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Technology firms and capital structure adjustment: Application of two-step system generalised method of moments

The study asks whether technology firms adjust their capital structures towards predetermined targets, and if so, at what speed? Also, is there an intra-industry leverage-level effect? The study empirically evaluates the listed technology firms in South Africa's Johannesburg Stock Exchange (JSE). Methodologically, a generalised method of moments (GMM) is employed on 34 firms over 21 years (1999–2019), resulting in a sample size of 714 observations. The results show that technology firms adjust their debt-equity ratios towards target levels with speed above other industries at 45 to 57%. A comparison with prior research shows that this adjustment pace is consistent with the experience of technology firms in Asian emerging markets but differs markedly from that of developed economies. These results support the literature observation that technology is characterised differently in less developed economies, yet research on technology firms' capital structure dynamics is scant. The results of this study should enlighten industrialists, investors, and policymakers involved with technology industries. Intuitively, the partial capital adjustment process should play an essential role in project financing decisions. Maintaining optimal capital adjustment speeds should lead to better industrial activity like maximised innovation and technology diffusion.

Keywords: capital adjustment; capital structure; adjustment speed; technology firms.
JEL classification: E22; G32; M21; O16.

1. Introduction

This study investigates the capital structure dynamics of technology firms in the emerging market environment of South Africa, taking the Johannesburg Stock Exchange (JSE) listed firms as a case study. A capital structure may be seen as primarily a mix of debt and equity in a firm. Myers (2001) further generalises that capital structure explains a fusion of securities and financing sources corporations use to finance real investment but concedes that no universal formula or theory defines a given firm's capital structure. Nevertheless, for empirical purposes, this is not an issue in the study of capital structure.

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Researchers (Ramjee, Gwatidzo, 2012; Dao, Ta, 2020) concur that the study of capital structure is critical for practitioners and academia due to its operational impact on business continuity. Research on corporate finance has evolved from the static capital structure theories (Modigiani, Miller, 1958, 1963; Kraus, Litzenberger, 1973; Myers, Majluf, 1984) to dynamic capital configurations (Fischer et al., 1989; Baker, Wurgler, 2002; Welch, 2004). Whereas historically, the corporate finance literature on firm financing tends to aggregate various industry firms into one sample for econometric analysis, the literate recently raised a reasonable concern about this (Smith et al., 2010; Bajaj et al., 2021). After surveying the relevant literature, Miao (2005) finds that "there is substantial inter- and intra-industry variation in leverage". In light of this statement, is it logical to expect inter-and intra-industry differences in capital adjustment towards optimal leverage? Intuitively this is probable, but it remains an empirical question pursued by the current study.

While assembling firms from different industries into one dataset for regression analysis may provide helpful generalisation, such sample design may raise some empirical concerns. Aggregation in sampling assumes that subjects are relatively comparable. That is, studying the characteristics of financing decisions (like capital structure determination and adjustment speed) for firms regardless of the industry may raise some questions. First, industries are subject to variable regulations like mines, financial sectors, parastatals, and technology firms with patent laws. Second, some industries have a more stable business operation over time (like defensive-stock firms) with less pressure to interrogate their capital structures. Others are more affected by demand-supply uncertainties (like cyclical-stock firms). Third, while some risks affect all industries, they influence others more, like hardware obsolescence, innovation uncertainties, technological change, software malfunction, international economic crises, and globalisation.

The aforesaid begs the question: Is an inter-industry consideration essential in capital structure dynamics? Few influential studies in this area (Maksimovic et al., 1999; MacKay, Phillips, 2005; Antoniou et al., 2008) agree that inter-industry heterogeneity exists. Rare studies have controlled for this with industry dummies (Hovakimian et al., 2001; Flannery, Rangan, 2006). Considering the econometric estimation methods usually used in partial capital adjustment, dummy indicators may not always be feasible because "these [industry] effects can only be investigated through the models in levels, not in differences" (Antoniou et al., 2008, p. 71, footnote 14). Owing to the importance of the technology industry as a catalyst of innovation in the economy and its invention distinguishing risk, the present study posits that a sector-specific examination technology industry is critical and a needed improvement on dummy-based industry effect studies. While most capital structure studies disregard sectoral effects, there are a few exceptions that examine the banking sector (Fidrmuc et al., 2018), the mining sector (Utami et al., 2020), the financial sector (Liaqat et al., 2021), and sparsely technology sector (Spitsin et al., 2022; Serrasqueiro et al., 2014). The present research question distinguishes the current study from the previous industry-specific studies. Past studies elaborate on the effects of firm-specific characteristics on capital structure. In contrast, the current study expands this literature to inquire whether technology firms practice capital structure adjustment towards target leverage and, if so, what is the adjustment speed. In this regard, we close the gap in the inter- and intra-industry literature on capital structure, particularly in the emerging markets of Africa.

Unlike static financing decisions, the issue of dynamic capital structure involves factors like market timing (Baker, Wurgler, 2002), which refers to the practice by the financial managers of a firm to issue securities at high prices and repurchase them at favourable low prices while aiming to exploit temporary market fluctuations. Other characteristics of dynamic capital structure involve leverage rebalancing (Welch, 2004) and partial capital adjustment (Ozkan, 2001). The current paper focuses on the latter and evaluates the technology firms' capital structure adjustment decisions and the speed of adjustment.

This study focuses on the technology sector in South Africa owing to its increasing value-add and topicality, as highlighted by the recent Covid-19 crisis, which demanded online economic activity. In recent decades, there has been considerable dissemination of technology globally that has led the world into an information-based society (Bahrini, Qaffas, 2019). South Africa has not been an exception in benefiting from the positive spillovers of technological advancement related to the 4th industrial revolution (4IR), including the digital economy (Hogan, Hutson, 2005). South Africa is ranked 61 in the Global Innovation Index (Soumitra et al., 2022), second in Africa (after Mauritius), and first in Sub-Saharan Africa. Furthermore, the introduction and survival of technology firms are essential for disseminating scientific knowledge, development, and circulation of innovation, particularly in emerging countries like South Africa (Rajah, Gopane, 2004). Also, it is well-known from growth theory studies (DeLong, Summers, 1991) and other literature streams (Zagorchev et al., 2011) that there is a positive association between technology performance and the nation's gross domestic product. This association is significant in emerging markets, and its implication in relation to firm financing decisions should be understood.

Due to its natural distinctiveness, understanding financing decision behaviours in the technology sector should benefit policymakers and advance academic knowledge. For instance, the literature on technology change and diffusion (Schumpeter, 1943; Fuentelsaz et al., 2003, 2009, 2015) flags certain market peculiarities regarding the technology industry, such as "creative destruction" being a process "through which incumbents are displaced from the market" possibly due to "myopic perspective" or misjudging the uncertain technological innovation (Fuentelsaz, 2015, p. 1780). The current study conjecture that, overall, technology firms are more likely to have financing decisions consistent with their unique business environment. However, this is an empirical question that has been largely ignored by the literature but is now examined in the current study. The rest of the paper is organised into a literature review in Section 2, methodology in Section 3, results report, interpretation, and discussion in Section 4, while Section 5 concludes the study.

2. Literature review

2.1. The evolution of static capital structure

The seminal paper of Modigliani, Miller (1958) proposed that capital structure is irrelevant when considering the value of a firm, implying that what determines firm value would be the type of investment venture the firm undertakes and the quality of the assets involved. The irrelevance theory of capital structure was formulated under perfect market conditions, which include the following assumptions: (i) taxes have little to no influence on capital structure choices; (ii) there are no transaction and bankruptcy costs; (iii) there is no information asymmetry in the perfect markets since managers and external investors of a firm are assumed to have the same information concerning future financial endeavours of the firm; (iv) agency costs are next to nothing as the goals of shareholders and various managerial stakeholders of the firm are assumed to be aligned, thereby reducing conflict of interest. Relaxing and examining these assumptions often led to new capital structure theories.

Throughout the history of corporate finance and firm behaviour, innovative research was undertaken to interrogate the sustainability of the above assumptions. It emerged that when the assumption of no corporate taxes is relaxed (Modigliani, Miller, 1963), there was an eminent benefit associated with tax deductibility (or tax shield) to firm value. This meant that, in principle, the more firms increased their debt in capital structure, the more they benefited linearly and continuously from tax shield. This is termed capital relevance theory. It was only a short time before corporate finance researchers (Baxter, 1967; Kraus, Litzenberger, 1973) discovered upon relaxing the assumption of no bankruptcy that the linear increase in firm value is not infinite. The possibility or threat of bankruptcy constrains the benefit of tax deductions associated with leverage. Therefore, this scenario created a plausible optimal capital structure (or leverage) that arises from balancing the benefit of tax shield against bankruptcy costs. This has come to be known as the Trade-off Theory of capital structure.

Research on the study of capital structure continued to probe assumptions of capital irrelevance theory. This time researchers relaxed the assumption of no information asymmetry, and suddenly the Pecking Order Theory of capital structure emerged (Myers, 1984; Myers, Majluf, 1984). This theory is based on the notion that managers have the advantage of internal firm information to have first-hand knowledge of the firm's true valuation. This leads them to prefer a pecking order of financing, starting with internal resources, then debt, with equity ranked last.

Contrary to the irrelevance theory postulates, agency costs are not zero. Financial economists know through research on firm behaviour that there is a potential conflict between equity and debt holders, and there are costs to firms associated with managing the rivalry. This explains the problem of agency cost theory. Jensen, Meckling (1976) define agency as a relationship that exists under a contract in which one actor (the principal) engages another actor (the agent) to perform duties in decision-making on behalf of the principal. As this relationship exists, the concept of agency costs arises. These costs to the firm arise when there are clashes between agents and principals when either party is not acting in the firm's best interest. Consistent with the trade-off theory, agency theory predicts that firms should use more debt because of its monitoring capacity upon the managers (Novaes, Zingales, 1995).

Subsequent to the pioneering work by Modigliani, Miller (1958, 1963), the theory of capital structure has indeed progressed from irrelevance theory, trade-off theory, agency cost theory, and pecking order theory, to mention the core foundations. All these theories have one thing in common: they were initially developed as single-period (or static) theories of capital structure. The realities of the changing nature of economic behaviour have since compelled advancement into dynamic capital structure, with which the current paper is concerned. The critical problem with static theories is potently observed by Fischer et al. (1989, p. 19) that "they ignore the firm's optimal restructuring choices in response to fluctuations in asset values over time". This persistent status quo obliges researchers to heed the long-standing advice that "we ought to give less attention to refining our static trade-off stories and relatively more to understanding what the adjustment costs are, why they are so important and how rational managers would respond to them" (Myers, 1984, p. 587). Evidently, the work on capital structure is incomplete but progressing, as there are still gaps in knowledge and inconclusiveness regarding the stylised facts from empirical research.

2.2. Optimal dynamic capital structure

The study of time-varying capital structure is an important development in corporate finance and evolves around dynamic trade-off theory (Kane et al., 1984; Fischer et al., 1989); market-timing theory (Baker, Wurgler, 2002); capital rebalancing (or inertia) proposition (Welch, 2004); as well as dynamic pecking order theory (Morellec, Schürhoff, 2011). Compared to static theory, optimal dynamic capital structure is more appealing owing to its practical intuition. Therefore, the current paper focuses on the application of dynamic trade-off theory.

In their ground-breaking paper on dynamic capital, Kane et al. (1984, p. 841) inquired: "What magnitude tax advantage to debt is consistent with the range of observed corporate debt ratios?" To formulate a conceptual answer to this question, the authors allowed tax and bankruptcy costs to vary with tax benefits under the continuous time configuration of the trade-off theory. This dynamic optimal capital structure framework emerged as favourable over static alternatives. In a supportive but empirically more friendly method, Fischer et al. (1989) built a time-varying model of a capital structure incorporating taxes as well as bankruptcy costs and found that firms have target debt ratios with periodic adjustment over time. Since the influential work of Fischer et al. (1989), many researchers from different countries (discussed later in Table 3) have sought to understand the magnitude and speed of adjustment for firms' target debt-equity ratios over time.

In a recent systematic literature review of capital structure studies, Bajaj et al. (2021, p. 173) examined 183 Scopus-published articles from 1999 to 2019. They made an important observation: "The findings revealed that … the capital structure research studies were largely conducted by considering all the industries together, whereas the focus on a particular industrial sector was meager." The current study bridges this research imbalance by focusing on the technology industry. The present study should serve as a reference study in some context since "the specificity of the high-tech companies in emerging and developing markets is slightly different in comparison to new technology-based firms from leading countries" (Kedzior et al., 2020, p. 2).

2.3. Motivation and hypotheses for the study

Given the above, studying capital structure for technology firms in emerging markets is imperative. Such an investigation should reveal some insights to harness the technology sector's potential as an engine of digitalisation and innovation transfer to other industries. Innovation firms are known to be fundamentally different from other industries (Hall, 2010; Lee et al., 2015; Abbas et al., 2021). The question arises: Does a difference in business configuration lead to distinct capital dynamics from the rest of industries? There is limited knowledge in the literature regarding the capital structure behaviour of technology firms, except for isolated works of Aghion et al. (2004) based on the UK's listed firms and Kedzior et al. (2020), who look at the Polish publicly traded companies. Both studies have a different empirical focus from the current study, where we investigate partial capital changes and speed of adjustment. Therefore, the current paper extends knowledge of capital structure in technology firms to emerging markets focusing on South Africa. Listed technology firms in South Africa present a useful case study due to the unique strategic economic position South Africa holds as a linkage to the technology-needy African continent. To illustrate, many multinational technology companies have installed subsidiary operations in South Africa, including Compaq, Dell, IBM, Intel, Microsoft, Novell, Unisys, and Systems Application Protocol (SAP). It is for this reason that some developed countries, like the U.S. International Trade Administration Agency (Bell, 2021, p. 1), see South Africa as a "regional hub and a supply base for neighbouring [African] countries". The U.S. Agency also observed that "South Africa's ICT products and services industry is penetrating the fast-growing African market".

The first hypothesis [H1]: the study hypothesises that technology firms engage in dynamic capital adjustment, but at what speed? Although the literature is yet to find harmony regarding the optimal partial adjustment rates, there is a preponderance of empirical evidence globally that firms adjust their capital structures towards target leverages (see reviews, Nivorozhkin, Kireu, 2019; Hanna, 2020; Bajaj et al., 2021; Nguyen et al., 2023). Accordingly, this study accepts that capital adjustment should also apply to technology firms, but what is uncertain is whether the adjustment speed should be similar or differ and by what margin from industry averages. Nevertheless, the literature on the co-determination of capital structure should give us some glue on technology firms' capital adjustment predictions. This theme of literature says that firms co-determine debt, ownership, and dividend policies (Jensen et al., 1992), debt and equity (Yang et al., 2010), debt ratio, risk, and technology (MacKay, Phillips, 2005), as well as debt and investment (Stenbacka, Tombak, 2002). While some industries may share the characteristics of heavy investment in technology as hi-tech firms, technology firms are expected to have different production objective functions and specific operational risks resulting in industry-aligned leverage optimisation. Note that "target capital structures are sometimes referred to as optimal capital structures" (De Haas, Peeters, 2006, p. 134). As we know from the literature that firms simultaneously co-determine capital structure and investment, technology firms' leverage should be in tandem with their investment plans, which should differ from other industries. Consequently, we conjecture that leverage targets should also differ, leading to different capital adjustment speeds. This reasoning is consistent with Kokoreva et al. (2017), who opines that technology firms should have less leverage than other industries.

The second hypothesis [H2]: this research hypothesises that an intra-industry variation in capital structure behaviour exists for the technology industry. In particular, since the hardware sector tends to be more fixed-asset intensive compared to its software counterpart, we conjecture that the two sectors should vary in their initial leverage levels. Hardware firms tend to possess high fixed investments, while software firms tend to have a higher concentration on intangible and human capital assets. For example, valuable employee skills and intellectual property in complex computer applications. Both fixed (Frank, Goyal, 2009) and intangible (Fidrmuc et al., 2018) assets affect capital variably. The intra-industry leverage-level effect will be tested with a zero-one dummy indicator (one if the sector is hardware, and zero otherwise). Therefore, this indicator tests whether the technology subsectors have common starting leverage positions in their adjustment process. Due to its first-mover position in the technology development hierarchy (Bresnahan, Greenstein, 1999) and its advantage of debt collateral, the hardware sector is more likely to have a head-start. This test is important since the capital adjustment literature (Smith et al., 2010; Nivorozhkin, Kireu, 2019) has demonstrably shown that firms with different leverage starting points also differ in their adjustment speeds.

3. Methodology and data

3.1. Model motivation

The study aims to evaluate whether technology firms adjust their capital structures towards target leverages and, if so, at what speed (H1). The secondary test examines whether there is an intra-industry leverage-level effect (H2). The applicable theory is the partial capital adjustment (PCA) framework presented in equations (1) to (3) below, while the economic background is elaborated in the early studies (Taggart, 1977; Jalilvand, Harris, 1984; Ozkan, 2001; Flannery, Rangan, 2006). Intuitively, the PCA model consists of two components: (i) a factor that defines the adjustment process, and (ii) the part that describes the desired target. Within the PCA model, leverage is a function of its first lag (part i) and a set of firm-specific characteristics refined in the literature (Frank, Goyal, 2009), that is, part (ii). The econometric model is specified in equations (4) to (5). To initiate regression analysis, it is important to ensure that the theoretical model and econometric procedure are compatible and that the best regression specification is applied. Econometric models that were utilised in similar past investigations include the mixed effects model (Byoun, 2008), the random effect Tobit model with zero-one double-censor (Elsas, Florysiak, 2015), the finite mixture model (Durand et al., 2022), and the generalised method of moments (GMM) which is more popular (mostly used by studies listed in Table 3). GMM is a preferred estimation model in the current study for several reasons. First, empirical works in corporate finance, like the current study, tend to involve large N (number of firms) and relatively short T (period), which is one of the properties of GMM. Second, the mix of cross-sectional data and time series, which allows for unbalanced panel data and maximising sample size, is consistent with GMM standard specification. Third, in a dynamic framework of PCA, the lagged dependent variable is correlated to other covariates. GMM is advantageous in controlling for the endogeneity problem while improving regression estimates' efficiency (Hsiao, 2014). Fourth, Moyo (2015) compared alternative estimators for PCA, and GMM emerged as a reliable and recommended procedure. Lastly, since GMM is widely used, this is a convenient choice to enable the current results to be more comparable with prior findings (listed in Table 3). Nevertheless, appropriate and procedural model specification is critical to ensure reliable results.

3.2. Econometric model

The empirical design is based on the corporate theory of capital structure and the widely used partial adjustment model (Ozkan, 2001; Flannery, Rangan, 2006; Huang, Ritter, 2009). In particular, the dynamic trade-off theory of capital structure suggests optimal leverage exists, which firms would want to achieve and maintain over time. In the firm's profit and loss statement, debt interest expenses are a deductible item for the purpose of filing corporate tax returns. This means that increasing leverage, other things constant, is beneficial to the company. However, increasing leverage beyond a certain magnitude may trigger possibilities of bankruptcy, and associated profit hindrances. Therefore, there is a trade-off between the benefits derived from increasing leverage and the potential bankruptcy costs implying that there is an optimal capital structure, also known as the debt-equity ratio, or simply leverage. The firm valuation corresponding to the optimal capital structure is the desired optimal value for the given operation capacity (or production factors).

Therefore, economic rationale shows that firms prefer to operate at optimal or target capital structure. Ideally, observed leverage for firm i at time t, (D_{it}) should be the same as the target or optimal leverage $\left(D_{it}^{*}\right)$ such that, $D_{it}=D_{it}^{*}$. Dynamically, over the firm's productive life, periodical change in leverage $\left(D_{it}-D_{it-1}\right)$ should equal the required difference in leverage $\left(D_{it}^{*}-D_{it-1}\right)$ for the firm to operate at an optimal level at time t, so that, $\left(D_{it}-D_{it-1}\right)=\left(D_{it}^{*}-D_{it-1}\right)$. However, given the process of adjusting to optimal leverage is constrained by adjustment costs, firms may not adjust fully but only partially, as represented by equation (1):

$$D_{it}-D_{it-1}=\delta\left(D_{it}^{*}-D_{it-1}\right), \quad 0<\delta<1. \tag{1}$$

Equation (1) says that the degree of leverage adjustment between the past $(t-1)$ and current (t) periods depends on δ. That is, the adjustment speed is determined by the magnitude of δ, and the closer this parameter is to unity, the faster the adjustment process. If $\delta=1$, then a full adjustment is achieved within one period, and the firm's leverage is at an optimal level at time t. If $\delta<1$, Then the firm's leverage adjustment falls short of the required difference to reach the target. An inverse relationship exists between the speed of adjustment and the defined adjustment costs. Adjustment costs refer to all relevant costs that may hinder the firm from reaching its target-debt equity ratio. In equation (1), $i=1,\ldots,N$ and $t=1,\ldots,T$. The variable, x is a set of explanatory variables, which is frequently applied in the literature (Frank, Goyal, 2009, Ramjee, Gwatidzo, 2012), β represents coefficients to be estimated, and finally, the error term is defined by u_{it}. In what follows, we explain in detail the rest of the mathematics of the PCA model. The target leverage D_{it}^{*} can be predicted as follows:

$$D_{it}^{*}=\beta x_{it}+u_{it}. \tag{2}$$

By substituting (2) into (1), the following equation emerges:

$$D_{it}=(1-\delta)D_{it-1}+\delta\left(\beta x_{it}+u_{it}\right). \tag{3}$$

Re-writing (3) as a Panel Data Model we have:

$$D_{it}=(1-\delta)D_{it-1}+\delta\left(\beta x_{it}+\mu_{i}+\lambda_{t}+u_{it}\right), \tag{4}$$

which may be re-written as a regression equation:

$$D_{it}=\delta_{0}D_{it-1}+\varphi x_{it}+\nu_{i}+\gamma_{t}+\varepsilon_{it}, \tag{5}$$

where $\delta_{0}=(1-\delta)$, $\varphi=\delta\beta$, $\nu_{i}=\delta\mu_{i}$, $\gamma_{t}=\delta\lambda_{t}$, $\varepsilon_{it}=\delta\mu_{it}$.

From equation (5), ν_i represents firm-fixed effects, that is, the undetectable firm-specific attributes that are regarded as consistent over i but fixed over time, while the parameter, γ_t represents time-fixed effects, and ε_{it} is the error term. Equation (5) is a dynamic Panel Data Model and will be estimated using GMM.

3.2.1. Determinants of target leverage

In this section we explain the proxy variables that are commonly used in the literature (Ozkan, 2001; Ramjee, Gwatidzo, 2012; Jooma, Gwatidzo, 2013; Moyo et al., 2013) as determinants of target leverage. Regarding, *corporate taxes (tax shields)*, the capital structure theory (Modigliani, Miller, 1958) considers borrowing as a main driver of borrowing owing to the benefits of tax shields. The literature (DeAngelo, Masulis, 1980) has shown that non-tax shields like depreciation and amortization are perfect substitutes for tax shields. The common proxy of tax shields is the ratio of depreciation to total assets, which gives a measure of the availability of non-tax shields. A negative relationship is expected between tax shields and leverage. *The profit-to-sales ratio (profit)* measures every dollar the company can retain for profit after all costs and taxes. It is computed as the operating income divided by the total sales. This ratio is important to the capital structure as it determines the firm's option of whether to finance activities using internal funds (profits) or to borrow externally. According to the Pecking order hypothesis (Myers 1984; Myers, Majluf, 1984) firms prefer internal financing to external funds (like borrowing), and the higher profitability the less likely borrowing occurs. Consequently, a negative correlation is expected between profit and leverage. This is because the ratio indicates whether a firm is making a profit or not. In the case that it is, it lessens the need for the firm to borrow funds externally as it can utilise the accumulated profits. *Asset tangibility* is the asset base of the firm and is calculated as the ratio of non-current assets to total assets. A negative relationship is expected between leverage and asset tangibility. An inverse relationship may arise because the firm uses a large portion of its reserve funds to finance capital structure activities as opposed to collateral when obtaining external funding. *Firm age* may be used to define the firm's reputation. A firm that has been a going concern for a long time is likely to have established a good reputation, therefore, access to external funding is easier compared with small start-up firms. A positive association between firm age and leverage is plausible for firms with relatively long years of existence. The *size (total assets)* of the firm is proxied with total assets. Large firms tend to be more diversified than smaller firms (Titman, Wessels, 1988). Also, larger firms are known to operate more on borrowed funds, as they experience lower asset volatility. Furthermore, they can use the assets of the firm as collateral, thereby giving access to external funds in comparison with smaller firms. All these factors imply a positive correlation with leverage. All the scale explanatory variables are transformed with natural logarithms for regression estimation.

3.2.2. Model selection criterion

The relevant statistical procedures should be followed to select the appropriate GMM estimator. The available variations of GMM estimators include Differenced GMM (Arellano, Bond, 1991), System GMM (Arellano, Bover, 1995), and each may be estimated as a one-step or two-step procedure. Bond et al. (2001) recommend a model selection criterion (hereafter, Bond-MSC) that researchers may apply to identify the correct model specification. The process begins by first estimating three regression models using the dataset for the study along with the same group of covariates, and the lagged dependent variable. The regression estimation is replicated using pooled ordinary least squares (POLS) model, least-squares dummy variable (LSDV) model, as well as differenced GMM model and then we compare the magnitudes of the coefficients of the lagged dependent variable (Delta). Accordingly, equation (5) is the reference equation, and Table A1 in Appendix reports the test results. Table A1 shows that the coefficients (Delta's) for POLS, LSDV, and differenced GMM are 0.79, 0.56, and 0.48, respectively. The decision criterion of Bond-MSC is that if the coefficient (Delta3) of the endogenous variable for differenced GMM is close to or less than the coefficient (Delta2) for the lagged dependent variable under the LSDV model, then the System GMM is recommended. Therefore, since 0.48 is less than and close to 0.56 then, the best-fit model to utilise in this study is the System GMM. The intuition, according to Bond et al. (2001), is that under POLS, the regression results are biased upwards, while under LSDV, they are biased downwards like the within-transformation estimator (Roodman, 2009).

A further refinement in the model selection process is to choose between One-Step and Two-Step System GMM. In this regard, relevant considerations include the fact that the current study utilises only 34 panels over 21 periods, which results in a modest sample size of 714. Under current data specifications and compared with One Step, the Two-System GMM is particularly appealing because of its transformation method of addressing endogeneity using orthogonal deviations, which has the important advantage of minimising data loss. In addition, the Two-Step System GMM benefits from the Windmeijer (2005) correction for small-sample bias. Further, some econometrists (Roodman, 2009) see the Two-Step System GMM as more robust to address the problems of autocorrelation and heteroscedasticity. After considering the above, the Two-Step System GMM model has become a preferred estimator in the current study. This choice is consistent with Adeleye et al. (2017, p. 189), who had a comparable sample size of 669.

3.3. Data characteristics

The appropriate data for the study was sourced from two online databases. Data on financial statements for 63 JSE-listed technology firms was collected from the Osiris database[2] and the Iress database[3]. Some data-elimination procedures were necessary as part of the data-cleaning process. Of the sourced entities, 29 companies were excluded owing to insufficient data for explanatory variables. Further, financial firms listed under the technology sector were excluded from the sample data because their capital structure is different from the capital structures of the technology industry. Financial firms tend to face more stringent and inflexible regulations regarding capital requirement adequacies (Jooma, Gwatidzo, 2013). A 21-year (1999–2019) period was selected since it was a time span when the majority of technology firms happened to satisfy the data requirements for the current study. Ultimately the unbalanced panel dataset led to 34 firms composed of JSE-listed and delisted firms. Therefore, the sample size for unbalanced GMM is 714 (34 firms × 21 years). Overall, the data-collection process has satisfactorily provided adequate data needed for empirical analysis in the study. Admittedly, a higher sample count is always preferable in regression analysis, but our sample count is reliable, and a comparable sample size has been used in the literature in the recent past (Barclay et al., 1995; Adeleye et al., 2017).

Table 1 presents the summary descriptive statistics of variables used in the study. The first five columns are in natural logs, the last two columns are ratios, and the sector is a dummy variable. The numbers show that the average leverage of the technology industry ranges from 6% (for book-value leverage) to 28% (for market leverage). A comparison with the averages of the all-industry non-financial firms from Jooma, Gwatidzo (2013) shows that the technology leverage ratios are lower than general industry averages while the determinants summary statistics are not radically far apart. For instance, the mean of total assets for the technology industry is 1.63, while for the all-industry average is 1.69. Most variables reveal the kurtosis statistic in the neighbourhood of three but slightly greater signalling leptokurtic pattern (or peakedness). Going by experience in real-world observations, the numbers are within reasonable possibilities.

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2 https://0-osiris-bvdinfo-com.ujlink.uj.ac.za.

3 http://research.mcgregorbfa.com.

Table 1. Summary descriptive statistics

Details	Asset tangibility	Tax	Profit	Total assets	Firm age	Sector dum	Book leverage	Market leverage
Mean	0.32	1.28	0.03	1.63	2.64	11.78	0.06	0.28
Maximum	1.35	1.64	0.26	2.90	4.43	30.00	0.71	1.26
Minimum	0.01	0.04	0.06	0.01	0.02	0.03	0.19	0.22
Standard Deviation	0.32	0.65	0.05	1.14	1.39	9.99	0.13	0.28
Skewness	0.92	0.04	2.02	–0.67	–1.233	0.27	2.05	–0.85
Kurtosis	3.25	3.08	2.08	1.57	2.89	1.66	3.52	3.64
Observations	714	714	714	714	714	714	714	714

3.4. Post-model validation

It is important to conduct a post-estimation diagnosis in line with the relevant econometric theory to ensure the reliability of results. The GMM regression is validated using Hansen's (1982) *J*-statistic, the Wald test, as well as the Arellano–Bond test (Arellano, Bond, 1991) of first-order, AR(1) and second-order, AR(2) serial correlation. Overall, the estimated GMM Model is satisfactory, as evidenced by the Hansen *J*-statistic of 9.71 (with a *p*-value of 0.47) and 8.82 (with a *p*-value of 0.45), reported in Table 2 under Panels A and B, respectively. Models 1 and 2 fail to reject the null hypothesis of over-identifying restrictions, thus supporting the choice of variables utilised in this study. Further robustness checks are conducted. The Wald test confirms the overall model fitness, and in both Model 1 and Model 2, we reject the null of inappropriate modelling at a 1% level of significance. The second Wald test is further applied to inspect whether the inclusion of fixed effects is relevant, and the test affirms inclusion at less than 1% significance level for both models. The Arellano–Bond test is based on differenced errors with the null of no autocorrelation. Regarding AR(1), when the level errors are serially uncorrelated then the errors in first differenced form, are correlated (Kiviet, 2020). So, in theory, the *p*-value for AR(1) should be statistically significant (say, at less than 0.05 level). On the contrary, Table 2 presents results for Models 1 and 2 of 0.26 and 0.10, respectively which fail to reject the null of no autocorrelation. General guidelines on GMM validation procedures (Roodman, 2004, 2009) and literature practice (Habimana, 2017) recommend researchers to disregard AR(1) if it fails the test and we heed the advice. The reason for this is that since ε_{it-1} is a common factor for computing $\Delta\varepsilon_{it}$ and $\Delta\varepsilon_{it-1}$, "…the first-order serial correlation is expected in differences and *evidence of it is uninformative*. Thus, to check for first-order serial correlation in levels, we look for *second-order* correlation in differences" (Roodman, 2009, p. 119, emphasis added). In Table 2, the test for AR(2) rejects the null of no autocorrelation in Models 1 and 2 with *p*-values of 0.38 and 0.18, respectively. These results provide favourable evidence for a stable model. It is good to note that the Arellano–Bond test is linked to the assumption of large *N* (number of entities). The literature (Roodman, 2009, p. 121) hints that although "large has no precise definition" it should be "worrisome" if *N* is at most twenty entities, which fairly exempts the current case study with thirty-four firms. In line with the established practice in the literature (Ozkan, 2001), the instruments used for the estimated GMM Model are the first lag of regressors, the second lag of dependent variables, and period dummies. The number of lags was minimised to avoid the problem of instrument proliferation.

Table 2. Results for Partial Capital Adjustment of technology firms in South Africa

Variable	Panel A *Model 1*: Dependent variable book value leverage, the long-term debt to total assets ratio		Panel B *Model 2*: The dependent variable is market leverage, the total debt-to-equity ratio	
	Coefficient	Standard Error	Coefficient	Standard Error
Lag of leverage	0.558***	0.035	0.436***	0.125
Asset tangibility	–0.0572*	0.0314	–0.196	0.359
Profit	–0.176**	0.076	–1.020*	0.539
Total assets	0.0794**	0.0352	0.463***	0.133
Tax shields	–0.0729*	0.0369	–0.771***	0.297
Hardware vs software	0.0624***	0.0351	0.0735***	0.0252
Fixed-period effects	Yes	Yes	Yes	Yes
		Model validation		
Wald $\chi^2(26)$	62197441***		74396.08***	
Wald $\chi^2(21)$	636.66***		210.32***	
Hansen *J*-statistic	9.713[a]		8.824[a]	
AR(1)	–1.113		–1.626	
AR(2)	–0.875[a]		–1.325[a]	
Observations	646		646	

Notes. Instruments: leverage, periods, age, age sqr, asset tangibility, profit, and tax shields, the period fixed (dummy variables).
Significance level: *** — 1%, ** — 5%, * — 10%.
Legend: a — the statistic is insignificant as desired, meaning that the model is stable.

4. Empirical results

Overall, the results confirm the proposed research hypotheses. First, firms set a target for the debt-equity ratio, which requires them to engage in partial capital adjustment to maintain such a target. In particular, the results show that the speed of capital adjustment for technology firms differs from the rest of the industries, explained in detail in the discussion of the results section. Second, the results confirm the hypothesis that hardware firms have higher initial leverage levels. Meaning that software firms have lower starting positions for capital adjustment compared to hardware firms. These results are explained in detail in Section 4.1 and discussed in Section 4.2.

4.1. Interpretation of results

The GMM Model (from equation (5)) is used to estimate the partial capital adjustment process, and the results are reported in Table 2. The regression model was estimated twice, and the results are presented in two panels: Panel A reports the results of Model 1, where the dependent variable is a ratio of long-term debt to total assets. That is, leverage based on book value (book leverage). Panel B presents the results for Model 2, in which the dependent variable is the ratio of debt to equity-plus-debt (market leverage). Models 1 and 2 regressed the same set of covariates (asset tangibility, profit, total assets, and tax value). The sectoral dummy is included to test hypothesis H2, whether there is a difference between the capital structures of hardware and software firms in terms of the starting positions of leverage adjustment. In Model 1, the intuition behind book leverage is that total assets are one of the major variables considered and used as collateral by firms when deciding to borrow externally or utilise internal funds. Alternatively, under Model 2, the conception of market leverage allows the firms to check if they are operating at balanced debt and equity levels. Models 1 and 2 include the lagged dependent variable (leverage) as one of the regressors and our primary variable of interest. The coefficient for the lagged dependent variable measures the speed of partial capital adjustment between the actual and target capital structure. The regression results are presented in Table 2.

To test hypothesis H1, the coefficient $(\delta_0 = 1 - \delta)$ of the lagged leverage is 0.55 and 0.43 for Models 1 and 2, respectively. These estimated parameters are statistically significant at 1% level. These coefficients translate into an adjustment speed of 45% $(= 1 - 0.55)$ for book leverage and 57% $(= 1 - 0.43)$ for market leverage. Based on these capital adjustment speeds, it will take 2.2 years to reach the target ratio with a speed of 45%. Alternatively, the adjustment period will be reduced to 1.8 years under market leverage with a speed of 57%.

The next step of interpretation is to explain the behaviour of control variables. All the scale covariates (asset tangibility, profit, total assets, and tax shields) are in natural logs, but not the dependent variables (book leverage and market leverage), which are in ratios. This means that the interpretation of the coefficients for the scale explanatory variables will follow the form: *a percentage change in x leads to an absolute change of $\varphi/100$ in leverage, other things constant* (see equation (5)). Asset tangibility is negative and significant at the 10% level for Model 1, suggesting that firms are inclined to utilise internal financing to fund their activities, hence an inverse relationship between asset tangibility and leverage. The profit variable has the expected negative coefficients in both models. These variables are statistically significant at conventional levels. The regressor, total assets, has an expected positive coefficient in both Model 1 and Model 2. The economic intuition of a positive association between firm size and leverage is that larger firms are more diversified and have better access to collateral assets meaning they have larger borrowing capacity (Ozkan, 2001).

The tax variable is statistically significant at 10% for both Models 1 and 2. In line with the economic rationale of the trade-off theory, the inverse association of the tax variables and leverage means firms consider the potential benefits of tax shields in their capital structure plans. Regarding hypothesis H2, the sector dummy takes the value of one to indicate firms that specialise in hardware and zero for the software subsector. The coefficient of the subsector dummy is positive and strongly significant at a one percent level, indicating that the hardware firms' start-off positions in the leverage adjustment process are higher than for software companies. This result confirms the economic reasoning outlined for H2. The comparison and contrast of these results with related studies are explained in the discussion section next.

4.2. Discussion of results

The current study finds a speed of partial capital adjustment for the South African exchange-listed firms in the range of 45 and 57% averaging 51%. Is this slow, average, or fast? Neither the theory of capital structure nor the partial adjustment model inform us of the ideal adjustment speed. Therefore, to make up for this shortcoming, and to profile our results in the context of prior studies, we benchmark with the literature sampled in Table 3. We list five cross-country studies and five individual studies from South Africa. All studies were estimated using the same framework as equations (1) to (5). Most of these panel studies are examined from 1990 to 2012, which is handy for a reasonable comparison.

We now profile the current study in light of past findings. Table 3 shows that transitional economies in Central and Eastern Europe have the lowest capital adjustment speed of 13% (De Haas, Peeters, 2006), followed by developed countries at 21% (Antoniou et al., 2008), the world average of 26%, (being an aggregation of 37 country-study by Öztekin, Flannery (2012), and 40 country-study by Clark et al. (2009)), emerging economies in Asia at 35% (Getzmann et al., 2014), and African countries at 39%, while the individual South African evaluations average 48% (Öztekin, Flannery, 2012; Clark et al., 2009; Moyo et al., 2013; Ramjee, Gwatidzo, 2012). From the above, we can conclude that technology firms in South Africa have capital adjustment speed (51%) towards the target level within the order of magnitude higher than the national average (48%), and double the global speed of 26%.

In terms of inter-industry studies of capital structure adjustment, our study compares closely to a cross-country study of 11 Asian economies (listed in Table 3) by Getzmann et al. (2014) in two important ways. The study finds sectoral speeds of 25% (consumer services), 27% (industrial), 28% (health), 31% (basic material), 32% (consumer goods), 35% (oil and gas), and 45% (technology). The first observation is that based on book leverage, the partial adjustment speed for the Asian technology sector is 45% which is exactly the same as our findings. Based on market leverage, our results exceed theirs by only 16% (comparing 47% and 57%). The second observation is that the speed of adjustment for Asian technology firms exceeds their all-industry average of 32%. As elucidated above, this is a similar pattern to our national results but for different magnitudes. In contrast, in the U.K., Aoun (2012) finds that the information communication technology (ICT) sector has a lower capital adjustment speed but is reasonably close to the non-ICT industries at 29 and 36%, respectively. Whereas the geographic effect of absolute levels is evident, the difference in speeds for emerging versus developed economies could be a literature confirmation that technology behaves differently in less developed countries (Kedzior et al., 2020)

The above discussion and the scan of Table 3 signal that partial adjustment speeds experience inter-industrial, geographical, developmental, and macroeconomic conditions (Douglas, Cook, 2010) variations. For example, we have observed that transitional economies in Central and Eastern Europe have adjustment speeds unique to their economic environment (De Haas, Peeters, 2006). Also, bank-based economies like Japan and Germany have adjustment speed that is different to those of market-based economies like the U.S. and U.K. (Antoniou et al., 2008).

To put it all together, we perceive that the data convey a message that technology firms adjust their capital structures towards target levels faster than the rest of the industries in emerging markets of Asia, Africa, and especially South Africa. Regarding the possible reason for rapid adjustment speed in technology firms, we know from the literature that technology firms are known to have less debt (Antoniou et al., 2008), with high complex industry risk (Zakrzewska-Bielawska, 2010), and both factors are associated with faster capital adjustment speed (Smith et al., 2010). Global characterisation of technology adjustment speed requires sectoral study in a cross-country setting to control for innovation spillovers and variation in geographic factors flagged above.

Table 3. Speed of adjustment from selected prior studies

No.	Study	Data period	Number of firms	Countries	List of countries	Industry	Ave. in %	Range in %
1	De Haas, Peeters (2006)	1993–2001	67125	10 countries: (Central, Eastern Europe)	A	All industries (non-financial)	13	4–49
2	Öztekin, Flannery (2012)	1991–2006	6976	37 countries: mixed	B	All industries (non-financial)	21	4–41
3	Antoniou et al. (2008)	1987–2000	57134	4 countries: developed	C	All Industries (non-financial)	24	11–39
4	Öztekin, Flannery (2012)	1991–2006	193	South Africa		All industries (non-financial)	27	
5	Clark et al. (2009)	1990–2006	26395	40 countries: mixed	D	Industrial	31	18–44
6	Getzmann et al. (2014)	1995–2009	1239	11 countries: Asia	E	All industries (non-financial)	35	24–45
7	Jooma, Gwatidzo (2013)	2001–2011	486	4 countries: Africa	F	Industrial (non-financial)	39	18–60
8	Clark et al. (2009)	1990–2006	3211	South Africa		Industrial	43	
9	Moyo et al. 2013	2000–2010.	87	South Africa		Manufacturing, mining, retail	50	42–58
10	Ramjee, Gwatidzo (2012)	1998–2008	178	South Africa		All industries (non-financial)	71	62–79

A 10 countries from Central and Eastern Europe: Bulgaria, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovak Republic, and Slovenia.

B 37 mixed countries: Argentina, Australia, Austria, Belgium, Brazil, Canada, Chile, Columbia, Denmark, Finland, France, Germany, Greece, Hong Kong, India, Indonesia, Ireland, Israel, Italy, Japan, Malaysia, Mexico, New Zealand, Norway, Pakistan, Peru, Philippines, Portugal, Singapore, South Africa, Spain, Switzerland, Thailand, Turkey, United Kingdom, United States.

C 4 developed countries: France, Germany, Japan, USA, and U.K.

D 40 mixed countries: Countries: Argentina, Australia, Austria, Belgium, Brazil, Canada, Chile, China, Denmark, Finland, France, Germany, Greece, Hong Kong, India, Indonesia, Ireland, Israel, Italy, Japan, Malaysia, Mexico, Netherlands, New Zealand, Norway, Pakistan, Peru, Philippines, Poland, Singapore, South Africa, South Korea, Spain, Sweden, Switzerland, Taiwan, Thailand, Turkey, United Kingdom, and United States.

E 11 Asian countries: China, India, Indonesia, Japan, Malaysia, Pakistan, Philippines, Singapore, South Korea, Taiwan, and Thailand.

F 4 African countries: Ghana, Kenya, Nigeria, and South Africa.

Source: Authors' compilation from cited studies.

5. Conclusion

The objective of this study was to evaluate the dynamic capital structure behaviour of technology firms using the JSE-listed firms of South Africa as a case study. The study employed a carefully validated two-system GMM model to estimate a partial capital adjustment process. The results are insightful. After a comprehensive interrogation of our research outcomes in light of prior cross-country and sectoral studies, we can submit that South African technology firms adjust their capital structures towards optimal targets faster than their counterparts within the country and Africa, consistent with evidence from the Asian emerging markets. To reiterate, our findings and the analysis of prior studies confirm Nivorozhkin, Kireu (2019, p. 112) results that "the speed of adjustment to target capital structure in developing economies is significantly higher than in advanced economies", to which we add that technology firms are even faster.

In conclusion, the results provide evidence that technology firms engage in dynamic partial leverage adjustment to achieve optimal capital structures, confirming hypothesis H1. Also, consistent with H2, the results reveal a sub-sector leverage-level effect where the hardware firms have higher starting positions of capital adjustment than software companies. This study corrects the knowledge gap observed in the literature that capital structure studies are "largely conducted by considering all the industries together, whereas the focus on a particular industrial sector [is] meagre" (Bajaj et al., 2021, p. 173). The outcome of this study should benefit technology investors, policymakers, and practitioners. Given that, for firms to achieve target capital structure levels will allow them to operate at optimal financing plans (Hovakimian et al., 2001) then, industrial policies that create an enabling environment for technology firms to optimise their leverage timeously should be supported.

The current study was constrained by a limited population of technology firms. Several improvements and expansions of the current study are possible and recommended. We encourage sector-level studies in a cross-country setting with a spotlight on technology industries since hitech firms are global by nature. Such broad panel data should also alleviate the problem of data limitations. All the studies reviewed in Table 3, including the current work, have one common area of desirable improvement. All employ constant speed of adjustment. Further studies need to move from this weakness and estimate models with time-varying adjustment speeds. Lastly, other dedicated works may investigate the impact of technology diffusion in the capital adjustment process.

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Appendix

Table A1. GMM selection test equations

Variables	Pool Ordinary Least Squares (POLS)		Least-Squares Dummy Variables (LSDV)		General Method of Moments (Differenced GMM)	
	Coefficient (Delta1)	Standard Error	Coefficient (Delta2)	Standard Error	Coefficient (Delta3)	Standard Error
Lagged leverage	0.791***	0.023	0.562***	0.032	0.476***	0.041
Asset tangible	0.042***	0.011	0.014	0.015	–0.048	0.035
Tax shields	–0.002	0.006	0.001	0.006	–2.807	2.583
Profit	0.005	0.050	–0.029	0.053	–0.025	0.089
Total assets	0.006	0.004	0.013***	0.005	0.070	0.070
Fixed time effects	Yes		Yes		Yes	

Notes. Statistical significance: *** — 1%.
Delta1=coefficient of POLS equation, Delta2=coefficient of LSDV equation, Delta3=coefficient of GMM equation.