School of Economics, Finance and Property

Investigations into Corporate Capital Structure

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This thesis is presented for the Degree of

Doctor of Philosophy

of

Curtin University

November 2020

Declaration

To the best of my knowledge and belief this thesis contains no material previously published by any other person except where due acknowledgment has been made.

Apart from proof reading corrections and guidance by my supervisors, this thesis is entirely of my own authorship. Any errors are my own.

This thesis contains no material which has been accepted for the award of any other degree or diploma in any university.

Signature:

Date: 5 November 2020

Acknowledgements

First and foremost, I would like to express my gratitude and indebtedness to my supervisors: Professor Robert Durand and Dr. John Gould from Curtin University and Professor Adrian Cheung from City University of Macau for accepting me as a PhD student and their invaluable guidance and support during my PhD study. Over the past few years of my PhD, they have always been very patient in helping me to develop my research skills, teaching me how to conduct analyses using different statistics software, and explaining statistical models. I have struggled a lot in understanding the concept and key points in finance field due to limited finance knowledge. My supervisors always explain the concept and theory in the papers to me whenever they have time, despite their busy schedule. I find each meeting and discussion with them always beneficial as it motivates me to learn and broaden my finance knowledge. Comments and feedback I received from them also teach me how to improve my writing skills. I would not have gone this far without their help. What I have learned from them during my PhD study has become a precious asset in my life and future career.

Second, I would like to thank the academic, teaching and administrative staff at School of Economics, Finance and Property, Curtin University. I truly appreciate the valuable comments from the academic staff on the three chapters of my thesis and also their help on my data analyses. I have been working as a teaching assistant at our school during my PhD study. Balancing time between teaching and research is an important issue to me during the assessment and exam periods. Without help and support from our teaching and administrative staff, I would not have been able to manage time well to continue my study at a steady pace. I find myself studying in a very comfortable and friendly environment over the past few years.

Third, I would really like to thank my mother and father. Family is always a haven to me and brings happiness to my life. I have had difficult times during my study, but I never feel alone or helpless. Parents' care and support always help me to go through those critical times and encourage me to face the challenges positively. I feel so fortunate to have my parents with me all the time.

Lastly, I would like to acknowledge the contribution of an Australian Government Research Training Program (RTP) Scholarship in supporting this research.

Abstract

This thesis investigates the research topic of corporate leverage with threefold essays. Corporate leverage is first investigated through the perspectives of measuring stability of leverage, followed by assessing stability of interest expense and the valuation implications of leverage management, and lastly the relationship between leverage management and firm default risk.

The first essay (i.e. Chapter 2) focuses on the determination of the optimal methodology to examine capital structure stability. Lemmon, Roberts, and Zender (2008) present evidence that firm leverage ratios are stable. DeAngelo and Roll (2015) present alternate evidence that leverage stability is only a short-run phenomenon. Chapter 2 aims to test the validity of methodologies used in both papers with different stable and unstable simulated datasets. Based on the simulation results, DeAngelo and Roll's (2015) methodology appears to be the more valid methodology as its results correctly match the simulated data features and its error rates are lower than the criteria in all scenarios. However, Lemmon et al.'s (2008) methodology is found to support leverage stability and with error rates exceeding the criterion under unstable scenarios. These findings show that DeAngelo and Roll's (2015) methodology, when compared to that of Lemmon et al. (2008), should be used in future studies for investigating leverage stability.

The second essay (i.e. Chapter 3) assesses the activity of leverage management in terms of firms' interest expense stabilities. Firms' annual interest expenses are found to be significantly more stable than EBIT and dividend out to a horizon beyond 10 years, which is interpreted as evidence of active leverage management. This *relative* interest expense stability exhibits cross-sectional variation associated with firm characteristics in a manner relatable to the imperatives of trade-off and pecking-order theories. The most important result reported in Chapter 3 is that there are adverse valuation consequences for firms with interest expense variability that deviates from expected.

The third essay (i.e. Chapter 4) extends Chapter 3 to examine the relationship between firm default risk and leverage management. Results show that both cases of firms having less interest expense variability than expected level and firms having greater interest expense variability than expected lead to increased default risk. In addition, structural equation modelling shows that firms' default risk acts as a key channel to the relationship between interest expense variability and firm valuation. Interest expense variability deviation from expected level in either positive or negative direction increases default risk which in turn reduces firm valuation. Such results support the findings in Chapter 3 and imply that expected or "normal" leverage management is broadly optimal. Having either too stable or unstable interest expenses would reduce firm valuation.

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List of Abbreviations

DD	Distance to Default
DR	DeAngelo and Roll (2015)
EDF	Expected Default Frequency
FEVD	Forecast-Error Variance
IRF	Impulse-Response Function
LRZ	Lemmon, Roberts, and Zender (2008)
MAIC	MMSC-Akaike Information Criteria
MBIC	MMSC-Bayesian Information Criteria
MMSC	Moment and Model Selection Criteria
MQIC	MMSC-Hannan-Quinn Information Criteria
PVAR	Panel Vector Autoregression
SEM	Structural Equation Modelling
VAF	Variance Accounted For
VIF	Variance Inflation Factor

1 Introduction

Although different theories such as trade-off and pecking-order theories have been proposed to explain how managers make their capital structure decisions, these theories do not imply that firms should have stable leverage over time. Under the trade-off theory, an optimal leverage has been postulated as the level when benefits of debt are balanced against costs of debt financing. However, this optimal leverage could vary due to changes in firms' characteristics over their lifespans. Whereas pecking-order theory assumes no optimal leverage ratios as debt is preferred over equity when firms seek external financing to mitigate the severity of information asymmetries between managers and investors. The frequent uses of debt financing under pecking-order theory imply instability of firms' leverage ratios over time. The competing motivations of these two theories postulate the question: are firms' leverage stable over time?

Seminal studies on the stability of leverage in recent years are conducted by Lemmon et al. (2008) (hereafter LRZ) and DeAngelo and Roll (2015) (hereafter DR). Although both studies investigate leverage stability of U.S. firms, they present contrary findings. LRZ present evidence of stable leverage over longer horizons, whereas DR argue that "capital structure stability is the exception, not the rule" (p.373) by showing that stable leverage is only a short-run phenomenon. In Chapter 2, we find that the conflicting results between the two studies are driven by their methodologies. Our first objective of this thesis is to resolve the tension between these two methodologies and decide the more valid methodology that can be used by researchers to examine leverage stability in the future. Based on the simulation tests, we find that DR's methodology appears to be the valid methodology with acceptable Type I and Type II error rates.

Second, one of the arguments raised by DR in their concluding notes is that leverage tends to be determined as a budgeting residual and being shaped by other financial targets such as maintaining stable dividends. This perspective motivates us to take a further investigation at this issue: are firms' leverage actively managed over time or are they really just a budgeting residual? In

Chapter 3 of this thesis, we assess the stability of interest expenses as an indicator of active leverage management, rather than the stability of leverage ratios. This is because under the trade-off theory paradigm, it is specifically the interest expense, not the leverage ratio, which provides the tax shield that motivates leverage targeting or management. We find that interest expenses are actively managed and being more stable than both EBIT and dividends out to a 20-year horizon, which can be seen as a strong evidence of leverage management. This evidence of active leverage management is also found to be conditional on firm characteristics such as size, market-to-book equity, leverage and dividend levels. The most important contribution made by Chapter 3 is that an optimal leverage management is not equivalent to leverage or interest expense stability, maintaining too stable interest expenses also carries negative impact to firms. Adverse valuation consequences are reported for firms experiencing *unexpected* interest expense variability (actual interest expense variability deviation from the expected level): either positive or negative *unexpected* interest expense variability.

Third, Chapter 3 reports that firms either keeping their interest expenses too stable with less variability than expected or having unstable interest expenses with greater variability than expected are found to entail adverse valuation consequences. This leads us to consider the question: is this because *unexpected* interest expense variability is an *ex-post* reaction to excessive financial risk, or does *unexpected* interest expense variability represent suboptimal leverage management that drives excessive financial risk? In Chapter 4 of this thesis, we investigate whether *unexpected* interest expense variability follows or drives increased financial risk in the form of expected default frequency. Our panel vector autoregression (PVAR) results prove the latter argument: suboptimal leverage management with *unexpected* interest expense variability drives excessive financial risk. With the use of structural equation modelling (SEM) approach, we find that expected default frequency acts as a key channel to mediate the effect of *unexpected* interest expense variability on firm future valuation. Both positive and negative *unexpected* interest expense variability lead to an increase in expected default frequency, which in turn decreases firm valuation. This result supports our findings in

Chapter 3 and further shows that an optimal leverage management to a firm is when it has minimal *unexpected* interest expense variability (or minimal deviation of interest expense variability from expected).

This thesis is structured as follows. Chapter 2 presents the framework proposed for both LRZ's and DR's methodologies and the error rates of both methodology under different simulated scenarios. Chapter 3 presents the evidence of leverage management indicated by interest expense stability and the relationship between *unexpected* interest expense variability and firm valuation. Chapter 4 shows the PVAR and regression results on the relationship between *unexpected* interest expense variability and expected default frequency, and SEM approach for testing the mediating effect of expected default frequency. Chapter 5 concludes this thesis.

2 The Corporate Capital Structure Stability Conundrum

2.1 Introduction

Are firms' leverage ratios stable? The question of leverage stability appears simple but two seminal studies conducted by Lemmon, Roberts, and Zender (2008) (hereafter LRZ) and DeAngelo and Roll (2015) (hereafter DR) highlight the difficulty of studying leverage stability and present contradictory evidence. LRZ provide evidence that leverage is stable over time; high/low leverage firms are found to stay as such even after two decades with the average leverage of each high/low portfolio remaining stable in the long run. However, DR provide counter-evidence that stability in leverage is only a short-run phenomenon. Rather, DR find leverage is unstable over time due to the decline in average R^2s (which assess leverage stability between cross sections) over time. As stated by DR, "capital structure stability is the exception, not the rule" (p.373).

The contradictory findings in the two papers are puzzling. Can we determine if LRZ or DR or neither LRZ nor DR present a true picture of corporate behaviour? This chapter considers the perplexing findings of LRZ and DR by considering the methodology behind the results. In particular, both LRZ and DR distil their key findings in figures (LRZ, 2008, p.1580 and DR, 2015, p.388) and it is the respective patterns reported in these figures on which we focus.

Our suspicions that the differences between LRZ and DR are methodological are piqued by two experiments. In Section 2.3 of this chapter, we create a dataset which is similar to the one used by LRZ and analyse it using DR's methodology; the results are consistent with DR's Figure 3 (2015, p.388). We then create another dataset which is similar to the one used by DR and analyse it using LRZ's methodology; our results are consistent with LRZ's Figure 1 (2008, p.1580).[1]

Given that our *prima facie* evidence is that the different findings of LRZ and DR on leverage stability are driven by their methodologies, we propose a simple framework within which the essential features of their methodologies are illustrated and compared in Section 2.4 of this chapter. The main contribution made by this chapter is to resolve the tension between the two conflicting methodologies. We believe it is of paramount importance to decide the optimal methodology for researchers to follow before any steps being taken to examine stability of leverage.

Datasets using real data may be of limited value as they cannot provide us the definite answers on which methodology should be used. We do not know how the real datasets are generated (i.e., what their data generating process is). Therefore, in Section 2.5 of this chapter, several simulation scenarios including extremely stable and unstable scenarios, guided by the same framework proposed for LRZ's and DR's approaches, are constructed to verify whether their methodologies can produce results that are consistent with simulated data features. Our simulation analyses support DR's methodology. Using DR's methodology, the results always correctly match the data features. For stable scenarios where there is only cross-sectional variation but no time-series variation in leverage, the average R^2s obtained based on DR's methodology are found to be constant at each point of time due to the time-invariant covariance of leverage. Whereas under the unstable scenario (with time-series variation), the average R^2s decrease due to the increasing covariance difference as time length increases, and this reflects leverage instability. However, with the use of LRZ's methodology, we always get the pattern of stable *average leverages* in the long run which supports leverage stability in all scenarios, even if the leverage data is simulated from an unstable process. We further calculate the Type I and Type II error rates

[1] We also use both LRZ and DR to analyse a phenomenon where there is some consensus that the behaviour of firms is stable: dividend policy (Lintner, 1956; Brav, Graham, Harvey, & Michaely, 2005). We follow LRZ's methodology and find dividend payout ratios are stable (which is consistent with their analysis for leverage). Then we follow DR's methodology and find dividend payout ratios are unstable (which is consistent with DR's analysis for leverage). Results are available upon request.

of both methodologies. We find that DR's methodology appears to be the valid methodology as it has lower error rates in all scenarios. For LRZ's methodology, its error rate under unstable scenario exceeds the maximum critical level (i.e. 0.8).

This chapter is designed as follows. Section 2.2 provides a brief literature review and discusses the main findings of LRZ and DR. Section 2.3 presents the results from applying both methodologies to different U.S. firm leverage datasets. Section 2.4 presents the methodological framework. Section 2.5 discusses the results generated from different simulation tests based on LRZ's and DR's methodologies. Lastly, Section 2.6 draws the conclusion.

2.2 Background

Different theories have been proposed to explain capital structure and how managers make capital structure decisions, for instance the well-known trade-off and pecking-order theories (Kraus & Litzenberger, 1973); Myers, 1984; and Myers & Majluf, 1984). The (static) trade-off theory takes into account the trade-off between benefits and costs arising from debt financing and proposes the optimal (target) capital structure at which value of the firm can be maximized. For example, a version of the (static) trade-off theory states that firms which are over-levered (with leverage above their target leverage) are likely to face higher bankruptcy costs, whereas firms that are under-levered (with leverage below their target leverage) may not fully take advantage of tax shields of debt. Jensen (1986) also argues that low-leverage firms that have excessive free cash flows may face agency costs of free cash flow, which could have been mitigated from taking on debt. These evidence support the maintenance of the optimal (target) capital structure as one of the top priorities of value-maximizing managers. Further, firms could be expected to have relatively stable leverage ratios close to their target over time (conditional on stability of the taxation and financial distress and bankruptcy costs conditions that drive the trade-off decision).

Pecking-order theory assumes that there are no optimal target ratios. Because of the severity of information asymmetry between managers and investors, managers prefer to use internal funds to finance investments when they are adequate and will prefer to issue debt when external financing is needed. Equity will only be used as the last resort. Such frequent use of debt implies capital structure instability as firms' leverage may change over time, depending on their external financing needs.

The comparative importance of the competing motivations of trade-off and pecking-order theories can be gauged by simply asking managers what they actually do. Graham and Harvey (2001) conduct a survey for CFOs of U.S. firms on corporate financial policies and ask about capital structure decisions. They report that 10% of firms have strict leverage targets and 19% of them have no target ratios, whereas the rest of them have either flexible target ratios or somewhat tight target ranges. An international survey was also conducted by Brounen, De Jong and Koedijk (2006) on four European countries: France, Germany, the Netherlands and the U.K. by following the method used by Graham and Harvey (2001). They report similar findings to Graham and Harvey (2001): only 10% of firms from these four countries have strict target leverage ratios. Apart from France, a larger proportion of firms from the other three countries are found to have either flexible target ratios or somewhat tight targets or ranges, which is quite similar to the U.S. evidence.[2] Further international evidence was also provided by Faff, Gray and Tan (2016) who find that only 13% of Australian firms have strict leverage targets.

The existence of target leverage ratios reported by the three survey papers accords with trade-off theory. However, target debt ratios do not necessarily imply stable targets, let alone stable leverage, in the long run. Further considering the proportion of managers that do not favour leverage targets leads to the reasonable expectation that, on average, leverage is not particularly stable. It is also worth noting that there is no established theoretical motivation for stable corporate leverage: only under some happenstances of conditions would trade-off or pecking order leverage

[2] Brounen et al. (2006) do not provide an explanation for more than two thirds of French firms having no target debt ratio in the paper. However, comparing with Germany, the Netherlands and the U.K., only a small percentage of French firms within the sample are publicly listed firms, but a higher percentage of them are regulated utilities. In addition, a quarter of French firms have zero long-term debt. Such differences of firm characteristics may explain this.

motivations result in stable leverage. This implies that evidence of leverage stability would depend on appropriate conditioning of the sample of firms being investigated.

The introduction to this chapter highlighted the contradictory findings reported by LRZ and DR. LRZ initiate the study of leverage stability by showing that firms have relatively stable leverage over longer time horizons and differences between their leverage persist over time. By sorting U.S. listed firms into four portfolios according to their initial leverage, LRZ find that, despite significant convergence in the short run, the *average leverages* of the four portfolios appear to be stable in the long run.

LRZ further identify the key role of initial leverage and firm fixed effects from regressions explaining leverage variation. LRZ argue that this confirms that firms have stable leverage ratios. The initial leverage of firms is found to be a key feature influencing leverage in subsequent years. More importantly, they find that around 60% of leverage variation is explained by firm fixed effects. LRZ hence conclude that the majority of leverage variation occurs cross-sectionally (across firms), rather than occurs temporally (within individual firms). Combining with their earlier findings on long-run stable *average leverages*, LRZ draw the conclusions: "Unobserved time-invariant effects (firm fixed effects) generate stable capital structures over time. High/Low leverage firms remain as such for over two decades" (p.1575).[3]

Following LRZ, a number of subsequent studies highlight the importance of firm fixed effects in explaining variation in leverage (Parsons & Titman, 2009; Graham & Leary, 2011; Hanousek & Shamshur, 2011).

Parsons and Titman (2009) present a review article and highlight how time-invariant firm fixed effects significantly improve the R^2 of leverage regression. Graham and Leary (2011) report that most of leverage variation occurs cross-sectionally which is in line with LRZ's findings. They also concur with LRZ that a large amount of leverage variation is captured by firm fixed effects, further emphasise the necessity for future studies to identify

[3] Such unique firm fixed effects explain the persistent differences in cross-sectional leverage (the *average leverages* of the four portfolios) over time.

time-invariant firm-specific determinants which explain leverage variation. Hanousek and Shamshur (2011) also provide international evidence confirming the importance of firm fixed effects in capturing leverage variation. They show that even in Central and Eastern European transition economies with rapidly changing economic environment, firms still have relatively stable leverage as a large amount of leverage variation is captured by firm fixed effects.

DR provide counter-evidence on capital structure stability. They show that "stable leverage regimes" are a short-lived phenomenon and mainly observed in firms with low leverage. If firms have stable leverage, DR argue that their leverage ratios will be kept within a narrow band with a small extent of within-firm variation over time. Furthermore, DR argue that high/low leverage firms would remain in similar positions in the future, which is consistent with LRZ. However, DR find that very few firms keep their leverage within such a narrow band which supports the notion of leverage instability. In addition, DR point out that LRZ do not take into account in their fixed effects analysis that there is a significant firm-specific time-series variation, which suggests that firm fixed effects vary over a certain period of time, such as across decades. A higher R^2 is also obtained for the model including firm-time interaction effect compared to the model with only constant firm fixed effects. The result contradicts the statement raised by LRZ that significant fixed effects lead to stable capital structures over time.

DR further argue the methodology adopted by LRZ to compute the *average leverages* seems to be non-informative for examining cross-sectional leverage stability. As described by DR, "(large-sample) averaging can – and, empirically, does – mask large time-series variation in leverage for firms in each group" (p.392). After assessing the explanatory power of leverage in current cross-sections in predicting leverage in future cross-sections based on the "average squared correlation coefficients"/R^2s, they find that leverage over shorter horizons is closely related, but this phenomenon fades over longer time horizons.[4] This is further confirmed by the large and pervasive

[4] DR measure the average R^2s between leverage in current cross-sections and leverage in future cross-sections. The significant decrease in average R^2s show the diminishing

firm migration away from their initial leverage quartiles over time based on examination of movements in individual firms' leverages.[5] Their findings are contrary to the conclusions drawn by LRZ that cross-sectional leverage differences persist as high/low leverage firms would tend to remain in initial leverage positions over extended periods of time.

In an unpublished working paper, Ito, Mikabe and Noma (2015) investigate firms listed in Japan with both LRZ's and DR's methodologies being applied to the leverage of Japanese firms. Based on LRZ's methodology, they notice that *average leverages* of initial leverage portfolios converge gradually but cross-sectional leverage differences persist over time, which imply that firms experience greater leverage variation in the short-run but remain stable in the long-run. This result supports cross-sectional stability in leverage. Based on DR's methodology, significant decreases are observed in the average R^2s as time goes by which imply that firms have more stable leverage in the short-run than they do in the long-run. The large decline in the average R^2s reflects the diminishing similarities in leverage between cross sections and hence cross-sectional instability in leverage. The similar patterns observed in leverage of Japanese firms compared to the analysis for leverage of U.S. firms further indicate the limited value of real datasets in deciding the optimal methodology. In addition, Ito et al. (2015) fail to address the tension in the different results based on different methodologies and do not take up the challenge, as we do, to consider if the methodologies chosen affect the results. Such contradictory findings generated from the same dataset raise the importance of understanding the construction of each methodology, and this motivates us to propose the framework to examine the features of methodologies developed by LRZ and DR.

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similarities in cross-sectional leverage as time goes by. But the average R^2s still remain low and positive for leverage with 20-year difference in cross-sections, which imply that stable leverage regimes still occur over time.

[5] Firms in the lowest initial quartile are found to have relatively more stable leverage, which explain why the average R^2s are still positive even for leverage with more than 20 years apart in cross-sections.

2.3 Application of LRZ's and DR's Methodologies on U.S. Datasets

LRZ and DR present contradictory evidence on leverage stability. As discussed in the previous section, both LRZ and DR have focused on U.S. listed firms, except over different investigation periods.[6] In this section, we test if LRZ's and DR's methodologies are sensitive to the investigation period used by them for U.S. firms.[7]

2.3.1 Data and Sample Selection

We first create two datasets which are similar to those used by LRZ and DR. We follow the restrictions imposed by LRZ and DR, which are described below.

In the first dataset (*Dataset LRZ*), where we follow LRZ, we include all U.S. firms which have been listed between 1964 and 2003 (based on Compustat database). We exclude utility and financial firms. We only keep observations with non-missing data for total assets. Book leverage is defined as *total debt/total assets*. We exclude those observations with missing values in book leverage and observations with book leverage greater than 1 or below 0.[8]

In the second dataset (*Dataset DR*), where we follow DR, we initially include all U.S. firms which have been listed during the period from fiscal year 1950 to 2008. We then exclude utility and financial firms. We only keep firms which are incorporated within the U.S. and firms with share code 10 or 11 (share code is obtained from CRSP database). In addition, we exclude firm-year observations with missing data for total assets and share price. Book leverage is defined as *total debt/total assets*. We keep book leverage (defined

[6] LRZ investigate all non-financial firms listed from 1965 to 2003, whereas DR's dataset covers the period from 1950 to 2008. For the preliminary tests, we use one dataset covering the period from fiscal year 1964 to 2003 which is similar to LRZ's dataset, and another dataset from 1950 to 2008, which is similar to DR's dataset.
[7] For all leverage datasets, we only focus on the book leverage of firms.
[8] Book leverage is defined as a ratio which lies within the interval [0, 1].

as a ratio of *total debt/total asse*ts) within the interval [0, 1] and exclude observations with missing values in book leverage.[9]

2.3.2 Results

Our main focus is only on the key methodologies used by LRZ and DR, which are the portfolio sorting and averaging method used by LRZ to compute the *average leverages* and the average R^2s between leverage in cross sections. These two methodologies lead to the controversial conclusions drawn by LRZ and DR on cross-sectional leverage stability. We first apply LRZ's methodology to *Dataset DR*, while at the same time DR's methodology is applied to *Dataset LRZ*.[10] Figure 2.1 shows the results generated from testing LRZ's methodology to DR's dataset (book leverage of firms) and Figure 2.2 present the results produced from testing DR's methodology on LRZ's dataset (book leverage of firms).

When we analyse DR data (*Dataset DR*) with LRZ's methodology, we get the pattern LRZ obtained with their own data (LRZ, 2008, p.1580). It is clearly shown that the *average leverages* partly converge within a short period of time and remain relatively stable over extended periods of time.[11] The pattern is consistent with findings in LRZ. Similarly, when we analyse LRZ data (*Dataset LRZ*) with DR's methodology, we get the pattern DR obtained with their own data: an almost identical graph to that produced by DR for the average R^2s is also produced in Figure 2.2 as the average R^2s continuously decrease over time which is in line with DR's argument. The results suggest that it is not different leverage data driving the difference between LRZ and DR. Rather, it would appear that differences in methodologies seem to be driving the conflicting results.

[9] Missing leverage data occurs when there is missing debt data or zero asset value. We do not know the reason for firms not reporting their total debt in certain years and hence exclude observations with missing debt values.
[10] We only focus on the full sample firms and book leverage. Our purpose is to test if LRZ's and DR's methodologies are sensitive to particular datasets or investigation periods used by them.
[11] The *average leverages* for the lowest and low/medium portfolios at event year 18 are 0.1820 and 0.1862; and at event year 19 are 0.1831 and 0.1845, respectively. Even though they seem have converged to a single point, there are still differences between the *average leverages* for these two portfolios.

Figure 2.1 – Average leverage of leverage portfolios in event time (with the use of Dataset DR)

Figure 2.1 is generated according to the methodology used by LRZ and tested with *Dataset DR*. *Dataset DR* has been created to mimic the one used by DR. Firms are first divided into different sub-samples based on the initial (fiscal) years they enter the full sample. For each sub-sample (those firms enter the sample in the same year), firms are sorted into four portfolios (quartiles) according to their initial leverage ratios (first non-missing leverage values) and are assumed to stay in their initial leverage portfolios over time. The fiscal years are converted into event years (initial year will be event year 0, subsequent fiscal years will in turn be converted into event year 1, 2, 3, and so on). The *average leverage* for each portfolio will be calculated. Then, the average of *average leverages* across all sub-samples will be computed.

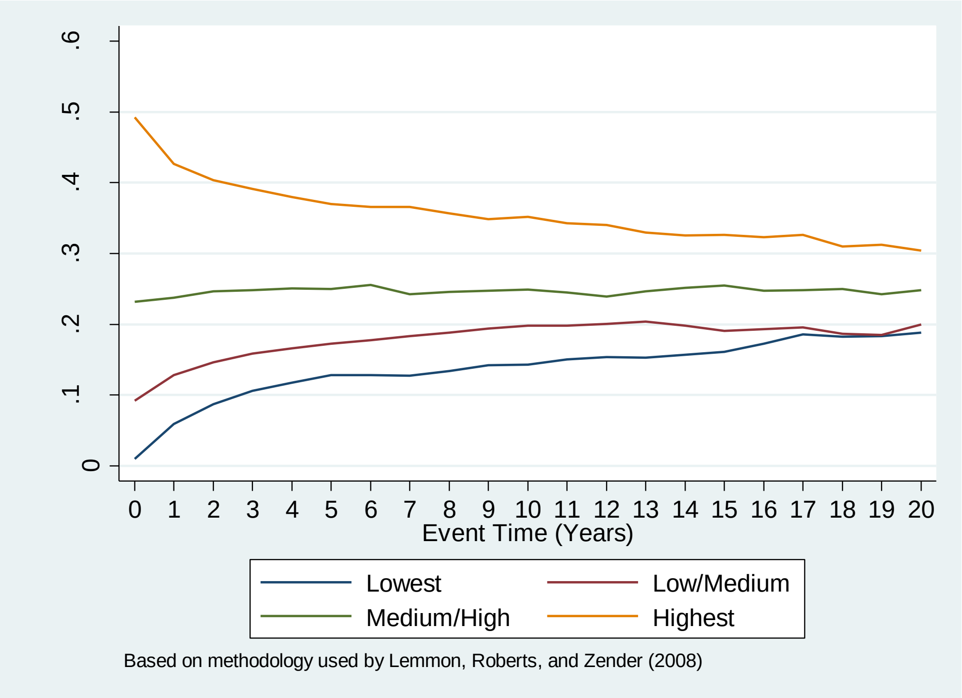
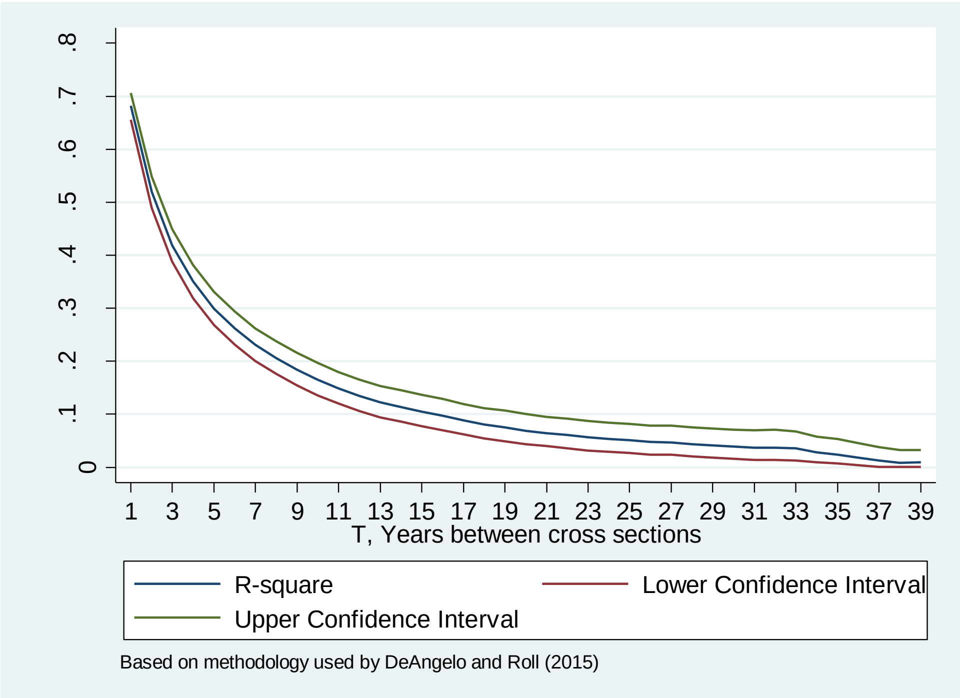


Figure 2.2 – Extent of leverage stability in cross-sections (with the use of Dataset LRZ)

Figure 2.2 is produced based on the methodology proposed by DR but with the use of *Dataset LRZ*. This figure presents the average R^2s between leverage in a given year and future leverage. The horizontal axis shows the number of years between leverage cross-sections. The vertical axis plots the average R^2s over all pairings of leverage in a given year and leverage after T years (T years refer to the number of years shown on the horizontal axis). For instance, to generate the average R^2 with one-year difference between cross sections, firms with non-missing leverage data in two adjacent years will be first identified such as firms with non-missing data in 1964 and 1965, 1965 and 1966, 1966 and 1967, so on. Each of them is treated as a pair and the average R^2 across all these pairings with exactly one-year apart is reported. Then the whole process is repeated using pairings with "each value of T" years apart. Bias-corrected confidence intervals are generated based on bootstrap procedure with 1000 replications.



In this section, contradictory findings are always generated from testing the same leverage dataset. The findings in LRZ and DR on stability of leverage are driven by their methodologies used. It is important to determine which methodology provides more valid answers. In order to achieve this, simulation tests will be performed to test the validities of both methodologies.

2.4 A Simple Framework for LRZ's and DR's Approaches

In this section, we illustrate, in the context of simple and stylized data generating processes, the two different approaches adopted by LRZ and DR in terms of the key measure(s) they use in their analyses. We start with DR's approach first which emphasizes R^2 of leverage for different lags, followed by LRZ's approach, which focus on *average leverages* across different lags.

We specify the following model for leverage:

$$Y_{it} = \phi_0 + \phi_1 X_{it} + \phi_2 \eta_i + \phi_3 Y_{it-1} + \varepsilon_{it} \tag{2.1}$$

In Eq. (2.1), the i and t index firm and year respectively; Y_{it} is the dependent variable which is defined as the leverage of firm i in the current year t; X_{it} represents control variable which is assumed to capture part of variation in each firm's leverage; η_i are the firm fixed effects; Y_{it-1} is the leverage of firm i in the previous year; ε_{it} are random errors.

Eq. (2.1) is consistent with models proposed by LRZ and DR. DR simulate leverage based on the model:

$$Y_{it} = \lambda \bar{Y} + (1-\lambda)(Y_{it-1} + \epsilon_{it}) \tag{2.2}$$

In Eq. (2.2), λ is the speed of adjustment to target leverage ratio; $\bar{Y}$ is the target leverage, which varies across firms as it is determined by all firm-specific variables. Suppose target leverage, or $\bar{Y}$ is determined by the control variable X_{it} and firm fixed effects η_i.

Hence, Eq. (2.2) can be rewritten as:

$$\begin{aligned} Y_{it} &= \lambda(\theta_0 + \theta_1 X_{it} + \theta_2 \eta_i) + (1-\lambda)(Y_{it-1} + \epsilon_{it}) \\ &= \lambda\theta_0 + \lambda\theta_1 X_{it} + \lambda\theta_2 \eta_i + (1-\lambda)Y_{it-1} + (1-\lambda)\epsilon_{it} \end{aligned} \tag{2.3}$$

Eq. (2.3) is in line with our model (2.1), where $\lambda\theta_0 = \phi_0$, $\lambda\theta_1 = \phi_1$, $\lambda\theta_2 = \phi_2$, $(1-\lambda) = \phi_3$, and $(1-\lambda)\epsilon_{it} = \varepsilon_{it}$.

On the other hand, LRZ assume leverage variation is captured by the following determinants as shown in Eq. (2.4):

$$Y_{it} = \alpha + \beta X_{it-1} + \eta_i + \nu_t + \xi_{it} \tag{2.4}$$

It is easy to see that $\alpha = \phi_0$, $\beta = \phi_1$, $\phi_2 = 1$, $\nu_t = \phi_3 Y_{it-1}$, and $\xi_{it} = \varepsilon_{it}$. Different from LRZ using ν_t, which is the year fixed effects, we use lagged leverage Y_{it-1} to capture time-series variation in Eq. (2.1). We also use contemporaneous control variable X_{it} rather than 1-year lagged control variable X_{it-1}.

LRZ also argue that initial leverage is important in explaining current leverage. Our model can also accommodate this argument. Without loss of generality, assume no control variable in Eq. (2.1). Then Eq. (2.1) can be rewritten as

$$\begin{aligned} Y_{it} &= \phi_0 + \phi_2\eta_i + \phi_3 Y_{it-1} + \varepsilon_{it} \\ &= \gamma_0 + \gamma_2\eta_i + \gamma_3 Y_{i1} + \zeta_{it} \end{aligned}$$

Where $\gamma_0 = \phi_0 \frac{(1-\phi_3^t)}{(1-\phi_3)}$, $\gamma_2 = \phi_2 \frac{(1-\phi_3^t)}{(1-\phi_3)}$, $\gamma_3 = \phi_3^t$ and ζ_{it} is an AR (p) process. In addition, Y_{i1} is assumed to be stationary.[12]

2.4.1 DR's Methodology to Measure Stability in Leverage

As discussed in Sections 2.2 and 2.3, DR measure the stability of leverage based on the "average squared correlation coefficients" (i.e. R^2s) for leverage with T years apart in cross sections and observe a decrease in the average R^2s as the lag length increases.

The R^2 (or squared correlation) for a first-order autoregressive process is just the square of the autoregressive coefficient, which may be computed as $(\frac{\text{Cov}\,[Y_{it}, Y_{it-1}]}{Var(Y_{it})})^2$. Stationarity implies that leverage at each t has the same variance (or standard deviation):

[12] See Section 2.5.1.2 for further information and analysis of the initial value that Y_{i1} may take.

$\sigma_{Y_{it}} = \sigma_{Y_{it-1}} = \sigma_{Y_{it-2}} = \ldots = \sigma_{Y_{it-j}} = \sigma_{Y_i}$

For leverage with one-year difference in cross sections, or with lag length being one, the correlation between them can be computed as $\frac{Cov\,[Y_{it}, Y_{it-1}]}{\sigma^2_{Yi}}$.

In general, the correlation between Y_{it} and Y_{it-j} can be rewritten as $\frac{Cov\,[Y_{it}, Y_{it-j}]}{Var(Y_i)}$. This expression suggests that to examine changes in the R^2s as lag length increases, we can focus on the difference between the covariance for leverage with different lags as the standard deviation (or variance) of leverage across all time is the same (i.e., the denominator remains unchanged for all lags).

Given Eq. (2.1), it is straightforward to show that the difference between $Cov\,[Y_{it}, Y_{it-1}]$ and $Cov\,[Y_{it}, Y_{it-j}]$ is captured by Eq. (2.5) in general and Eq. (2.6) if j goes to infinity. See Appendix A for the proof.

$$Cov\,[Y_{it}, Y_{it-1}] - Cov\,[Y_{it}, Y_{it-j}] = \left(\frac{\phi_0\phi_1}{1-\phi_3}\right)(\phi_3 + {\phi_3}^2 + {\phi_3}^3 + \cdots + {\phi_3}^{j-1})E(X_{it}) + (\phi_1)^2(\phi_3 + {\phi_3}^2 + {\phi_3}^3 + \cdots + {\phi_3}^{j-1})E(X_{it})^2 + (\phi_1)^2(\phi_3 + {\phi_3}^2 + {\phi_3}^3 + \cdots + {\phi_3}^{j-1})E(X_{it}X_{it-j}) - (\phi_1)^2(\phi_3 + {\phi_3}^2 + {\phi_3}^3 + \cdots + {\phi_3}^{j-1})\sum_j^\infty {\phi_3}^j\, E(X_{it}X_{it-j}) + (\phi_3 + {\phi_3}^2 + {\phi_3}^3 + \cdots + {\phi_3}^{j-1})E(\varepsilon_{it})^2$$

$$= \left(\frac{\phi_0\phi_1}{1-\phi_3}\right)\left(\frac{1-\phi_3^j}{1-\phi_3} - 1\right)E(X_{it}) + (\phi_1)^2\left(\frac{1-\phi_3^j}{1-\phi_3} - 1\right)E(X_{it})^2 + \left(\frac{1-\phi_3^j}{1-\phi_3} - 1\right)E(\varepsilon_{it})^2 \tag{2.5}$$

$$= \left(\frac{\phi_0\phi_1}{1-\phi_3}\right)\left(\sum_{j=0}^\infty \phi_3^j - 1\right)E(X_{it}) + (\phi_1)^2\left(\sum_{j=0}^\infty \phi_3^j - 1\right)E(X_{it})^2 + \left(\sum_{j=0}^\infty \phi_3^j - 1\right)E(\varepsilon_{it})^2$$

$$= \left(\frac{\phi_0\phi_1}{1-\phi_3}\right)\left(\frac{1}{1-\phi_3} - 1\right)E(X_{it}) + (\phi_1)^2\left(\frac{1}{1-\phi_3} - 1\right)E(X_{it})^2 + \left(\frac{1}{1-\phi_3} - 1\right)E(\varepsilon_{it})^2 \; if\; j \to \infty \tag{2.6}$$

There are five salient points to be made from Eq. (2.5). First, Eq. (2.5) shows that differences in the covariance between different lags in leverage are driven by four sources of variations: the mean of the control variable (E(X_{it})), the variance of the control variable ($\text{E}(X_{it})^2$), the time variation in the control variable ($\text{E}(X_{it}X_{it-j})$) and the variance of the error term ($\text{E}(\varepsilon_{it})^2$). Any increase (decrease) in one of these sources of variation would also lead to a further increase (decrease) in the covariance differences between different lags in leverage. Second, with the assumption of stationarity (i.e., $0 \leq \phi_0$, ϕ_1, ϕ_2 and $\phi_3 < 1$), differences in the covariance between different lags are expected to be smaller (greater) if there is a decrease (an increase) in one particular coefficient: ϕ_0, ϕ_1 or ϕ_3. Third, Eq. (2.5) reveals that the differences in the covariance becomes larger as lag length increases. Fourth, firm fixed effects (or its coefficient, ϕ_2) are found to have no effect on the differences in the covariance between different lags because firm fixed effects are, by construction, time-invariant. Fifth, given Eq. (2.5), it is expected that the differences in the square of covariance between different lags would become even larger as lag length increases, which explains the significant decrease in the average R^2s produced from DR's methodology. Note that Eq. (2.6) shows a special case of Eq. (2.5) where *j* approaches infinity.[13] The main difference between Eq. (2.6) and Eq. (2.5) is that there is no role for the time variation in the control variable ($\text{E}(X_{it}X_{it-j})$) now in this static (or equilibrium) case.

2.4.2 LRZ's Methodology to Measure Stability in Leverage

As discussed earlier in this chapter, LRZ have adopted a different approach to measure cross-sectional stability in leverage. The focus of their approach is on the *average leverage*, in particular, they sort firms into four portfolios (or quartiles) based on their initial leverage and examine the *average leverage* of each leverage portfolio.

Given our leverage model (i.e., Eq. (2.1)), we show that the average leverage is captured by Eq. (2.7) in general and Eq. (2.8) if *j* goes to infinity. See Appendix A for the proof.

[13] This case does not apply when $t < j$ because the implicit assumption is that $t \geq j$.

For $t = j$: $E(Y_{ij}) = \phi_0(1 + \phi_3 + {\phi_3}^2 + {\phi_3}^3 + \cdots + {\phi_3}^{j-1}) +$

$$\phi_1(1 + \phi_3 + {\phi_3}^2 + {\phi_3}^3 + \cdots + {\phi_3}^{j-1})E(X_{ij}) +$$

$$\phi_2(1 + \phi_3 + {\phi_3}^2 + {\phi_3}^3 + \ldots + {\phi_3}^{j-1})E(\eta_i)$$

$$= \frac{\phi_0(1-\phi_3^j)}{1-\phi_3} + \frac{\phi_1(1-\phi_3^j)}{1-\phi_3}E(X_{ij}) + \frac{\phi_2(1-\phi_3^j)}{1-\phi_3}E(\eta_i) \qquad (2.7)$$

$$= \frac{\phi_0(\sum_{j=0}^{\infty}\phi_3^j)}{1-\phi_3} + \frac{\phi_1(\sum_{j=0}^{\infty}\phi_3^j)}{1-\phi_3}E(X_{ij}) + \frac{\phi_2(\sum_{j=0}^{\infty}\phi_3^j)}{1-\phi_3}E(\eta_i)$$

$$= \frac{\phi_0}{1-\phi_3} + \frac{\phi_1}{1-\phi_3}E(X_{ij}) + \frac{\phi_2}{1-\phi_3}E(\eta_i)\ if\ j \to \infty \qquad (2.8)$$

Eq. (2.7) shows that the *average leverage* is determined by the constant, the mean of the control variable (E(X_{it})) and the firm fixed effects. Any increase (decrease) in one of these three sources of variation would lead to a further increase (decrease) in the *average leverage* at each *t*. In addition, an increase (a decrease) in one of the four coefficients observed in Eq. (2.7): ϕ_0, ϕ_1, ϕ_2 or ϕ_3 would also increase (decrease) the *average leverage* at each *t*. In particular, an increase (a decrease) in ϕ_3 will increase (decrease) each coefficient of Eq. (2.7), resulting in an overall increase (decrease) in the mean leverage. In general, the incremental increase will follow a *Maclaurin series* as shown in Eq. (2.7), which explains the convergence in mean leverage at each point of time (t) towards a long-run mean (2.7), as shown in Appendix A. Eq. (2.8) shows the incremental increase when *j* approaches infinity.[14]

Regarding both approaches, we find that the variation in predictions made by the two approaches arises from time-series variation in leverage. The predictions of both approaches are summarized in Table 2.1 below.

[14] This case does not apply when t < j because the implicit assumption is that t ≥ j.

Table 2.1 – Predictions of the LRZ and DR methodologies

This table summarizes the predictions of both LRZ and DR approaches using the models in Section 2.4. Panel A summarizes the predictions by assuming that there is no time-series variation in leverage. Panel B assumes that time-series variation exists in leverage.

Panel A. Leverage stability assuming no time-series variation		
	Model prediction	Leverage stability prediction
DR approach	Lagged leverage coefficient in the model or $\phi_3 = 0$ Covariance difference or $Cov\,[Y_{it}, Y_{it-1}] - Cov\,[Y_{it}, Y_{it-j}] = 0$ for different *j*	R^2 computed as $\frac{\mathrm{Cov}[Y_{it},Y_{it-j}]}{Var(Y_i)}$, is same between different lags (different *j*), which indicates stable leverage.
LRZ approach	Average leverage or $E(Y_{ij})$ is the same for each *t*, with *t* = *j*	Average leverage is constant over time indicating stable leverage.
Panel B. Leverage stability in the presence of time-series variation		
DR approach	For lagged leverage coefficient, *0* ≤ ϕ_3 < *1* Covariance differences or $Cov\,[Y_{it}, Y_{it-1}] - Cov\,[Y_{it}, Y_{it-j}]$ increase as *j* increases (lag length increases)	R^2 decreases due to the increase in covariance differences when the lag length increases: this indicates unstable leverage over time.
LRZ approach	$E(Y_{ij})$ follows *Maclaurin series* and $E(Y_{ij}) = \frac{\phi_0}{1-\phi_3} + \frac{\phi_1}{1-\phi_3}E(X_{ij}) + \frac{\phi_2}{1-\phi_3}E(\eta_i)$ if *j* goes infinity.	Average leverage converges towards a long-run mean over time.

If we assume there is no time-series variation with the lagged leverage coefficient (ϕ_3) being zero, using DR's approach, we find that there will be no difference in the covariance and the R^2 will be the same between different lags. Using LRZ's approach, the *average leverage* will be the same for each *t*. Hence, both approaches would predict that leverage is stable (the constant R^2s between different lags and constant *average leverage* at each *t*). However, in the presence of time-series variation in leverage ($0 \leq \phi_3 < 1$), we find that the predictions of both approaches would differ from each other. As mentioned, we find that differences in the covariance will become larger as the lag length increases based on DR's approach. Further, the mean leverage at each point of time (t) converges towards a long-run mean (2.7). The extent of covariance differences between different lags and the convergence towards a long-run mean depends on the magnitude of the lagged leverage coefficient (ϕ_3). The predictions of both approaches with and without time-series variations are tested by different simulation scenarios in the next section.

2.5 Simulation Tests on LRZ's and DR's Methodologies

In the previous section, we have shown that the patterns observed from earlier graphs depend on the methodology used. By looking at *a posteriori* firm data, the stability issue of leverage cannot be resolved by LRZ's and DR's methods because we do not know what the true data generating process is and how the data is generated.

We therefore use simulated data to test the two methodologies as simulation method allows us to derive different samples with predetermined properties of data. Different from real datasets, with the use of simulation methods, the actual behaviour of data can be specified beforehand by setting different parameters.[15] It is therefore clearer to see the validities of both methodologies in different scenarios, particularly the extreme scenarios. More specifically, we can examine when we might reject LRZ in favour of DR or vice versa. To capture the essential features of the real data we have examined so far, three simulation scenarios have been generated and can be classified into two

[15] This is different from Chen (2010) who has used the market data (p.3 & 14).

categories. The first category refers to stable scenarios where the main focus is on cross-sectional variation, and the second category refers to unstable scenarios where the focus is on time-series variation.[16]

To generate simulated data, we use our model of leverage (Eq. (2.1), p.15):

$$Y_{it} = \phi_0 + \phi_1 X_{it} + \phi_2 \eta_i + \phi_3 Y_{it-1} + \varepsilon_{it}$$

With the *i* and *t* index firm and year respectively; Y_{it} is the dependent variable which is defined as the leverage of firm *i* in the current year *t*; X_{it} represents the control variable which is assumed to capture part of variation in each firm's leverage; η_i are the firm fixed effects; Y_{it-1} is the leverage of firm *i* in the previous year; ε_{it} are random errors.

Eq. (2.1) can be divided into two parts: the static or cross-sectional component and the dynamic component of leverage variation. The cross sectional component is driven by three sources of variation: the constant (ϕ_0), independent (or control) variable(s) (X_{it}), and the firm fixed effects (η_i). The dynamic component is captured by the previous year's or lagged leverage (Y_{it-1}).

Since both LRZ and DR have focused on the stability of leverage of *survivor firms* over extended periods of time, which are those firms with non-missing leverage data for at least 20 consecutive years, we create for each simulation scenario a large number of firms (i.e., N = 2000 firms), with each of them having 20 years of data (i.e., T = 20 years).[17]

We follow LRZ's and DR's methodologies for each simulation scenario. For LRZ's methodology, we sort firms into four portfolios (quartiles) according to their initial leverage ratios and assume firms stay in their initial leverage portfolios (quartiles) over time. The *average leverage* for each portfolio will be calculated.[18] For DR's methodology, we plot the average R^2s over all

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[16] This is different from Chang and Dasgupta (2009) who also consider simulated data (p.1777 & 1787); we create different simulation scenarios, both stable and unstable. Our main focus is to compare the performance of LRZ's methodology to DR's under different simulation features.

[17] To draw conclusion as to whether a particular methodology prevails in a particular scenario, we repeat the same simulation process for a certain number of trials (such as 200 iterations).

[18] We compute the *average leverage* for each leverage portfolio across all simulation iterations (200 iterations).

pairings of leverage in a given year and future leverage (leverage after T years).[19]

[19] We compute the average R^2s over all pairings with T-year difference in leverage cross sections across all simulation iterations (200 iterations).

Table 2.2 – Summary of simulation parameters

This table summarizes the value assigned to each parameter used in the three simulated scenarios in Section 2.5. For each simulated scenario, error term ($\boldsymbol{\varepsilon_{it}}$) is assumed to be normally distributed with mean of 0 and standard deviation of 0.01.

Scenario category	Variables	Values assigned to each variable
Scenario 1 – Stable scenario (section 2.5.1.1, p.26)	Constant	ϕ_0 =0.05
	Control variable, X_{it}	ϕ_1= 0.1
	Firm fixed effects, η_i	$\phi_2 = 0.8$
Scenario 2 – Stable scenario (section 2.5.1.2, p.30)	Constant	$\phi_0 = 0.05$
	Control variable, X_{it}	ϕ_1= 0.1
	Firm fixed effects, η_i only for generating initial leverage	$\phi_2 = 0.8$
	Initial leverage, Y_{i1}	$\phi_3 = 0.8$
Scenario 3 – Unstable scenario (section 2.5.2.1, p.34)	Constant	$\phi_0 = 0.05$
	Lagged leverage, Y_{it-1}	$\phi_3 = 0.2$

Different parameters are set for the purpose of testing whether both methodologies can be easily accepted or rejected in different (or extreme) scenarios. The values assigned for each parameter in each scenario are summarized in Table 2.2.

We start with the stable leverage scenarios first, followed by the unstable leverage scenarios. In addition, for the two extreme scenarios, either extremely stable or unstable (Scenarios 1 and 3), we compare the results from the framework outlined in Section 2.4 with the results from simulation tests.

2.5.1 Stable Leverage Scenarios

LRZ argue that firms have stable leverage over time because of the significant time-invariant firm fixed effects and because firms' initial leverage are closely related with future leverage. In addition, they find that most of leverage variation is due to cross-sectional variation in leverage (captured by firm fixed effects) as the explanatory power of year fixed effects if found to be extremely low. In order to generate stable leverage scenarios, we operationalize these statements and construct three scenarios. First, we generate a scenario by hypothesizing that there is no time-series variation in the stable leverage models and leverage is only explained by cross-sectional variation. Second, we design a scenario by highlighting the role of initial leverage in determining firms' future leverages.

We would expect the *average leverage* of each leverage portfolio to remain quite stable over time with the use of LRZ's methodology with similar patterns observed in Figure 2.1. For DR's methodology, the average R^2s between leverage with T years apart are not expected to decrease significantly over time. In addition, we expect the average R^2s to remain high over time. This is because "*current leverage*" must be closely related with "*future leverage*" if leverage is stable.

2.5.1.1 Scenario 1 - Stable Leverage Due to Substantial Firm Fixed Effects

We modify Eq. (2.1, p.15) by assuming that firms' leverage are extremely stable and there is no dynamic variation in leverage over time (i.e. ϕ_3 is assumed to be zero). Hence leverage variation is only caused by the cross-sectional components in the model, which is shown in Eq. (2.9).

$$Y_{it} = \phi_0 + \phi_1 X_{it} + \phi_2 \eta_i + \varepsilon_{it} \tag{2.9}$$

In Eq. (2.9), we randomly draw firm fixed effects (η_i) from a uniform distribution with interval [0, 0.8], U ~ (0, 0.8).[20] Firm fixed effects are expected to remain constant over time for each firm but vary across firms (so each firm has a unique firm fixed effect). According to LRZ's statement, the majority of variation in leverage is captured by firm fixed effects, and its time-invariant characteristics of firm fixed effects which lead to stable leverage over time. Hence, a higher weight is assigned to the firm fixed effects ($\phi_2 = 0.8$) to indicate its importance in generating stable leverage.

The control variable (X_{it}) is assumed to be uniformly distributed on the interval [-0.5, 1] (Elsas & Florysiak, 2015). A small coefficient is assigned to the control variable (ϕ_1= 0.1) showing that it has a small effect on leverage as most of leverage variation has been explained by the firm fixed effects.

The constant is set to be equal to 0.05 ($\phi_0 = 0.05$). The error term (ε_{it}) is assumed to be normally distributed with mean of 0 and standard deviation of 0.01, i.e. N $(0,0.01^2)$.

Implication for DR's methodology (i.e., Eq. (2.5))

Since this scenario refers to the stable scenario where only cross-sectional variation is included in the model and there is no dynamic variation, $\phi_3 = 0$. With regular assumptions (see Eqs. (A1.11), (A1.12), (A1.13) and (A1.14) in Appendix A), Eq. (2.5, p.17) collapses to the following:

[20] Both LRZ and DR include firm dummies in the leverage regression. In our study, we have 2000 firms for each simulation scenario. Instead of generating 2000 firm dummy variables, we choose to create only one variable, which is the uniformly distributed firm fixed effects.

$$Cov\,[Y_{it}, Y_{it-1}] - Cov\,[Y_{it}, Y_{it-2}] = Cov\,[Y_{it}, Y_{it-1}] - Cov\,[Y_{it}, Y_{it-3}] = \cdots Cov\,[Y_{it}, Y_{it-1}] - Cov\left[Y_{it}, Y_{it-j}\right] = 0$$

In other words, we expect that there is no difference between covariance for different lags, which suggests that the R^2s between leverage with T years apart are expected to be constant over time.

Implications for LRZ's methodology (i.e., Eq. (2.7))

Since there is no dynamic variation in the model (i.e. $\phi_3 = 0$) and with regular assumptions (see Eqs. (A1.15), (A1.16), (A1.17), (A1.18) and (A1.19) in Appendix A), Eq. (2.7, p.19) becomes:

$$E(Y_{ij}) = \phi_0 + \phi_1 \mathrm{E}(\mathrm{X}_{ij}) + \phi_2 \mathrm{E}(\eta_i)$$

Thus, the *average leverages* are expected to be stable over time (with no convergence).

Figures 2.3 and 2.4 present the simulation results generated according to LRZ's and DR's methodologies, respectively. For Scenario 1, it is clear to see that the results from simulation tests with the use of both LRZ's and DR's methodologies are consistent with our expectation based on the frameworks. We obtain stable *average leverages* with the use of LRZ's methodology without any convergence in the short-run as shown in Figure 2.3. In addition, the *average leverages* are extremely stable in the long-run. We also obtain stable average R^2s based on DR's methodology as shown in Figure 2.4. The average R^2s remain extremely high and unchanged which reflect the great degrees of cross-sectional leverage stability.

Figure 2.3 – Average leverage of simulated leverage portfolios in event time (LRZ's methodology)

Figure 2.3 is generated for 2.5.1.1 - Scenario 1 (p.26) according to the methodology used by LRZ, based on the assumption that there is no dynamic variation in leverage over time. Firms' leverage are extremely stable due to substantial time-invariant firm fixed effects. Firms are sorted into four portfolios (or quartiles) based on their initial leverage ratios (leverage at t =1) and assumed to stay in the same portfolio over time. We repeat the same simulation process 200 times. The *average leverage* for each portfolio across all simulation iterations (200 iterations) will be computed.

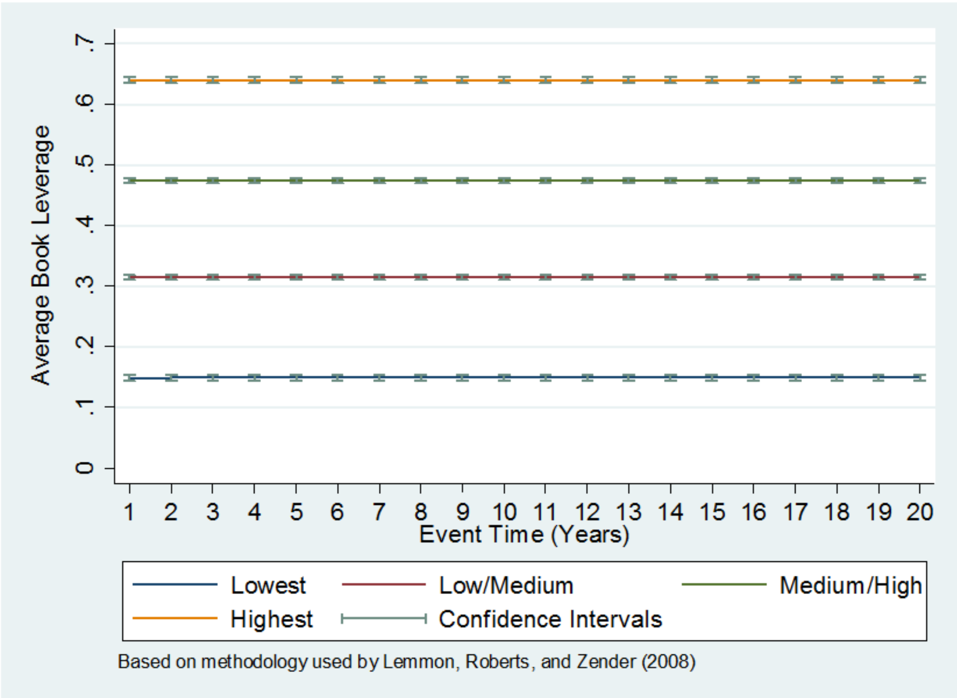
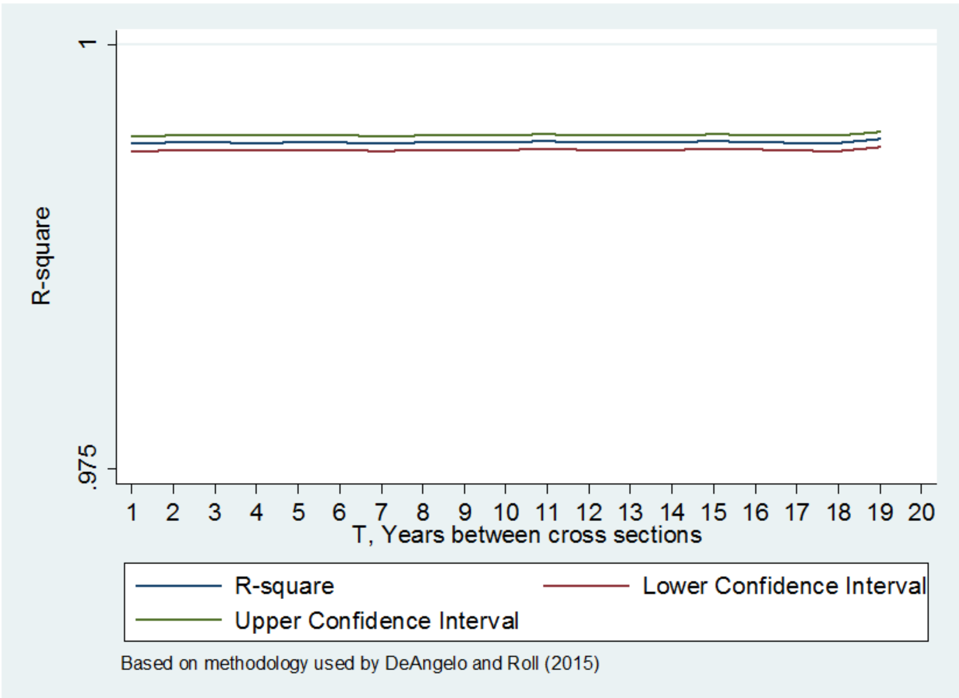


Figure 2.4 – Extent of leverage stability in cross-sections (DR's methodology)

Figure 2.4 is generated for 2.5.1.1 - Scenario 1 (p.26) according to the methodology used by DR, based on the assumption that there is no dynamic variation in leverage over time. Firms' leverage are extremely stable due to significant time-invariant firm fixed effects. This figure presents the average $R^2 s$ between leverage in a given year and future leverage across all simulation iterations (200 iterations). The horizontal axis shows the number of years between leverage cross-sections. The vertical axis plots the average $R^2 s$ over all pairings of leverage in a given year and leverage after T years (T years refer to the number of years shown on the horizontal axis). For instance, to generate the average R^2 with one-year difference between cross sections, firms with non-missing leverage data in two adjacent years will be first identified such as firms with non-missing data in event years 1 and 2, 2 and 3, 3 and 4, so on. Each of them is treated as a pair and the average R^2 across all these pairings with exactly one-year apart is reported. Then the whole process is repeated using pairings with "each value of T" years apart. Bias-corrected confidence intervals are generated based on bootstrap procedure with 500 replications.



2.5.1.2 Scenario 2 - Role of Initial Leverage and Firm Fixed Effects

In this scenario, both firm fixed effects and initial leverage significantly contribute to leverage stability. As discussed in Section 2, one of the key findings in LRZ is that initial leverage is closely related to future leverage. This further supports their argument that firms' leverage are stable over time and are driven by the time-invariant firm fixed effects. In addition, because firms follow their initial leverage paths, the differences in *average leverages* of all four initial portfolios persist over time. In order to take into account the role of initial leverage, we replace Y_{it-1} by Y_{i1} in Eq. (2.1, p.15) and get

$$Y_{it} = \phi_0 + \phi_1 X_{it} + \phi_3 Y_{i1} + \varepsilon_{it} \tag{2.10}$$

Consistent with the initial assumption that Y_{i1} is stationary, we start off with the assumption that initial leverage is driven by cross sectional variation of control variable, fixed effect and noise in the following form:

$$Y_{i1} = \phi_0 + \phi_1 X_{i1} + \phi_2 n_i + \varepsilon_{i1} \tag{2.11}$$

As we hypothesize that unique firm fixed effects are significant to firms' initial leverage ratios, we set a large coefficient for the firm fixed effects ($\phi_2 = 0.8$). This is consistent with the idea that there is a large difference between the *average leverages* of initial leverage portfolios at event time zero (shown in Figure 2.1). In addition, firms keep leverage stable over time by following their initial leverage paths. We also set a large coefficient for the initial leverage ($\phi_3 = 0.8$) to indicate its significant explanatory power in explaining future leverage. As in Scenario 1, we assume that firm-specific control variable (X_{it}) is uniformly distributed on the interval [-0.5, 1] and assign a low coefficient with ϕ_1= 0.1. The constant is set being equal to 0.05 ($\phi_0 = 0.05$). Firm fixed effects (η_i) are randomly drawn from a uniform distribution with interval [0, 0.8], U ~ (0, 0.8). Error term (ε_{it}) is assumed to be normally distributed with mean of 0 and standard deviation of 0.01.

Figure 2.5 – Average leverage of simulated leverage portfolios in event time (LRZ's methodology)

Figure 2.5 is generated for 2.5.1.2 - Scenario 2 (p.30) according to the methodology used by LRZ, by hypothesizing that firms follow their initial leverage paths and therefore have stable leverage. Firms are sorted into four portfolios (or quartiles) based on their initial leverage ratios (leverage at t =1) and assumed to stay in the same portfolio over time. We repeat the same simulation process 200 times. The *average leverage* for each portfolio across all simulation iterations (200 iterations) will be computed.

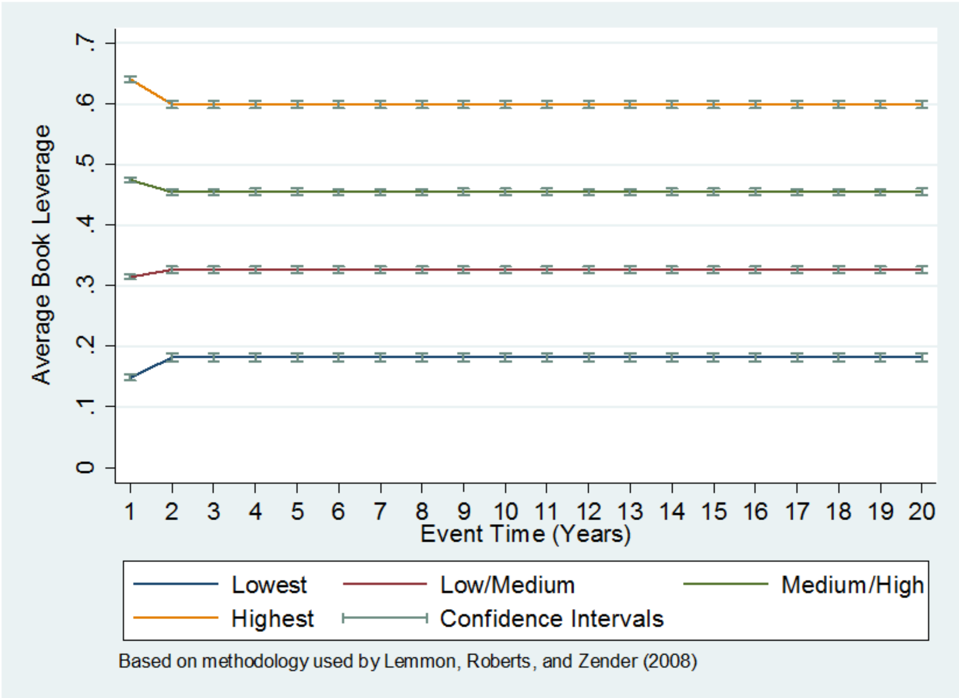
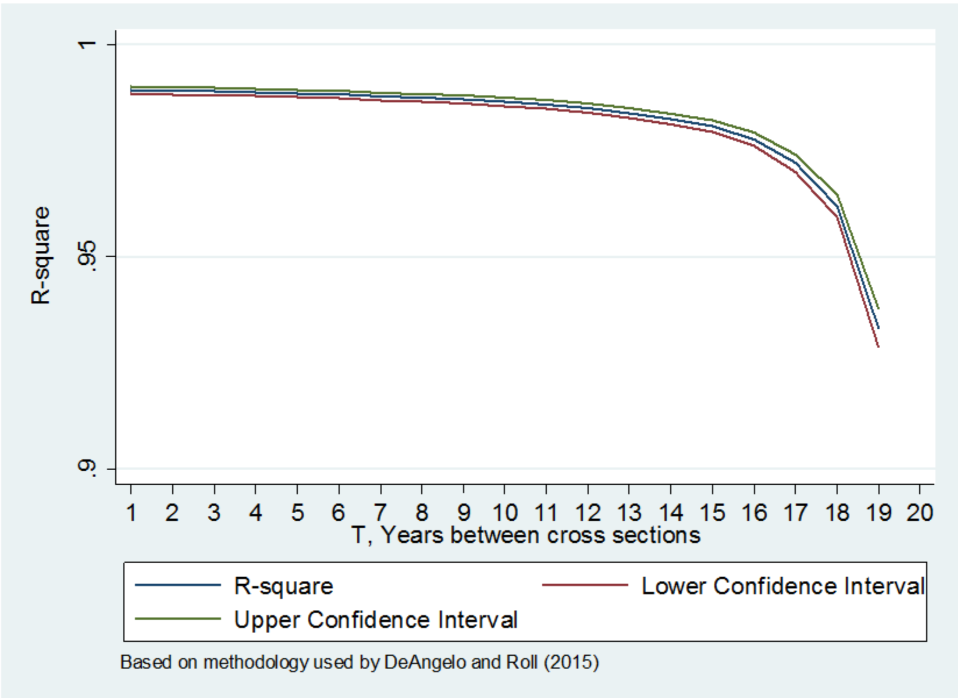


Figure 2.6 – Extent of leverage stability in cross-sections (DR's methodology)

Figure 2.6 is generated for 2.5.1.2 - Scenario 2 (p.30) according to the methodology used by DR, by hypothesizing that firms follow their initial leverage paths and therefore have stable leverage. This figure presents the average R^2s between leverage in a given year and future leverage across all simulation iterations (200 iterations). The horizontal axis shows the number of years between leverage cross-sections. The vertical axis plots the average R^2s over all pairings of leverage in a given year and leverage after T years (T years refer to the number of years shown on the horizontal axis). For instance, to generate the average R^2 with one-year difference between cross sections, firms with non-missing leverage data in two adjacent years will be first identified such as firms with non-missing data in event years 1 and 2, 2 and 3, 3 and 4, so on. Each of them is treated as a pair and the average R^2 across all these pairings with exactly one-year apart is reported. Then the whole process is repeated using pairings with "each value of T" years apart. Bias-corrected confidence intervals are generated based on bootstrap procedure with 500 replications.



Figures 2.5 and 2.6 present the simulation results generated according to LRZ's and DR's methodologies, respectively. Figure 2.5 shows that *average leverages* converge quickly (i.e., in event year 2). After the second event year, the *average leverages* remain constant with persistent cross-sectional differences; this result matches our data generating process, which is, in this scenario, largely driven by cross-sectional differences in fixed effects. By applying DR's methodology, we obtain high average R^2s which decrease slightly and slowly over time (see Figure 2.6). In particular, the average R^2s stay above 0.9 for leverage with 19 years apart in cross sections. This result is not surprising. In this scenario, firms' initial leverage, which is mainly determined by differences in fixed effects ($\phi_2 = 0.8$), affects subsequent leverages in a significant way ($\phi_3 = 0.8$). Hence there are only slight differences in future leverage (such as leverage in year 2 and year 3) due to small variation in control variable and random errors, meaning that future leverages are highly related with each other (e.g. leverage in year 2 and year 3) than with the initial leverage (e.g. leverage in year 2 and year 1 or year 3 and year 1). The slight decrease in average R^2s for longer lags may be explained by the fact that we obtain less number of pairs with high R^2s as lag length in leverage cross sections increases.[21]

2.5.1.3 Discussion on Stable Leverage Scenarios

The stable simulation tests show that LRZ's and DR's results are consistent with our expectation. In particular, the results produced from both methodologies match the data features that strong stable leverage regimes should exhibit. For LRZ's methodology, in both stable scenarios, we find that the *average leverages* generated remain relatively stable in the long-run with persistent cross-sectional differences. For DR's methodology, the

[21] For example leverage with one-year difference in cross sections (T=1), we would have 18 pairs with similar high R^2s (e.g. leverage in year 2 and 3, leverage in year 3 and 4) and one pair with relatively lower R^2, which is (leverage in year 1, leverage in year 2). Similarly, for leverage with two years apart (T=2), we would have 17 pairs with similar high R^2s (e.g. leverage in year 2 and 4, leverage in year 3 and 5) and one pair with relatively lower R^2, which is (leverage in year 1, leverage in year 3). There is a decrease in number of pairs with similar high R^2s as lag length increase.

average R^2s are extremely high reflecting the great degree of cross-sectional leverage stability.

2.5.2 Unstable Leverage Scenarios

If LRZ's methodology is applied in unstable leverage scenarios, we would not expect to observe the pattern of short-run convergence and long-run stability of the *average leverage* of each leverage portfolio over event time. However, if DR's methodology is applied, we do expect the average R^2s between leverage with horizon T years apart to decrease significantly with increasing horizon, which is similar to the patterns we have observed in Figure 2.2.

2.5.2.1 Scenario 3 - Unstable Leverage Due to Significant Time-series Variation

To reflect the extremely unstable leverage over time, we assume that firms' leverage are only driven by the dynamic or time-series variation. We modify Eq. (2.1, p.15) by excluding the cross-sectional components, as shown in Eq. (2.12).

$$Y_{it} = \phi_0 + \phi_3 Y_{it-1} + \varepsilon_{it} \tag{2.12}$$

Y_{it-1} is the leverage of firm *i* in the previous year. We use lagged leverage to capture time-series variation in leverage. If firms' leverage is unstable over time, firms' leverage in current year should be not closely related with their leverage in previous year. We set a small coefficient to the lagged leverage ($\phi_3 = 0.2$) to show that firms' leverage are unstable over time. The constant is 0.05 ($\phi_0 = 0.05$). Error term (ε_{it}) is assumed to be normally distributed with mean of 0 and standard deviation of 0.01.

Implications for DR's methodology (i.e., Eq. (2.5))

This scenario refers to the unstable leverage scenario where only dynamic variation (but not control variable and firm fixed effects) is included in the model. With regular assumptions (see Eqs. (A1.11), (A1.12), (A1.13) and (A1.14) in Appendix A), Eq. (2.5, p.17) becomes:

$Cov\ [Y_{it}, Y_{it-1}] - Cov\ [Y_{it}, Y_{it-2}] = \phi_3 E(\varepsilon_{it})^2$

$Cov\ [Y_{it}, Y_{it-1}] - Cov\ [Y_{it}, Y_{it-3}] = (\phi_3 + {\phi_3}^2) E(\varepsilon_{it})^2$

$Cov\ [Y_{it}, Y_{it-1}] - Cov\ \left[Y_{it}, Y_{it-j}\right] = \left(\frac{1}{1-\phi_3} - 1\right) E(\varepsilon_{it})^2\ if\ j\ \rightarrow\ \infty$

The above results suggest the difference between covariance for different lags increases as lag length increases. In other words, the $R^2 s$ between leverage with T years apart are expected to be decreasing over time (as T increases).

Implications for LRZ's methodology (i.e., Eq. (2.7))

Since there is no control variable and firm fixed effects in the model and with regular assumptions (see Eqs. (A1.15), (A1.16), (A1.17), (A1.18) and (A1.19) in Appendix A), Eq. (2.7, p.19) collapses to the following:

$E(Y_{i1}) = \phi_0$

$E(Y_{i2}) = \phi_0(1 + \phi_3)$

$E(Y_{i3}) = \phi_0(1 + \phi_3 +\ {\phi_3}^2)$

$E\left(Y_{ij}\right) = \frac{\phi_0}{1-\phi_3}\ if\ j\ \rightarrow\ \infty$

The above results suggest that *average leverages* are expected to be converging towards the long-run mean leverage over time.

Figure 2.7 – Average leverage of simulated leverage portfolios in event time (LRZ's methodology)

Figure 2.7 is generated for 2.5.2.1 - Scenario 3 (p.34) according to the methodology used by LRZ, based on the assumption that firms have unstable leverage as their leverage ratios are only driven by the dynamic or time-series variation. Firms are sorted into four portfolios (or quartiles) based on their initial leverage ratios (leverage at t =1) and assumed to stay in the same portfolio over time. We repeat the same simulation process 200 times. The *average leverage* for each portfolio across all simulation iterations (200 iterations) will be computed.

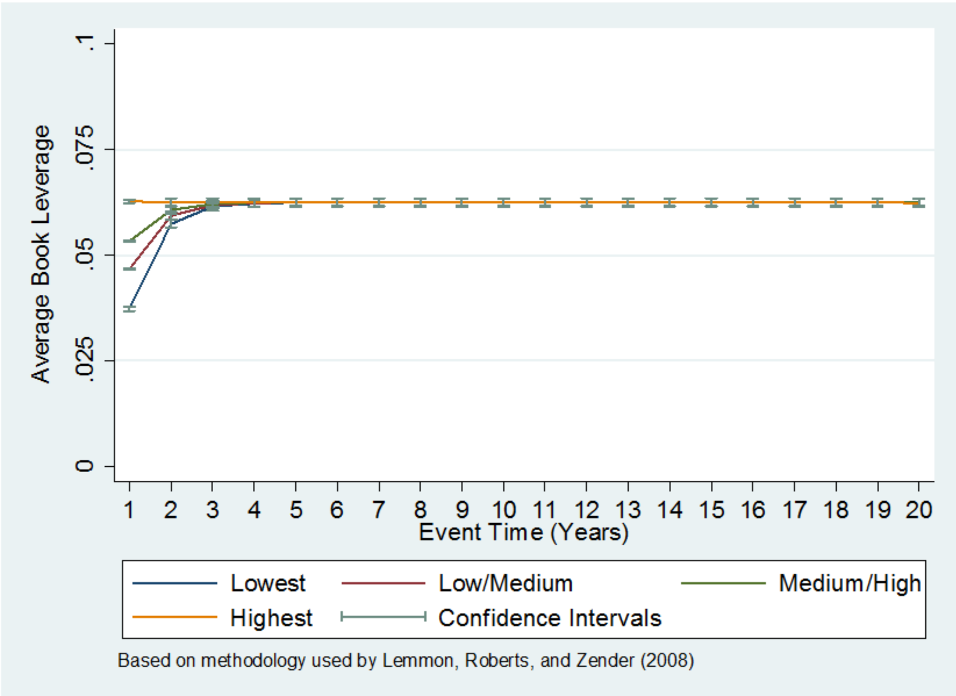
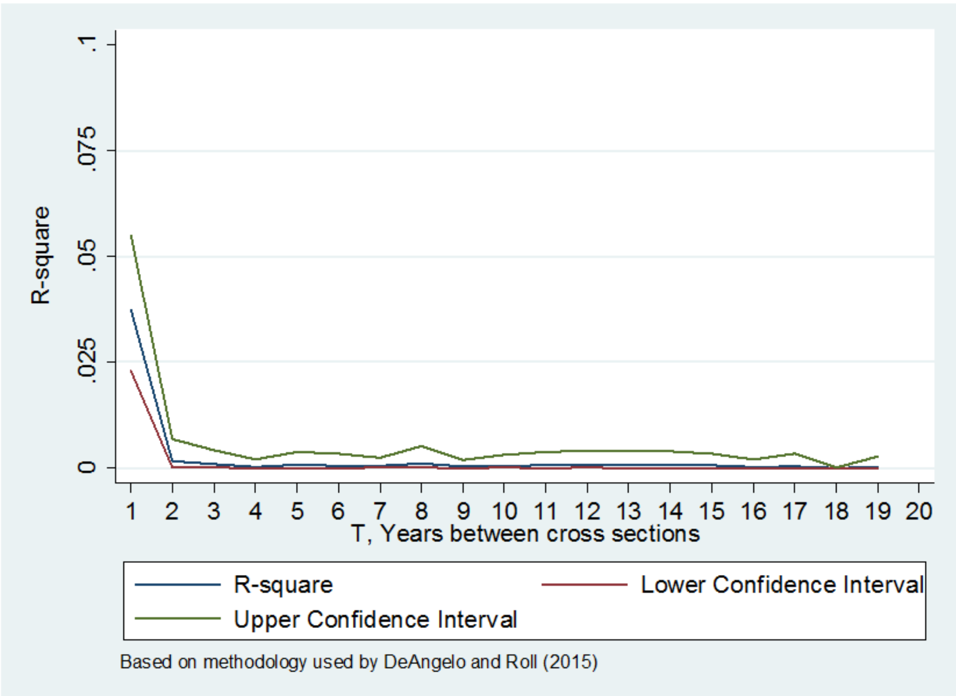


Figure 2.8 – Extent of leverage stability in cross-sections (DR's methodology)

Figure 2.8 is generated for 2.5.2.1 - Scenario 3 (p.34) according to the methodology used by DR, based on the assumption that firms have unstable leverage as their leverage ratios are only driven by the dynamic or time-series variation. This figure presents the average R^2s between leverage in a given year and future leverage across all simulation iterations (200 iterations). The horizontal axis shows the number of years between leverage cross-sections. The vertical axis plots the average R^2s over all pairings of leverage in a given year and leverage after T years (T years refer to the number of years shown on the horizontal axis). For instance, to generate the average R^2 with one-year difference between cross sections, firms with non-missing leverage data in two adjacent years will be first identified such as firms with non-missing data in event years 1 and 2, 2 and 3, 3 and 4, so on. Each of them is treated as a pair and the average R^2 across all these pairings with exactly one-year apart is reported. Then the whole process is repeated using pairings with "each value of T" years apart. Bias-corrected confidence intervals are generated based on bootstrap procedure with 500 replications.



Figures 2.7 and 2.8 present the simulation results generated according to LRZ's and DR's methodologies, respectively. Figure 2.7 clearly shows that the *average leverages* (based on LRZ's methodology) of the four initial portfolios almost converge to a single level after a short period of time and remain quite stable in the long run.[22] The convergence of *average leverages* towards the long-run mean is in line with the expected outcome from our framework (Eq. (2.7), p.19). Based on DR's methodology, Figure 2.8 depicts that the average R^2s for leverage with one-year difference in cross-sections (leverage in adjacent years) are below 0.1, followed by a large decline in the average R^2s for leverage with two years apart in cross-sections. Despite the fact that all of the average R^2s are small, the significant decrease in the average R^2s is consistent with the expected outcome from the framework for DR's methodology (Eq. (2.5), p.17), except it decreases faster from one-year lag to two-year lag difference in leverage cross sections than the pattern DR obtained with their own data and Figure 2.2. This pattern is similar to the pattern we observed in the original graphs (i.e., DR, 2015, p.388 and Figure 2.2).

2.5.2.2 Discussion on Unstable Leverage Scenario

Based on the results we obtained from the unstable leverage scenario, we find that the results generated based on LRZ's methodology do not match our data features. We still observe the short-run converging and long-run stable pattern in the *average leverages* even though leverage is unstable over time.

For DR's methodology, we find that the average R^2s correctly reflect data features. We observe a decrease in the average R^2s which indicate that similarities in cross-sectional leverage is diminishing over time. These results show that DR's methodology produces results consistent with the unstable scenarios, whereas LRZ's methodology does not.

[22] Cross-sectional determinants are not included in Scenarios 3, which explains why there is no cross-sectional differences in the *average leverages* of the four portfolios (seem to converge to a single point).

2.5.3 Type I and Type II Error Rates of LRZ's and DR's Methodologies

Based on the *average leverage* and R^2 graphs in previous subsections (sections 2.5.1 and 2.5.2), we find that DR's methodology captures the features of the data better than LRZ's methodology. The R^2 graphs generated from DR's methodology match our simulation data features by correctly supporting leverage stability and instability under different scenarios, whereas the average *leverage* graph using LRZ's methodology always supports leverage stability, despite the changes in simulation parameters data features. However, such conclusions are drawn based on a "snapshot" of 200 simulation iterations as the results examined are the averages computed across all simulation iterations (the average of *average leverage* and the average of R^2s computed). We would therefore wish to make some further effort to ensure that our inferences are sound. We assess the validity of each methodology by considering the error rates of both methodologies under each simulated scenario. In other words, we calculate the Type I and Type II error rates.

We propose the null and alternative hypotheses as follow:

H_0 : Leverage data is stable.

H_1 : Leverage data is unstable.

For each methodology, we calculate the Type I error rate, which is the probability of rejecting the true null hypothesis. In our study, the Type I error rate is calculated as the number of times out of 200 iterations each methodology detects leverage instability when in fact the simulated leverage data is stable.

We also calculate the Type II error rate or the statistical power (1- Type II error) of each methodology. By definition, the Type II error rate is the probability of failing to reject the false null hypothesis. In our case, under unstable scenario, the Type II error is calculated as the number of times out of 200 iterations each methodology failing to detect leverage instability.

To consider the error rates or the power of the simulations we have presented, we follow Cohen's (1988) five-eighty convention to set the Type I error rate at 0.05 and the Type II error rate at 0.2 (or a minimum statistical power of

0.8). These are the maximum Type I and Type II error rates we are willing to tolerate.

2.5.3.1 Error Rates of LRZ's Methodology

We start with LRZ's methodology. We first calculate the Type I error rate of LRZ's methodology under stable scenarios (scenarios 1 and 2 on pages 26 and 30, respectively) using the following procedure. For each simulation iteration, we find out the difference between the *average leverage* of the lowest portfolio (quartile) and the *average leverage* of the highest portfolio (quartile) in the first 10 years, and the last 10 years, respectively.[23] We then conduct a t-test at 5% level of significance for the *average leverage* difference for the first and last 10-year comparisons. If the p-values of the t-test are insignificant (i.e. p-value is greater than 0.05), then we can conclude that the *average leverages* are stable over time, and LRZ's methodology successfully detects stability in leverage as the null hypothesis is not rejected. If the p-values are found to be significant (i.e. p-value is less than or equal to 0.05), then LRZ's methodology has incorrectly detected instability (or the null hypothesis is incorrectly rejected). We count the number of times instability is incorrectly detected, and this determines the Type I error rate of LRZ's methodology.

Results of LRZ's Type I error rates are shown in Table 2.3. For scenario 1, we find that 15 out of 200 iterations report significant p-values for the t-test. This result shows that the probability of rejecting the true null hypothesis or the Type I error rate of LRZ's methodology under scenario 1 is 0.075. In addition, this has exceeded the maximum critical level for Type I error rate (i.e. 0.05). For the second stable scenario, we do not find any iterations with significant p-values. Hence, LRZ's methodology successfully detects leverage stability 200 times over 200 simulations. Since we have no instance where we fail to detect stability, the probability of rejecting the true null hypothesis or the Type I error rate is 0.

[23] This is achieved using the t-test mean comparison.

Table 2.3 – Error rates of LRZ's methodology

This table presents the results on the Type I and Type II error rates of LRZ's methodology in detecting leverage stability or instability. For each simulation iteration, we find out the difference between the *average leverage* of the lowest portfolio (quartile) and the *average leverage* of the highest portfolio (quartile) in the first 10 years, and the last 10 years, respectively. T-test is conducted for the *average leverage* differences between the first and last 10-year comparisons. P-values of the t-test are used to determine whether LRZ's methodology successfully detects the stability condition of each simulated scenario. If p-values are insignificant, then null hypothesis of stable leverage is not rejected. If p-values are significant, the null hypothesis is rejected which imply that leverage stable is unstable. For stable scenarios or scenarios 1 and 2, we divide the number of iterations that detects leverage instability when in fact it is stable by the total 200 iterations to calculate the Type I error rate. For unstable scenario or scenario 3, we divide the number of iterations that fails to detect leverage instability by the total 200 iterations to calculate the Type II error rate.

Scenario	Number of iterations detects the incorrect condition	Total number of iterations for each scenario	Type I error rate (scenarios 1 & 2); Type II error rate (scenario 3)
Stable Scenario (incorrectly detect instability and reject the true null)			
Scenario 1	15	200	0.075
Scenario 2	0	200	0.000
Unstable Scenario (fail to detect instability or reject the false null)			
Scenario 3	200	200	1.000

We then repeat the same steps for scenario 3 which is the scenario with unstable simulated data (p.34). If the p-values of the t-test are significant, this means that the null hypothesis will be rejected and LRZ's methodology successfully detects instability. Otherwise, the methodology fails to detect instability or reject the false null.

We find that, out of the 200 iterations, all of p-values observed are greater than 0.05. These results indicate that LRZ's methodology fails to reject the false null hypothesis for all iterations under the unstable scenario. Hence, the Type II error rate of LRZ's methodology is 1.00. Alternatively, we could say that the statistical power for LRZ's methodology is 0 under the unstable scenario.

2.5.3.2 Error Rates of DR's Methodology

To assess the validity of DR's methodology in detecting the stability/instability condition of each simulated scenario, we use the new F-statistic constructed by Lund et al. (2016), which assesses ANOVA with autocorrelated data. DR's methodology computes the average R^2 at each horizon. However, each R^2 is computed based on overlapping observations. For instance, the average R^2 at one-year horizon is computed by taking the average of R^2s for pairs of leverage data that differ by 1 year in cross sections: (year 1 leverage, year 2 leverage), (year 2 leverage, year 3 leverage), (year 3 leverage, year 4 leverage), and so on. Hence, there exists autocorrelation in the average R^2s computed across horizons. The new F-statistic constructed by Lund et al. (2016) is computed based on one-step-ahead prediction residual. According to equation (2.7) in Lund et al. (2016, p.56):

$$\tilde{F}_R = \frac{n\sum_{i=1}^{m}\left(\bar{\tilde{R}}_i - \bar{\bar{\tilde{R}}}\right)^2 / (m-1)}{\sum_{i=1}^{m}\sum_{t=1}^{n}\left(\tilde{R}_{t,i} - \bar{\tilde{R}}_i\right)^2 / [m(n-1)]}$$

With $\tilde{R}_{t,i} = X_{t,i} - \hat{\tilde{X}}_{t,i}$, which is the prediction residual, and $\bar{\tilde{R}}_i = \frac{\sum_{t=1}^{n}\tilde{R}_{t,i}}{n}$ and $\bar{\bar{\tilde{R}}} = \frac{\sum_{i=1}^{m}\sum_{t=1}^{n}\tilde{R}_{t,i}}{mn}$

In our case, m is the number of simulation iterations for each scenario, which is 200. N is the total number of R^2 observations (initially 19 R^2 observations) excluding the first observation (N equals 18), which is used to compute the fitted or predicted R^2 value for the next period. When we generate the F-statistic, we rewrite Lund et al.'s (2016) equation (2.7, p.56) as:

$$\tilde{F}_R = \frac{n \times Var(\bar{\tilde{R}}_i)}{Var(\tilde{R}_{t,i}) \times (mn-1)/[m(n-1)]}$$

The null hypothesis is that leverage data is stable. According to Lund et al. (2016), the F-critical value should be computed based on the $(1-\alpha)^{th}$ quantile and the numerator and denominator degrees of freedom should be (m-1) and [m(n-1)], respectively. For 5% level of significance (α = 0.05), the upper tail F-critical value with 199 numerator degrees of freedom and 3400 (200 * (18-1)) denominator degrees of freedom is approximately 1.1765. We compare the critical value with the F-statistic computed for each iteration of each simulated scenario. If the F-statistic computed is greater than the F-critical value, this indicates leverage instability and the null hypothesis of stable leverage will be rejected.

For stable scenarios, we count the number of iterations that have detected leverage instability when in fact leverage is stable (i.e. the F-statistics are found to be greater than the F-critical value). Based on this number, we calculate the Type I error rate. Then we repeat the same steps for the unstable scenario. We count the number of iterations that fail to detect instability or reject the false null hypothesis (i.e. F-statistics are less than the F-critical value). Based on this number, we also calculate the Type II error rate. The error rates of DR's methodology are presented in Table 2.4 below.

Table 2.4 – Error rates of DR's methodology

This table presents the results on the Type I and Type II error rates of DR's methodology. To assess the validity of DR's methodology, we follow Lund et al. (2016) to construct the one-step-ahead F-statistic. For each simulated scenario, we compute the F-statistic for each iteration. We then compare the computed F-statistic with the F-critical value. According to Lund et al. (2016), F-critical value should be computed based on the $(1-\alpha)^{th}$ quantile and the numerator and denominator degrees of freedom should be (m-1) and [m(n-1)]. In our case, m is the number of simulation iterations for each scenario, which is 200. N is the total number of R^2 observations (initially 19 R^2 observations) excluding the first observation (N equals 18). Hence, F-critical value at 5% level of significance with 199 numerator degrees of freedom and 3400 (200 * (18-1)) denominator degrees of freedom is approximately 1.1765. For stable scenarios or scenarios 1 and 2, we divide the number of iterations that detects leverage instability when in fact it is stable by the total 200 iterations to calculate the Type I error rate. For unstable scenario or scenario 3, we divide the number of iterations that fails to detect leverage instability by the total 200 iterations to calculate the Type II error rate.

Scenario	Number of iterations detects the incorrect condition	Total number of iterations for each scenario	Type I error rate (scenarios 1 & 2); Type II error rate (scenario 3)
Stable Scenario (incorrectly detect instability and reject the true null)			
Scenario 1	4	200	0.020
Scenario 2	0	200	0.000
Unstable Scenario (fail to detect instability or reject the false null)			
Scenario 3	21	200	0.105

From Table 2.4, we find that 4 out of 200 iterations for stable scenario 1 have incorrectly detected leverage instability (F-statistics greater than the F-critical value), and rejected the true null hypothesis of stable leverage. This gives us the Type I error rate of 0.02. For stable scenario 2, we find that the Type I error rate is 0 as the F-statistics are less than the critical value for all iterations (correctly detect stability).

Lastly, for the unstable scenario (scenario 3, p.34), 21 out of 200 iterations are found to have F-statistics less than the F-critical value and fail to detect instability. This shows that the Type II error rate of failing to reject the false null hypothesis is 0.105. Alternatively, we could say that the statistical power is 89.5% for DR's methodology under unstable scenario.

2.5.3.3 Error Rate and Power Test Comparisons

Comparing the results in Tables 2.3 and 2.4, we find that both LRZ's and DR's methodologies perform well under the stable scenarios with low Type I error rates under stable scenarios. Although LRZ's methodology is found to have a Type I error rate greater than the criterion 0.05 in scenario 1, we still consider it as valid methodology as its error rates are less than 0.05 in the other stable scenario. However, for unstable scenario, LRZ's methodology has a higher Type II error rate (1.00) and a smaller statistical power of 0% than DR's methodology (Type II error rate at 0.105 and statistical power of 89.5%). In addition, LRZ's methodology does not achieve the minimum power of 80%. Hence, DR's methodology is considered to be the valid methodology.

2.6 Conclusion

Leverage stability remains a conundrum as we do not know whether firms have stable or unstable leverage. LRZ and DR present contradictory evidence on the stability issue of leverage and provide us two methodologies for examining leverage stability. However, based on our preliminary tests with leverage datasets, we find that the findings in both papers are driven by their methodologies. We use simulation methods to test the validities of both methodologies since we do not know the data generating process of real data. Based on the results from simulation tests, we find that the pattern we observe with the use of LRZ's methodology always supports leverage stability, even simulated leverage data is unstable. On the other hand, we find results from DR's methodology correctly match the simulated data features. These findings are further supported by the analyses of the Type I and Type II error rates of each methodology under different scenarios. We find that DR's methodology has lower error rates in all scenarios. For LRZ's methodology, it only performs well in stable scenarios, but fails to detect instability (with a low statistical power and high Type II error rate). We hence conclude that DR's methodology, when compared to that of LRZ, should be used in future study for investigating leverage stability.

3 The Stability of Interest Payment Commitment

3.1 Introduction

Is leverage stability a desirable goal? Graham and Harvey (2001, Fig 6) report that 44% of surveyed CFOs have a “very strict target” (10%) or a “somewhat tight target/range” (34%) for debt-to-equity ratios, but the regularity of review or change to such targets is not recorded. Although trade-off theory and pecking-order theory provide rationales for corporate leverage decisions, these theories do not necessarily imply that leverage measures such as the debt-to-equity ratio should be stable over time. Thus the issue of leverage management, not specifically leverage stability, must be given sensible context.

Under the premise that leverage decisions are undertaken by management, via negotiation with lenders, with due respect for the ability of the underlying corporate assets to support the commitment to interest payments, we use EBIT to represent the fundamental ability of a firm’s assets to support interest expense. Based on the methodology of DR we find that, on average, across all US listed firms from 1962 to 2016, annual interest expense standardized by market value of assets (int/MVA) are significantly more stable than EBIT over MVA (EBIT/MVA) out to a horizon of 20 years. Thus we conclude that, on average, corporate commitment to leverage, in terms of the consequential interest expense, is relatively stable over time.[24]

Furthermore, we identify firm characteristics that are strongly associated with greater subsequent relative stability of interest expense levels. In particular, large firms and high dividend-paying firms exhibit significantly more int/MVA stability than EBIT/MVA stability for beyond 10 years, whereas small firms and low dividend firms exhibit comparatively little such relative stability of int/MVA. We argue that this is consistent with the differing

[24] In contrast, in terms of debt-to-assets, DR argue that “[c]apital structure stability is the exception, not the rule” (p.373).

motivations of trade-off and pecking-order capital structure theories having differing imperative across the cross-section of firm characteristics.

Our critical contribution is to address the question, “does it matter?” That is, does leverage management, as indicated by interest expense stability, have any implication for firm values? To do this we develop a model for the expected interest expense variability of individual firms as a function of their characteristics, and then investigate the relationship between unexpected interest expense variability and valuation outcome. In terms of both market-to-book value of assets ratio and abnormal stock returns, our key result is that there are adverse valuation consequences for firms with interest expense variability that deviates from expected (for given firm characteristics): in other words, interest expense *stability* different from expected is associated with lower firm value and stock return. The implication is that leverage management does matter, and expected or “normal” leverage management is broadly optimal.

This paper is structured as follows. Section 3.2 details the background and motivation for our study. Section 3.3 describes the data sample. Section 3.4 presents our aggregate interest expense stability evidence. Section 3.5 presents our modelling of the interest expense variability of individual firms. Section 3.6 presents our analysis of the relationship between interest expense variability and firm performance. Section 3.7 concludes.

3.2 Background

In this section we review capital structure theories and the empirical evidence that set the context for corporate leverage management and our analysis. Optimal corporate leverage, or more specifically, value maximizing leverage, is a balance of costs and benefits: optimal leverage is the level at which the negative valuation consequences of an additional dollar of debt finance equals the positive valuation consequences. Trade-off theory, in its most traditional sense, considers the balance (for the marginal unit of leverage) of the present value of expected corporate tax savings (due to the tax deductibility of interest expense) versus the present value of expected deadweight financial distress and bankruptcy costs. The value of interest expense tax shields depends on the presence of taxable profit, which depends on the presence of other tax shields such as carry-forward losses, and depreciation and R&D expenses. Other valuation costs and benefits of leverage may stem from, for example, the agency costs of free cash flow (Jensen, 1986), the agency costs of debt (Jensen and Meckling, 1976; Myers, 1977), the presence of a personal tax penalty within the interest rate for debt (Miller, 1977), and the transaction costs associated with active leverage management.

Myers' (1984) pecking-order theory suggests that information asymmetry between corporate managers and investors, combined with the fact that financially troubled firms are motivated to issue new equity, results in adverse selection risk for investors in firms that are seeking new equity finance. Conversely, firms with good prospects that are underappreciated by investors will be unperturbed by the financial risk from new debt finance. In this context the value of the leverage decision stems from avoiding the negative valuation signal associated with issuing equity, or seeking the positive valuation signal associated with issuing debt. However, when new finance is being sought, the pecking-order preference for debt over equity will optimally be balanced with pecking-order considerations for potential future investment opportunities that may be curtailed by insufficient spare capacity for debt (i.e. financial slack).[25] In effect, information asymmetry/signaling and financial slack considerations entail additional costs and benefits (in terms of firm valuation) to be balanced in the optimal leverage decision.

Within a value maximizing leverage paradigm, a firm's optimal leverage decision is likely to vary greatly through its life cycle as a consequence of changing growth opportunities, profitability, information asymmetry and other characteristics (Faff, Kwok, Podolski, & Wong, 2016; Karpavičius & Yu, 2019a, 2019b). A stereotypical "mature" firm will have reliable

[25] Myers (1984) notes that "financial slack (liquid assets or reserve borrowing power) is valuable, and the firm may rationally issue stock to acquire it". This underpins Fama and French's (2002) description of "complex" pecking-order behaviour entailing "soft", one-sided leverage targeting. Graham and Harvey (2001, Fig.5) report that, of a range of factors affecting the decision to issue debt, surveyed CFOs considered "Financial flexibility" to be the most important, ahead of, for example, "Insufficient internal funds", "Interest tax savings", and "Bankruptcy/distress costs".

profitability, low non-interest expense tax shields (e.g. relatively low depreciation and R&D charges, and no carry-forward losses), substantial tangible assets available to serve as security for lenders, limited growth opportunities, and relatively low information asymmetry: such a firm's optimal leverage will be more strongly driven by the considerations of trade-off theory rather than pecking-order theory. Conversely, a stereotypical "growth" firm will have unreliable profitability, ample depreciation, R&D or carry-forward loss tax shields, limited tangible assets, and relatively high information asymmetry: such a firm will be bound by pecking-order considerations.

LRZ and DR investigate the leverage "stability" of firms. The notion of leverage stability as an active management choice stems from a presumption of leverage targeting. Graham and Harvey (2001) report that 44% of surveyed CFOs employ leverage targeting: a considerable proportion, but a minority nonetheless. Leverage targeting can be motivated with trade-off theory. Although trade-off theory is intuitively appealing, an *optimal* leverage target can be a nebulous concept that varies over time: some managers may simply satisfice with stable leverage targets. Stable leverage may also arise by chance: for instance, the special case of leverage stability at very low levels can stem from pecking-order behaviour by firms with negligible requirements for external finance. Nevertheless, even when leverage targeting is employed, it is not to be automatically expected that the target will be stable: Cook et al. (2016) and Ippolito et al. (2019) present evidence of target leverage instability. Thus, on balance, there is little premise for expecting firms to exhibit stable leverage on average, which concurs with the evidence of DR but clashes with the evidence of LRZ. In addition, Chapter 2 of this thesis has shown that the contradictory results reported by LRZ and DR on leverage stability are due to their different methodologies, thus suggest that DR's evidence is more "reliable" because they have used a more appropriate methodology than LRZ (p.45).

DR's (p.411) concluding discussion notes that, given the "stylized facts" that firms are reluctant to issue equity (Myers, 1984) and are desirous of stable dividends (Lintner, 1956),[26] leverage will tend to be determined as a budgeting residual (e.g. see Lambrecht and Myers, 2012). It is this perspective that sets the foundation for our methodological approach. Fundamentally, it is the expected ability of a firm's ongoing EBIT to specifically support *interest payments* (plus sticky dividend payments) which limits the leverage decision.[27] Furthermore, under a trade-off theory paradigm, it is specifically interest expenses, not leverage, which provide the tax shield that motivates leverage targeting; and the interest expense decision is balanced against the likelihood of financial distress and bankruptcy, which depends on EBIT reliability (in comparison to the interest expense level). Hence, in this study, we assess firms' leverage management in terms of interest expense stability relative to EBIT stability. That is, we investigate whether firms' interest expense payments are less stable than their EBITs, as would generally be the case if leverage is determined as a budgeting residual; or whether interest expense payments are more stable than EBITs, which would tend to be the case if leverage is actively targeted.[28] We use DR's squared-correlations across event-time methodology to track the stability of interest expense standardized by market value of assets (int/MVA), and EBIT over MVA (EBIT/MVA), for event-time horizons up to 20 years. We also compare interest expense stability to dividend payout stability.[29]

Firms' leverage management decisions will be variously affected by different motivations depending on their individual circumstances, which are likely to be correlated with firm characteristics. For example, Graham and Harvey's (2001) survey results show that, in comparison to small firms, the leverage

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[26] A dividend cut is akin to new equity finance which entails adverse selection risk for investors and poses a negative valuation signal as per pecking-order theory. Hence firms will be reluctant to cut dividends, and they will be cautious about increasing dividends for fear of a later need to reverse the increase.

[27] Credit ratings agency Fitch's assessment of corporate debt-servicing capacity "attributes substantially more weight to cash-flow measures than equity-based ratios such as debt-to-equity" (*Corporate Rating Criteria*, Fitch Ratings, 7 August 2017, p.5, accessed 4 July 2019, https://www.fitchratings.com/site/home/viewer?file=/api/v2/report/901296/file).

[28] In the short-run, corporate cash-holdings can be used to smooth out imbalances between EBIT, interest payments and dividends, but the medium to long-run will determine if firms are more committed to leverage targets or dividend targets.

[29] We specifically investigate pre-tax interest expense stability because a firm's gross (pre-tax) interest expense commitment specifically reflects management choice in response to various imperatives including exogenous taxation rates.

decisions of large firms ascribe significantly more importance to “[t]he tax advantage of interest deductibility” and “[their] credit rating (as assigned by rating agencies)” (Table 6, pp.212-213), and to the sentiment “[w]e issue debt when interest rates are particularly low” (Table 9, p.220); whereas large firms are significantly less likely to ascribe importance to the sentiment “[w]e issue debt when our recent profits (internal funds) are not sufficient to fund our activities” (Table 9, p.220). This suggests that, on average, trade-off theory is more pertinent for large firms and pecking-order theory is more pertinent for small firms. Thus, when testing for evidence of active leverage management, we control for various firm characteristics including size.

Firms’ circumstances change across time: accordingly it is reasonable to expect variation in firms’ use of leverage across time. Thus evidence about the stability of leverage variables depends on a time-scale gauge for stability: is “long-run” stability indicated after, say, 5 years, 10 years or 20 years? We use CEO tenure to gauge the long-run. Investment and financing strategies may be correlated with CEO “vision” and risk preferences (Frank & Goyal, 2007; Jiraporn, Chintrakarn & Liu, 2012; Karpavičius & Yu, 2019b). Further, variation in firms’ use of leverage can be affected by CEO decisions, such as altering corporate debt maturity structure (Huang, Tan, & Faff, 2016). Graham and Harvey (2001) define CEO tenure longer than 9 years to be “long tenure”, which represents 34% of their sample of CEOs (p.194). Thus we commensurately define the long-run to be 9 years or more.

We also consider the question, “does it matter?” That is, is leverage management a value-adding activity? Real-world capital market imperfections void Modigliani and Miller’s (1958) capital structure irrelevance proposition. Miller (1977) suggests there is an optimal level of aggregate leverage across all firms, but firms’ individual leverage decisions are inconsequential due to the marginal lender’s lending rate capturing all of the net valuation benefit of the leverage decision. DeAngelo and Masulis (1980) counter that availability of non-debt tax shields (e.g. depreciation expenses) limits demand for debt finance so that the marginal lending rate does leave some net valuation benefit for firms’ leverage decisions. To address the “does it matter?” question, we first estimate a model for firms’ expected interest expense variability based on individual firm characteristics, and then investigate the valuation outcomes for firms that have higher, or lower, interest expense variability than expected. If there is no benefit to managing leverage, we should see no valuation effect for firms that exhibit interest-expense variability different to expected. Alternatively, if leverage management does matter, we need to consider whether the empirically estimated model for expected interest expense variability presents an optimal level, too much, or too little. If firms generally get interest expense variability about right, positive or negative variation from expectation would be value destroying. Riddiough and Steiner (2017) propose that lower leverage and more stable leverage add value through a financial flexibility channel: they present evidence of a positive relationship between leverage stability and market-to-book valuations for equity REITs, which suggests that "normal" levels of leverage stability are too low (i.e. leverage variability is generally too high). In other circumstances it could be possible that over-zealous commitment to stale leverage targets might cause normal levels of leverage stability to be too high. Our study's key result is that there are adverse valuation consequences for firms with interest expense variability that deviates from expected (for given firm characteristics): the implication is that expected/normal leverage management is broadly optimal.

3.3 Data

Our sample selection generally follows Fama and French (2001, p41). Our starting sample includes all US listed firms in the CRSP/Compustat Merged Database for firm fiscal years 1962 to 2016.[30] For unique firm j, time specification t refers to the firm's fiscal year. We exclude financial and utility firms (SIC codes 4900-4949 and 6000-6999, respectively), firms incorporated outside the US (FIC code not equal to "USA"), firms that are non-publicly traded (share code, SHRCD, not equal to 10 or 11), and subsidiaries (stock ownership code, STKO, equal to one or two). Additionally, we require firms to have non-missing data for the following

[30] Compustat data before 1962 are biased towards large firms (Strebulaev & Yang, 2013).

variables: total assets (Compustat item AT), stock price (PRCC_F), common shares outstanding (CSHO), and interest expense (IB). Our sample amounts to 171,478 firm-year observations from 1962 to 2016: an average of 3,118 cross-sectional firm observations each fiscal year, with a minimum (maximum) of 406 (5,326) observations in 1962 (1996).

Firms' financial variables are obtained by firm fiscal year (point-in-time variables are as at fiscal year-end). Market value of equity (ME) is obtained from the multiple of the stock price and common shares outstanding. As per Fama and French (2001, p41), we calculate book value of equity (BE) from stockholder equity (SEQ) (or common equity (CEQ) plus preferred equity,[31] or total assets (AT) minus total liabilities (LT)) minus preferred equity, plus deferred taxes and investment tax credit (TXDITC) if available, minus post-retirement benefit assets (PRBA) if available. Firms with book equity less than $250,000 or total assets below $500,000 are excluded from our sample. Book value of total debt (D) is obtained from the sum of short-term and long-term debt (DLC and DLTT, respectively). Firm size is measured as "market value" of assets (MVA), calculated as the sum of ME and D. Annual operating profit is EBIT. Profitability is EBIT/MVA. Annual interest expense (int/MVA) is computed as interest expense (XINT or sum of XINST and XINTD) divided by MVA. Annual dividend payout (div/MVA) is computed as dividends paid on common stock (DVC) divided by MVA. Note that we do not exclude firms with zero interest expense or zero dividend payout. Market leverage is D/MVA. Non-missing market leverage data, and market leverage between 0 and 1 inclusive, is required for sample inclusion. Market-to-book value of equity is ME divided by BE. Table 3.1 lists the definitions and formulations of our variables. All variables are winsorized at the 1st and 99th percentiles. Table 3.2 provides summary statistics and Table 3.3 presents correlations for our variables.

[31] Preferred equity (PE) is obtained from, by order of priority, preferred stock liquidating value (PSTKL), or preferred stock redemption value (PSTKRV), or preferred stock capital (PSTK). Firms with missing values for all three measures are excluded.

Table 3.1 – Definitions of variables

For each sample firm j and firm fiscal year t, this table presents the formulation of key variables in terms of Compustat variable codes. Point-in-time variables are fiscal year-end.

Variable		Formulation in terms of Compustat variable codes♣,♣♣
Market value of equity	ME_t^j	$PRCC\_F_t^j \times CSHO_t^j$.
Preferred equity	PE_t^j	$PSTKL_t^j$, or $PSTKRV_t^j$, or $PSTK_t^j$. Observations with missing values for all three measures are excluded.
Book value of equity	BE_t^j	$SEQ_t^j - PE_t^j + TXDITC_t^j - PRBA_t^j$, or $CEQ_t^j + TXDITC_t^j - PRBA_t^j$, or $AT_t^j - LT_t^j - PE_t^j + TXDITC_t^j - PRBA_t^j$. Missing values for $TXDITC_t^j$ or $PRBA_t^j$ are set to zero. Observations with $BE_t^j <$ \$250,000 or $AT_t^j <$ \$500,000 are excluded.
Debt	D_t^j	$DLC_t^j + DLTT_t^j$; $DLC_t^j + 0.5 \times DLTT_t^j$ for calculation of expected default frequency
Market value of assets	MVA_t^j	$ME_t^j + D_t^j$.
Operating profit	$EBIT_t^j$	$EBIT_t^j$
Operating profitability	$(EBIT/MVA)_t^j$	$EBIT_t^j/MVA_t^j$.
Interest expense	$(int/MVA)_t^j$	$XINT_t^j/MVA_t^j$, or $(XINST_t^j + XINTD_t^j)/MVA_t^j$
Dividend	$(div/MVA)_t^j$	DVC_t^j/MVA_t^j .
Leverage	$(D/MVA)_t^j$	D_t^j/MVA_t^j .
Market-to-book equity	$(ME/BE)_t^j$	ME_t^j/BE_t^j .

♣ Multiple formulations for a variable are listed in order of priority for use.

♣♣ Refer to https://wrds-web.wharton.upenn.edu/wrds/ds/compd/funda/index.cfm?navId=83 for definitions of Compustat variable codes PRCC_F, CSHO, PSTKL, PSTKRV, PSTK, SEQ, TXDITC, PRBA, CEQ, AT, LT, DLC, DLTT, EBIT, IB, DVC

Table 3.2 – Summary statistics

Summary statistics for variables defined in Table 1 for sample firm j and firm fiscal year $t \in \{1962, \dots, 2016\}$. The sample includes all US listed firms in the CRSP/Compustat Merged Database for firm fiscal years 1962 to 2016, excluding: financial and utility firms, firms incorporated outside the US, non-publicly traded firms, subsidiaries, and firms which have missing data for total assets, stock price, common shares outstanding or interest expense. All variables are winsorized at the 1st and 99th percentiles.

Variable		Firm-year obs.	Min	Max	Mean	Median	St. dev.
End-of-year market value of equity ($m)	ME_t^j	171,478	1.152	28,995	1,096	81.990	3,780
Book value of equity ($m)	BE_t^j	171,478	0.694	10,885	448	48.305	1,433
Debt ($m)	D_t^j	171,478	0.000	7,302	277	11.471	973
Market value of assets ($m)	MVA_t^j	171,478	2.732	43,186	1,710	140.27	5,736
Operating profit ($m)	$EBIT_t^j$	171,478	-84.626	2,651	95.927	5.551	348
Profitability	$(EBIT/MVA)_t^j$	171,478	-0.522	0.244	0.030	0.054	0.115
Interest expense	$(int/MVA)_t^j$	171,478	0.000	0.085	0.016	0.010	0.019
Dividend	$(div/MVA)_t^j$	171,324*	0.000	0.053	0.006	0.000	0.011
Leverage	$(D/MVA)_t^j$	171,478	0.000	0.704	0.182	0.134	0.179
Market-to-book equity	$(ME/BE)_t^j$	171,478	0.240	24.442	2.830	1.692	3.637

* The difference between the firm-year observations for div/MVA and those for other variables is due to 154 discarded values in the variable Dividends Common/Ordinary (DVC) in the Compustat dataset.

Table 3.3 - Correlations

Correlations between variables defined in Table 1 for sample firm j and firm fiscal year $t \in \{1962, \ldots, 2016\}$. The sample includes all US listed firms in the CRSP/Compustat Merged Database for firm fiscal years 1962 to 2016, excluding: financial and utility firms, firms incorporated outside the US, non-publicly traded firms, subsidiaries, and firms which have missing data for total assets, stock price, common shares outstanding or interest expense. All variables are winsorized at the 1st and 99th percentiles. A natural logarithm transformation is applied to the MVA variable. All correlations are significant at better than the 1% level.

Correlation	$(EBIT/MVA)_t^j$	$(int/MVA)_t^j$	$(div/MVA)_t^j$	$(D/MVA)_t^j$	$(ME/BE)_t^j$
LN(MVA_t^j)	0.2053	-0.1278	0.1376	-0.0163	0.1276
$(EBIT/MVA)_t^j$		0.0583	0.3344	0.1202	-0.1527
$(int/MVA)_t^j$			-0.0856	0.8378	-0.2384
$(div/MVA)_t^j$				-0.0605	-0.1441
$(D/MVA)_t^j$					-0.2721

Table 3.2 shows that, across all firm-years, the standard deviation of profitability (EBIT/MVA) is far greater than that of interest expense (int/MVA). Also, the standard deviation of interest expense is greater than that of dividend payout (div/MVA), which indicates that, by firm-year, the leverage decision (in terms of interest expense) is more variable than the dividend payout decision. By firm-year, mean and median interest expense are greater than for dividend payout, indicating that the leverage decision is more "substantial" than the dividend decision in terms of cash flow commitments.

Table 3.3 shows that, although interest expense (int/MVA) and leverage (D/MVA) are strongly positively correlated, they exhibit notably different correlations with firm size (LN(MVA)) and profitability (EBIT/MVA): this confirms that interest expense and leverage measures have importantly distinct implications for the analysis of leverage management. As might be expected, profitability is positively correlated with both int/MVA and D/MVA, but the correlation with D/MVA is more than twice that with int/MVA (0.1202 versus 0.0583). Although firm size is negatively correlated with both int/MVA and D/MVA, the negative correlation with int/MVA is several times stronger than with D/MVA (-0.1278 versus -0.0163). Dividend payout (div/MVA) is negatively related to both int/MVA and D/MVA at similar levels.[32]

3.4 Aggregate Interest expense stability

Using the methodology of DR, for event-time horizons of one to 20 years, we obtain the average of the squared-correlations (R^2) of firms' interest expense (int/MVA), profitability (EBIT/MVA) and dividend (div/MVA) across event-time. For example, for an event-time horizon of 10 years (1 year, 5 years), for our 1962 to 2016 sample period we have 45 (54, 50) overlapping 10-year (1-year, 5-year) event windows for which we obtain 45 (54, 50) correlations between event window starting and ending values of int/MVA, EBIT/MVA

[32] The Table 3.3 correlations show that, in terms of levels, interest expense is negatively related to firm size and dividend payout. However, our subsequent analysis shows that interest expense *stability* is positively related to firm size and dividend payout.

and div/MVA. Event window starting and ending correlation pairings are by sample firm: hence, for a firm to be included in a correlation calculation it must survive across the event window. Each event window correlation (R) is the square-root of the regression-R^2 obtained from univariate regression of end-of-window values against start-of-window values. Table 3.4 presents our comparative correlation results for the 10-year and 20-year event windows. Figure 3.1 graphs the average squared-correlations for event windows of one to 20 years.

We use Figure 3.1 (and, later, Figure 3.2) to qualitatively depict the comparative stabilities of interest expense, profitability and dividend payout. Similar to DR's results for leverage, Figure 3.1 shows that our average-R^2 for int/MVA falls quickly with increasing event-time horizon, suggesting instability. However, this R^2 decay is even stronger for EBIT/MVA and div/MVA. Firms operate in dynamic economic environments: variability in firms' financial circumstances is the natural order of things, hence the apparent instability of corporate interest expense levels warrants consideration relative to the even greater instability of profitability and dividend levels.

For the purposes of quantitative evaluation, we analyse our samples of correlations (rather than squared-correlations) obtained for specific event-time horizons. Table 3.4 presents the statistics for the int/MVA, EBIT/MVA and div/MVA correlations for long-run horizons of 10 years and 20 years: the average correlations are all significantly greater than zero. To consider whether int/MVA is more stable than EBIT/MVA or div/MVA, we are interested in the correlation differences (see the last four columns of Table 3.4): the correlation differences for int/MVA versus EBIT/MVA and versus div/MVA are all significantly positive. That is, the average long-run correlation of int/MVA is significantly higher than that of either EBIT/MVA or div/MVA. It is therefore fair to conclude that, on average, in aggregate, firms manage their leverage so as to maintain *relatively* stable interest expense levels (in comparison to profitability and dividend levels).

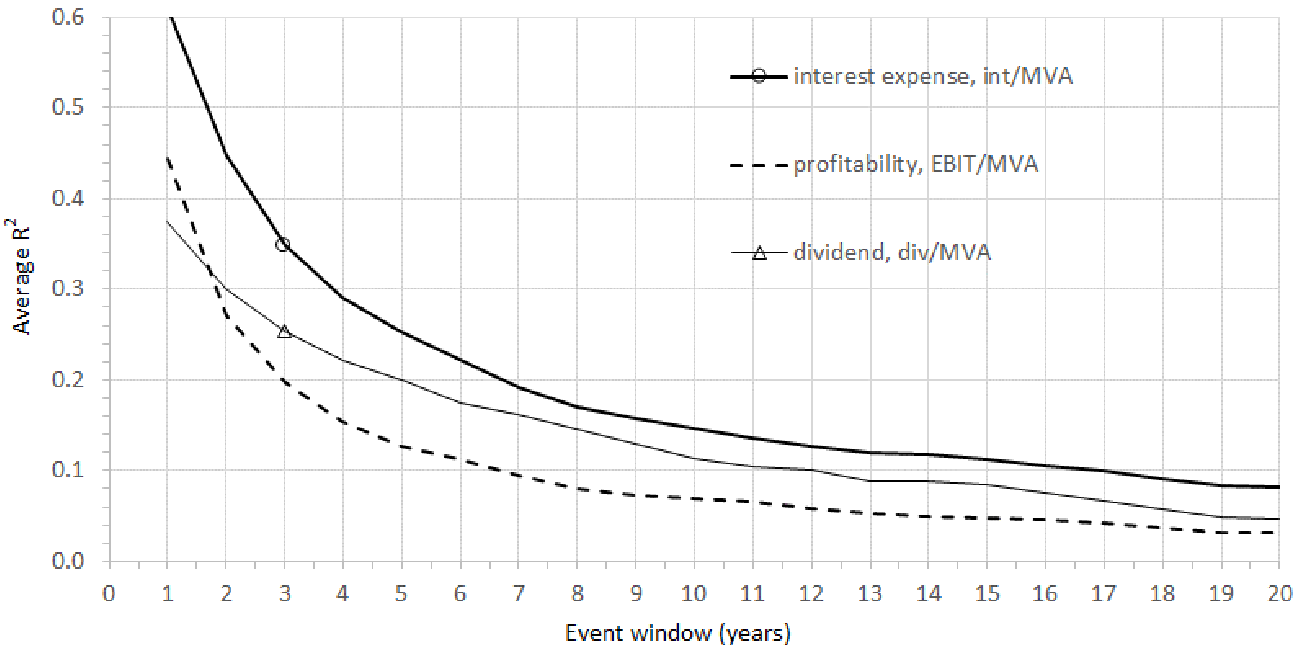
Table 3.4 – Comparative 10-year and 20-year stabilities of interest expense, EBIT and dividend

Comparative statistics for 10-year and 20-year horizon correlations of firms' interest expense (int/MVA), profitability (EBIT/MVA) and dividend (div/MVA). For event windows of 10 years and 20 years within the period 1962 to 2016 (entailing 45 overlapping 10-year windows and 35 overlapping 20-year windows), firms are sampled cross-sectionally at the start of each event window and are required to survive for the entire event window (resulting in an average of 1,513 firm observations per 10-year window and 815 observations per 20-year window). Correlation (*R*) for each window, which is the square-root of the regression-R^2, is obtained via univariate regression of end-of-window int/MVA (EBIT/MVA, div/MVA) against start-of-window value. Newey-West t-stats (and p-values in parentheses) are used to assess the significance of the correlations and correlation differences: *, ** and *** indicate significant difference from zero at the 10%, 5% and 1% levels, respectively.

	10-year correlations			20-year correlations			Correlation differences: int/MVA vs. EBIT/MVA		Correlation differences: int/MVA vs. div/MVA	
	int/MVA	EBIT/MVA	div/MVA	int/MVA	EBIT/MVA	div/MVA	10-years	20-years	10-years	20-years
Mean	0.377	0.249	0.295	0.281	0.160	0.186	0.129	0.120	0.082	0.095
Median	0.384	0.234	0.221	0.279	0.157	0.178	0.158	0.136	0.107	0.118
Min.	0.238	0.099	0.082	0.129	-0.013	0.008	-0.171	-0.122	-0.207	-0.206
Max.	0.485	0.433	0.567	0.378	0.340	0.484	0.295	0.292	0.327	0.280
St.dev.	0.059	0.084	0.160	0.049	0.079	0.112	0.115	0.101	0.155	0.106
t-stat	43.09***	19.87***	12.36***	33.89***	12.06***	9.86***	4.53***	4.88**	2.24**	4.03***
(p-value)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.030)	(0.000)

Figure 3.1 – Comparative stabilities of interest expense, profitability and dividend

Event-time horizon average of the squared-correlations (R^2) of firms' interest expense (int/MVA), profitability (EBIT/MVA) and dividend (div/MVA) across event-time. For event windows of one to 20 years within the period 1962 to 2016 (entailing 54 one-year windows, …, 45 overlapping 10-year windows, …, and 35 overlapping 20-year windows), firms are sampled cross-sectionally at the start of each event window and are required to survive for the entire event window. R^2 for each window is obtained by univariate regression of end-of-window int/MVA (EBIT/MVA, div/MVA) against start-of-window value. The R^2's are then averaged by common event window horizon.



Given that MVA is fundamentally related to the present value of expected future EBITs, EBIT/MVA will intrinsically entail some level of stability, whereas the long-run stabilities of int/MVA and div/MVA depend on active corporate financing and payout strategies. Lambrecht and Myers (2012) explain that dividend stability and leverage targeting cannot coexist. Lintner's (1956) signaling theory of dividends provides a rationale for stable dividend-per-share payments, and Brav, Graham, Harvey and Michaely's (2005) survey evidence shows that almost 90% of firms smooth dividends from year to year. Nevertheless, our evidence emphatically indicates that, on average, across the long-run, firms manage their leverage so that their interest expense commitments exhibit significant stability in comparison to their EBIT and dividend levels. Further indicative of comparative interest expense stability, Table 3.4 shows that the standard-deviations of the long-run correlations for int/MVA compared to EBIT/MVA compared to div/MVA are increasing. Our results indicate that, given the budgeting constraint of EBIT, in general across the long-run, interest expense is targeted, and the dividend decision is a budgeting residual.

Our evidence for interest expense stability is found to be a conditional on firm characteristics. The Table 3.4 analysis is repeated for subsamples of large and small firms, high and low dividend firms, high and low leverage firms, and high and low market-to-book value of equity firms, identified at the start of each event window by market capitalization, div/MVA, D/MVA and ME/BE rankings in the top third and bottom third, respectively. Tables 3.5, 3.6, 3.7 and 3.8 present the results for large and small firms, high and low dividend firms, and high and low leverage firms, respectively.

Table 3.5 – Comparative 10-year stabilities of interest expense, EBIT and dividend for large and small firms

Comparative statistics for 10-year horizon correlations of large firms' and small firms' interest expense (int/MVA), profitability (EBIT/MVA) and dividend (div/MVA). For each event windows of 10 years within the period 1962 to 2016 (entailing 45 overlapping 10-year windows), firms are sampled cross-sectionally and split into subsamples of large and small firms classified by starting market capitalization rankings in the top third and bottom third respectively, and then required to survive for the entire event window (resulting in an average of 607 (411) firm observations per 10-year window for large (small) firms). Correlation (R) for each window, which is the square-root of the regression-R^2, is obtained via univariate regression of end-of-window int/MVA (EBIT/MVA, div/MVA) against start-of-window value. Newey-West t-stats (and p-values in parentheses) are used to assess the significance of the correlations and correlation differences: *, ** and *** indicate significant difference from zero at the 10%, 5% and 1% levels, respectively.

	10-year correlation						10-year correlation differences						
	Large firms (top 3rd by market cap.)			Small firms (bottom 3rd by market cap.)			int/MVA vs. EBIT/MVA		int/MVA vs. div/MVA		Large vs. small firms		
	int/MVA	EBIT/MVA	div/MVA	int/MVA	EBIT/MVA	div/MVA	Large firms	Small firms	Large firms	Small firms	int/MVA	EBIT/MVA	div/MVA
Mean	0.4892	0.2325	0.5386	0.3197	0.2220	0.4985	0.2567	0.0977	-0.0494	-0.1788	0.1696	0.0105	0.0402
Median	0.4983	0.2446	0.5593	0.3204	0.1836	0.5159	0.2462	0.1333	-0.0770	-0.1788	0.1678	0.0423	0.0382
Min.	0.3481	-0.0327	0.3175	0.1952	0.0843	0.3348	0.0290	-0.2217	-0.2454	-0.3348	-0.0348	-0.4722	-0.1216
Max.	0.6048	0.5064	0.6896	0.4716	0.4593	0.6047	0.5409	0.3696	0.2079	-0.0380	0.3376	0.2661	0.2338
St.dev.	0.0511	0.1019	0.0970	0.0650	0.0978	0.0787	0.1131	0.1420	0.1186	0.0753	0.0821	0.1480	0.0793
t-stat	64.28***	15.31***	37.27***	32.99***	15.22***	42.49***	11.80***	2.71***	-1.57	-13.73***	8.53***	0.33	2.33**
(p-value)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.010)	(0.124)	(0.000)	(0.000)	(0.745)	(0.024)

Table 3.5 shows that, for the long-run (i.e. 10 years), int/MVA correlations are, on average, significantly higher than EBIT/MVA correlations for both large and small firms, however this int/MVA stability (relative to EBIT/MVA) is much more pronounced for large firms. Comparing large firms to small firms, 10-year int/MVA correlations are significantly higher by a mean of 0.17. Large firms also have significantly more stable div/MVA than small firms, but only by a mean difference in correlations of 0.04: that is, in comparing large firms to small firms, their greater int/MVA stability is much more prominent than their greater div/MVA stability. Comparing the interest expense and dividend payout decisions: the int/MVA stability of large firms is not significantly different to their div/MVA stability; whereas the int/MVA stability of small firms is significantly less than their div/MVA stability. These findings indicate that interest expense management and stability is a much greater priority for large firms than for small firms. For small firms specifically, dividend payout stability has greater priority than interest expense stability. These results are consistent with trade-off theory financing imperatives dominating pecking-order financing imperatives for large firms, and vice versa for small firms.

Similar to the results for large and small firms, Table 3.6 shows that long-run int/MVA correlations are, on average, significantly higher than long-run EBIT/MVA correlations for both high and low dividend firms, and that this int/MVA versus EBIT/MVA comparative stability is stronger for high dividend firms. Comparing high dividend firms to low dividend firms, 10-year int/MVA correlations are significantly higher by a mean of 0.07. There is no significant difference in the div/MVA stability of high and low dividend firms. Comparing the interest expense and dividend payout decisions: the int/MVA stability of large firms is significantly greater than their div/MVA stability; whereas the int/MVA stability of small firms is not significantly different to their div/MVA stability. These findings indicate that interest expense management and stability is a much greater priority for high dividend firms than for low dividend firms. This is consistent with trade-off theory imperatives dominating pecking-order imperatives for high dividend firms, and vice versa for low dividend firms.

Table 3.6 – Comparative 10-year stabilities of interest expense, EBIT and dividend for high and low dividend firms

Comparative statistics for 10-year horizon correlations of high dividend (div/MVA) firms' and low dividend firms' interest expense (int/MVA), profitability (EBIT/MVA) and dividend. For event windows of 10 years within the period 1962 to 2016 (entailing 45 overlapping 10-year windows), firms are sampled cross-sectionally and split into subsamples of high and low dividend firms classified by starting div/MVA rankings in the top third and bottom third respectively, and then required to survive for the entire event window (resulting in an average of 451 (790) firm observations per 10-year window for high (low) dividend firms). Correlation (*R*) for each window, which is the square-root of the regression-R^2, is obtained via univariate regression of end-of-window int/MVA (EBIT/MVA, div/MVA) against start-of-window value. Newey-West t-stats (and p-values in parentheses) are used to assess the significance of the correlations and correlation differences: *, ** and *** indicate significant difference from zero at the 10%, 5% and 1% levels, respectively.

	10-year correlation						10-year correlation differences						
	High dividend firms (top 3rd by div/MVA)			Low dividend firms (bottom 3rd by div/MVA)			int/MVA vs. EBIT/MVA		int/MVA vs. div/MVA		High vs. low dividend firms		
	int/MVA	EBIT/MVA	div/MVA	int/MVA	EBIT/MVA	div/MVA	High dividend firms	Low dividend firms	High dividend firms	Low dividend firms	int/MVA	EBIT/MVA	div/MVA
Mean	0.4342	0.1602	0.3221	0.3651	0.1980	0.2920	0.2740	0.1670	0.1121	0.0731	0.0692	-0.0378	0.0301
Median	0.4351	0.1548	0.3213	0.3544	0.1663	0.3066	0.2770	0.1931	0.0990	0.0498	0.0766	-0.0017	0.0270
Min.	0.2778	-0.0978	-0.0013	0.2563	-0.0457	0.0347	-0.0930	-0.1387	-0.0434	-0.2517	-0.1874	-0.4623	-0.4814
Max.	0.5792	0.4039	0.4781	0.4984	0.4501	0.5888	0.5355	0.4393	0.4412	0.3480	0.2174	0.2983	0.3613
St.dev.	0.0660	0.0993	0.0864	0.0513	0.1187	0.1735	0.1287	0.1287	0.0978	0.1827	0.0856	0.1808	0.2118
t-stat	44.16***	10.82***	25.00***	47.73***	11.19***	11.29***	9.48***	5.20***	5.70***	1.43	3.76***	-0.81	0.53
(p-value)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.160)	(0.000)	(0.421)	(0.601)

Table 3.7 presents the results for interest expense stability for firms categorized by leverage. The interest expense management motivations of high leverage firms are especially ambiguous. High leverage may be motivated by either trade-off or pecking-order imperatives, or it may be an indicator of financial distress that needs to be remedied regardless of trade-off or pecking-order imperatives. Conversely, low leverage is more clearly a signal of pecking-order motivation, which should then be associated with interest expense instability: this is confirmed by our Table 3.7 results. For low leverage firms, long-run int/MVA correlations are significantly lower than long-run div/MVA correlations by a mean of 0.32, and significantly lower (at 10% significance level) than long-run EBIT/MVA correlations by a mean of 0.08: that is, the leverage decision appears to be the budgeting residual. This is consistent with pecking-order imperatives dominating trade-off imperatives for low leverage firms. This interest expense *in*stability result for low leverage firms is the "flip" of the full sample results presented by Table 3.4 and Figure 3.1, which importantly demonstrates that interest expense stability/instability is dependent on firm characteristics, and, clearly, that interest expense stability (relative to profitability and dividend stabilities) is not the "natural" result.

Our results for high and low ME/BE firms presented in Table 3.8 indicate that long-run interest expense stability greater than profitability stability is, on average, a characteristic of low ME/BE firms, but not of high ME/BE firms. To the extent that low ME/BE categorizes "mature" firms with limited growth opportunities, this result is consistent with trade-off theory financing imperatives dominating pecking-order financing imperatives for mature firms.

Table 3.7 – Comparative 10-year stabilities of interest expense, EBIT and dividend for high and low leverage firms

Comparative statistics for 10-year horizon correlations of high leverage (D/MVA) firms' and low leverage firms' interest expense (int/MVA), profitability (EBIT/MVA) and dividend (div/MVA). For event windows of 10 years within the period 1962 to 2016 (entailing 45 overlapping 10-year windows), firms are sampled cross-sectionally and split into subsamples of high and low leverage firms classified by starting D/MVA rankings in the top third and bottom third respectively, and then required to survive for the entire event window (resulting in an average of 445 (551) firm observations per 10-year window for high (low) leverage firms). Correlation (R) for each window, which is the square-root of the regression-R^2, is obtained via univariate regression of end-of-window int/MVA (EBIT/MVA, div/MVA) against start-of-window value. Newey-West t-stats (and p-values in parentheses) are used to assess the significance of the correlations and correlation differences: *, ** and *** indicate significant difference from zero at the 10%, 5% and 1% levels, respectively.

	10-year correlation						10-year correlation differences						
	High leverage firms (top 3rd by D/MVA)			Low leverage firms (bottom 3rd by D/MVA)			int/MVA vs. EBIT/MVA		int/MVA vs. div/MVA		High vs. low leverage firms		
	int/MVA	EBIT/MVA	div/MVA	int/MVA	EBIT/MVA	div/MVA	High leverage firms	Low leverage firms	High leverage firms	Low leverage firms	int/MVA	EBIT/MVA	div/MVA
Mean	0.2164	0.1959	0.4654	0.1947	0.2761	0.5126	0.0206	-0.0813	-0.2490	-0.3179	0.0217	-0.0802	-0.0471
Median	0.2225	0.1856	0.5184	0.1908	0.2706	0.5332	0.0343	-0.0749	-0.2838	-0.3339	0.0304	-0.0895	-0.0478
Min.	0.0850	0.0825	0.2495	0.0075	0.1155	0.3330	-0.2151	-0.4341	-0.4831	-0.5104	-0.2310	-0.2693	-0.2510
Max.	0.3265	0.4608	0.6185	0.3704	0.4776	0.6250	0.1349	0.2159	0.0628	-0.0217	0.3005	0.1131	0.1934
St.dev.	0.0583	0.0870	0.1067	0.0906	0.0907	0.0793	0.0842	0.1564	0.1307	0.1095	0.1113	0.0883	0.0946
t-stat	24.90***	15.11***	29.26***	14.42***	20.42***	43.38***	1.59	-1.96*	-7.67***	-13.66***	0.85	-5.35***	-2.07**
(p-value)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.119)	(0.057)	(0.000)	(0.000)	(0.398)	(0.000)	(0.044)

Table 3.8 – Comparative 10-year stabilities of interest expense, EBIT and dividend for high and low market-to-book equity firms

Comparative statistics for 10-year horizon correlations of high market-to-book equity (ME/BE) firms' and low market-to-book equity firms' interest expense (int/MVA), profitability (EBIT/MVA) and dividend (div/MVA). For event windows of 10 years within the period 1962 to 2016 (entailing 45 overlapping 10-year windows), firms are sampled cross-sectionally and split into subsamples of high and low market-to-book equity firms classified by starting ME/BE rankings in the top third and bottom third respectively, and then required to survive for the entire event window (resulting in an average of 545 (444) firm observations per 10-year window for high (low) ME/BE firms). Correlation (*R*) for each window, which is the square-root of the regression-R^2, is obtained via univariate regression of end-of-window int/MVA (EBIT/MVA, div/MVA) against start-of-window value. Newey-West t-stats (and p-values in parentheses) are used to assess the significance of the correlations and correlation differences: *, ** and *** indicate significant difference from zero at the 5%, 1% and 0.01% levels, respectively.

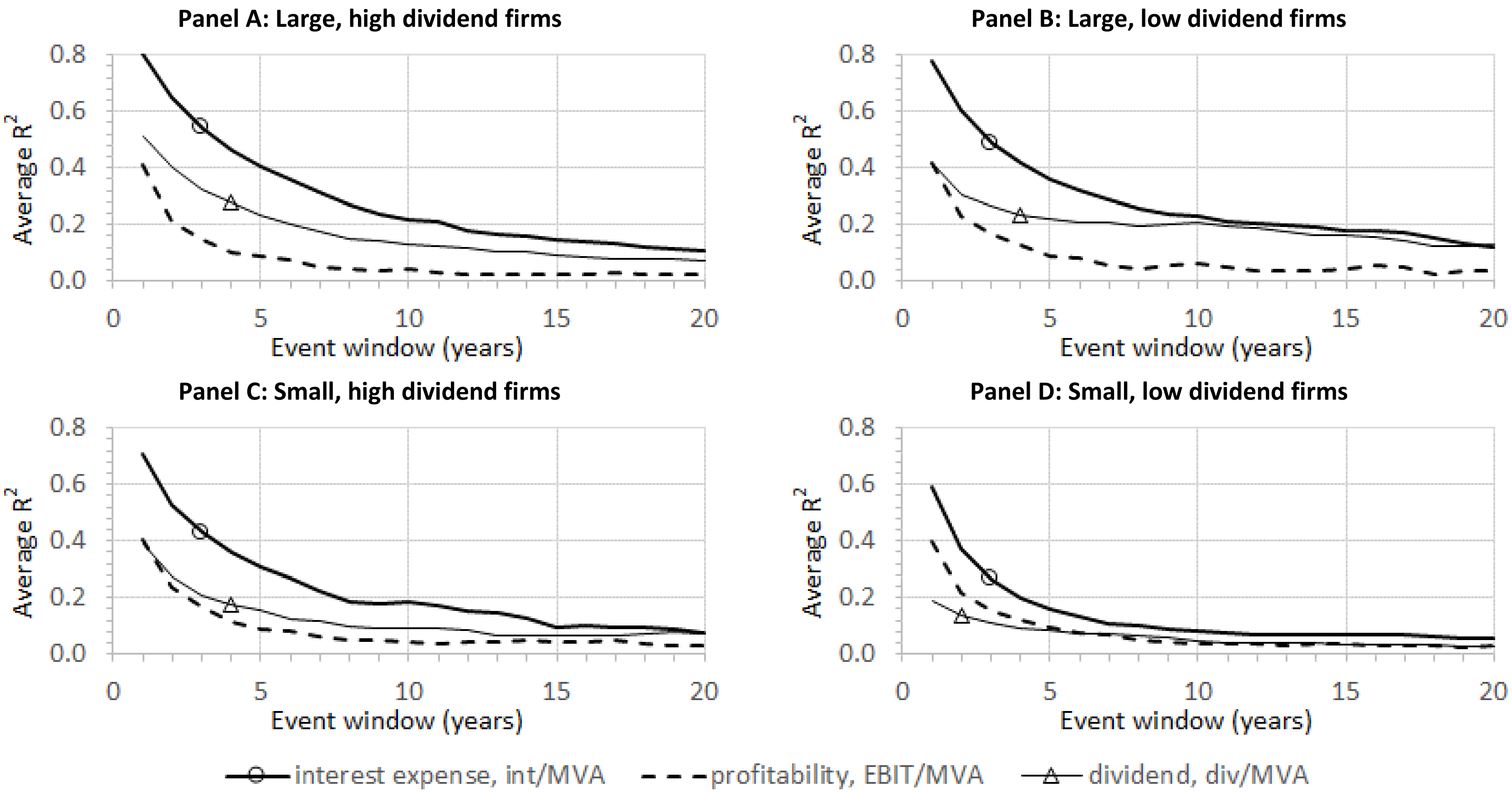
	10-year correlation						10-year correlation differences						
	High ME/BE firms (top 3rd by ME/BE)			Low ME/BE firms (bottom 3rd by ME/BE)			int/MVA vs. EBIT/MVA		int/MVA vs. div/MVA		High vs. low ME/BE firms		
	int/MVA	EBIT/MVA	div/MVA	int/MVA	EBIT/MVA	div/MVA	High ME/BE firms	Low ME/BE firms	High ME/BE firms	Low ME/BE firms	int/MVA	EBIT/MVA	div/MVA
Mean	0.3787	0.3180	0.5932	0.3567	0.2107	0.4592	0.0607	0.1460	-0.2145	-0.1026	0.0220	0.1074	0.1340
Median	0.3694	0.3251	0.6139	0.3358	0.1981	0.4783	0.0545	0.1488	-0.2240	-0.1131	0.0162	0.1350	0.1313
Min.	0.2335	0.0410	0.3911	0.2670	0.0317	0.2433	-0.2377	-0.0933	-0.3530	-0.2537	-0.1300	-0.1810	-0.0503
Max.	0.4977	0.5700	0.6856	0.4934	0.4746	0.6134	0.4232	0.4083	-0.0859	0.1181	0.2265	0.2987	0.2902
St.dev.	0.0655	0.1321	0.0805	0.0492	0.0903	0.0884	0.1634	0.1056	0.0755	0.0980	0.0837	0.1098	0.0707
t-stat	38.80***	16.15***	49.45***	48.66***	15.66***	34.86***	1.47	6.51***	-12.29***	-4.67***	1.43	4.44***	11.24***
(p-value)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.149)	(0.000)	(0.000)	(0.000)	(0.160)	(0.000)	(0.000)

We have demonstrated the relationship between several firm characteristics and relative interest expense stability. In particular, interest expense stability is prominent for large firms and high dividend firms. We further investigate comparative interest expense, profitability and dividend stabilities for firms chosen with a two-way sort for characteristics: Figure 3.2 presents the average squared-correlations for int/MVA, EBIT/MVA and div/MVA for event windows of one to 20 years for subsample intersections of large and small firms with high and low dividend firms. Figure 3.2 qualitatively shows that the extent to which interest expense stability is more prominent than profitability and/or dividend stabilities varies across the four different firm characteristic combinations, and from short to medium to long-run time horizons. To quantitatively analyse the influence of multiple interdependent firm characteristics and different time horizons, we apply a firm-level multivariate regression approach in Section 3.5.

In summary, we find that characteristics stereotypical of a “mature” firm, being large size and high dividend payout, are associated with significant interest expense stability (relative to profitability and dividend stabilities). This is consistent with the proposition that mature firms’ leverage management will tend to be driven by trade-off theory imperatives (reliable profitability; low non-interest expense tax shields such as depreciation or R&D expenses, or carry-forward losses; substantial tangible assets available to serve as security for lenders; limited growth opportunities; and relatively low information asymmetry). Conversely, characteristics stereotypical of a “growth” firm, being small size and low dividend payout, are associated with an absence of interest expense stability (relative to profitability and dividend stability). This is consistent with the proposition that growth firms’ leverage management will tend to be driven by pecking-order theory imperatives (unreliable profitability; ample depreciation, R&D or carry-forward loss tax shields; limited tangible assets; and relatively high information asymmetry).

Figure 3.2 - Comparative stabilities of interest expense, profitability and dividend for subsample intersections of large and small firms with high and low dividend firms

Event-time horizon average of the squared-correlations (R^2) of firms' interest expense (int/MVA), profitability (EBIT/MVA) and dividend (div/MVA) across event-time. For event windows of one to 20 years within the period 1962 to 2016 (entailing 54 one-year windows, …, 45 overlapping 10-year windows, …, and 35 overlapping 20-year windows), firms are sampled cross-sectionally at the start of each event window and are required to survive for the entire event window: each cross-sectional sample is then split into four subsamples obtained from the sorting intersections of large and small firms (classified by starting market capitalization rankings in the top third and bottom third respectively) with high and low dividend firms (classified by starting div/MVA rankings in the top third and bottom third respectively). R^2 for each window is obtained by univariate regression of end-of-window int/MVA (EBIT/MVA, div/MVA) against start-of-window value. The R^2's are then averaged by common event window horizon. Panel A (B; C; D) presents results for large, high dividend (large, low dividend; small, high dividend; small, low dividend) firms.



Panel A: Large, high dividend firms
Panel B: Large, low dividend firms
Panel C: Small, high dividend firms
Panel D: Small, low dividend firms
Average R^2
Event window (years)
0.8
0.6
0.4
0.2
0.0
0
5
10
15
20
interest expense, int/MVA
profitability, EBIT/MVA
dividend, div/MVA

3.5 Firm-Level Interest Expense Variability

Our Section 3.4 analysis considers interest expense stability in comparison to profitability and dividend stability at an aggregate sample level. We now apply multivariate cross-sectional analysis to investigate the relationship between firm-level interest expense variability and firm characteristics. For sample firm j (selected as per Section 3.3), firm fiscal year t, and fiscal year event-time horizon $T \in \{1,2,3,6,9,12\}$, the following regression models are estimated:

$$\begin{aligned}\left|(int/MVA)_{t+T}^{j} - (int/MVA)_{t}^{j}\right| \\ = a + b_1\left|(EBIT/MVA)_{t+T}^{j} - (EBIT/MVA)_{t}^{j}\right| \\ + b_2\left|(div/MVA)_{t+T}^{j} - (div/MVA)_{t}^{j}\right| \\ + b_{MVA}LN(MVA_{t}^{j}) + b_{div}(div/MVA)_{t}^{j} + b_{D}(D/MVA)_{t}^{j} \\ + b_{MB}(ME/BE)_{t}^{j} + b_{EBIT}(EBIT/MVA)_{t}^{j} \\ + (firm\ j\ and\ fiscal\ year\ t\ fixed\ effects) + \varepsilon_{t}^{j}\end{aligned} \tag{3.1}$$

$$\begin{aligned}\left|(int/MVA)_{t+T}^{j} - (int/MVA)_{t}^{j}\right| \\ = \cdots + b_2 MEDIAN[|\Delta(div/MVA)|]_{t \to t+T}^{industry(j)} + \cdots\end{aligned} \tag{3.2}$$

$$\begin{aligned}\left|(int/MVA)_{t+T}^{j} - (int/MVA)_{t}^{j}\right| \\ = \cdots + b_2\left|\widehat{(div/MVA)_{t+T}^{j} -} (div/MVA)_{t}^{j}\right| + \cdots\end{aligned} \tag{3.3}$$

The dependent variable, $\left|(int/MVA)_{t+T}^{j} - (int/MVA)_{t}^{j}\right|$, being the absolute value of the change in interest expense (standardized by MVA) over the event window, indicates interest expense variability.[33] Similarly, the variables $\left|(EBIT/MVA)_{t+T}^{j} - (EBIT/MVA)_{t}^{j}\right|$ and $\left|(div/MVA)_{t+T}^{j} - (div/MVA)_{t}^{j}\right|$ respectively indicate the variability of EBIT and dividend (standardized by MVA): these are included as fundamental drivers of interest expense variability. Due to interest expense and dividend being jointly constrained by EBIT, the relationship between int/MVA and div/MVA is subject to endogeneity: consequently, in addition to regression model (3.1), we consider models (3.2) and (3.3) which, in comparison to model (3.1), only differ by the

[33] Changes in int/MVA (EBIT/MVA and div/MVA) over the T-year horizon could either be positive or negative, but both cases imply that interest expenses (EBIT and dividends) are not stable over time. Hence, we only focus on the magnitude of changes in int/MVA (EBIT/MVA and div/MVA), rather than the direction.

use of an instrumental variable in place of the $\left|(div/MVA)_{t+T}^{j} - (div/MVA)_{t}^{j}\right|$ variable. Model (3.2) replaces firm j's individual dividend variability with the median dividend variability for the same event window for all cross-sectional sample firms having the same GICS industry classification as firm j. Model (3.3) replaces firm j's actual dividend variability with expected dividend variability, estimated as a function of concurrent EBIT variability and lagged dividend variability:

$$\begin{aligned} \left|(div/MVA)_{t+T}^{j} \widehat{-} (div/MVA)_{t}^{j}\right| \\ &= c + d_1\left|(EBIT/MVA)_{t+T}^{j} - (EBIT/MVA)_{t}^{j}\right| \\ &+ d_2\left|(div/MVA)_{t}^{j} - (div/MVA)_{t-T}^{j}\right| \end{aligned} \tag{3.4}$$

where coefficients c, d_1 and d_2 are estimated with a first-stage out-of-sample regression for non-overlapping event windows from sample years 1962 to 1986 (the second-stage regression model (3.3) is then applied for sample years 1986 to 2016).

In particular we are interested in how firm-level interest expense variability relates to initial firm characteristics included as independent variables in the regression models (3.1), (3.2) and (3.3). These firm characteristics are: size, as indicated by the natural log of the market value of assets, $LN(MVA_t^j)$; dividend, $(div/MVA)_t^j$; leverage, $(D/MVA)_t^j$; market-to-book value of equity, $(ME/BE)_t^j$; and, profitability, $(EBIT/MVA)_t^j$. Table 3.9 presents the results for regression models (3.1) and (3.2), and Table 3.10 presents the results for regression model (3.3), estimated with non-overlapping event windows.

A firm's ability to maintain leverage depends on its earnings reliability: accordingly, Table 3.9 (Panels A and B) and Table 3.10 (Panel B) show that interest expense variability is consistently significantly positively related to EBIT variability for most event horizons (up to 12 years in Table 3.9, and nine years in Table 3.10). Panel A of Table 3.9 also shows a significant positive relationship between interest expense variability and dividend variability for most event horizons; this positive relationship persists when dividend variability is replaced with an instrument (Panel B of Table 3.9, and Panel B of Table 3.10), but the significance is diminished or non-existent. [34]

[34] Table 3.9 has also been replicated using variables scaled by book value of assets: the results are similar to those reported here using variables scaled by MVA. In addition, we have also used lagged industry median dividend variability to estimate the expected dividend variability for Panel B of Table 3.10: similar results were obtained.

Table 3.9 – Firm-level interest expense variability determinants

Firm-level interest expense variability, $\left|(int/MVA)_{t+T}^{j} - (int/MVA)_{t}^{j}\right|$, regression coefficient results for model (3.1) and model (3.2) presented in Section 3.5, for fiscal year event horizons $T \in \{1,2,3,6,9,12\}$ corresponding to non-overlapping event windows $(t, t+T) \in \{$(1962,63), (1963,64), …, (2015,16); (1962,64), (1964,66), …, (2014,16); (1962,65), (1965,68), …, (2013,16); (1962,68), (1968,74), …, (2010,16); (1962,71), (1971,80), …, (2007,16); (1962,74), (1974,86), …, (1998,2010)$\}$. Panel A presents the model (3.1) regression results. Panel B presents the model (3.2) regression results. Compared to model (3.1), model (3.2) replaces the dividend variability variable with an instrumental variable: median industry dividend variability. Firm and year fixed effects are included in the regressions. HAC t-stats are in parentheses: * and ** indicate significance at the 5% and 1% levels, respectively.

Panel A:

Event horizon, T (fiscal years)	1	2	3	6	9	12
Number of non-overlapping event windows within 1962-2016 sample	54	27	18	9	6	4
Firm-year observations	151,304	67,237	39,384	14,182	6,268	2,977
Regression variable						
EBIT variability, $\left\|(EBIT/MVA)_{t+T}^{j} - (EBIT/MVA)_{t}^{j}\right\|$	0.0120**	0.0131**	0.0155**	0.0139**	0.0076	0.0173**
	(22.886)	(16.100)	(12.530)	(5.813)	(1.728)	(3.122)
Dividend variability, $\left\|(div/MVA)_{t+T}^{j} - (div/MVA)_{t}^{j}\right\|$	0.0466**	0.0262**	0.0319**	0.0252	0.0765**	0.0933**
	(11.110)	(3.882)	(3.471)	(1.545)	(3.147)	(2.609)
Natural log of market value of assets, $LN(MVA_{t}^{j})$	-0.0004**	-0.0004**	-0.0006**	-0.0004**	-0.0006*	-0.0008*
	(-12.302)	(-6.259)	(-6.279)	(-2.727)	(-2.316)	(-2.262)
Dividend, $(div/MVA)_{t}^{j}$	-0.0282**	-0.0257**	-0.0355**	-0.0316*	0.0052	-0.0280
	(-10.047)	(-4.934)	(-4.821)	(-2.237)	(0.251)	(-0.847)
Leverage, $(D/MVA)_{t}^{j}$	0.0147**	0.0155**	0.0173**	0.0193**	0.0231**	0.0326**
	(56.281)	(31.100)	(23.880)	(14.927)	(11.830)	(12.079)
Market-to-book equity, $(ME/BE)_{t}^{j}$	0.0000	-0.0000	0.0000	0.0000	0.0001	0.0001
	(1.576)	(-0.236)	(0.652)	(0.332)	(1.716)	(0.860)
Profitability, $(EBIT/MVA)_{t}^{j}$	-0.0024**	-0.0014	0.0008	-0.0028	-0.0008	-0.0117*
	(-5.554)	(-1.973)	(0.729)	(-1.363)	(-0.211)	(-2.461)
F-stat	724.5	220.1	124.8	43.68	24.20	26.58
Adj. R-squared	0.321	0.342	0.357	0.389	0.369	0.410

Panel B:

Event horizon, T (fiscal years)		1	2	3	6	9	12
Number of non-overlapping event windows within 1962-2016 sample		54	27	18	9	6	4
Firm-year observations		151,384	67,276	39,406	14,190	6,275	2,982
Regression variable	EBIT variability, $\left|(EBIT/MVA)_{t+T}^{j} - (EBIT/MVA)_{t}^{j}\right|$	0.0121**	0.0131**	0.0156**	0.0140**	0.0084	0.0178**
		(23.047)	(16.056)	(12.598)	(5.871)	(1.897)	(3.200)
	Industry median dividend variability, $MEDIAN[|\Delta(div/MVA)|]_{t\rightarrow t+T}^{industry(j)}$	0.0633**	0.0051	0.0294	0.0663*	0.0811*	0.1245*
		(5.347)	(0.300)	(1.273)	(2.041)	(1.996)	(2.092)
	Natural log of market value of assets, $LN(MVA_t^j)$	-0.0004**	-0.0004**	-0.0006**	-0.0004**	-0.0005*	-0.0008*
		(-12.414)	(-6.312)	(-6.273)	(-2.704)	(-2.180)	(-2.326)
	Dividend, $(div/MVA)_t^j$	-0.0146**	-0.0170**	-0.0263**	-0.0277*	0.0218	-0.0022
		(-5.467)	(-3.395)	(-3.699)	(-1.995)	(1.050)	(-0.069)
	Leverage, $(D/MVA)_t^j$	0.0146**	0.0155**	0.0173**	0.0193**	0.0230**	0.0327**
		(56.196)	(31.083)	(23.887)	(14.937)	(11.787)	(12.129)
	Market-to-book equity, $(ME/BE)_t^j$	0.0000	-0.0000	0.0000	0.0000	0.0001	0.0001
		(1.888)	(-0.123)	(0.693)	(0.355)	(1.781)	(0.897)
	Profitability, $(EBIT/MVA)_t^j$	-0.0024**	-0.0015*	0.0008	-0.0028	-0.0004	-0.0116*
		(-5.683)	(-2.026)	(0.709)	(-1.361)	(-0.107)	(-2.432)
F-stat		703.5	216.6	122.9	44.00	22.94	26.63
Adj. R-squared		0.320	0.341	0.357	0.389	0.367	0.408

Table 3.10 – Firm-level interest expense variability determinants (2-stage approach)

First-stage firm-level dividend variability,
$\left|(div/MVA)_{t+T}^{j}-(div/MVA)_{t}^{j}\right| = c + d_1\left|(EBIT/MVA)_{t+T}^{j}-(EBIT/MVA)_{t}^{j}\right| + d_2\left|(div/MVA)_{t}^{j}-(div/MVA)_{t-T}^{j}\right| + \varepsilon_{t}^{j}$,
regression coefficient results for fiscal year event horizons $T \in \{1,2,3,6,9\}$ corresponding to non-overlapping event windows $(t, t+T) \in$ {(1963,64), (1964,65), …, (1985,86); (1964,66), (1966,68), …, (1984,86); (1965,68), (1968,71), …, (1983,86); (1968,74), (1974,80), (1980,86); (1971,80)}; and second-stage firm-level interest expense variability, $\left|(int/MVA)_{t+T}^{j}-(int/MVA)_{t}^{j}\right|$, regression coefficient results for model (3.3) presented in Section 3.5, for fiscal year event horizons $T \in \{1,2,3,6,9\}$ corresponding to non-overlapping event windows $(t, t+T) \in$ {(1986,87), (1987,88), …, (2015,16); (1986,88), (1988,90), …, (2014,16); (1986,89), (1989,92), …, (2013,16); (1986,92), (1992,98), …, (2010,16); (1986,95), (1995,2004), (2004,13)}. Panel A presents the first-stage dividend variability regression results; and Panel B presents the second-stage interest expense variability regression results with expected dividend variability, $\left|\widehat{(div/MVA)_{t+T}^{j}-(div/MVA)_{t}^{j}}\right|$, obtained using the first-stage (out-of-sample) regression coefficients. Firm and year fixed effects are included in the second-stage regressions. HAC t-stats are in parentheses: * and ** indicate significance at the 5% and 1% levels, respectively.

Panel A: First-stage dividend variability regressions

	Event horizon, T (fiscal years)	1	2	3	6	9
	Number of non-overlapping event windows within 1962-1986 sample	23	11	7	3	1
	Firm-year observations	46,107	18,691	9,818	2,789	978
Regression variable	Intercept	0.0017**	0.0027**	0.0032**	0.0045**	0.0048**
		(48.828)	(35.364)	(29.250)	(16.176)	(8.911)
	EBIT variability,	0.0030**	0.0058**	0.0115**	0.0143**	0.0153**
	$\left\|(EBIT/MVA)_{t+T}^{j}-(EBIT/MVA)_{t}^{j}\right\|$	(5.968)	(6.297)	(8.317)	(4.878)	(2.658)
	Lagged dividend variability,	0.3556**	0.3252**	0.2700**	0.2903**	0.3312**
	$\left\|(div/MVA)_{t}^{j}-(div/MVA)_{t-T}^{j}\right\|$	(35.256)	(26.834)	(17.852)	(11.497)	(7.194)
	F-stat	623.2	362.1	194.4	74.89	28.71
	Adj. R-squared	0.130	0.119	0.089	0.095	0.130

Panel B: Second-stage interest expense variability regressions

	Event horizon, T (fiscal years)	1	2	3	6	9
	Number of non-overlapping event windows within 1986-2016 sample	30	15	10	5	3
	Firm-year observations	86,472	34,270	18,328	4,751	1,202
Regression variable	EBIT variability,	0.0102**	0.0109**	0.0182**	0.0128*	0.0323
	$\left\|(EBIT/MVA)_{t+T}^{j} - (EBIT/MVA)_t^j\right\|$	(15.394)	(9.784)	(9.439)	(2.535)	(1.959)
	Expected dividend variability,	0.0339**	0.0101	0.0170	0.0759	0.1331
	$\left\|\widehat{(div/MVA)_{t+T}^{j}} - (div/MVA)_t^j\right\|$	(2.664)	(0.393)	(0.418)	(0.980)	(1.312)
	Natural log of market value of assets,	-0.0004**	-0.0007**	-0.0010**	-0.0007*	0.0002
	$LN(MVA_t^j)$	(-8.230)	(-7.468)	(-7.150)	(-2.307)	(0.365)
	Dividend, $(div/MVA)_t^j$	-0.0178**	-0.0185**	-0.0283**	-0.0648**	-0.0537
		(-4.759)	(-2.600)	(-2.649)	(-3.071)	(-1.286)
	Leverage, $(D/MVA)_t^j$	0.0162**	0.0200**	0.0245**	0.0280**	0.0336**
		(44.990)	(27.349)	(21.683)	(10.785)	(7.527)
	Market-to-book equity, $(ME/BE)_t^j$	0.0000*	0.0000	0.0001	-0.0000	0.0000
		(2.096)	(1.244)	(1.414)	(-0.043)	(0.344)
	Profitability, $(EBIT/MVA)_t^j$	-0.0026**	-0.0005	0.0040*	-0.0006	0.0122
		(-4.976)	(-0.471)	(2.424)	(-0.132)	(1.053)
	F-stat	409.4	143.9	93.41	24.36	9.929
	Adj. R-squared	0.341	0.359	0.362	0.375	0.503

Consistent with our aggregate evidence in Section 3.4 (specifically Tables 3.5 and 3.6), our firm-level results in Tables 3.9 and 3.10 show that firm size (i.e. LN(MVA)) and dividend payout (div/MVA) are significantly negatively related to interest expense variability (i.e. positively related to interest expense stability) for most event horizons, with the significance tending to peter out beyond the six-year event horizon. In Tables 3.9 and 3.10, leverage (D/MVA) is consistently significantly positively related to interest expense variability.[35] Tables 3.9 and 3.10 show that market-to-book equity (ME/BE) and profitability (EBIT/MVA) are generally unrelated to interest expense variability, except that EBIT/MVA is significantly negatively related to one-year interest expense variability.

3.6 The Value of Interest expense Stability

Having shown that interest expense variability is sensibly a function of firm characteristics, we now question whether "normal" interest expense variability is optimal. That is, are there any valuation implications for firms with interest expense variability that differs from what could normally be expected given their characteristics? Our first approach is to investigate market-to-book value of assets outcomes, $(MVA/BVA)_{t+T}^{j}$, as a function of unexpected interest expense variability with the following regression model:

$$\begin{aligned}(MVA/BVA)_{t+T}^{j} &= a \\ &+b_1\max\Big[0,\Big(\big|(int/MVA)_{t+T}^{j}-(int/MVA)_{t}^{j}\big| \\ &\qquad -\big|\widehat{(int/MVA)_{t+T}^{j}-(int/MVA)_{t}^{j}}\big|\Big)\Big] \\ &+b_2\min\Big[0,\Big(\big|(int/MVA)_{t+T}^{j}-(int/MVA)_{t}^{j}\big| \\ &\qquad -\big|\widehat{(int/MVA)_{t+T}^{j}-(int/MVA)_{t}^{j}}\big|\Big)\Big] \\ &+(firm\ j\ and\ fiscal\ year\ t\ fixed\ effects)+\varepsilon_{t}^{j}\end{aligned} \tag{3.5}$$

[35] Our Table 3.7 results in Section 3.4 indicate that, at an aggregate level, low leverage firms exhibit low interest expense stability in comparison to their profitability and dividend stabilities. However, the Table 3.7 results also show no significant difference in the aggregate interest expense stabilities of high and low leverage firms. Our firm-level multivariate results in Tables 3.9 and 3.10 show that higher leverage is associated with higher interest expense variability.

where $\left|(int/MVA)_{t+T}^{j}-(int/MVA)_{t}^{j}\right|-\left|\widehat{(int/MVA)_{t+T}^{j}-}(int/MVA)_{t}^{j}\right|$ is unexpected interest expense variability, and the $\max[0,\cdot]$ ($\min[0,\cdot]$) operator obtains the variable if it is positive (negative) and zero otherwise. Expected interest expense variability, $\left|\widehat{(int/MVA)_{t+T}^{j}-}(int/MVA)_{t}^{j}\right|$, is obtained by application of model (3.1) from Section 3.5 (but without fixed effects) with coefficient estimates obtained with a first-stage out-of-sample regression for each fiscal year event horizon $T \in \{1,2,3,6,9\}$ corresponding to non-overlapping event windows $(t, t+T) \in$ {(1962,63), (1963,64), …, (1985,86); (1962,64), (1964,66), …, (1984,86); (1962,65), (1965,68), …, (1983,86); (1962,68), (1968,74), …, (1980,86); (1962,71), (1971,80), (1980,89)}. The second-stage regression model (3.5) is then applied for $T \in \{1,2,3,6,9\}$ corresponding to non-overlapping event windows $(t, t+T) \in$ {(1986,87), (1987,88), …, (2015,16); (1986,88), (1988,90), …, (2014,16); (1986,89), (1989,92), …, (2013,16); (1986,92), (1992,98), …, (2010,16); (1989,98), (1998,2007), (2007,2016)}.[36]

Panel A of Table 3.11 shows that the out-of-sample coefficient estimates for our expected interest expense variability models are similar to the full sample estimates presented in Table 3.9. Panel B of Table 3.11 shows how the MVA/BVA firm valuation outcome depends on whether interest expense variability has been greater or lower than expected.

[36] We use non-overlapping event windows to eliminate time-series dependencies in data. Skogsvik (2008) also uses this approach to eliminate time-series dependencies in overlapping stock returns.

Table 3.11 – Firm-level market-to-book value of assets determinants

First-stage firm-level interest expense variability, $\left|(int/MVA)_{t+T}^{j} - (int/MVA)_{t}^{j}\right|$, regression coefficient results for model (3.1) presented in Section 3.5, for fiscal year event horizons $T \in \{1,2,3,6,9\}$ corresponding to non-overlapping event windows $(t, t+T) \in$ {(1962,63), (1963,64), …, (1985,86); (1962,64), (1964,66), …, (1984,86); (1962,65), (1965,68), …, (1983,86); (1962,68), (1968,74), …, (1980,86); (1962,71), (1971,80), (1980,89)}; and second-stage firm-level market-to-book value of assets, $(MVA/BVA)_{t+T}^{j}$, regression coefficient results for model (3.5) presented in Section 3.6, for fiscal year event horizons $T \in \{1,2,3,6,9\}$ corresponding to non-overlapping event windows $(t, t+T) \in$ {(1986,87), (1987,88), …, (2015,16); (1986,88), (1988,90), …, (2014,16); (1986,89), (1989,92), …, (2013,16); (1986,92), (1992,98), …, (2010,16); (1989,98), (1998,2007), (2007,16)}. Panel A presents the first-stage interest expense variability regression results; and Panel B presents the second-stage market-to-book value of assets regression results with expected interest expense variability, $\left|\widehat{(int/MVA)_{t+T}^{j} - (int/MVA)_{t}^{j}}\right|$, obtained using the first-stage (out-of-sample) regression coefficients. Firm and year fixed effects are included in the second-stage regressions. HAC t-stats are in parentheses: * and ** indicate significance at the 5% and 1% levels, respectively.

Panel A: First-stage interest expense variability regressions

	Event horizon, T (fiscal years)	1	2	3	6	9
	Number of non-overlapping event windows within first-stage regression sample	24	12	8	4	3
	Firm-year observations	52,541	24,088	14,378	5,822	3,185
Regression variable	Intercept	0.0052**	0.0080**	0.0106**	0.0166**	0.0159**
		(32.545)	(24.812)	(23.554)	(17.570)	(12.926)
	EBIT variability, $\lvert(EBIT/MVA)_{t+T}^{j}-(EBIT/MVA)_{t}^{j}\rvert$	0.0225**	0.00280**	0.0236**	0.0242**	0.0222**
		(20.473)	(17.037)	(11.556)	(6.765)	(4355)
	Dividend variability, $\lvert(div/MVA)_{t+T}^{j}-(div/MVA)_{t}^{j}\rvert$	0.0848**	0.0871**	0.0832**	0.0953**	0.0450
		(8.636)	(6.409)	(4.983)	(3.501)	(1.378)
	Natural log of market value of assets, $LN(MVA_{t}^{j})$	-0.0005**	-0.0006**	-0.0008**	-0.0009**	-0.0010**
		(-24.945)	(-14.561)	(-13.828)	(-8.251)	(-6.371)
	Dividend, $(div/MVA)_{t}^{j}$	-0.0801**	-0.1329**	-0.1421**	-0.1768**	-0.1519**
		(-26.050)	(-21.017)	(-15.957)	(-10.739)	(-6.192)
	Leverage, $(D/MVA)_{t}^{j}$	0.0156**	0.0182**	0.0216**	0.0177**	0.0194**
		(59.470)	(35.750)	(30.782)	(13.179)	(9.278)
	Market-to-book equity, $(ME/BE)_{t}^{j}$	0.0000**	0.0001**	0.0001	0.0005**	0.0002
		(2.586)	(3.594)	(1.117)	(4.055)	(1.162)
	Profitability, $(EBIT/MVA)_{t}^{j}$	0.0020**	0.0033**	-0.0006	-0.0149**	0.0051
		(3.073)	(2.726)	(-0.361)	(-4.604)	(1.085)
	F-stat	1167	572.8	399.9	129.1	47.49
	Adj. R-squared	0.175	0.155	0.172	0.135	0.098

Panel B: Second-stage market-to-book value of assets regressions

	Event horizon, T (fiscal years)	1	2	3	6	9
	Number of non-overlapping event windows within second-stage regression sample	30	15	10	5	3
	Firm-year observations	98,862	43,426	25,480	8,867	3,574
Regression var.	Positive unexpected interest expense variability, $\max[0,(\left\|(int/MVA)^j_{t+T}-(int/MVA)^j_t\right\| - \widehat{\left\|(int/MVA)^j_{t+T}-(int/MVA)^j_t\right\|})]$	-15.8734** (-19.019)	-10.9120** (-10.596)	-12.1781** (-8.535)	-4.6832 (-1.724)	-18.0243* (-2.476)
	Negative unexpected interest expense variability, $\min[0,(\left\|(int/MVA)^j_{t+T}-(int/MVA)^j_t\right\| - \widehat{\left\|(int/MVA)^j_{t+T}-(int/MVA)^j_t\right\|})]$	30.4718** (20.823)	5.8651** (3.840)	3.8681 (1.908)	-9.0584** (-3.151)	5.1032 (0.892)
	F-stat	278.7	56.35	38.47	10.59	3.208
	Adj. R-squared	0.517	0.487	0.486	0.441	0.377

Panel B of Table 3.11 shows that firm valuation outcome is negatively related to greater than expected (i.e. positive unexpected) interest expense variability out to a nine-year event horizon (with statistical significance only lacking for the six-year horizon): that is, the more a firm's interest expense variability exceeds its normal/expected level, the lower the valuation outcome. For shorter event horizons of one year and two years, valuation outcome is also significantly lower the more that actual interest expense variability is lower than its normal/expected level (i.e. valuation outcome is positively related to negative unexpected interest expense variability). For event horizons of three years and longer there is no consistent relationship between valuation outcome and lower than expected interest expense variability. The overall implication of these results is that, at shorter event horizons up to about three years, positive or negative deviation of interest expense variability from expected is associated with adverse valuation outcomes (meaning that normal/expected interest expense variability is broadly optimal); and, at longer event horizons beyond about three years, higher than expected interest expense variability is associated with adverse valuation outcomes.

Our second approach at assessing the valuation implications of unexpected interest expense variability is to obtain the asset pricing alphas for investment portfolios formed according to future realized unexpected interest expense variability: such an investment strategy is not available to firm outsiders, but is viable for firm insiders to the extent that firm insiders (i.e. managers) are able to control unexpected interest expense variability. That is, we are assessing whether there is stock return alpha available to managers dependent upon their management of interest expense variability relative to expected/normal interest expense variability (for given firm characteristics).

At yearly intervals from 1987 onwards, the cross-section of sample firms are sorted into decile portfolios according to their ensuing unexpected interest expense variability, $\left|(int/MVA)^j_{t+T} - (int/MVA)^j_t\right| - \left|\widehat{(int/MVA)^j_{t+T} - (int/MVA)^j_t}\right|$, for event horizons of $T \in \{1,2,3,6,9\}$ fiscal years, where expected interest expense variability, $\left|\widehat{(int/MVA)^j_{t+T} - (int/MVA)^j_t}\right|$, is obtained by application of model (3.1) from Section 3.5 (but without fixed effects) with the out-of-sample coefficients presented in Panel A of Table 3.11. Monthly equal-weighted and value-weighted decile portfolio returns are then obtained and regressed against the Fama-French five factor asset pricing model (Fama and French, 2015):[37] the alphas (i.e. regression intercepts) are presented in Table 3.12 (Panel A presents the equal-weighted portfolio alphas, and Panel B presents the value-weighted portfolio alphas). Also presented are the alphas for the decile 1 minus decile 10 (long-short) portfolios.

Table 3.12 (both Panel A and Panel B) shows that the decile 10 stock portfolios (for firms with the highest unexpected interest expense variability) generally earn significant negative alpha for interest expense variability event horizons up to about three years. The decile 1 portfolios (for firms with interest expense variability most extremely less than expected) also earn significant negative alphas for the one-year interest expense variability event horizon, but generally insignificant alphas for longer event horizons. The decile 10 portfolios underperform the decile 1 portfolios, however, the value-weighted decile 1 minus decile 10 (long-short) portfolios yield insignificant alphas. The middle decile portfolios (the decile 5 and decile 6 portfolios in particular, containing firms with interest expense variabilities about equal to expectation) tend to exhibit significantly positive alphas for event horizons up to about three years.

Across the decile portfolios the overall alpha pattern shown in Table 3.12 is an inverted U-shape (or, better descriptive of the decile 1 versus decile 10 asymmetry, an inverted J-shape) for interest expense variability event horizons up to about three years (see Figure 3.3). That is, consistent with the MVA/BVA valuation outcome results presented in Table 3.11, firms with interest expense variabilities that deviate from normal/expected suffer adverse stock return consequences in comparison to firms with minimal unexpected interest expense variability.

[37] The monthly stock returns for individual firms are obtained from the CRSP database. The Fama-French factors are obtained from the Kenneth French Data Library (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html).

Table 3.12 – Unexpected interest expense variability decile portfolio returns

At yearly intervals from 1987 onwards, the cross-section of sample firms are sorted into decile portfolios according to their future unexpected interest expense variability, $\left|(int/MVA)_{t+T}^{j} - (int/MVA)_{t}^{j}\right| - \left|\widehat{(int/MVA)_{t+T}^{j} - (int/MVA)_{t}^{j}}\right|$. Expected interest expense variability, $\left|\widehat{(int/MVA)_{t+T}^{j} - (int/MVA)_{t}^{j}}\right|$, is obtained using model (3.1) from Section 3.5 (but without fixed effects) with the out-of-sample regression coefficients presented in Panel A of Table 3.11. Fama-French 5 factor asset pricing model alphas are obtained for monthly equal-weighted and value-weighted stock returns for each decile portfolio, and the decile 1 minus decile 10 (long-short) portfolio. HAC t-stats are in parentheses: * and ** indicate significance at the 5% and 1% levels, respectively.

Panel A: Fama-French 5 factor model alphas for monthly equal-weighted portfolios

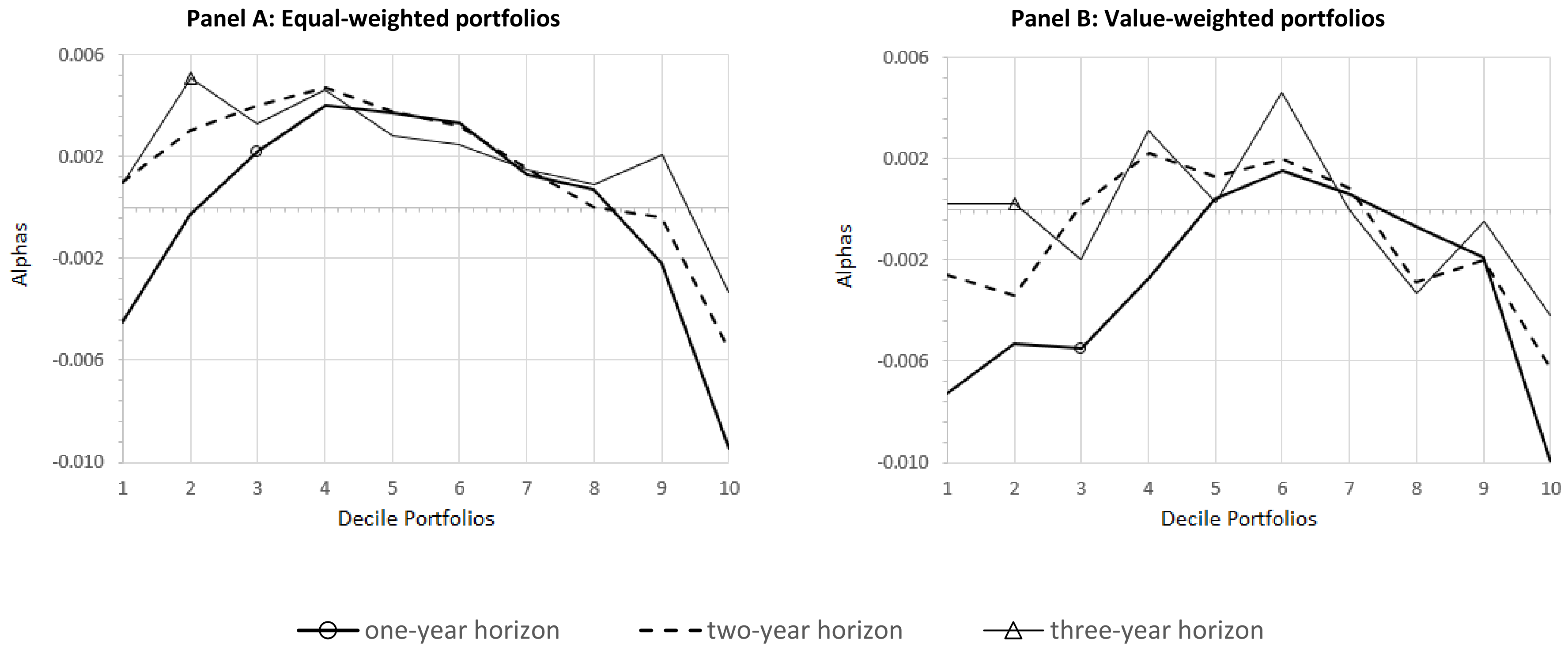
Fiscal year event horizon for unexpected interest expense variability, *T*	1	2	3	6	9
Portfolio time series length (months)	372	372	372	372	309
Decile 1 low unexpected interest expense variability stocks	-0.0045*	0.0010	0.0010	0.0077**	0.0095
	(-2.266)	(0.506)	(0.424)	(2.620)	(1.569)
Decile 2	-0.0003	0.0030	0.0051*	0.0029**	0.0067**
	(-0.185)	(1.791)	(2.089)	(2.008)	(2.535)
Decile 3	0.0022	0.0040**	0.0033	0.0049	0.0059**
	(1.869)	(3.008)	(1.204)	(1.305)	(2.761)
Decile 4	0.0040**	0.0047**	0.0046**	0.0024*	0.0038*
	(4.018)	(3.518)	(3.937)	(1.674)	(1.831)
Decile 5	0.0037**	0.0038**	0.0028	0.0034**	0.0059
	(4.795)	(4.706)	(1.464)	(2.527)	(1.798)
Decile 6	0.0033**	0.0032**	0.0025**	0.0024	0.0017
	(4.325)	(3.819)	(2.672)	(1.436)	(0.568)
Decile 7	0.0013	0.0015	0.0015	0.0000	0.0037
	(1.805)	(1.719)	(1.064)	(0.039)	(1.789)
Decile 8	0.0007	-0.0000	0.0009	-0.0035	0.0050
	(0.705)	(-0.018)	(0.504)	(-1.201)	(1.090)
Decile 9	-0.0022	-0.0004	0.0021	-0.0004	-0.0022
	(-1.482)	(-0.285)	(1.659)	(-0.133)	(-0.602)
Decile 10 high unexpected interest expense variability stocks	-0.0095**	-0.0056**	-0.0033	0.0012	0.0053
	(-4.587)	(-2.746)	(-1.669)	(0.526)	(1.890)
Decile 1 minus decile 10 (long-short) portfolio	0.0050**	0.0066**	0.0043*	0.0065*	0.0040
	(3.445)	(3.589)	(2.118)	(2.021)	(0.731)

Panel B: Fama-French 5 factor model alphas for monthly value-weighted portfolios

Fiscal year event horizon for unexpected interest expense variability, *T*	1	2	3	6	9
Portfolio time series length (months)	372	372	372	372	309
Decile 1 low unexpected interest expense variability stocks	-0.0073**	-0.0026	0.0002	0.0024	-0.0033
	(-3.846)	(-1.338)	(0.130)	(0.691)	(-0.549)
Decile 2	-0.0053**	-0.0034*	0.0002	0.0008	0.0025
	(-3.208)	(-2.366)	(0.088)	(0.388)	(0.901)
Decile 3	-0.0055**	0.0002	-0.0020	0.0033	0.0047*
	(-4.240)	(0.163)	(-0.698)	(0.786)	(2.132)
Decile 4	-0.0027*	0.0022	0.0031**	-0.0000	0.0054*
	(-2.347)	(1.240)	(2.379)	(-0.000)	(2.289)
Decile 5	0.0004	0.0013	0.0003	0.0018	0.0044
	(0.350)	(1.173)	(0.174)	(1.367)	(1.314)
Decile 6	0.0015*	0.0020*	0.0046**	0.0020	0.0017
	(1.942)	(2.098)	(3.387)	(1.047)	(0.604)
Decile 7	0.0006	0.0008	0.0000	-0.0011	0.0009
	(0.810)	(0.691)	(0.020)	(-0.753)	(0.395)
Decile 8	-0.0007	-0.0029*	-0.0033	-0.0053	0.0044
	(-0.990)	(-2.319)	(-1.708)	(-1.779)	(0.925)
Decile 9	-0.0019	-0.0020*	-0.0005	-0.0015	0.0013
	(1.629)	(-1.940)	(-0.426)	(-0.628)	(0.312)
Decile 10 high unexpected interest expense variability stocks	-0.0100**	-0.0063**	-0.0042**	-0.0009	-0.0004
	(-5.514)	(-2.982)	(-2.527)	(-0.613)	(-0.196)
Decile 1 minus decile 10 (long-short) portfolio	0.0028	0.0036	0.0045	0.0033	-0.0034
	(1.277)	(1.453)	(1.937)	(0.870)	(-0.534)

Figure 3.3 – Decile portfolio alphas

Monthly equal-weighted and value-weighted decile portfolio alphas extracted from Table 3.11 are graphed for event horizons of three years. Panel A presents the decile alpha graph for equal-weighted portfolios and Panel B presents the decile alpha graph for value-weighted portfolios.



3.7 Conclusion

We have shown that firms' annual interest expenses are significantly more stable than their profitability out to a long-run horizon of 10 years and beyond. This *relative* interest expense stability exhibits cross-sectional variation associated with firm characteristics in a manner relatable to the imperatives of trade-off and pecking-order theories. Our most important result is that there are adverse valuation consequences for firms whose interest expense variabilities deviate from expectations (which are dependent on firm characteristics). The implication of this is that optimal leverage management is not equivalent to interest expense stability (such as lower variability than expected). Interest expense variability that is either lower or higher than expected, whether due to excessive or insufficient management intervention, leads to lower firm valuation; this implies that expected or "normal" leverage management is broadly optimal.

4 Default Risk and Leverage Management

4.1 Introduction

Any firm's optimal (i.e. value-maximizing) leverage decision is a function of the risk that the firm will not be able to service its liabilities (e.g. Leland and Toft, 1996). However, the survey evidence of Graham and Harvey (2001, Table 6, p.212) indicates that only about half of all firms consider "[t]he volatility of [their] earnings and cash flows" to be an important factor for their debt choices; and an even paltrier 20% of firms consider "[t]he potential costs of bankruptcy, near-bankruptcy, or financial distress" to be a similarly important factor. This survey evidence suggests that many firms' debt choices might be sub-optimally *reactive* rather than optimally *proactive* with regard to excessive financial risk and consequential value destruction. Specifically it is the interest/coupon payments associated with debt choices that lever-up earnings and cash flow risk, and, thereby, financial risk. Chapter 3 of this thesis shows that leverage management resulting in unexpected interest expense variability entails adverse valuation consequences for firms. According to Doherty (2000, p.460): "management of the capital structure of the firm and risk management are inseparable". The results reported in the previous chapter lead us to the question: is unexpected interest expense variability an *ex-post* reaction to excessive financial risk, or does unexpected interest expense variability represent suboptimal leverage management that drives excessive financial risk? In this chapter, we test these two competing hypotheses to investigate whether unexpected interest expense variability follows or drives increased financial risk in the form of expected default frequency.

A paper similar to our study is conducted by Dierker, Lee, and Seo (2019) who examine the impact of firms' risk changes in terms of stock return volatility, default probability and implied asset volatility on their future leverage and external financing activity changes. They find that firms are more likely to issue equity and buy back debt following risk increases, issue debt and buy back equity following risk decreases. Their findings show that risk change is a key factor to drive the future changes in firms' leverage and external financing activities. However, they only examine the unidirectional relationship between firms' leverage decisions and risk changes by assuming that leverage changes are driven by risk changes. They do not consider the causal relationship between these two variables. Second, different from Dierker, Lee, and Seo (2019), we investigate the relationship between the level of optimal leverage management and default risk.

To investigate this relationship, we divide our study into two parts. In the first part of this study, we examine the direction of the relationship between firm risk and firms' unexpected interest expense variabilities. We adopt the panel vector autoregression (hereafter PVAR) approach to study whether current level of unexpected interest expense variability affects future risk of firm, or current level of risk of firm leads to fluctuation in unexpected interest expense variability. To the best of our knowledge, this is the first study to investigate the relationship between leverage management in terms of interest expense variability and firm default risk. Use of the PVAR method in this regard is also novel.

To capture the firm risk or the default risk, we follow Brogaard, Li, and Xia's (2017) methodology to compute the expected default frequency (EDF). We also follow Chapter 3 of this thesis to estimate the expected interest expense variability for each firm. Unexpected interest expense variability is computed as the difference between actual interest expense variability and expected interest expense variability. Based on the PVAR approach, we find that a positive unidirectional relationship between current unexpected interest expense variabilities of firms and their future expected default frequencies. This result implies that firms with interest expenses being less variable than expected, tend to have lower expected default frequencies in the future.

Although the PVAR approach shows us a positive relationship between unexpected interest expense variability and expected default frequency, this relationship could be affected by the direction of unexpected interest expense variability. Hence, in the second part of this chapter, we further investigate this issue and find that both firms with less interest expense variability than expected (negative unexpected interest expense variability) and firms with greater interest expense variability than expected (positive unexpected interest expense variability) have higher default risks.

The previous chapter (i.e. Chapter 3) has shown that both positive and negative unexpected interest expense variability considered as suboptimal leverage management lead to reduced firm valuation. We re-investigate this observed relationship and show that previous findings of both positive and negative unexpected interest expense variabilities having negative impacts on firm valuation is due to increased default risk. Based on structural equation modelling (SEM), expected default frequency is found to act as a key channel to mediate the negative effect of unexpected interest expense variability on firm valuation. Deviation in interest expense variability from expected level in either positive or negative direction increases firm default risk, which in turn decreases its valuation. These findings are consistent with our previous results in Chapter 3 and show that optimal leverage management should be considered as having minimal deviation in interest expense variability from expected.

This paper is constructed as follows. Section 4.2 describes the data sample. Section 4.3 conducts the PVAR approach to examine the direction of the interrelationship between the two variables. Section 4.4 presents the analysis and results on expected default frequency and unexpected interest expense variability. Section 4.5 performs the SEM approach to examine the mediating role of expected default frequency to the relationship between unexpected interest expense variability and firm valuation. Section 4.6 concludes.

4.2 Data and Sample Selection

Our sample selection and regression variable generation follow the previous chapter's data filtering techniques (Chapter 3, p.53). To compute the expected default frequency, we merge our annual dataset with monthly data from CRSP based on Permno and calendar (year, month) and follow Brogaard et al.'s (2017) models as shown below:

$$DD_t^j = \frac{\mathrm{Ln}\left(\frac{D_t^j + ME_t^j}{D_t^j}\right) + (r_{t-1}^j - \frac{\sigma^2{}_{Vt}^j}{2}) \times T_t^j}{\sigma_{Vt}^j \times \sqrt{T_t^j}} \tag{4.1}$$

$$\sigma_{Vt}^j = \frac{ME_t^j}{D_t^j + ME_t^j} \times \sigma_{Et}^j + \frac{D_t^j}{D_t^j + ME_t^j} \times (0.05 + 0.25 \times \sigma_{Et}^j) \tag{4.2}$$

$$EDF_t^j = N(-DD_t^j) \tag{4.3}$$

In Eqs. (4.1) to (4.3), *j* and *t* index firm and (fiscal) year respectively. Debt is computed in a different way for the calculation of expected default frequency. It is computed as the sum of short-term debt and one-half of long-term debt following Brogaard et al.'s (2017) method; r_{t-1}^j is firm *j*'s previous year's annual return, which is the geometric average of twelve months' returns over the previous year; σ_{Et}^j is firm *j*'s annual stock return volatility, which is computed as the standard deviation of past twelve months' returns over the previous year; DD_t^j is the distance to default of firm *j* at each fiscal year end. Expected default frequency, or EDF_t^j is computed as the cumulative standard normal distribution of negative DD_t^j.

Our objective is to examine the relationship between expected default frequency and unexpected interest expense variability. Unexpected interest expense variability is computed as actual interest expense variability minus the expected interest expense variability. Expected interest expense variability for the out-of-sample dataset is computed based on the application of Eq. (3.1) in Chapter 3 (p.72).

Our out-of-sample dataset contains 112,819 observations. Table 4.1 presents summary statistics for out-of-sample datasets. Actual interest expense variability ranges from 0 to 0.085, expected interest expense variability ranges from 0 to 0.026 and the unexpected interest expense variability ranges from -0.023 to 0.082. Table 4.1 also shows that the distance to default and expected default frequency range from 0.253 and 0 (minimum) to 29.435 and 0.400 (maximum), respectively. The average distance to default and expected default frequency across all firm years are 6.767 and 0.022, respectively.

Table 4.1 – Summary statistics for out-of-sample datasets

Summary statistics for variables defined in Table 1 by sample firm j (identified by Compustat GVKEY) and firm fiscal year $t \in \{1986, \dots, 2016\}$. The sample includes all US listed firms in the CRSP/Compustat Merged Database for firm fiscal years 1986 to 2016 excluding financial and utility firms, firms incorporated outside the US, firms that are non-publicly traded and subsidiaries, and which have non-missing data for total assets, stock price, common shares outstanding and interest expense. All variables are winsorized at the 1st and 99th percentiles.

Variable		Obs.	Min	Max	Mean	Median	St. dev.
Firm size	$\ln(MVA_t^j)$	112,819	1.005	10.673	5.569	5.439	2.143
Operating profitability	$(EBIT/MVA)_t^j$	112,819	-0.522	0.244	0.007	0.042	0.118
Interest expense	$(int/MVA)_t^j$	112,819	0.000	0.085	0.014	0.007	0.017
Dividend	$(div/MVA)_t^j$	112,819	0.000	0.053	0.004	0.000	0.009
Leverage	$(D/MVA)_t^j$	112,819	0.000	0.704	0.159	0.102	0.173
Market-to-book equity	$(ME/BE)_t^j$	112,819	0.240	24.698	3.241	1.974	3.966
Actual interest expense variability	$\left\lvert\left(\frac{int}{MVA}\right)_{t+1}^j - \left(\frac{int}{MVA}\right)_t^j\right\rvert$	98,555	0.000	0.085	0.005	0.002	0.008
Expected interest expense variability	$\left\lvert\widehat{\left(\frac{int}{MVA}\right)_{t+1}^j - \left(\frac{int}{MVA}\right)_t^j}\right\rvert$	98,396	-0.002	0.026	0.006	0.005	0.003
Unexpected interest expense variability	Actual – expected interest expense variability	98,396	-0.023	0.082	-0.000	-0.002	0.008
Distance to default	$(DD)_t^j$	81,829	0.253	29.435	6.767	5.224	5.565
Expected default frequency	$(EDF)_t^j$	81,829	0.000	0.400	0.022	0.000	0.067

4.3 Panel Vector Autoregression (PVAR) Approach

Our study starts with the examination of the relationship between expected default frequency and the unexpected interest expense variability. We propose two competing hypotheses (4.1 & 4.2) on the bidirectional lagged relationship between these two variables. That is, the current values of a firm's unexpected interest expense variability are useful in predicting its future expected default frequency, and vice versa. If a firm has higher expected default frequency, then the firm is more likely to change its current situation by reducing its interest expense burden. On the other hand, a firm with lower expected default frequency will be able to increase debt financing to achieve its financing and investment strategy goals. Managing a firm's interest expenses will lead to a change in future interest expense variability – this change may be expected, or more or less than expected. Alternatively, we could also argue that if a firm changes its current interest expense level (such as aiming to maximize interest expense tax shield or achieving investment or financing strategy targets), this may not affect firm's current expected default frequency level, but will affect its future expected default frequency. More variability in interest expenses than expected level could increase the level of uncertainty of expected future cash outflows and hence increase its future expected default frequency.

Hypothesis 4.1: Unexpected interest expense variability is an ex-post reaction to firms' current expected default frequencies.

Hypothesis 4.2: Unexpected interest expense variability represents suboptimal leverage management that drives the changes in firms' future expected default frequencies.

To explore the lagged relationship between these two variables and test these two competing hypotheses, we adopt the PVAR approach, which allows us to examine the effect of one variable on other variables and the bidirectional causality we hypothesized previously. As discussed by Canova and Ciccarelli (2013), PVAR has three features: dynamic interdependences (endogenous interaction between variables across firms), static interdependences (autocorrelated error terms across firms) and cross-sectional interdependences (heterogeneous coefficients on lagged variables across firms). Considering these features, PVAR is considered to be a suitable approach in our case as we are interested to examine the effect or shock of one variable on another (across firms) and the bidirectional relationship we hypothesized previously.

It is necessary to check for the stationarity of the employed variables before estimating their relationship. We conduct a Fisher-type unit root test based on the augmented Dickey-Fuller test for expected default frequency and unexpected interest expense variability.[38] The selection of the optimal lag length is determined based on the Hansen's (1982) J statistic from the lag-order selection test. To decide the optimal lag length for the relationship, we use the second to the sixth lags of expected default frequency and unexpected interest expense variability as instruments in the model which give more acceptable p-values at the 5% alpha level for the Hansen tests (J-stat p-value greater than 0.05).[39] Results are presented in Table 4.2 below.

According to Andrews and Lu (2001), the preferred model should be the lag order with smallest MBIC, MAIC and MQIC.[40] Based on Table 4.2, we observe that the first-order PVAR has the smallest MBIC and MQIC. Although the second-order PVAR has the smallest MAIC, the difference in MAIC between the first- and second-order models is very small. The p-value for the Hansen test for the first-order PVAR model (J-stat p-value) is greater than 0.05 which indicates that the model is not overidentified at 5% alpha level. Our results for the unit root tests with lag order (1) are significant (p-values less than 0.01), indicating that both variables are stationary and the

[38] The Fisher-type unit root test is used because our panel data is unbalanced. In addition, we drop panels with less than 10 observations to mitigate the problem of gaps in data when unit root test is conducted. We repeated all PVAR analyses with panels having at least 10 observations and do not find any significant changes in the relationship between the two endogenous variables discussed in the main text.
[39] Initially we use the first five lags of expected default frequency and excess variability of interest expenses as instruments. However, we find that all models have low p-values which reject Hansen's overidentification restriction at 5% alpha level (J-stat p-value less than 0.05. This indicates possible misspecification in our models which could be due to the issue of autocorrelation in model residuals, as discussed by Arbigo and Love (2016).
[40] According to Andrews and Lu (2001), the optimal lag order decision is made based on the three selection criteria: Moment and Model Selection Criteria (MMSC)-Bayesian Information Criteria (MBIC), MMSC-Akaike Information Criteria (MAIC) and MMSC-Hannan-Quinn Information Criteria (MQIC).

panel data does not contain unit roots. Such results support us to examine the bidirectional relationship between the two variables through PVAR.

Table 4.2 – Lag-order selection

This table presents the results for the first- and fourth-order PVAR models with the use of the second to the sixth lags of endogenous variables (unexpected interest expense variability and expected default frequency) as instruments.

Lag-order test using the second to the sixth lags of endogenous variables as instruments				
Lag	J-stat p-value	MBIC	MAIC	MQIC
1	0.0766	-137.5461	-7.3697	-49.4848
2	0.1812	-105.4078	-7.7755	-39.3618
3	0.2930	-71.4717	-6.3835	-27.4410
4	0.7507	-38.6256	-6.0815	-16.6103

The first-order PVAR model is shown below.

$$Y_t^j = A_0 + A_1 Y_{t-1}^j + \mu^j + \nu_t + \varepsilon_t^j \tag{4.4}$$

In Eq. (4.4), Y_t^j is a vector of endogenous or dependent variables, namely expected default frequency and unexpected interest expense variability. A_0 is a vector of constant. The superscript j refers to firm and subscript t refers to year. A_1 is the lag operator of the endogenous variables. μ^j and ν_t are firm and time fixed effects, respectively. ε_t^j is a vector of error terms. In the PVAR model, we do not include the control variables: size, profitability, leverage, dividend and market-to-book equity. The reason of not including these variables in the model is that PVAR will treat all variables as endogenous variables and assume two-way causality. That is, each PVAR variable is assumed to rely on not only its historical values and also other variables. For instance, control variable size will be assumed to rely on its past values and also past values of other variables such as expected default frequency when size is treated as endogenous variable. However, in our study, these control variables are only determinants of expected default frequency, but not vice versa. Hence, the effects of control variables on expected default frequency are examined based on panel regressions in Section 4.4 of this study, rather than through PVAR.

We then perform the panel vector autoregression by fitting the first-order PVAR model with same instrument specification. The result is presented in Table 4.3. "GMM-style" instruments of expected default frequency and unexpected interest expense variability are used to obtain more efficient estimates by avoiding the problem of dropping missing data when instrument lags are used in the model. In addition, to eliminate the panel-specific fixed effect terms, we follow Arbigo and Love (2016) to use the forward orthogonal deviation or Helmert transformation, rather than the first difference procedure. The reason for not using first difference is that unbalanced panel data is used in this study. As discussed by Arbigo and Love (2016), gap in unbalanced data is magnified if first difference transformation is used on variables.

Table 4.3 – First-order PVAR model

This table presents the results by fitting the first-order PVAR model with "GMM-style" instruments of one-year lagged unexpected interest expense variability and expected default frequency. "GMM-style" instruments are used to avoid the problem of dropping observations with missing data when lags of instruments are used. Robust t-statistics are presented in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

VARIABLES	(1) Unexpected interest expense variability	(2) Expected default frequency
1-year lagged unexpected interest expense variability	0.6324*** (4.66)	1.5819* (1.83)
1-year lagged expected default frequency	-0.0041 (-0.78)	0.4027*** (9.55)
Number of Observations	52,808	52,808
Number of panels	6,442	6,442

As shown in model (1) of Table 4.3, we do not find any significant impact of 1-year lagged expected default frequency on the unexpected interest expense variability. For the expected default frequency equation, which is shown in model (2) of Table 4.3, we obtain a statistically significant positive result for the 1-year lagged unexpected interest expense variability at the 10% level of significance. This implies that firms with higher levels of unexpected interest expense variability (actual interest expense variability is increasing compared to the expected level) tend to have higher expected default frequencies in the future.

To further investigate the lagged relationship between these two variables, we conduct the Granger causality test, which tests whether past values of one variable is useful in the prediction of another variable (Granger, 1969). In our case, we are interested to know whether the current value of a firm's unexpected interest expense variability (expected default frequency) affects its future expected default frequency (unexpected interest expense variability). The Granger causality test results are presented in Table 4.4.

The null hypothesis for Granger-causality test is that the coefficient of the one-year lag of unexpected interest expense variability (expected default frequency) on the expected default frequency (unexpected interest expense variability) equation is equal to zero. In other words, Excluded variable unexpected interest expense variability (expected default frequency) does not Granger-cause the Equation variable expected default frequency (unexpected interest expense variability). Panel A of Table 4.4 shows that the null hypothesis of "expected default frequency does not Granger-cause unexpected interest expense variability" is not rejected with a p-value of 0.434. For our second null hypothesis of "unexpected interest expense variability does not Granger-cause expected default frequency", it is found to be rejected only at 10% level of significance with a p-value of 0.067, as shown by Panel B of Table 4.4. The results in Tables 4.3 and 4.4 support *Hypothesis 4.2*, and we can conclude that the direction of the relationship should be unidirectional, with the current value of a firm's unexpected interest expense variability affecting its future expected default frequency.

Table 4.4 – Granger-causality test

This table presents the results from Granger-causality test. That is, whether unexpected interest expense variability “Granger-causes” expected default frequency, or expected default frequency “Granger-causes” unexpected interest expense variability. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Equation	Excluded	Chi-squared	Degrees of freedom	P-values (Prob > Chi2)
Panel A. Unexpected interest expense variability				
	Expected default frequency	0.612	1	0.434
Panel B. Expected default frequency				
	Unexpected interest expense variability	3.349	1	0.067*

We further compute the forecast-error variance decompositions (hereafter FEVD) to examine the unidirectional relationship between unexpected interest expense variability and expected default frequency. FEVD would show us the effects of exogenous changes in each of unexpected interest expense variability and expected default frequency (considered as endogenous variables) in the model. Before we estimate FEVD, we check the stability condition of the model. If the PVAR system is not stationary, this means that the shock will act as a permanent effect, rather than a transitory effect. Results on the stability condition of the system are shown in Table 4.5. Based on Table 4.5, we find that the moduli of all eigenvalues are less than 1, which indicates that the PVAR model is stable.

Since the PVAR system satisfies the stability condition, we compute FEVD with a forecast horizon of 10 periods and 200 Monte Carlo draws are used according to our estimated PVAR system. FEVD shows us the percentage of variation (or forecast-error variance) in future expected default frequency that can be explained by the exogenous shock to unexpected interest expense variability at each horizon, and vice versa. The outputs of FEVD are presented in Table 4.6.

Based on Table 4.6, we find that after 10 periods, around 16% percent of variation in future expected default frequency can be explained by the unexpected interest expense variability. On the other hand, we find that around only 0.13% of variation in future unexpected interest expense variability is explained by expected default frequency. Majority of variation in unexpected interest expense variability is captured by the past values of this variable. Results in Table 4.6 show that unexpected interest expense variability has influence on firms' future expected default frequencies, but not vice versa.

Table 4.5 – Stability condition of the system

This table presents the results on the eigenvalue stability condition of the PVAR system. The estimated PVAR model is considered to be stable if the moduli of all eigenvalues are less than 1.

Eigenvalue		
Real	Imaginary	Modulus
0.5990	0	0.5990
0.4361	0	0.4361

Table 4.6 – Forecast-error variance decomposition (FEVD)

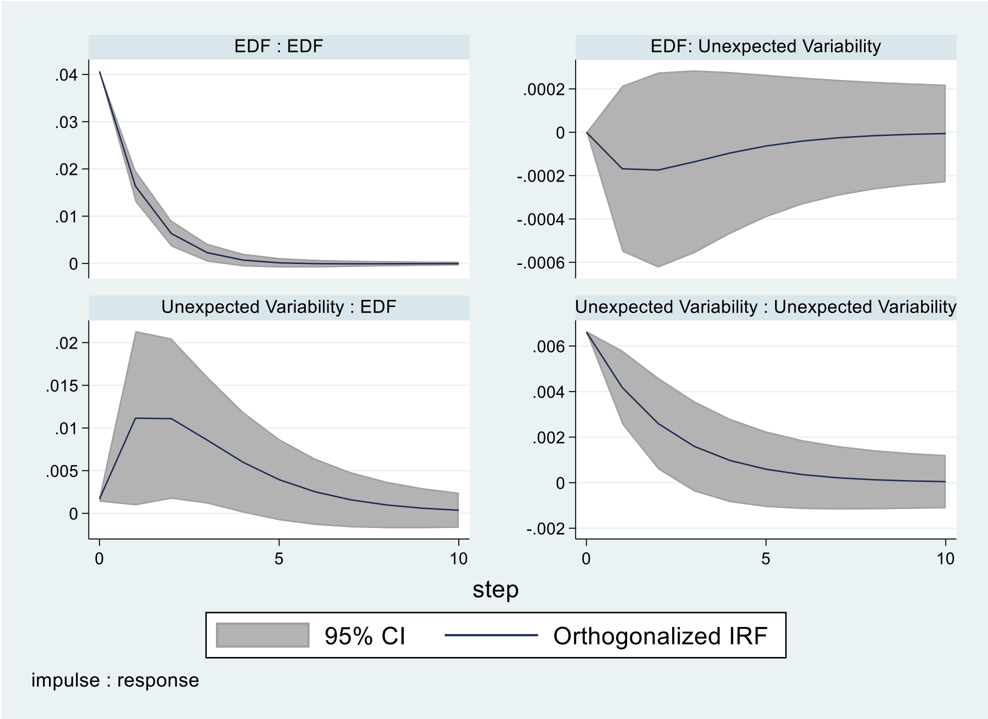
This table shows the outputs of the FEVD test, how much of future variation in each of the endogenous variables (expected default frequency and unexpected interest expense variability) can be explained by exogenous shock to the other variable at each horizon. Outputs are generated based on 200 Monte Carlo draws.

Response variable and forecast horizon		**Impulse variable**	
		Unexpected interest expense variability	Expected default frequency
Unexpected interest expense variability			
	0	0.0000	0.0000
	1	1.0000	0.0000
	2	0.9995	0.0005
	3	0.9991	0.0009
	4	0.9989	0.0011
	5	0.9988	0.0012
	6	0.9987	0.0013
	7	0.9987	0.0013
	8	0.9987	0.0013
	9	0.9987	0.0013
	10	0.9987	0.0013
Expected default frequency			
	0	0.0000	0.0000
	1	0.0017	0.9983
	2	0.0621	0.9379
	3	0.1132	0.8868
	4	0.1415	0.8585
	5	0.1547	0.8453
	6	0.1603	0.8397
	7	0.1626	0.8374
	8	0.1635	0.8365
	9	0.1638	0.8362
	10	0.1639	0.8361

The FEVD results are further supported by the orthogonalized impulse-response function (hereafter IRF) graphs, which present the dynamic behaviour of our model. Based on Figure 4.1, we do not observe a significant impact of expected default frequency on unexpected interest expense variability. As shown by the top right graph of Figure 4.1, the 95% confidence intervals contain the zero line over the 10 periods. When we examine the impact of unexpected interest expense variability on expected default frequency in the bottom left graph of Figure 4.1, current shock on unexpected interest expense variability is found to have a persistent positive impact on future expected default frequency. These results support our previous findings of unexpected interest expense variability Granger-causes expected default frequency, but not vice versa and further prove that the relationship between these two variables to be unidirectional as stated by *Hypothesis 4.2*: unexpected interest expense variability drives firm default risk.

Figure 4.1 – Impulse-response functions (IRFs)

Figure 4.1 calculates and graphs the orthogonalized impulse-response functions with 95% confidence intervals. Expected default frequency (EDF) and unexpected interest expense variability are treated as impulse and response variables in turn. Confidence intervals are generated based on 200 Monte Carlo draws.



4.4 Expected Default Frequency Regression Analyses

Table 4.4 from the previous section examines the relationship between expected default frequency and unexpected interest expense variability. The results show that the relationship is unidirectional with current unexpected interest expense variability affecting future expected default frequency. Generally we expect that greater unexpected variability in a firm's interest expenses lead to an increase in the level of uncertainty of its expected future cash outflows, and hence increase its expected default frequency. On the other hand, if a firm has interest expenses that are less variable than expected, the level of uncertainty of cash outflows is reduced, expected default frequency can also be reduced. However, the previous chapter has shown that unexpected interest expense variability (either positive or negative deviation from expected interest expense variability) has adverse effects on firm valuation. The more interest expense variability deviates from its expected level regardless of the direction (which signals suboptimal leverage management), the lower the firm valuation. Such findings also trigger the question: does unexpected interest expense variability represents suboptimal leverage management also lead to excessive financial risk? Alternatively, could the observed positive relationship between unexpected interest expense variability and expected default frequency based on PVAR approach be affected by the positive and negative values of unexpected interest expense variability?

To answer this question, we propose the following model:

$$\begin{aligned}(EDF)_t^j = a &+ b_1 \max\left[0, \left(\left|(int/MVA)_t^j - (int/MVA)_{t-1}^j\right| - \left|\widehat{(int/MVA)_t^j - (int/MVA)_{t-1}^j}\right|\right)\right] + \\ &b_2 \min\left[0, \left(\left|(int/MVA)_t^j - (int/MVA)_{t-1}^j\right| - \left|\widehat{(int/MVA)_t^j - (int/MVA)_{t-1}^j}\right|\right)\right] \\ &+ b_{MVA} LN(MVA_{t-1}^j) + b_{div}(div/MVA)_{t-1}^j \\ &+ b_D (D/MVA)_{t-1}^j + b_{MB}(ME/BE)_{t-1}^j \\ &+ b_{EBIT}(EBIT/MVA)_{t-1}^j \\ &+ (firm\ j\ and\ fiscal\ year\ t\ fixed\ effects) + \varepsilon_t^j\end{aligned} \tag{4.5}$$

where $\left|(int/MVA)_{t+T}^{j} - (int/MVA)_{t}^{j}\right| - \left|\widehat{(int/MVA)_{t+T}^{j} - (int/MVA)_{t}^{j}}\right|$ is unexpected interest expense variability, and the $\max[0,\cdot]$ ($\min[0,\cdot]$) operator obtains the variable if it is positive (negative) and zero otherwise. Control variables such as size, profitability (EBIT/MVA), leverage, dividend and market-to-book equity are also included in the model, but lagged by 1 year to reduce the problem of reverse causality in the expected default frequency.[41]

Our regression results are presented in Table 4.7. In model (1), we regress expected default frequency only on 1-year lagged positive and negative unexpected interest expense variability without including any control variables. We observe a negative significant coefficient for the 1-year lagged negative unexpected interest expense variability, which implies that interest expense variability lower than expected level leads to an increase in firms' future expected default frequencies. Further, a positive significant coefficient is observed for 1-year lagged positive unexpected interest expense variability, which indicates that greater interest expense variability than expected increases firm expected default frequency. In addition, the effects of negative and positive unexpected interest expense variabilities are found to remain statistically significant when we include lagged control variables in the model, as shown in model (2) in Table 4.7. Results shown in models (1) and (2) imply that both positive and negative deviations of interest expense variability from expected are associated with higher expected default frequency. These results are consistent with our conclusion in Chapter 3 that deviation of interest expense variability from expected in either positive or negative direction represents suboptimal leverage management.

[41] Judson and Owen (1999) show that the least squares dummy variable (LSDV) estimator performs better than the GMM estimator when T>= 30 and panel is unbalanced. Hence, we use fixed effects method.

Table 4.7 – Expected default frequency regressions

This table presents the results from expected default frequency panel regressions. Models (1) and (2) present the regression output for expected default frequency on 1-year lagged positive and negative unexpected interest expense variabilities without and with control variables, respectively. We further split the sample into subsamples based on positive and negative unexpected interest expense variability separately. Models (3) and (4) correspond to Eqs. (4.6.1) and (4.6.2). Model (3) presents the relationship between 1-year lagged POSITIVE unexpected interest expense variability and expected default frequency. Model (4) presents the relationship between 1-year lagged NEGATIVE unexpected interest expense variability and expected default frequency. Firm and year fixed effects are included in all four models. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

VARIABLES	(1) EDF	(2) EDF	(3) EDF	(4) EDF
1-year Lagged (Unexpected Interest Expense Variability*NEGATIVE)	-2.1876***	-0.5509***		
	(-17.789)	(-4.654)		
1-year Lagged (Unexpected Interest Expense Variability*POSITIVE)	1.6547***	1.1424***		
	(23.105)	(16.603)		
1-year Lagged POSITIVE Unexpected Interest Expense Variability			1.1432***	
			(12.466)	
1-year Lagged NEGATIVE Unexpected Interest Expense Variability				-0.6700***
				(-4.553)
1-year lagged Size		0.0034***	0.0082***	0.0009**
		(9.709)	(9.323)	(2.332)
1-year lagged EBIT/MVA		-0.0774***	-0.1369***	-0.0519***
		(-21.162)	(-13.847)	(-13.716)
1-year lagged Leverage		0.1494***	0.1450***	0.1480***
		(50.906)	(26.307)	(40.411)
1-year lagged Dividend/MVA		0.0045	0.1583**	-0.0682**
		(0.159)	(2.075)	(-2.405)
1-year lagged M/B		-0.0006***	-0.0011***	-0.0003***
		(-8.921)	(-5.414)	(-4.782)
Constant	0.0125***	-0.0257***	-0.0467***	-0.0145***
	(30.879)	(-12.181)	(-9.003)	(-6.341)
Observations	80,022	80,022	22,625	54,691
R-squared	0.446	0.502	0.532	0.549
Adjusted R-squared	0.377	0.440	0.391	0.478
F-statistic	316.5	564.7	209.8	368.9

To further test if this result is affected by the inclusion of both positive and negative unexpected interest expense variabilities in the regression model, we split the full sample into subsamples of firms with only negative unexpected interest expense variabilities and firms with only positive unexpected interest expense variabilities. The following regression models are estimated:

$$\begin{aligned}(EDF)_t^j = a &+ b_1 \max\left[0, \left(\left|(int/MVA)_t^j - (int/MVA)_{t-1}^j\right| - \left|\widehat{(int/MVA)_t^j - (int/MVA)_{t-1}^j}\right|\right)\right] \\ &+ b_{MVA} LN(MVA_{t-1}^j) + b_{div}(div/MVA)_{t-1}^j \\ &+ b_D(D/MVA)_{t-1}^j + b_{MB}(ME/BE)_{t-1}^j \\ &+ b_{EBIT}(EBIT/MVA)_{t-1}^j \\ &+ (firm\ j\ and\ fiscal\ year\ t\ fixed\ effects) + \varepsilon_t^j\end{aligned} \tag{4.6.1}$$

$$\begin{aligned}(EDF)_t^j = a &+ b_2 \min\left[0, \left(\left|(int/MVA)_t^j - (int/MVA)_{t-1}^j\right| - \left|\widehat{(int/MVA)_t^j - (int/MVA)_{t-1}^j}\right|\right)\right] \\ &+ b_{MVA} LN(MVA_{t-1}^j) + b_{div}(div/MVA)_{t-1}^j \\ &+ b_D(D/MVA)_{t-1}^j + b_{MB}(ME/BE)_{t-1}^j \\ &+ b_{EBIT}(EBIT/MVA)_{t-1}^j \\ &+ (firm\ j\ and\ fiscal\ year\ t\ fixed\ effects) + \varepsilon_t^j\end{aligned} \tag{4.6.2}$$

Eqs. (4.6.1) and (4.6.2) are regressed for positive and negative unexpected interest expense variabilities separately and the results are presented in models (3) and (4) of Table 4.7, respectively. We also have checked for potential multicollinearity problems in the regression models based on the variance inflation factor (VIF) test with results presented in Table 4.8. As a rule of thumb, VIF greater than 10 indicates multicollinearity. A more conservative threshold of 3.3 is used by Kock and Lynn (2012). We do not find any VIF greater than 10 for models (3) and (4). In addition, the mean of all VIFs in each model is not considerably larger than 1. Hence, we can conclude that there is no evidence of multicollinearity in our models.

Table 4.8 – Variance inflation factor (VIF) tests

This table presents the VIF values for regressors in Eqs. (4.6.1) and (4.6.2). Since we are splitting the sample into subsamples based on positive and negative unexpected interest expense variability, VIF values are reported for each subsample. According to Table 4.7, model (3) shows the relationship between 1-year lagged POSITIVE unexpected interest expense variability and expected default frequency. Model (4) presents the relationship between 1-year lagged NEGATIVE unexpected interest expense variability and expected default frequency. If one of the regressors in each model has VIF greater than 10, there is evidence of multicollinearity in the regression model.

Variables	VIF for Model (3)	1/VIF for Model (3)	VIF for Model (4)	1/VIF for Model (4)
$Unexpected\ int\ /MVA\ variability$	1.28	0.7789	1.53	0.6529
LN(MVA_{t-1}^{j})	1.21	0.8253	1.42	0.7046
$(EBIT/MVA)_{t-1}^{j}$	1.19	0.8415	1.33	0.7537
$(div/MVA)_{t-1}^{j}$	1.16	0.8632	1.20	0.8363
$(D/MVA)_{t-1}^{j}$	1.14	0.8776	1.13	0.8873
$(ME/BE)_{t-1}^{j}$	1.11	0.8994	1.11	0.8993
Mean VIF	1.18		1.29	

Similar to the results shown by models (1) and (2), we find that positive unexpected interest expense variability (i.e. greater variability than expected) leads to higher expected default frequency. A negative relationship is documented for negative unexpected interest expense variability suggesting that less variability than expected also leads to higher expected default frequency.

4.5 Firm Valuation and Structural Equation Modelling (SEM)

Results from section 4.4 show that lagged unexpected interest expense variability has a significant effect on expected default frequency. Firms with positive unexpected interest expense variability and firms with negative unexpected interest expense variability will have higher expected default frequency in the future. In the previous chapter, we have found that both positive and negative unexpected interest expense variabilities lead to reduced firm valuation. These results motivate us to consider the question: could the negative relationship between unexpected interest expense variability and firm valuation be channelled through the expected default frequency? In other words, we are more interested in investigating whether expected default frequency can act as a key channel (or mediator) to transmit the impact of unexpected interest expense variability onto firms' values. In this section, we examine the degree of significance in the mediating role of expected default frequency. That is, how much of the effect of unexpected interest expense variability on firms' future market-to-book ratio can be captured by expected default frequency.[42]

We adopt structural equation modelling (SEM) approach to test the mediation effect of expected default frequency. We hypothesize that the observed relationship of unexpected variability in interest expenses decreases firms' future valuation (Chapter 3, p.85) is influenced by the mediator expected default frequency. Since both positive and negative unexpected interest

[42] Following Chapter 3, we continue using the ratio of market value of assets to book value of assets as a proxy for firm valuation.

expense variabilities reduce firm valuation, we should focus on the magnitude of unexpected interest expense variability (i.e. how much deviation from expected), rather than its direction. Hence, we take the absolute value of unexpected interest expense variability. The paths of these relationships between the variables are shown by the framework in Figure 4.2.

We decompose the relationships between the 1-year lagged unexpected interest expense variability (absolute value), current expected default frequency and firms' future market-to-book ratio. The effect of lagged unexpected interest expense variability on future market-to-book ratio can be classified into three categories: total effect, direct effect and indirect effect. We apply the bootstrapping method to obtain these effects and their statistical significances. The number of bootstrap replications is decided based on the total number of observations we have for the structural model. Initially, we have 71,559 observations, and we use 3,500 replications, which is close to 5% of the number of observations. The SEM approach is conducted twice, and all effects without the control variables are presented in models (1), effects obtained after including the control variables are shown in model (2) of Table 4.9. The strength of the unexpected interest expense variability, expected default frequency and future market-to-book ratios in each path with and without the inclusion of lagged control variables are presented in Figure 4.3 and Figure 4.4, respectively.

Figure 4.2 – SEM framework

This figure shows the framework and the paths of relationships among variables.

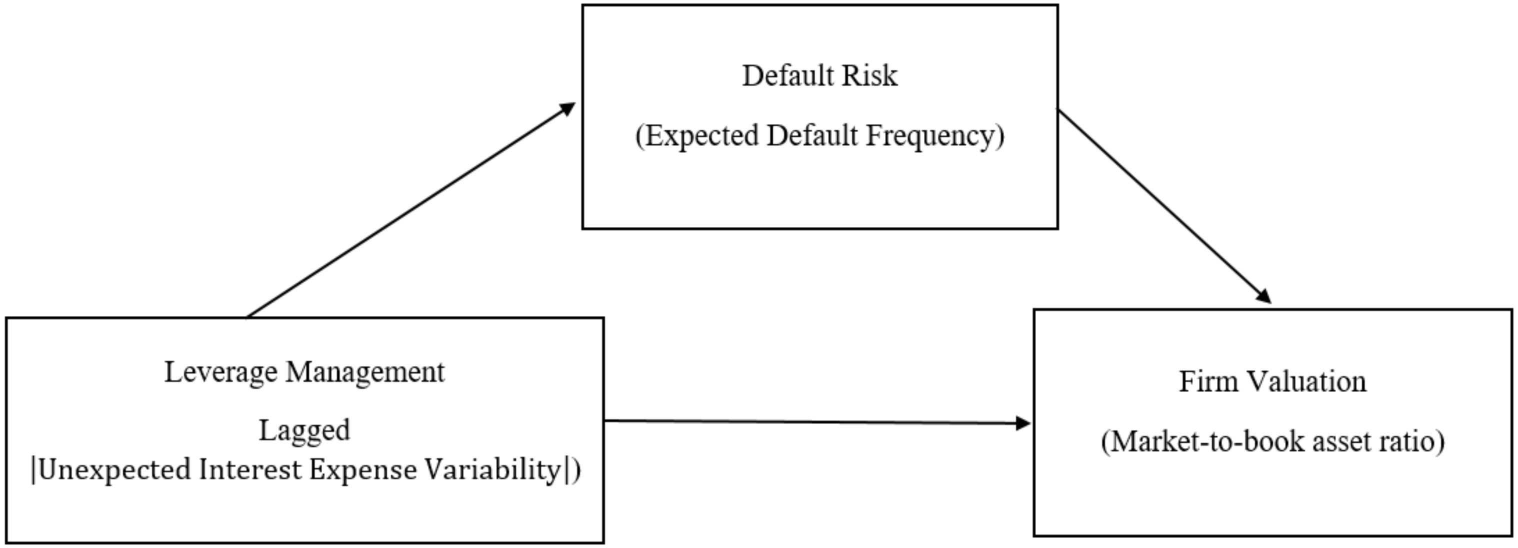


Table 4.9 – SEM decomposition of path effects

This tables presents SEM results and effects decomposition. Bootstrapping method is used to obtain the direct, indirect and total effects with 3,500 replications. In model (1), we examine the role of expected default frequency (EDF) as a mediator by decomposing the direct, indirect and total effects of unexpected interest expense variability (which is in its absolute value) on firms' future market-to-book ratios (M/B). We compute three ratios: direct to total effects, indirect to total effects and indirect to direct effects. Our main focus is on indirect to direct effects ratio, which will show us the percentage of total effects that is mediated by expected default frequency. In model (2), we also add the lagged control variables which are used in previous regressions, and repeat the same steps to compute the percentage of total effects mediated by expected default frequency. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

SEM mediation analysis						
Path	Model (1) Direct effects	Model (1) Indirect effects	Model (1) Total effects	Model (2) Direct effects	Model (2) Indirect effects	Model (2) Total effects
Lagged Unexpected Variability –> EDF	2.7375***	–	2.7375***	2.7375***	–	2.7375***
	(73.54)		(73.54)	(73.54)		(73.54)
EDF –> future M/B	-2.9250***	–	-2.9250***	-0.4578***	–	-0.4578***
	(-33.23)		(-33.23)	(-5.64)		(-5.64)
Lagged Unexpected Variability –> EDF –> future M/B	-13.3098***	-8.0072***	-21.3170***	-9.6278***	-1.2532***	-10.8810***
	(-12.90)	(-33.42)	(-20.29)	(-10.47)	(-8.32)	(-12.08)
Number of observations	3,500	3,500	3,500	3,500	3,500	3,500

Figure 4.3 – SEM without control variables

This figure presents the path coefficients with their degrees of significant when control variables are not included in the model. ***, **, * indicate significance at 1%, 5% and 10% levels, respectively.

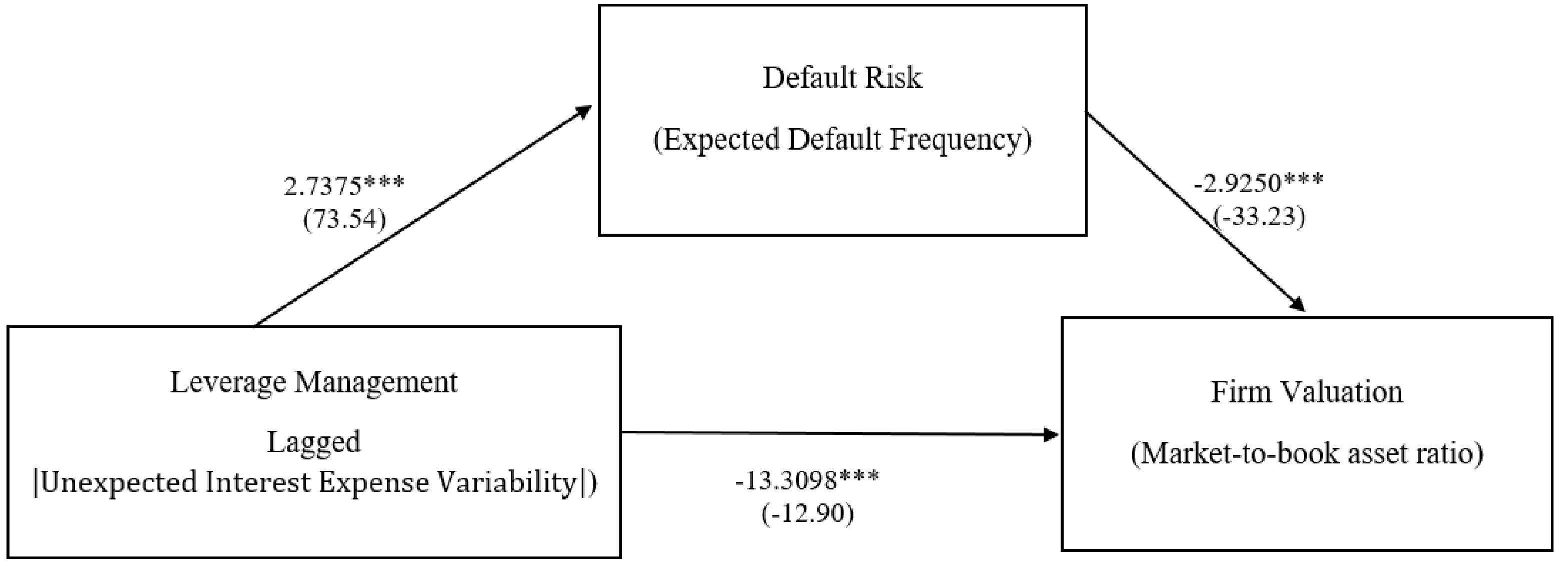
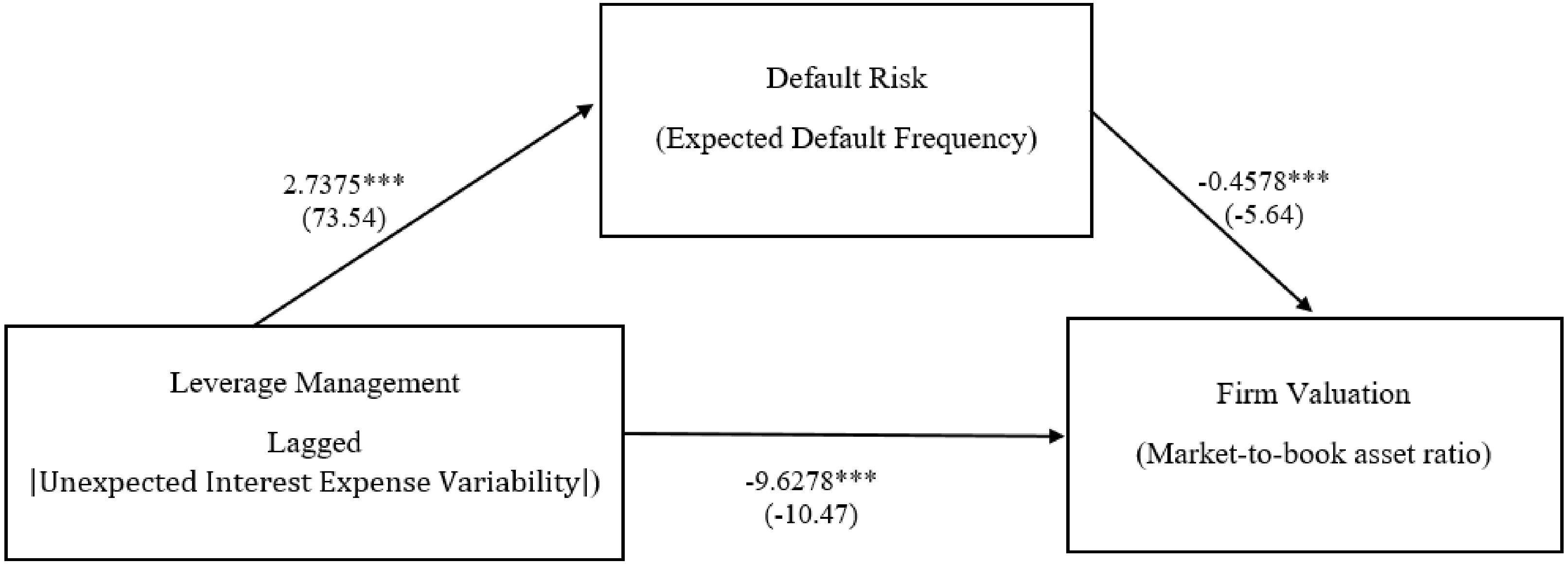


Figure 4.4 – SEM with control variables

This figure presents the path coefficients with their degrees of significant when control variables are included in the model. ***, **, * indicate significance at 1%, 5% and 10% levels, respectively.



Based on Table 4.9, a positive significant coefficient is observed for the path of Lagged Unexpected Variability –> EDF for both models (1) and (2). This shows that any deviations of interest expense variability from the expected level (with unexpected interest expense variability in its absolute value) will lead to higher expected default frequency. A negative coefficient is reported for the path of EDF –> future M/B, which shows that higher expected default frequency leads to reduced firm valuation. To examine whether the relationship between lagged unexpected interest expense variability and firms' future market-to-book ratios is mediated by the expected default frequency, we focus on the path of Lagged Unexpected Variability –> EDF –> future M/B. According to Model (1) in Table 4.9 (depicted in Figure 4.3), we note that without the mediator EDF, the direct effect of unexpected interest expense variability is -13.3098. The result is statistically significant and the negative sign shows that deviations of interest expense variability from expected regardless of its direction tend to decrease firms' future M/B ratios. The indirect effect of the unexpected interest expense variability, which passes through the mediator expected default frequency is -8.0072. We find that the indirect effect is also statistically significant. Lastly the total effect of unexpected interest expense variability is found to be -21.3170 (and statistically significant).

We also test whether the indirect effect of expected default frequency on future market-to-book ratio remains statistically significant when other control variables are added into the model, such as firm size, profitability, leverage, market-to-book equity and dividend. To reduce the endogeneity issue between expected default frequency and the control variables, we lag all control variables by 1 periods, which is same lag length as the unexpected interest expense variability variable.

According to Model (2) in Table 4.9 (depicted in Figure 4.4), we find that the direct effect of the unexpected interest expense variability is -10.8810. Similar to Model (1), the direct effect is statistically significant. We find that indirect effect of unexpected interest expense variability is -1.2532. Although the indirect effect is much smaller than the direct effect when compared to

Model (1), the model without control variables, it is still statistically significant. Lastly, the total effect is found to be -9.6278.[43]

To further examine the mediating role of expected default frequency, we compute the ratios of direct to total effect, indirect to total effect, and the ratio of indirect effect to direct effect. The ratio of indirect to total effects, which is known as the percentage of variance accounted for (VAF) indicates whether there is mediation effect of expected default frequency in our structural model. The results are presented in Table 4.10 along with the lower and upper bounds of these estimates (for 95% confidence interval) which were obtained based on 3,500 bootstrap replications.

Based on Model (1) in Table 4.10, we find that the direct effect of unexpected interest expense variability is about 62% of the total effect if we do not include any control variables in the structural model. The indirect effect of unexpected interest expense variability is about 38% of the total effect, which implies that 38% of the negative effect of unexpected interest expense variability on firms' future M/B ratios passes through their expected default frequencies.

For Model (2) of Table 4.10, we find that the direct effect contributes up to 88% of the size of total effect if control variables are included. However, the indirect effect after adding control variables is now only about 12% of the size of the total effect. A possible reason for this decrease in VAF might be that the role of expected default frequency has been diluted by the control variables in the model, which could also be the determinants of expected default frequency.

[43] SEM has also been performed without ME/BE in model (2) of Table 4.10 as the dependent variable is future M/B ratio. The path effects are similar to previous results when ME/BE was included in the model (in terms of statistical significance).

Table 4.10 – SEM ratio analyses

This tables presents the direct-to-total, indirect-to-total (known as VAF) and indirect-to-direct ratios, along with the normal-based 95% confidence intervals. Bootstrapping method is used to obtain the confidence intervals with 3,500 replications. Model (1) excludes control variables in the structural model, whereas model (2) includes control variables.

SEM mediation analysis						
Ratios	Model (1) Ratio estimate	Model (1) Lower bound	Model (1) Upper bound	Model (2) Ratio estimate	Model (2) Lower bound	Model (2) Upper bound
Direct-to-total	0.6242	0.6236	0.6249	0.8842	0.8837	0.8848
Indirect-to-total (VAF)	0.3758	0.3752	0.3764	0.1158	0.1152	0.1163
Indirect-to-direct	0.6020	0.6004	0.6040	0.1309	0.1302	0.1316
Number of observations	3,500	3,500	3,500	3,500	3,500	3,500

To examine the significance of the mediating role of expected default frequency, we adopt two approaches. First, according to Hair Jr, Hult, Ringle, and Sarstedt, (2016), a VAF less than 20% indicates no mediation in the model, a VAF lies between 20% and 80% indicates partial mediation and a VAF greater than 80% indicates full mediation. We find that a partial mediation of expected default frequency only exists when there are no control variables included in the model. However, if control variables are added into the structural model, expected default frequency is found to have no mediation.

Our second approach is to conduct a statistical test of significance of VAF. We propose the following null and alternative hypotheses. To test whether the direct-to-total effect and VAF are significant, we test whether these two ratios are significantly different from zero, as shown by the first two hypotheses. The last two hypotheses are proposed to test whether the size of indirect effect equals the size of direct effect.

Tests for direct-to-total effect and VAF

H_0 : Direct-to-total / VAF = 0

H_1 : Direct-to-total / VAF $\neq$ 0

Tests for indirect-to-direct effect

H_0 : Indirect-to-direct = 1

H_1 : Indirect-to-direct $\neq$ 1

In Table 4.10, we find that the 95% lower and upper bounds of all of the VAFs reported do not contain zero. This indicates that the VAFs are significantly different from zero and the null hypotheses can be rejected in all the instances we report. Hence, we can conclude that there is a significant mediating effect of expected default frequency on the negative relationship between unexpected interest expense variability and firm's future valuation. For Model 1, we find that the indirect effect is about 65% of the size of direct effect. The confidence intervals for this estimate do not include 1, hence we can reject the hypothesis that these two effects are equal. Conversely, for Model 2, the indirect effect is only around 7% of the direct effect, suggesting that the inclusion of additional variables leads to the conclusion that the direct effect has the greatest effect on future M/B ratios. Again, the ratio does not include 1 indicating that the difference is statistically significantly.

4.6 Conclusion

This study investigates the inter-relationship between firm risk and firm leverage management decision changes. We use expected default frequency as a measure of firm risk and unexpected interest expense variability as an indicator of leverage management. We first examine the direction of the relationship between firm risk and leverage management decisions.

Based on the PVAR approach, we find that the relationship is unidirectional with current unexpected interest expense variabilities positively affecting firms' future expected default frequencies. This result implies that firms with more variable interest expense (greater variability than expected) tend to have higher future expected default frequencies. On the other hand, firms with less variable interest expenses (which imply that their interest expenses have been actively managed over time) tend to have lower expected default frequencies in the future.

However, by splitting firms into groups based on their positive and negative unexpected interest expense variabilities, we find that both positive and negative unexpected interest expense variabilities lead to higher expected default frequencies. These findings concur with our results reported in Chapter 3 of this thesis and show that any deviations of interest expense variability from expected represent suboptimal leverage management. In other words, expected/normal leverage management is broadly optimal.

Finally, we extend Chapter 3 by re-investigating the negative relationship between unexpected interest expense variability and firm valuation. Chapter 3 shows that both positive and negative unexpected interest expense variabilities cause adverse valuation consequences. Based on structural equation modelling, we identify expected default frequency as a key channel to the relationship between unexpected interest expense variability and firm valuation (i.e. future market-to-book ratios). Suboptimal leverage management as indicated by any positive and negative deviations of interest expense variability from expected leads to higher expected default frequency, which in turn reduces firm valuation (i.e. market-to-book ratios) in the future.

5 Conclusion

Motivated by the opposing results presented by Lemmon et al. (2008) and DeAngelo and Roll (2015) on the issue of leverage stability, we demonstrate that their results are driven by the different methodology used in each paper. Deciding the optimal or more valid methodology for future studies to examine leverage stability should be seen as a paramount objective. By testing both methodologies under different stable and unstable simulation scenarios in Chapter 2, we show that DeAngelo and Roll's (2015) methodology is the valid methodology as its results correctly match different simulated data features with acceptable error rates lower than the criteria in all scenarios. However, Lemmon et al.'s (2008) methodology appears to be invalid as its result is found to support leverage stability under unstable scenario and its error rate exceeds the criterion.

We also investigate the question "is leverage actively managed or determined as a budgeting residual?" as one of the arguments raised by DeAngelo and Roll (2015) in Chapter 3. Stability of interest expenses is assessed as an indicator of active leverage management. Based on DeAngelo and Roll's (2015) methodology, we find that there is strong evidence of active leverage management as firms' interest expenses are found to be significantly more stable than their EBIT and dividend out to a horizon of 20 years. In addition, we also show that active leverage management is correlated with firm characteristics. Firms that follow trade-off theory such as large and high-dividend firms consider active leverage management and interest expense stability as a first priority. Leverage is determined as a budgeting residual in firms follow pecking-order theory for instance low-levered firms and interest expense stability is of second-order importance when it is compared to dividend stability.

We further investigate whether there are any valuation implications for leverage management through examining the relationship between firms' *unexpected* interest expense variability (deviation of actual interest expense variability from its expected level) and firm valuation. Results show that both positive and negative *unexpected* interest expense variabilities lead to decreased firm valuation. Such results show that optimal leverage management should be considered as having minimal deviation of interest expense variability from expected.

In Chapter 4, we further show that firms maintaining too stable interest expenses with negative *unexpected* interest expense variability and firms experiencing unstable interest expenses with positive *unexpected* interest expense variability face increased default risks. In addition, the relationship between *unexpected* interest expense variability and firm valuation is mediated by firms' default risks. Deviation in interest expense variability from expected level in either positive or negative direction leads to increased default risks, which in turn reduce firm valuation. The results reported in Chapter 3 and Chapter 4 prove that optimal leverage management is not equivalent to interest expense stability (lower variability than expected), but minimal variability from expected level. This aspect can be extended in future research by investigating the causes of less interest expense variability than expected to have increased default risk. In other words, what causes a firm with stable interest expenses and lower variability than its expected level to have higher default risk?

References

Abrigo, M. R., & Love, I. (2016). Estimation of panel vector autoregression in Stata. *The Stata Journal, 16*(3), 778-804.

Andrews, D. W., & Lu, B. (2001). Consistent model and moment selection procedures for GMM estimation with application to dynamic panel data models. *Journal of Econometrics, 101*(1), 123-164.

Brav, A., Graham, J. R., Harvey, C. R., & Michaely, R. (2005). Payout policy in the 21st century. *Journal of Financial Economics, 77*(3), 483-527.

Brogaard, J., Li, D., & Xia, Y. (2017). Stock liquidity and default risk. *Journal of Financial Economics, 124*(3), 486-502.

Brounen, D., De Jong, A., & Koedijk, K. (2006). Capital structure policies in Europe: Survey evidence. *Journal of Banking & Finance, 30*(5), 1409-1442.

Canova, F., & Ciccarelli, M. (2013). Panel vector autoregressive models: A survey. *Var models in macroeconomics–new developments and applications: Essays in honor of Christopher A. Sims*, 205-246.

Chang, X., & Dasgupta, S. (2009). Target behavior and financing: how conclusive is the evidence? *The Journal of Finance, 64*(4), 1767-1796.

Chen, Y. (2010). Capital Structure Convergence: Is It Real or Mechanical? *Available at SSRN 1689713*.

Cohen, J. (1988). *Statistical Power Analysis for the Behavioral Sciences (2nd ed.).* Hillsdale, NJ: Lawrence Erlbaum Associates.

Cook, D., Fu, X., & Tang, T. (2016). Are target leverage ratios stable? Investigating the impact of corporate asset restructuring. *Journal of Empirical Finance, 35*, 150-168.

DeAngelo, H., & Masulis, R. (1980). Optimal capital structure under corporate and personal taxation. *Journal of Financial Economics, 8*, 3-29.

DeAngelo, H., & Roll, R. (2015). How stable are corporate capital structures? *The Journal of Finance, 70*(1), 373-418.

Dierker, M., Lee, I., & Seo, S. W. (2019). Risk changes and external financing activities: Tests of the dynamic trade-off theory of capital structure. *Journal of Empirical Finance*, *52*, 178-200.

Doherty, N. (2000). *Integrated risk management: Techniques and strategies for managing corporate risk*: McGraw Hill Professional.

Elsas, R., & Florysiak, D. (2015). Dynamic capital structure adjustment and the impact of fractional dependent variables. *Journal of Financial and Quantitative Analysis*, *50*(5), 1105-1133.

Faff, R. W., Gray, S., & Tan, K. J. K. (2016). A contemporary view of corporate finance theory, empirical evidence and practice. *Australian Journal of Management*, *41*(4), 662-686.

Faff, R., Kwok, W. C., Podolski, E. J., & Wong, G. (2016). Do corporate policies follow a life-cycle? *Journal of Banking & Finance*, *69*, 95-107.

Fama, E., & French, K. (2001). Disappearing dividends: Changing firm characteristics or lower propensity to pay? *Journal of Financial Economics*, *60*(1), 3-43.

Fama, E., & French, K. (2002). Testing trade-off and pecking order predictions about dividends and debt. *Review of Financial Studies*, *15*(1), 1-33.

Fama, E., & French, K. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, *116*(1), 1-22.

Frank, M. Z., & Goyal, V. K. (2007). Corporate leverage: How much do managers really matter? *Available at SSRN 971082*.

González, F. (2016). Creditor rights, bank competition, and corporate investment during the global financial crisis. *Journal of Corporate Finance*, *37*, 249-270.

Graham, J. R., & Harvey, C. R. (2001). The theory and practice of corporate finance: Evidence from the field. *Journal of Financial Economics*, *60*(2), 187-243.

Graham, J. R., & Leary, M. T. (2011). A review of empirical capital structure research and directions for the future. *Annual Review Financial Economics*, *3*(1), 309-345.

Granger, C. W. (1969). Investigating causal relations by econometric models and cross-spectral methods. *Econometrica: Journal of the Econometric Society*, 424-438.

Hair Jr, J. F., Hult, G. T. M., Ringle, C., & Sarstedt, M. (2016). *A primer on partial least squares structural equation modeling (PLS-SEM)*. 2nd edition, Thousand Oaks: Sage.

Hanousek, J., & Shamshur, A. (2011). A stubborn persistence: Is the stability of leverage ratios determined by the stability of the economy? *Journal of Corporate Finance*, *17*(5), 1360-1376.

Hansen, L. P. (1982). Large sample properties of generalized method of moments estimators. *Econometrica: Journal of the Econometric Society*, 1029-1054.

Huang, R., Tan, K. J. K., & Faff, R. W. (2016). CEO overconfidence and corporate debt maturity. *Journal of Corporate Finance*, *36*, 93-110.

Ippolito, F., Sacchetto, S., & Steri, R. (2019). The Tortoise and the Snail: Reconciling the Evidence on Capital Structure Stability. *Swiss Finance Institute Research Paper*, (17-59).

Ito, A., Mikabe, T., & Noma, M. (2015). The Long-Term Stability of Corporate Capital Structure: Evidence from Japanese Firms. *Available at SSRN 2722890*.

Jensen, M. C. (1986). Agency costs of free cash flow, corporate finance, and takeovers. *The American Economic Review, 76*(2), 323-329.

Jensen, M., & Meckling, W. (1976). Theory of the firm: managerial behavior, agency costs and ownership structure. *Journal of Financial Economics, 3*(4), 305-360.

Jiraporn, P., Chintrakarn, P., & Liu, Y. (2012). Capital structure, CEO dominance, and corporate performance. *Journal of Financial Services Research*, *42*(3), 139-158.

Judson, R. A., & Owen, A. L. (1999). Estimating dynamic panel data models: a guide for macroeconomists. *Economics letters*, *65*(1), 9-15.

Karpavičius, S., & Yu, F. (2019a). External growth opportunities and a firm's financing policy. *International Review of Economics & Finance*, *62*, 287-308.

Karpavičius, S., & Yu, F. (2019b). Managerial risk incentives and a firm’s financing policy. *Journal of Banking & Finance*, *100*, 167-181.

Kock, N., & Lynn, G. (2012). Lateral collinearity and misleading results in variance-based SEM: An illustration and recommendations. *Journal of the Association for Information Systems*, *13*(7).

Kraus, A., & Litzenberger, R. H. (1973). A state-preference model of optimal financial leverage. *The Journal of Finance*, *28*(4), 911-922.

Lambrecht, B. M., & Myers, S. C. (2012). A Lintner model of payout and managerial rents. *The Journal of Finance*, *67*(5), 1761-1810.

Leland, H. E., & Toft, K. B. (1996). Optimal capital structure, endogenous bankruptcy, and the term structure of credit spreads. *The Journal of Finance*, *51*(3), 987-1019.

Lemmon, M. L., Roberts, M. R., & Zender, J. F. (2008). Back to the beginning: persistence and the cross-section of corporate capital structure. *The Journal of Finance*, *63*(4), 1575-1608.

Lintner, J. (1956). Distribution of incomes of corporations among dividends, retained earnings, and taxes. *The American Economic Review*, *46*(2), 97-113.

Lund, R., Liu, G., & Shao, Q. (2016). A new approach to ANOVA methods for autocorrelated data. *The American Statistician*, *70*(1), 55-62.

Miller, M. H. (1977). Debt and taxes. *The Journal of Finance*, *32*(2), 261-275.

Modigliani, F., & Miller, M. H. (1958). The cost of capital, corporation finance and the theory of investment. *The American Economic Review*, *48*(3), 261-297.

Myers, S. C. (1977). Determinants of corporate borrowing. *Journal of Financial Economics*, *5*(2), 147-175.

Myers, S. C. (1984). The capital structure puzzle. *The Journal of Finance*, *39*(3), 574-592.

Myers, S. C., & Majluf, N. S. (1984). Corporate financing and investment decisions when firms have information that investors do not have. *Journal of Financial Economics*, *13*(2), 187-221.

Parsons, C., & Titman, S. (2009). Empirical capital structure: A review. *Foundations and Trends® in Finance*, *3*(1), 1-93.

Riddiough, T. J., & Steiner, E. (2017). Financial Flexibility and Manager-Shareholder Conflict. *Available at SSRN 2975543*.

Skogsvik, S. (2008). Financial statement information, the prediction of book return on owners' equity and market efficiency: the Swedish case. *Journal of Business Finance & Accounting, 35*(7-8), 795-817.

Strebulaev, I. A., & Yang, B. (2013). The mystery of zero-leverage firms. *Journal of Financial Economics*, *109*(1), 1-23.

Appendix A

DR Approach

Eq. (2.1) is a first-order autoregressive lag model and hence we can rewrite this equation as in terms of lag operator:

$$Y_{it} - \phi_3 Y_{it-1} = \phi_0 + \phi_1 X_{it} + \phi_2 \eta_i + \varepsilon_{it}$$

$$(1 - \phi_3 L)\, Y_{it} = \phi_0 + \phi_1 X_{it} + \phi_2 \eta_i + \varepsilon_{it}$$

$$Y_{it} = \frac{\phi_0}{1-\phi_3 L} + \frac{\phi_1 X_{it}}{1-\phi_3 L} + \frac{\phi_2 \eta_i}{1-\phi_3 L} + \frac{\varepsilon_{it}}{1-\phi_3 L} \qquad \text{(A1.1)}$$

Since $\frac{1}{1-\phi_3 L} = 1 + \phi_3 L + {\phi_3}^2 L^2 + {\phi_3}^3 L^3 + \cdots, with\ |\phi_3|$ <1 or $|L|$ >1,

Eq. (A1.1) can also be written in an infinite form as[44]:

$$Y_{it} = \frac{\phi_0}{1-\phi_3} + \phi_1 \sum_{j=0}^{\infty} {\phi_3}^j X_{it-j} + \frac{\phi_2 \eta_i}{1-\phi_3} + \sum_{j=0}^{\infty} {\phi_3}^j \varepsilon_{it-j} \qquad \text{(A1.2)}$$

Based on Eq. (A1.2), we can derive models for different lags. For example,

$$Y_{it-1} = \frac{\phi_0}{1-\phi_3} + \phi_1 \sum_{j=1}^{\infty} {\phi_3}^j X_{it-j} + \frac{\phi_2 \eta_i}{1-\phi_3} + \sum_{j=1}^{\infty} {\phi_3}^j \varepsilon_{it-j} \qquad \text{(A1.3)}$$

$$Y_{it-2} = \frac{\phi_0}{1-\phi_3} + \phi_1 \sum_{j=2}^{\infty} {\phi_3}^j X_{it-j} + \frac{\phi_2 \eta_i}{1-\phi_3} + \sum_{j=2}^{\infty} {\phi_3}^j \varepsilon_{it-j} \qquad \text{(A1.4)}$$

$$Y_{it-3} = \frac{\phi_0}{1-\phi_3} + \phi_1 \sum_{j=3}^{\infty} {\phi_3}^j X_{it-j} + \frac{\phi_2 \eta_i}{1-\phi_3} + \sum_{j=3}^{\infty} {\phi_3}^j \varepsilon_{it-j} \qquad \text{(A1.5)}$$

We proceed the proof by induction. We start off with simple cases and then generalise from these cases an expression that we will use to understand the key measure of DR approach.

[44] Firm fixed effect (η_i) is time-invariant. It differs across firms but remains constant over time for each firm. It is not a function of *j* and hence is treated as a constant.

A.1 Covariance between $\mathbf{Y_{it}}$ and $\mathbf{Y_{it-1}}$

$$Cov\,[Y_{it}, Y_{it-1}] = E\,\{\left(\frac{\phi_0}{1-\phi_3} + \phi_1 \sum_{j=0}^{\infty} {\phi_3}^j X_{it-j} + \frac{\phi_2\eta_i}{1-\phi_3} + \sum_{j=0}^{\infty} {\phi_3}^j \varepsilon_{it-j}\right) \times \left(\frac{\phi_0}{1-\phi_3} + \phi_1 \sum_{j=1}^{\infty} {\phi_3}^j X_{it-j} + \frac{\phi_2\eta_i}{1-\phi_3} + \sum_{j=1}^{\infty} {\phi_3}^j \varepsilon_{it-j}\right)\}$$

We can decompose $\phi_1 \sum_{j=0}^{\infty} {\phi_3}^j X_{it-j}$ into two parts: $\phi_1 \sum_{j=0}^{\infty} {\phi_3}^j X_{it-j} = \phi_1 \sum_{j=1}^{\infty} {\phi_3}^j X_{it-j} + \phi_1 {\phi_3}^0 X_{it}$. Similarly, $\sum_{j=0}^{\infty} {\phi_3}^j \varepsilon_{it-j} = \sum_{j=1}^{\infty} {\phi_3}^j \varepsilon_{it-j} + {\phi_3}^0 \varepsilon_{it}$.

Therefore:

$$\begin{aligned} Cov\,[Y_{it}, Y_{it-1}] = E\,\{ & \left(\frac{\phi_0}{1-\phi_3}\right)^2 + \left(\frac{\phi_0}{1-\phi_3}\right)\left(\phi_1 \sum_{j=1}^{\infty} {\phi_3}^j X_{it-j}\right) + \\ & \left(\frac{\phi_0}{1-\phi_3}\right)\left(\frac{\phi_2\eta_i}{1-\phi_3}\right) + \left(\frac{\phi_0}{1-\phi_3}\right)\left(\sum_{j=1}^{\infty} {\phi_3}^j \varepsilon_{it-j}\right) + \\ & \left(\phi_1 \sum_{j=1}^{\infty} {\phi_3}^j X_{it-j} + \phi_1 {\phi_3}^0 X_{it}\right)\left(\frac{\phi_0}{1-\phi_3}\right) + \\ & \left(\phi_1 \sum_{j=1}^{\infty} {\phi_3}^j X_{it-j} + \phi_1 {\phi_3}^0 X_{it}\right)\left(\phi_1 \sum_{j=1}^{\infty} {\phi_3}^j X_{it-j}\right) + \\ & \left(\phi_1 \sum_{j=1}^{\infty} {\phi_3}^j X_{it-j} + \phi_1 {\phi_3}^0 X_{it}\right)\left(\frac{\phi_2\eta_i}{1-\phi_3}\right) + \\ & \left(\phi_1 \sum_{j=1}^{\infty} {\phi_3}^j X_{it-j} + \phi_1 {\phi_3}^0 X_{it}\right)\left(\sum_{j=1}^{\infty} {\phi_3}^j \varepsilon_{it-j}\right) + \\ & \left(\frac{\phi_2\eta_i}{1-\phi_3}\right)\left(\frac{\phi_0}{1-\phi_3}\right) + \left(\frac{\phi_2\eta_i}{1-\phi_3}\right)\left(\phi_1 \sum_{j=1}^{\infty} {\phi_3}^j X_{it-j}\right) + \left(\frac{\phi_2\eta_i}{1-\phi_3}\right)^2 + \\ & \left(\frac{\phi_2\eta_i}{1-\phi_3}\right)\left(\sum_{j=1}^{\infty} {\phi_3}^j \varepsilon_{it-j}\right) + \left(\sum_{j=1}^{\infty} {\phi_3}^j \varepsilon_{it-j} + {\phi_3}^0 \varepsilon_{it}\right)\left(\frac{\phi_0}{1-\phi_3}\right) + \\ & \left(\sum_{j=1}^{\infty} {\phi_3}^j \varepsilon_{it-j} + {\phi_3}^0 \varepsilon_{it}\right)\left(\phi_1 \sum_{j=1}^{\infty} {\phi_3}^j X_{it-j}\right) + \\ & \left(\sum_{j=1}^{\infty} {\phi_3}^j \varepsilon_{it-j} + {\phi_3}^0 \varepsilon_{it}\right)\left(\frac{\phi_2\eta_i}{1-\phi_3}\right) + \\ & \left(\sum_{j=1}^{\infty} {\phi_3}^j \varepsilon_{it-j} + {\phi_3}^0 \varepsilon_{it}\right)\left(\sum_{j=1}^{\infty} {\phi_3}^j \varepsilon_{it-j}\right)\} \end{aligned}$$

We assume all variables to be independent of each other and let error term ε_{it} be white noise:

$E(X_{it-j}\eta_i) = 0$ for all t and j;

$E(X_{it-j}\varepsilon_{it-j}) = 0$ for all t and j;

$E(\eta_i \varepsilon_{it-j})$ = 0 for all t and j;

$E(\varepsilon_{it-j})$ = 0 for all t and j; and

$E(\varepsilon_{it}\varepsilon_{it-j})$ = 0 for all t and j and with j ≠ 0 (A1.6)

In addition, we also assume the following:

$E(X_{it}) = E(X_{it-1}) = E(X_{it-2}) = \ldots = E(X_{it-j})$

$E(X_{it}X_{it-1}) = E(X_{it}X_{it-3}) = E(X_{it}X_{it-2}) = \ldots = E(X_{it}X_{it-j})$

$E(X_{it})^2 = E(X_{it-1})^2 = E(X_{it-2})^2 = \ldots = E(X_{it-j})^2$

$E(\varepsilon_{it}) = E(\varepsilon_{it-1}) = E(\varepsilon_{it-2}) = \ldots = E(\varepsilon_{it-j})$

$E(\varepsilon_{it})^2 = E(\varepsilon_{it-1})^2 = E(\varepsilon_{it-2})^2 = \ldots = E(\varepsilon_{it-j})^2$ (A1.7)

$$\begin{aligned}
Cov\,[Y_{it}, Y_{it-1}] = E\Big\{ &\left(\frac{\phi_0}{1-\phi_3}\right)^2 + 2\left(\frac{\phi_0}{1-\phi_3}\right)\left(\phi_1 \textstyle\sum_{j=1}^{\infty} \phi_3{}^j X_{it-j}\right) + \\
&2\left(\frac{\phi_0}{1-\phi_3}\right)\left(\frac{\phi_2\eta_i}{1-\phi_3}\right) + (\phi_1 X_{it})\left(\frac{\phi_0}{1-\phi_3}\right) + \\
&(\phi_1 \textstyle\sum_{j=1}^{\infty} \phi_3{}^j X_{it-j})^2 + (\phi_1 X_{it})\left(\phi_1 \textstyle\sum_{j=1}^{\infty} \phi_3{}^j X_{it-j}\right) + \\
&\left(\frac{\phi_2\eta_i}{1-\phi_3}\right)^2 + \left(\textstyle\sum_{j=1}^{\infty} \phi_3{}^j \varepsilon_{it-j}\right)^2 \Big\} \\
= &\left(\frac{\phi_0}{1-\phi_3}\right)^2 + 2\left(\frac{\phi_0\phi_1}{1-\phi_3}\right) \textstyle\sum_{j=1}^{\infty} \phi_3{}^j E(X_{it-j}) + \\
&2\left(\frac{\phi_0}{1-\phi_3}\right)\left(\frac{\phi_2}{1-\phi_3}\right) E(\eta_i) + \left(\frac{\phi_0\phi_1}{1-\phi_3}\right) E(X_{it}) + \\
&(\phi_1)^2 \textstyle\sum_{j=1}^{\infty} \phi_3{}^j E(X_{it-j})^2 + \\
&(\phi_1)^2 \textstyle\sum_{j=1}^{\infty} \phi_3{}^j\, E(X_{it}X_{it-j}) + \left(\frac{\phi_2}{1-\phi_3}\right)^2 E(\eta_i)^2 + \\
&\textstyle\sum_{j=1}^{\infty} \phi_3{}^j E(\varepsilon_{it-j})^2 \qquad \text{(A1.8)}
\end{aligned}$$

A.2 Covariance between $\mathbf{Y_{it}}$ and $\mathbf{Y_{it-2}}$

$$\begin{aligned}
Cov\,[Y_{it}, Y_{it-2}] = E\{ &\left(\frac{\phi_0}{1-\phi_3} + \phi_1 \textstyle\sum_{j=0}^{\infty} \phi_3{}^j X_{it-j} + \frac{\phi_2\eta_i}{1-\phi_3} + \textstyle\sum_{j=0}^{\infty} \phi_3{}^j \varepsilon_{it-j}\right) \times \\
&\left(\frac{\phi_0}{1-\phi_3} + \phi_1 \textstyle\sum_{j=2}^{\infty} \phi_3{}^j X_{it-j} + \frac{\phi_2\eta_i}{1-\phi_3} + \textstyle\sum_{j=2}^{\infty} \phi_3{}^j \varepsilon_{it-j}\right) \}
\end{aligned}$$

We can decompose $\phi_1 \sum_{j=0}^{\infty} \phi_3{}^j X_{it-j}$ into three parts:

$$\phi_1 \sum_{j=0}^{\infty} {\phi_3}^j X_{it-j} = \phi_1 \sum_{j=2}^{\infty} {\phi_3}^j X_{it-j} + \phi_1 {\phi_3}^0 X_{it} + \phi_1 {\phi_3}^1 X_{it-1}$$

$$= \phi_1 \sum_{j=2}^{\infty} {\phi_3}^j X_{it-j} + \phi_1 X_{it} + \phi_1 \phi_3 X_{it-1}$$

Similarly, $\sum_{j=0}^{\infty} {\phi_3}^j \varepsilon_{it-j} = \sum_{j=2}^{\infty} {\phi_3}^j \varepsilon_{it-j} + \varepsilon_{it} + \phi_3 \varepsilon_{it-1}$.

Therefore:

$$\begin{aligned} Cov\,[Y_{it}, Y_{it-2}] = E\{ & \left(\frac{\phi_0}{1-\phi_3}\right)^2 + \left(\frac{\phi_0}{1-\phi_3}\right)\left(\phi_1 \sum_{j=2}^{\infty} {\phi_3}^j X_{it-j}\right) + \\ & \left(\frac{\phi_0}{1-\phi_3}\right)\left(\frac{\phi_2 \eta_i}{1-\phi_3}\right) + \left(\frac{\phi_0}{1-\phi_3}\right)\left(\sum_{j=2}^{\infty} {\phi_3}^j \varepsilon_{it-j}\right) + \\ & \left(\phi_1 \sum_{j=2}^{\infty} {\phi_3}^j X_{it-j} + \phi_1 X_{it} + \phi_1 \phi_3 X_{it-1}\right)\left(\frac{\phi_0}{1-\phi_3}\right) + \\ & \left(\phi_1 \sum_{j=2}^{\infty} {\phi_3}^j X_{it-j} + \phi_1 X_{it} + \right. \\ & \left. \phi_1 \phi_3 X_{it-1}\right)\left(\phi_1 \sum_{j=2}^{\infty} {\phi_3}^j X_{it-j}\right) + \left(\phi_1 \sum_{j=2}^{\infty} {\phi_3}^j X_{it-j} + \right. \\ & \left. \phi_1 X_{it} + \phi_1 \phi_3 X_{it-1}\right)\left(\frac{\phi_2 \eta_i}{1-\phi_3}\right) + \left(\phi_1 \sum_{j=2}^{\infty} {\phi_3}^j X_{it-j} + \right. \\ & \left. \phi_1 X_{it} + \phi_1 \phi_3 X_{it-1}\right)\left(\sum_{j=2}^{\infty} {\phi_3}^j \varepsilon_{it-j}\right) + \left(\frac{\phi_2 \eta_i}{1-\phi_3}\right)\left(\frac{\phi_0}{1-\phi_3}\right) + \\ & \left(\frac{\phi_2 \eta_i}{1-\phi_3}\right)\left(\phi_1 \sum_{j=2}^{\infty} {\phi_3}^j X_{it-j}\right) + \left(\frac{\phi_2 \eta_i}{1-\phi_3}\right)^2 + \\ & \left(\frac{\phi_2 \eta_i}{1-\phi_3}\right)\left(\sum_{j=2}^{\infty} {\phi_3}^j \varepsilon_{it-j}\right) + \left(\sum_{j=2}^{\infty} {\phi_3}^j \varepsilon_{it-j} + \varepsilon_{it} + \right. \\ & \left. \phi_3 \varepsilon_{it-1}\right)\left(\frac{\phi_0}{1-\phi_3}\right) + \left(\sum_{j=2}^{\infty} {\phi_3}^j \varepsilon_{it-j} + \varepsilon_{it} + \right. \\ & \left. \phi_3 \varepsilon_{it-1}\right)\left(\phi_1 \sum_{j=2}^{\infty} {\phi_3}^j X_{it-j}\right) + \left(\sum_{j=2}^{\infty} {\phi_3}^j \varepsilon_{it-j} + \varepsilon_{it} + \right. \\ & \left. \phi_3 \varepsilon_{it-1}\right)\left(\frac{\phi_2 \eta_i}{1-\phi_3}\right) + \left(\sum_{j=2}^{\infty} {\phi_3}^j \varepsilon_{it-j} + \varepsilon_{it} + \right. \\ & \left. \phi_3 \varepsilon_{it-1}\right)\left(\sum_{j=2}^{\infty} {\phi_3}^j \varepsilon_{it-j}\right) \} \end{aligned}$$

Based on the assumptions in (A1.6) and (A1.7), $Cov\,[Y_{it}, Y_{it-2}]$ can be simplified as:

$$\begin{aligned} Cov\,[Y_{it}, Y_{it-2}] = E\{ & \left(\frac{\phi_0}{1-\phi_3}\right)^2 + 2\left(\frac{\phi_0}{1-\phi_3}\right)\left(\phi_1 \sum_{j=2}^{\infty} {\phi_3}^j X_{it-j}\right) + \\ & 2\left(\frac{\phi_0}{1-\phi_3}\right)\left(\frac{\phi_2 \eta_i}{1-\phi_3}\right) + (\phi_1 X_{it} + \phi_1 \phi_3 X_{it-1})\left(\frac{\phi_0}{1-\phi_3}\right) + \\ & (\phi_1 \sum_{j=2}^{\infty} {\phi_3}^j X_{it-j})^2 + (\phi_1 X_{it} + \\ & \phi_1 \phi_3 X_{it-1})\left(\phi_1 \sum_{j=2}^{\infty} {\phi_3}^j X_{it-j}\right) + \left(\frac{\phi_2 \eta_i}{1-\phi_3}\right)^2 + \\ & \left(\sum_{j=2}^{\infty} {\phi_3}^j \varepsilon_{it-j}\right)^2 \} \end{aligned}$$

$$= \left(\frac{\phi_0}{1-\phi_3}\right)^2 + 2\left(\frac{\phi_0\phi_1}{1-\phi_3}\right)\sum_{j=2}^{\infty}\phi_3{}^{j}E(X_{it-j}) +$$
$$2\left(\frac{\phi_0}{1-\phi_3}\right)\left(\frac{\phi_2}{1-\phi_3}\right)E(\eta_i) + \left(\frac{\phi_0\phi_1}{1-\phi_3}\right)(1+\phi_3)E(X_{it}) +$$
$$(\phi_1)^2\sum_{j=2}^{\infty}\phi_3{}^{j}E(X_{it-j})^2 + (\phi_1)^2(1+$$
$$\phi_3)\sum_{j=2}^{\infty}\phi_3{}^{j}\,E(X_{it}X_{it-j}) + \left(\frac{\phi_2}{1-\phi_3}\right)^2E(\eta_i)^2 +$$
$$\sum_{j=2}^{\infty}\phi_3{}^{j}E(\varepsilon_{it-j})^2 \qquad \text{(A1.9)}$$

A.3 Covariance between $\mathbf{Y_{it}}$ and $\mathbf{Y_{it-3}}$

$$Cov\ [Y_{it}, Y_{it-3}] = E\{\left(\frac{\phi_0}{1-\phi_3} + \phi_1\sum_{j=0}^{\infty}\phi_3{}^{j}X_{it-j} + \frac{\phi_2\eta_i}{1-\phi_3} + \sum_{j=0}^{\infty}\phi_3{}^{j}\varepsilon_{it-j}\right)\times$$
$$\left(\frac{\phi_0}{1-\phi_3} + \phi_1\sum_{j=3}^{\infty}\phi_3{}^{j}X_{it-j} + \frac{\phi_2\eta_i}{1-\phi_3} + \sum_{j=3}^{\infty}\phi_3{}^{j}\varepsilon_{it-j}\right)\}$$

Note that

$$\phi_1\sum_{j=0}^{\infty}\phi_3{}^{j}X_{it-j} = \phi_1\sum_{j=3}^{\infty}\phi_3{}^{j}X_{it-j} + \phi_1\phi_3{}^{0}X_{it} + \phi_1\phi_3{}^{1}X_{it-1} +$$
$$\phi_1\phi_3{}^{2}X_{it-2}$$
$$= \phi_1\sum_{j=3}^{\infty}\phi_3{}^{j}X_{it-j} + \phi_1X_{it} + \phi_1\phi_3X_{it-1} +$$
$$\phi_1\phi_3{}^{2}X_{it-2}$$

Similarly, $\sum_{j=0}^{\infty}\phi_3{}^{j}\varepsilon_{it-j} = \sum_{j=3}^{\infty}\phi_3{}^{j}\varepsilon_{it-j} + \varepsilon_{it} + \phi_3\varepsilon_{it-1} + \phi_3{}^{2}\varepsilon_{it-2}$.

Therefore:

$$Cov\ [Y_{it}, Y_{it-3}] = E\{\left(\frac{\phi_0}{1-\phi_3}\right)^2 + \left(\frac{\phi_0}{1-\phi_3}\right)\left(\phi_1\sum_{j=3}^{\infty}\phi_3{}^{j}X_{it-j}\right) +$$
$$\left(\frac{\phi_0}{1-\phi_3}\right)\left(\frac{\phi_2\eta_i}{1-\phi_3}\right) + \left(\frac{\phi_0}{1-\phi_3}\right)\left(\sum_{j=3}^{\infty}\phi_3{}^{j}\varepsilon_{it-j}\right) +$$
$$\left(\phi_1\sum_{j=3}^{\infty}\phi_3{}^{j}X_{it-j} + \phi_1X_{it} + \phi_1\phi_3X_{it-1} +\right.$$
$$\left.\phi_1\phi_3{}^{2}X_{it-2}\right)\left(\frac{\phi_0}{1-\phi_3}\right) + \left(\phi_1\sum_{j=3}^{\infty}\phi_3{}^{j}X_{it-j} + \phi_1X_{it} +\right.$$
$$\left.\phi_1\phi_3X_{it-1} + \phi_1\phi_3{}^{2}X_{it-2}\right)\left(\phi_1\sum_{j=3}^{\infty}\phi_3{}^{j}X_{it-j}\right) +$$
$$\left(\phi_1\sum_{j=3}^{\infty}\phi_3{}^{j}X_{it-j} + \phi_1X_{it} + \phi_1\phi_3X_{it-1} +\right.$$
$$\left.\phi_1\phi_3{}^{2}X_{it-2}\right)\left(\frac{\phi_2\eta_i}{1-\phi_3}\right) + \left(\phi_1\sum_{j=3}^{\infty}\phi_3{}^{j}X_{it-j} + \phi_1X_{it} +\right.$$
$$\left.\phi_1\phi_3X_{it-1} + \phi_1\phi_3{}^{2}X_{it-2}\right)\left(\sum_{j=3}^{\infty}\phi_3{}^{j}\varepsilon_{it-j}\right) +$$
$$\left(\frac{\phi_2\eta_i}{1-\phi_3}\right)\left(\frac{\phi_0}{1-\phi_3}\right) + \left(\frac{\phi_2\eta_i}{1-\phi_3}\right)\left(\phi_1\sum_{j=3}^{\infty}\phi_3{}^{j}X_{it-j}\right) + \left(\frac{\phi_2\eta_i}{1-\phi_3}\right)^2 +$$

$\left(\frac{\phi_2\eta_i}{1-\phi_3}\right)\left(\sum_{j=3}^{\infty}\phi_3{}^j\varepsilon_{it-j}\right)+\left(\sum_{j=3}^{\infty}\phi_3{}^j\varepsilon_{it-j}\ +\varepsilon_{it}+\right.$

$\left.\phi_3\varepsilon_{it-1}+\phi_3{}^2\varepsilon_{it-2}\right)\left(\frac{\phi_0}{1-\phi_3}\right)+\left(\sum_{j=3}^{\infty}\phi_3{}^j\varepsilon_{it-j}\ +\varepsilon_{it}+\right.$

$\left.\phi_3\varepsilon_{it-1}+\phi_3{}^2\varepsilon_{it-2}\right)\left(\phi_1\sum_{j=3}^{\infty}\phi_3{}^jX_{it-j}\right)+$

$\left(\sum_{j=3}^{\infty}\phi_3{}^j\varepsilon_{it-j}\ +\varepsilon_{it}+\ \phi_3\varepsilon_{it-1}+\phi_3{}^2\varepsilon_{it-2}\right)\left(\frac{\phi_2\eta_i}{1-\phi_3}\right)+$

$(\sum_{j=3}^{\infty}\phi_3{}^j\varepsilon_{it-j}\ +\varepsilon_{it}+\ \phi_3\varepsilon_{it-1}+$

$\phi_3{}^2\varepsilon_{it-2})\left(\sum_{j=3}^{\infty}\phi_3{}^j\varepsilon_{it-j}\right)\}$

Based on the assumptions in (A1.6) and (A1.7), $Cov\,[Y_{it},Y_{it-3}]$ can be simplified as:

$Cov\,[Y_{it},Y_{it-3}]=E\{\left(\frac{\phi_0}{1-\phi_3}\right)^2+2\left(\frac{\phi_0}{1-\phi_3}\right)\left(\phi_1\sum_{j=3}^{\infty}\phi_3{}^jX_{it-j}\right)+$

$2\left(\frac{\phi_0}{1-\phi_3}\right)\left(\frac{\phi_2\eta_i}{1-\phi_3}\right)+\left(\phi_1X_{it}+\phi_1\phi_3X_{it-1}+\right.$

$\left.\phi_1\phi_3{}^2X_{it-2}\right)\left(\frac{\phi_0}{1-\phi_3}\right)+(\phi_1\sum_{j=3}^{\infty}\phi_3{}^jX_{it-j})^2+\left(\phi_1X_{it}+\right.$

$\left.\phi_1\phi_3X_{it-1}+\phi_1\phi_3{}^2X_{it-2}\right)\left(\phi_1\sum_{j=3}^{\infty}\phi_3{}^jX_{it-j}\right)+$

$\left(\frac{\phi_2\eta_i}{1-\phi_3}\right)^2+\left(\sum_{j=3}^{\infty}\phi_3{}^j\varepsilon_{it-j}\right)^2\}$

$=\ \left(\frac{\phi_0}{1-\phi_3}\right)^2+2\left(\frac{\phi_0\phi_1}{1-\phi_3}\right)\sum_{j=3}^{\infty}\phi_3{}^jE(X_{it-j})+$

$2\left(\frac{\phi_0}{1-\phi_3}\right)\left(\frac{\phi_2}{1-\phi_3}\right)E(\eta_i)+\left(\frac{\phi_0\phi_1}{1-\phi_3}\right)(1+\phi_3+\phi_3{}^2)E(X_{it})+$

$(\phi_1)^2\sum_{j=3}^{\infty}\phi_3{}^jE(X_{it-j})^2+(\phi_1)^2(1+\phi_3+$

$\phi_3{}^2)\sum_{j=3}^{\infty}\phi_3{}^j\,E(X_{it}X_{it-j})+\ \left(\frac{\phi_2}{1-\phi_3}\right)^2E(\eta_i)^2+$

$\sum_{j=3}^{\infty}\phi_3{}^jE(\varepsilon_{it-j})^2$ (A1.10)

A.4 Difference between $Cov\,[Y_{it},Y_{it-1}]$and $Cov\,[Y_{it},Y_{it-2}]$

$Cov\,[Y_{it},Y_{it-1}]-Cov\,[Y_{it},Y_{it-2}]=\left\{\left(\frac{\phi_0}{1-\phi_3}\right)^2+\right.$

$2\left(\frac{\phi_0\phi_1}{1-\phi_3}\right)\sum_{j=1}^{\infty}\phi_3{}^jE(X_{it-j})+2\left(\frac{\phi_0}{1-\phi_3}\right)\left(\frac{\phi_2}{1-\phi_3}\right)E(\eta_i)+$

$\left.\left(\frac{\phi_0\phi_1}{1-\phi_3}\right)E(X_{it}\right)+(\phi_1)^2\sum_{j=1}^{\infty}\phi_3{}^jE\left(X_{it-j}\right)^2+$

$(\phi_1)^2\sum_{j=1}^{\infty}\phi_3{}^j\,E(X_{it}X_{it-j})+\ \left(\frac{\phi_2}{1-\phi_3}\right)^2E(\eta_i)^2+$

$$\sum_{j=1}^{\infty} {\phi_3}^j E\left(\varepsilon_{it-j}\right)^2 \} - \{ \left(\frac{\phi_0}{1-\phi_3}\right)^2 +$$

$$2\left(\frac{\phi_0\phi_1}{1-\phi_3}\right)\sum_{j=2}^{\infty} {\phi_3}^j E(X_{it-j}) + 2\left(\frac{\phi_0}{1-\phi_3}\right)\left(\frac{\phi_2}{1-\phi_3}\right)E(\eta_i) +$$

$$\left(\frac{\phi_0\phi_1}{1-\phi_3}\right)(1+\phi_3)E(X_{it}) + (\phi_1)^2 \sum_{j=2}^{\infty} {\phi_3}^j E\left(X_{it-j}\right)^2 +$$

$$(\phi_1)^2(1+\phi_3)\sum_{j=2}^{\infty} {\phi_3}^j E(X_{it}X_{it-j}) + \left(\frac{\phi_2}{1-\phi_3}\right)^2 E(\eta_i)^2 +$$

$$\sum_{j=2}^{\infty} {\phi_3}^j E(\varepsilon_{it-j})^2 \}$$

Following the assumptions in (A1.7), the above equation can be simplified as

$$Cov\,[Y_{it}, Y_{it-1}] - Cov\,[Y_{it}, Y_{it-2}] = \left(\frac{\phi_0\phi_1}{1-\phi_3}\right)\phi_3 E(X_{it}) +$$

$$(\phi_1)^2\phi_3 E(X_{it-1})^2 + (\phi_1)^2\phi_3 E(X_{it}X_{it-1}) -$$

$$(\phi_1)^2(\phi_3)\sum_{j=2}^{\infty} {\phi_3}^j E(X_{it}X_{it-j}) + \phi_3 E(\varepsilon_{it-1})^2$$

$$= \left(\frac{\phi_0\phi_1}{1-\phi_3}\right)\phi_3 E(X_{it}) + (\phi_1)^2\phi_3 E(X_{it-j})^2 +$$

$$(\phi_1)^2\phi_3 E(X_{it}X_{it-j}) -$$

$$(\phi_1)^2(\phi_3)\sum_{j=2}^{\infty} {\phi_3}^j E(X_{it}X_{it-j}) + \phi_3 E(\varepsilon_{it})^2 \qquad \text{(A1.11)}$$

A.5 Difference between $\boldsymbol{Cov}\,[\boldsymbol{Y_{it}}, \boldsymbol{Y_{it-1}}]$and $\boldsymbol{Cov}\,[\boldsymbol{Y_{it}}, \boldsymbol{Y_{it-3}}]$

$$Cov\,[Y_{it}, Y_{it-1}] - Cov\,[Y_{it}, Y_{it-3}] = \left\{ \left(\frac{\phi_0}{1-\phi_3}\right)^2 + \right.$$

$$2\left(\frac{\phi_0\phi_1}{1-\phi_3}\right)\sum_{j=1}^{\infty} {\phi_3}^j E(X_{it-j}) + 2\left(\frac{\phi_0}{1-\phi_3}\right)\left(\frac{\phi_2}{1-\phi_3}\right)E(\eta_i) +$$

$$\left(\frac{\phi_0\phi_1}{1-\phi_3}\right)E(X_{it}\Big) + (\phi_1)^2\sum_{j=1}^{\infty} {\phi_3}^j E\left(X_{it-j}\right)^2 +$$

$$(\phi_1)^2\sum_{j=1}^{\infty} {\phi_3}^j E(X_{it}X_{it-j}) + \left(\frac{\phi_2}{1-\phi_3}\right)^2 E(\eta_i)^2 +$$

$$\sum_{j=1}^{\infty} {\phi_3}^j E\left(\varepsilon_{it-j}\right)^2 \} - \{\left(\frac{\phi_0}{1-\phi_3}\right)^2 +$$

$$2\left(\frac{\phi_0\phi_1}{1-\phi_3}\right)\sum_{j=3}^{\infty} {\phi_3}^j E(X_{it-j}) + 2\left(\frac{\phi_0}{1-\phi_3}\right)\left(\frac{\phi_2}{1-\phi_3}\right)E(\eta_i) +$$

$$\left(\frac{\phi_0\phi_1}{1-\phi_3}\right)(1+\phi_3+{\phi_3}^2)E(X_{it}) +$$

$$(\phi_1)^2\sum_{j=3}^{\infty} {\phi_3}^j E(X_{it-j})^2 + (\phi_1)^2(1+\phi_3+$$

$${\phi_3}^2)\sum_{j=3}^{\infty} {\phi_3}^j E(X_{it}X_{it-j}) + \left(\frac{\phi_2}{1-\phi_3}\right)^2 E(\eta_i)^2 +$$

$$\sum_{j=3}^{\infty} {\phi_3}^j E(\varepsilon_{it-j})^2 \}$$

Following the assumptions in (A1.7), the above equation can be simplified as

$$Cov\ [Y_{it}, Y_{it-1}] - Cov\ [Y_{it}, Y_{it-3}] = \left(\frac{\phi_0\phi_1}{1-\phi_3}\right)(\phi_3 + {\phi_3}^2)E(X_{it}) + (\phi_1)^2(\phi_3 + {\phi_3}^2)E(X_{it})^2 + (\phi_1)^2\phi_3 E(X_{it}X_{it-1}) + (\phi_1)^2{\phi_3}^2 E(X_{it}X_{it-2}) - (\phi_1)^2(\phi_3)\sum_{j=3}^{\infty}{\phi_3}^j E(X_{it}X_{it-j}) - (\phi_1)^2({\phi_3}^2)\sum_{j=3}^{\infty}{\phi_3}^j E(X_{it}X_{it-j}) + (\phi_3 + {\phi_3}^2)E(\varepsilon_{it})^2$$

$$= \left(\frac{\phi_0\phi_1}{1-\phi_3}\right)(\phi_3 + {\phi_3}^2)E(X_{it}) + (\phi_1)^2(\phi_3 + {\phi_3}^2)E(X_{it})^2 + (\phi_1)^2(\phi_3 + {\phi_3}^2)E(X_{it}X_{it-j}) - (\phi_1)^2(\phi_3 + {\phi_3}^2)\sum_{j=3}^{\infty}{\phi_3}^j E(X_{it}X_{it-j}) + (\phi_3 + {\phi_3}^2)E(\varepsilon_{it})^2 \qquad \text{(A1.12)}$$

A.6 Difference between $Cov\ [Y_{it}, Y_{it-1}]$and $Cov\ [Y_{it}, Y_{it-j}]$

By comparing Eqs. (A1.11) and (A1.12), it is easy to infer a general pattern as follows:

In general, as shown in the main text (i.e., Eqs. (2.5) and (2.6)),

$$Cov\ [Y_{it}, Y_{it-1}] - Cov\ [Y_{it}, Y_{it-j}] = \left(\frac{\phi_0\phi_1}{1-\phi_3}\right)(\phi_3 + {\phi_3}^2 + {\phi_3}^3 + \cdots + {\phi_3}^{j-1})E(X_{it}) + (\phi_1)^2(\phi_3 + {\phi_3}^2 + {\phi_3}^3 + \cdots + {\phi_3}^{j-1})E(X_{it})^2 + (\phi_1)^2(\phi_3 + {\phi_3}^2 + {\phi_3}^3 + \cdots + {\phi_3}^{j-1})E(X_{it}X_{it-j}) - (\phi_1)^2(\phi_3 + {\phi_3}^2 + {\phi_3}^3 + \cdots + {\phi_3}^{j-1})\sum_{j}^{\infty}{\phi_3}^j E(X_{it}X_{it-j}) + (\phi_3 + {\phi_3}^2 + {\phi_3}^3 + \cdots + {\phi_3}^{j-1})E(\varepsilon_{it})^2$$

$$= \left(\frac{\phi_0\phi_1}{1-\phi_3}\right)\left(\frac{1-\phi_3^j}{1-\phi_3} - 1\right)E(X_{it}) + (\phi_1)^2\left(\frac{1-\phi_3^j}{1-\phi_3} - 1\right)E(X_{it})^2 + \left(\frac{1-\phi_3^j}{1-\phi_3} - 1\right)E(\varepsilon_{it})^2 \qquad \text{(A1.13)}$$

$$= \left(\frac{\phi_0\phi_1}{1-\phi_3}\right)\left(\sum_{j=0}^{\infty}\phi_3^j - 1\right)E(X_{it}) + (\phi_1)^2\left(\sum_{j=0}^{\infty}\phi_3^j - 1\right)E(X_{it})^2 + \left(\sum_{j=0}^{\infty}\phi_3^j - 1\right)E(\varepsilon_{it})^2$$

$$= \left(\frac{\phi_0\phi_1}{1-\phi_3}\right)(\frac{1}{1-\phi_3} - 1)E(X_{it}) + (\phi_1)^2(\frac{1}{1-\phi_3} - 1)E(X_{it})^2 + \left(\frac{1}{1-\phi_3} - 1\right)E(\varepsilon_{it})^2 \; if\; j \rightarrow \infty \qquad \text{(A1.14)}$$

LRZ approach

We start with the general model of leverage as shown by Eq. (2.1).

In addition to E(η_{i}) remains unchanged across all *t*, we assume the following:

$E(X_i)$ = $E(X_{i1})$ = $E(X_{i2})$ = $E(X_{i3})$ = … = $E(X_{it})$ across all *i*.

$E(\varepsilon_{it})$ = 0 for all *t* and *i*.

ϕ_0, $\phi_{1,}$ ϕ_2 and ϕ_3 are greater than or equal to zero, but less than 1.

Based on the above assumptions,

For *t* = 1: $Y_{i1} = \phi_0 + \phi_1 X_{i1} + \phi_2 \eta_i + \varepsilon_{i1}$

$$E(Y_{i1}) = \phi_0 + \phi_1 E(X_{i1}) + \phi_2 E(\eta_i) \qquad \text{(A1.15)}$$

For *t* = 2: $Y_{i2} = \phi_0 + \phi_1 X_{i2} + \phi_2 \eta_i + \phi_3 Y_{it-1} + \varepsilon_{i2}$

$$= \phi_0 + \phi_1 X_{i2} + \phi_2 \eta_i + \phi_3(\phi_0 + \phi_1 X_{i1} + \phi_2 \eta_i + \varepsilon_{i1}) + \varepsilon_{i2}$$

$$E(Y_{i2}) = \phi_0 + \phi_1 E(X_{i2}) + \phi_2 E(\eta_i) + \phi_3\phi_0 + \phi_3\phi_1 E(X_{i1}) + \phi_3\phi_2 E(\eta_i)$$

$$= \phi_0(1+\phi_3) + \phi_1(1+\phi_3)E(X_{i2}) + \phi_2(1+\phi_3)E(\eta_i) \qquad \text{(A1.16)}$$

For *t* = 3: $Y_{i3} = \phi_0 + \phi_1 X_{i3} + \phi_2 \eta_i + \phi_3 Y_{it-2} + \varepsilon_{i3}$

$$= \phi_0 + \phi_1 X_{i3} + \phi_2 \eta_i + \phi_3(\phi_0 + \phi_1 X_{i2} + \phi_2 \eta_i + \phi_3(\phi_0 + \phi_1 X_{i1} + \phi_2 \eta_i + \varepsilon_{i1}) + \varepsilon_{i2}) + \varepsilon_{i3}$$

$$E(Y_{i3}) = \phi_0 + \phi_1 E(X_{i3}) + \phi_2 E(\eta_i) + \phi_3\phi_0 + \phi_3\phi_1 E(X_{i2}) + \phi_3\phi_2 E(\eta_i) + {\phi_3}^2\phi_0 + {\phi_3}^2\phi_1 E(X_{i1}) + {\phi_3}^2\phi_2 E(\eta_i)$$

$$= \phi_0(1+\phi_3+{\phi_3}^2) + \phi_1(1+\phi_3+{\phi_3}^2)E(X_{i3}) + \phi_2(1+\phi_3+{\phi_3}^2)E(\eta_i) \qquad \text{(A1.17)}$$

By comparing Eqs. (A1.15) and (A1.16), we observe that each coefficient of Eq. (A1.15) will increase by ϕ_3, resulting in an overall increase in the mean leverage from the first year to the second year (*t* =1 to *t* =2). Similarly, the mean leverage will further increase by ${\phi_3}^2$ from the second year to the third year (t=2 to t=3), it is easy to infer a general pattern as follows:

In general, as shown in the main text (i.e., Eqs. (2.7) and (2.8)),

For $t = j$: $E(Y_{ij}) = \phi_0(1 + \phi_3 + {\phi_3}^2 + {\phi_3}^3 + \cdots + {\phi_3}^{j-1}) +$

$\phi_1(1 + \phi_3 + {\phi_3}^2 + {\phi_3}^3 + \cdots + {\phi_3}^{j-1})E(X_{ij}) +$

$\phi_2(1 + \phi_3 + {\phi_3}^2 + {\phi_3}^3 + \ldots + {\phi_3}^{j-1})E(\eta_i)$

$$= \frac{\phi_0(1-\phi_3^j)}{1-\phi_3} + \frac{\phi_1(1-\phi_3^j)}{1-\phi_3}E(X_{ij}) + \frac{\phi_2(1-\phi_3^j)}{1-\phi_3}E(\eta_i) \qquad \text{(A1.18)}$$

$$= \frac{\phi_0(\sum_{j=0}^{\infty}\phi_3^j)}{1-\phi_3} + \frac{\phi_1(\sum_{j=0}^{\infty}\phi_3^j)}{1-\phi_3}E(X_{ij}) + \frac{\phi_2(\sum_{j=0}^{\infty}\phi_3^j)}{1-\phi_3}E(\eta_i)$$

$$= \frac{\phi_0}{1-\phi_3} + \frac{\phi_1}{1-\phi_3}E(X_{ij}) + \frac{\phi_2}{1-\phi_3}E(\eta_i)\ if\ j \to \infty \qquad \text{(A1.19)}$$