CSHO is the number of shares outstanding, and RLC an index between 0 (unknown) and 1 (top rating AAA) created from SPLTICRM/S&P Domestic Long-Term Issuer Credit Rating.
$mbRSDA_{it}$	Market-to-book ratio short	$(PRCC_{it} \times CSHO_{it} + DLC_{it} + DLTT_{it})/AT_{it} \times RSC_{it}$ where RSC is an index between 0 (unknown) and 1 (top rating A-1+) created from SPSTICRM/S&P Domestic Short-Term Issuer Credit Rating. [65]
$DIVA_{it}$	Dividends paid	DV_{it}/AT_{it} where DV is cash dividends.
$rcostd1_{it}$	Relative cost of debt	$DVC_{it}/(PRCC_{it-1} \times CSHO_{it-1})-XINT_{it}/FD_{it-1} \times (1-TaxRate_t)$, where DVC is common/ordinary dividends, XINT is interest and related expense, and TaxRate is the corporate statutory tax rate.
$ndts_{it}$	Depreciation	DP_{it}/AT_{it} with DP depreciation/amortization expenses. [66]
$ndts\_lGAIN_{it}$	Non-debt tax shields	$ndts_{it} \times lGAIN_{it}$, is an index equal to 1 if $ebit\_ta_{it-1} > 0$.
$Tang_{it}$	Tangibility	$PPENT_{it}/AT_{it}$ with PPENT property, plant, and equipment
$ebit\_ta_{it}$	Profitability	$(IB_{it}+XINT_{it}+TXT_{it})/AT_{it}$ where IB is income before extraordinary items, XINT is interest and related expense, and TXT is income taxes.
$Intan_{it}$	Intangible assets	$INTAN_{it}/AT_{it}$ with INTAN intangible assets/total.

Table A2.1 presents the sample distribution by industry and size, and the corresponding averages of total, long- and short-term debt ratios; the last column report short-term debt over total debt. The sample is the one used to estimate equations (11), composed by 63,356 observations. Short-term debt prevails in small companies; industry-classification is based on the Fama-French 12-industry classification.[67]

Table A2.1 - Sample distribution by industry and size

Industry	%	Average debt ratios			
		Total	Long	Short	Share of short
1-Non-Durables	6.83	0.237	0.175	0.062	0.293
2-Durables	3.2	0.241	0.172	0.068	0.299
3-Manufacturing	18.47	0.244	0.193	0.052	0.238
4-Energy	6.13	0.246	0.209	0.037	0.188
5-Chemicals	3.71	0.247	0.192	0.055	0.258
6-Business Equipment	9.24	0.180	0.120	0.061	0.376
7-Telecommunications	3.15	0.359	0.317	0.042	0.143
8-Utilities	9.97	0.407	0.357	0.049	0.123
9-Trade, shops	6.08	0.259	0.193	0.067	0.268
10-Hotels	5.52	0.201	0.147	0.054	0.343
11-Finance	13.9	0.226	0.138	0.088	0.472
12-Other	13.8	0.265	0.209	0.057	0.261

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[65] Compustat does not report data on ratings before 1985. Thus, the variable is set equal to zero for all firms prior to 1985.
[66] As a robustness check, we used other measures of *ndts* which include TLCF (Net operating loss carry forward) and ITCB (Investment tax credit-balance sheet); it does not change any qualitative results.
[67] This classification aggregates Standard Industrial Classification (SIC) codes into economic industries and can be found on Ken French's Web site at
http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_12_ind_port.html.

N. of employees	%	Total	Long	Short	Share of short
1: 1-49	4.43	0.204	0.127	0.077	0.440
2: 50-249	10.25	0.228	0.159	0.068	0.365
3: 250-999	15.91	0.255	0.188	0.067	0.310
4: 1000-2499	18.4	0.269	0.210	0.059	0.270
5: 2500-5000	15.32	0.259	0.205	0.054	0.268
6: >=5000	35.69	0.265	0.211	0.054	0.244
Total	63,356	0.257	0.197	0.059	0.280

Fama-French 12-industry classification. Total is *TDA*, total debt ratio, defined as FD/AT, where FD = DLC + DLTT is financial debt, given by the sum of debt in current liabilities (DLC) and long-term debt (DLTT), and AT is total assets. Long is *LDA* = DLTT/AT; Short is *SDA* = DLC/AT. Share of short is the ratio DLC/(DLC+DLTT).

Table A2.2 reports the decomposition of total variability of the different types of debt in the cross-sectional variability (between *i*), the temporal variability due to common macroeconomic shocks affecting all the companies (between *t*) and the temporal variability due to specificities of companies (within). The long-term debt is the debt most affected by cross sectional variability, while temporal variability dominates in the short-term, as expected given the maturity within the year. Macroeconomic effects, as captured by time dummies, are the lowest in the long-term debt, possibly because long-term debt is established in a structural manner derived from some optimization rules by the companies and it is more difficult to be changed; on the opposite side, short-term debt is the most affected by contingent situations that can hidden the firms. The total debt combines the characteristics of long- and short-term debts according to the weights of each type of debt. Overall, the picture confirms the relevance of firm-specific assessment of stationarity in the debt ratios.

Table A2.2 – Variability of debt ratios

Debt	Mean	Standard deviation	% between *i*	% between *t*	% within
Total	0.257	0.188	60.53	0.42	39.05
Long	0.197	0.171	61.98	0.21	37.80
Short	0.059	0.088	41.47	0.59	57.94

Total is *TDA*, total debt ratio, defined as FD/AT, where FD = DLC + DLTT is financial debt, given by the sum of debt in current liabilities (DLC) and long-term debt (DLTT), and AT is total assets. Long is *LDA* = DLTT/AT; Short is *SDA* = DLC/AT.

Table A2.3 – A multilevel index of heterogeneous dynamics: comparison among alternative definitions of the debt ratios

Values and meaning (^{a})	Total (FD/AT)	%	Long-term (DLTT/AT)	%	Short-term (DLC/AT)	%
1 - TO static	7,955	12.88	8,070	13.17	5,605	9.57
2 - TO with D* changing	3,777	6.11	4,741	7.74	18,042	30.82
3 - TO with D* even less stable	2,777	4.5	3,092	5.05	4,521	7.72
4 - PO driven by INV/CF	28,832	46.67	25,786	42.1	11,585	19.79
5 - PO/MT driven by stock market	18,436	29.84	19,567	31.94	18,794	32.1
Total	61,777	100	61,256	100	58,547	100

	Total (FD/BCP)	%	Total (LT/AT)	%	Total (FD/MCP)	%
1 - TO static	8,372	14.06	6,240	9.85	8,067	14.59
2 - TO with D* changing	4,618	7.75	2,663	4.2	3,758	6.8
3 - TO with D* even less stable	2,642	4.44	2,285	3.61	1,909	3.45
4 - PO driven by INV/CF	26,754	44.92	34,451	54.37	27,841	50.34
5 - PO/MT driven by stock market	17,177	28.84	17,720	27.97	13,730	24.83
Total	59,563	100	63,359	100	55,305	100

	Bank (NP/AT)	%	Bonds (DD+DN)/AT	%	Leasing (DCLO/AT)	%	Rental Leverage	%
1 - TO static	4,786	8.63	4,492	8.97	1,639	4.48	3,878	10.64
2 - TO with D* changing	17,961	32.39	5,716	11.42	10,629	29.05	1,904	5.23
3 - TO with D* even less stable	5,992	10.81	3,962	7.92	5,220	14.27	1,233	3.38
4 - PO driven by INV/CF	9,179	16.55	13,821	27.61	3,476	9.5	19,039	52.26
5 - PO/MT driven by stock market	17,531	31.62	22,060	44.08	15,625	42.7	10,379	28.49
Total	55,449	100	50,051	100	36,589	100	36,433	100

The upper part of the table replicates Table 5, Value 1: stationarity according to the linear model **A1**/DFGLS *AND* no breaks according to **B1**/BT1/BT2; Value 2: stationarity according to **A1**/DFGLS *AND* one break according to **B1**/BT1 (over the sample there are two targets); Value 3: stationarity according to **A1**/DFGLS *AND* two breaks according to **B1**/BT2 (the target changes twice); Value 4: non-stationarity in linear model (**A1**/DFGLS does not reject the null) *AND* no breaks according to **B1**/BT1/BT2; Value 5: non-stationarity according to **A1**/DFGLS *AND* 1 or 2 breaks according to **B1**/BT1/BT2. See the above definition of the debt ratios: FD/AT is total financial debt ratio, defined as DLTT/AT+DLC/AT. FD/BCP is financial debt over the book value of capital. LT/AT is total liabilities over total assets and FD/MCP is financial debt over the market value of capital. Bank debt is NP/AT, with NP notes payable. Bonds (public debt) is (DD+DN)/AT, with DD Debentures and DN Notes. Leasing is given by DCLO/AT, with DCLO capitalised lease obligations. Rental Leverage is computed as in Rampini and Viswanathan (2013), and it is given by 10 times rental expense (Compustat mnemonic XRENT) divided by lease adjusted assets (total assets, AT, plus 10 times rental expense).