University of Connecticut

Department of Economics Working Paper Series

Firm Size, Corporate Debt, R&D Activity, and Agency Costs: Exploring Dynamic and Non-Linear Effects

by

Giorgio Canarella
University of Nevada - Las Vegas

Stephen M. Miller
University of Nevada - Las Vegas

Working Paper 2019-05
March 2019

365 Fairfield Way, Unit 1063
Storrs, CT 06269-1063
Phone: (860) 486-3022
Fax: (860) 486-4463
http://www.econ.uconn.edu/

Firm size, corporate debt, R&D activity, and agency costs: Exploring dynamic and non-linear effects

Giorgio Canarella[a]
giorgio.canarella@unlv.edu

and

Stephen M. Miller[a,*]
stephen.miller@unlv.edu

Abstract: This paper empirically investigates firm-specific determinants of agency costs, a relatively new and unexplored area in corporate finance. We estimate dynamic agency costs models, linking debt, firm size, and R&D activity to agency costs for a panel of U.S. information and communication technology (ICT) firms over 1990-2013. We adopt the Blundell and Bond (1998) two-step system GMM technique, which explicitly accounts for persistence, endogeneity, and unobservable firm heterogeneity. We provide the first evidence that our inverse proxy for agency costs, namely asset turnover (Ang, et al., 2000), exhibits an inverted U-shaped relationship with debt and a U-shaped relationship with firm size and R&D activity. These findings imply that agency costs experience a minimum value (in case of debt) and a maximum value (in case of firm size and R&D activity) and, therefore, that agency costs are higher at both low and high levels of debt, and lower at both low and high levels of firm size and R&D activity. We find that the level of debt of the average firm in the sample falls below the level that minimizes agency costs. We also document that, consistent with the agency literature, short-term debt provides an additional effective monitoring mechanism to alleviate agency costs. Our findings reveal that agency costs are dynamic in nature, mean-reverting, and persistent over time. This notion confirms the Florackis and Ozkan (2009) conjecture that managers behave as though an optimal level of agency costs exist that they pursue. Finally, we find a positive association between firm profitability and agency costs and a negative association between agency costs and firm growth. Extensive additional analysis confirms the robustness of our results.

Keywords: ICT industry; agency costs; non-linearity; dynamic adjustment; system GMM

JEL classification: G21; G28; G32; G34

[a] Department of Economics, Lee Business School, University of Nevada, Las Vegas; Las Vegas, Nevada

* Corresponding author

1. Introduction

Building on the influential work of Jensen and Meckling (1976) and Myers (1977), the corporate finance literature has extensively analyzed agency conflicts and their associated costs. These costs arise because of the separation of ownership and control in firms creates conflicts of interest between shareholders and managers. That is, managers often indulge in activities that enhance their personal benefits rather than maximize the firm value (Jensen, 1986). Baker and Powell (2005) classify agency costs into direct and indirect agency costs. Shareholders incur direct costs in the form of bonuses, stock options, audit fees, and other managerial incentives to reduce managerial opportunistic activities and behavior that results in direct expropriation of shareholder wealth, such as consumption of executive perquisites, shirking behavior, and insufficient effort. In contrast, indirect agency costs result from managerial failure to make profitable investments. This may occur in many ways. Managers may either invest in risky projects that yield a negative expected return or may fail to invest in projects that yield a positive expected return. Economists call these problems the overinvestment or asset substitution problem (Jensen and Meckling, 1976), and the underinvestment or debt overhang problem (Myers, 1977).[1]

Most empirical work emphasizes the role of agency costs from the perspective of the determinants of capital structure and firm performance (see, e.g., Titman and Wessels, 1988; Rajan and Zingales, 1995; and Ozkan, 2001). Studies that measure agency costs and explicitly examine the direct effects of firm characteristics on agency costs are relatively recent and few. Some analyses exist of the determinants of agency costs reported for U.S. firms (Ang, et al., 2000; Singh and

[1] Researchers frequently use the free-cash-flow and the monitoring theories to explain agency conflicts. The free-cash-flow theory argues that, absent effective monitoring, agency problems associate with conflicts over the use of free cash flow (Jensen, 1986; Stulz, 1990). Since only managers only observe cash flows, they can then underreport and divert these cash flows for their own private benefit. The monitoring theory, on the other hand, asserts that managers desire to avoid the external monitoring of creditors and the bonding of cash payments that comes with debt (Jensen, 1986).

Davidson, 2003; Jelinek and Stuerke, 2009), U.K. firms (McKnight and Weir, 2009; Florackis and Ozkan, 2009; Florackis, 2008; Zhang and Lee, 2008), and Australian firms (Fleming, et al., 2005; Truong and Heaney, 2013), where the emphasis predominantly focuses on the normative role of corporate governance in alleviating agency costs. While these papers constitute an important step toward more realistic tests of agency costs, they remain silent on other factors that play a role in capital structure discussions and, consequently, on agency costs.

This paper opens an alternative perspective on the analysis of agency costs and, using a panel of U.S. information and communication technology (ICT) firms over 1990-2013, provides empirical evidence that sheds some light on three relatively unexplored areas of the empirical agency literature, namely the effects of R&D activity, firm size, and corporate debt on agency costs. Our results support the view that agency costs respond crucially to these firm-specific factors.

R&D activity plays a pivotal role in the dynamics of ICT firms and, from an agency theory viewpoint, proves unique in terms of uncertainty and managerial discretion (Aghion, et al., 2004; Chen, 2017; Carpenter and Petersen, 2002; Brown and Petersen, 2009). ICT firms are high technology firms, whose "knowledge capital" (Laperche, 2007) provides an essential means not only to maintain or increase their competiveness but also to survive (Porter, 1990). The benefits of R&D activity are far more uncertain than the benefits from ordinary investment in plant and equipment (Kothari, et al., 2002). Managers may undertake R&D spending to promote their immediate personal interest at the expenses of shareholders' interests (Jensen, 1993), may engage in excessive R&D spending as part of their short-term reputation building efforts to enhance their visibility in the labor market (Hirshleifer, 1993), or may hesitate to fund fully R&D investment because of the uncertainties surrounding this type of activity.

R&D activity confront problems of asymmetric information. R&D activity involves mostly technical and scientific factors, leaving shareholders generally less informed than managers about their prospects and effect on the long-run performance of the firm (Jensen and Smith, 2000). This produces high monitoring costs, which, in turn, translates into high agency costs. Managers benefit from the success of R&D activity but do not actually suffer losses from their failures (Gompers and Lerner, 2001, 2003). Gompers and Lerner (2001, 2003) argue that agency problems are greater for intangible assets. The difficulty in assessing the performance of intangible assets means that managers may invest in R&D activity with high personal returns but low expected monetary payoff to shareholders. Tangible assets prove easier to sell upon liquidation of the firm and, therefore, require less monitoring.

R&D activity raises the issue of risk-related agency costs (i.e., agency costs resulting from the managers' risk attitude). Managers and shareholders possess different risk profiles (Jensen and Meckling, 1976; Amihud and Lev, 1981; Smith and Stulz, 1985; Holmström , 1999). Managers are more risk-averse than shareholders, since they cannot diversify the firm's risk (i.e., they can only maximize their job effort), while shareholders can diversify their investments across many firms. In this case, when choosing between two projects, managers will prefer a low risk one that likely will succeed, because their personal earnings depend on the firm's fate. Thus, motivated by risk aversion (or career concerns), managers "play it safe" and take on less risk than what diversified shareholders want. When risk, rather than private benefits, drives managerial preferences, corporate policies that maximize shareholder value may produce the opposite effects. For example, the increasingly widespread use of equity-based executive compensation (Frydman and Jenter, 2010) and the prospects of termination of CEOs for poor corporate performance (Jenter and Lewellen, 2015) may exacerbate, rather than alleviate, risk-related agency conflicts, because they increase the manager's incentive to reduce the firm's risk.

No consensus exists on the effect of firm size on agency costs. Larger firms may generate economies of scale that increase the value of the firm and reduce agency costs, or generate coordination and management problems that reduce the value of the firm and increases agency costs. Jensen and Meckling (1976) and Jensen (1986) argue that agency conflicts more likely prevail in large firms. Doukas, et al. (2000) find that larger firms more likely exhibit higher agency costs given their greater complexity and the greater informational difficulties faced by the shareholders. Managers may expand firm size to further their own "empire-building" interests rather than the interests of shareholders.

Several possible reasons explain why managers benefit from larger firms: (i) the prestige and reputation of managing larger firms (Stulz 1990), (ii) the scope of divertible resources grows with size (Shleifer and Vishny 1989), (iii) managerial compensation relates to firm size (Jensen and Murphy 1990), (iv) larger firms diversify more than smaller firms, reducing bankruptcy and employment risks (Amihud et al. 1983), or (v) larger firms increase managerial entrenchment (Shleifer and Vishny 1989).

Managers of smaller firms may obtain better alignment with shareholders compared to larger firms (Demsetz and Lehn, 1985). Demsetz (1983) actually argues that "largeness" may itself be an agency cost, where managers expand the size of the firm at shareholders' expense to increase their own consumption perquisites. Fama and Jensen (1983) argue that agency costs increase with firm size as monitoring becomes more difficult with larger firms. On the other hand, agency costs may be greater for smaller firms than for larger firms because smaller firms do not face large institutional outside monitoring and oversight, as a smaller number of security analysts follow their actions.

In contrast, Ang, et al. (2000) and Singh and Davidson (2003) find that larger firms benefit from economies of scope, implying that larger companies more likely experience lower agency costs. Larger, more diversified firms, therefore, prove less prone to bankruptcy (Titman and Wessels, 1988). Firm size may also reflect the strength of governance mechanisms. Weaker corporate governance structures cause greater agency problems (Core et al., 1999). Larger (smaller) companies adopt stronger (weaker) and more (less) advanced corporate governance structures, including external security-analyst monitoring of earning forecasts (Knyazeva, 2007), which reduces (increases) agency costs. Larger firms adopt more effective governance mechanisms.

The literature identifies debt as a major firm governance mechanism (e.g., Shleifer and Vishny, 1997; Armstrong et al., 2010; Jensen, 1986, 1993; Williams, 1987; Stulz, 1990; Grossman and Hart, 1982; Hart and Moore, 1995). According to agency theory, debt holders more closely monitor firms with higher levels of debt and, thus, managers exert less managerial discretion to pursue opportunistic activities. Debt commits managers and reduces the free cash flow available to managers (Jensen, 1986; Stulz, 1990), resulting in the reduction of resources under their control for empire building (Jensen, 1986; Stulz, 1990). The existence of debt causes managers to use fewer perquisites, to become more efficient, to avoid the probability of bankruptcy, and to avoid the loss of corporate control. Debt increases monitoring of managers by debt holders, such as banks, which, in turn, puts pressure on managers to run a profitable organization (Ang, et al., 2000). Debt-holders monitor the activities of managers and the performance of firms (Jensen and Meckling, 1976) to ensure the payment of interest and principal.

This external monitoring by debt-holders helps shareholders in monitoring managers and reduces the shareholders cost of monitoring. Debt increases the threat of bankruptcy, reducing the benefits managers receive from the firm (Grossman and Hart, 1986; Williams, 1987). The threat of bankruptcy forces managers to run a profitable business. This creates a threat of managers losing their jobs with the liquidation of the firm. This threat puts pressure on managers to run the business profitably and stops them from exploiting the resources of the firm and using them inefficiently. In this way, debt disciplines managers and forces them to purse profit maximizing activities.

Some agency literature emphasizes the role of the debt maturity structure, in addition to the level of debt, in mitigating agency problem (e.g., Hart and Moore, 1995, 1998; and Shleifer and Vishny, 1992). Agency theory argues that short-term debt mitigates agency problems more effectively that long-term debt. Stulz (2002, p.172) asserts that "short-term debt can be an extremely powerful tool to monitor management". Short-term debt provides creditors the ability to monitor managers with minimum effort (Rajan and Winton, 1995; Stulz, 2002) and forces managers to revisit the capital markets more frequently, exposing them to scrutiny by external parties, thereby mitigating agency costs (Datta et al. 2005; Hart and Moore, 1995; Flannery, 1986; Diamond, 1984, 1991; Lummer and McConnell, 1989). Myers (1997) argues that short-term debt proves more beneficial, since it alleviates the underinvestment and asset substitution problems. Leland and Toft (1996) similarly show that short-term debt reduces or eliminates "asset-substitution" agency costs. Childs et al. (2005) argue that short-term debt can mitigate both the underinvestment and overinvestment problems. Among empirical studies, Johnson (2003) and Brockman et al (2010) find evidence that short-term debt alleviates the agency problems. Jensen and Meckling (1976) suggest that the effect of debt on agency costs may not be monotonic. Altman (1984) and Titman (1984) indicate that when the proportion of debt in the capital structure reaches a certain point, further increases may generate significant agency costs.

Little systematic research exists into the non-linear relationships between agency problems, firm size, debt, and R&D activity, although the corporate finance literature documents that the benefits of debt may be offset by anticipated bankruptcy costs or financial distress, which puts the managers' private benefits at risk. Agency theory does not predict linear relationships. Rather, linearity implies that the effects are homogeneous (i.e., the effect of debt, firm size, and R&D activity on agency costs do not depend on their respective levels). Non-linearity, on the other hand, implies that the effect of debt, firm size, and R&D activity on agency costs is heterogeneous (i.e., the effect depends on their respective levels). Agency theory does not predict non-linear relationships either. Imposing linearity *a priori* may inadequately represent the data, however. Polynomial specifications can test for linearity against low-order polynomials.

Little systematic research considers agency costs as a dynamic process. Florackis and Ozkan (2009) provide one exception by considering the dynamics of agency costs, developing a dynamic model to examine the effect of managerial entrenchment on agency costs from U.K. panel data. The model captures the dynamics of agency costs, including persistence, adjustment costs, and mean reversion. Additionally, the dynamic approach reveals that a level of agency costs exists that managers regard as equilibrium. The equilibrium implies a trade-off at the margin between the private managerial benefits of expropriation of shareholders' wealth and the private managerial costs that such conduct may entail. The trade-off results in an optimal level of expropriation from the managers' viewpoint.[2] In line with this view, Florackis and Ozkan (2009) argue that the optimal level of exploitation of shareholders' wealth by managers defines the optimal level of agency costs sustained by shareholders. When managers deviate from this optimal level, they will attempt to revert to it. Such adjustments, however, may occur slowly, and it may take some time because of adjustment costs.

[2] For a theoretical treatment of the optimal level of exploitation, see La Porta, et al. (2002).

In this paper, we employ a dynamic panel-data model to examine the non-linearities in the relationships between agency costs and firm size, debt, and R&D activity. Specifically, we apply the two-step system GMM estimator of Blundell and Bond (1998) to estimate a dynamic agency-cost process that includes quadratic polynomials in firm size, debt, and R&D activity. The two-step system GMM estimator addresses several serious econometric issues that usually associate with the estimation of dynamic panel–data models, including endogeneity, heteroskedasticity, autocorrelation, and unobserved firm heterogeneity, using the instrumental-variable approach (Flannery and Hankins, 2013). Additionally, this methodology addresses the concern of biases due to potential omitted variables (Arellano and Bond, 1991). Prior studies, such as Ang, et al., (2000), Singh and Davidson (2003), Jelinek and Stuerke (2009), and Truong and Heaney (2013) do not address the endogeneity issue.

We make several contributions to the literature. First, we find significant evidence in favor of the heterogeneous-effects hypothesis. In particular, using the recently developed Lind and Mehlum (2010) test, we obtain robust and consistent evidence that the relationship between firm size, R&D activity, and debt are not monotonic. Specifically, we document that U-shaped agency benefits of increasing debt and inverted U-shaped agency costs of increasing firm size and R&D activity exist. These findings imply that agency costs experience a minimum value (in case of debt) and a maximum values (in case of firm size and R&D activity) and, therefore, agency costs are higher at both low and high levels of debt, and lower at both low and high levels of firm size and R&D activity. Our results, however, indicate that the average ICT firm in the sample operates at a level that falls below the optimal capital structure.

Second, we document that agency costs are dynamic in nature, and that they are mean-reverting and persistent over time. This confirms the Florackis and Ozkan (2009) conjecture that managers behave as though an optimal (i.e., equilibrium) level of agency costs exist that they wish to achieve. Our findings, however, indicate that the adjustment process is costly and managers cannot adjust to the desired level of agency costs instantaneously.

Third, we show that short-term debt provides an effective corporate governance mechanism.

Finally, we find evidence that firm growth negatively relates to agency costs and firm profitability positively relates to agency costs. These findings are robust to alternative regression specifications and to subsampling analysis.

The rest of paper proceeds as follows. Section 2 outlines the linear and quadratic dynamic specifications of the empirical agency costs model and discusses the econometric issues and the statistical methodology relevant for the estimation of dynamic panel-data models. Section 3 reports the descriptive characteristics of the sample and the main econometric results based on GMM estimation. Section 4 assesses the robustness of the results using sub-sampling analysis and alternative specifications. Section 5 provides a summary and conclusion.

2. Empirical framework and econometric strategy

2.1 A dynamic agency cost model

We estimate the effect of firm size (*SIZE*), total debt (*DEBT*), R&D activity (*R&D*), and short-term debt (*SDEBT*) on agency costs (*AC*) by adopting a dynamic panel-data model (Florackis and Ozkan, 2009) represented by

$$AC_{it} = \lambda AC_{it-1} + \beta_1 R\&D_{it-1} + \beta_2 DEBT_{it-1} + \beta_3 SIZE_{it-1} + \beta_4 SDEBT_{it-1} + \vartheta_i + \vartheta_t + \upsilon_{it} \qquad (1)$$

In the model, firms are represented by the subscript i ($i = 1,\ldots, N$) and years by the subscript t ($t = 1,\ldots, T$), and AC stands for agency costs.

Following Ang, et al. (2000), Singh and Davidson (2003), and Florackis and Ozkan (2008, 2009), we measure agency costs (*AC*) by the asset-turnover ratio (*ATR*), defined as the ratio of annual sales to total assets, a measure of asset utilization.[3] The ratio inversely measures agency costs, as it measures managerial ability to employ assets efficiently. A high asset-turnover ratio shows a large amount of sales and ultimately cash flow generated for a given level of assets. A low ratio, on the other hand, indicates that managers use assets in activities that do not generate cash flow (Singh and Davidson, 2003). Thus, firms with considerable agency conflicts will experience lower asset turnover ratios relative to those experiencing less agency conflicts. Thus, the ratio inversely measures agency costs, as it proxies for the loss in revenue per dollar of investment attributable to inefficient asset use. This can result from poor investment decisions, such as investment in negative net-present-value (NPV) projects, failure to use assets productively, or consumption perquisites, managerial entrenchment, and shirking conduct.

The main explanatory variables include *SIZE*, computed as the logarithm of the total assets (Florackis, 2008; Florackis and Ozkan, 2009; Aghion, et al., 2004; Truong and Heaney, 2013) as a measure of firm size; *DEBT*, computed as the ratio of total debt (long-term debt plus debt in current liabilities) to total assets (Flannery and Rangan, 2006; Truong and Heaney, 2013) as a measure of leverage; *R&D*, computed as the ratio of R&D expenditure to sales (Aghion, et al., 2004; Fleming et al., 2005; Jelinek and Stuerke, 2009) as a measure of R&D activity; and *SDEBT*, computed as the ratio of short-term debt (one-year maturity) to total debt (Florackis and Ozkan, 2009; Florackis, 2008) as a measure of short-term debt maturity structure. An extended version of equation (1) also includes *GROWTH*, computed as growth in total assets, as a proxy for a firm's growth potential and

[3] Ang et al. (2000), instead of using the ratio directly, use the difference in the ratios of the firm with a certain ownership and management structure and the no-agency-cost base-case firm.

future investment opportunities (Fama and French, 2002; Titman and Wessels, 1988), and *PROF*, measured by the ratio of net income to total assets, as a measure of firm profitability.

All variables are expressed in ratio or logarithmic form to account for firm heterogeneity. The time-invariant, firm-specific effects ϑ_i captures the effects of unobserved firm heterogeneity (i.e., various unobservable characteristics of the firm that exert significant effect on agency costs). They change across firms, but remain fixed for a given firm over time. Differences in managerial skills, abilities, motivation, and attitudes toward risk are examples of time-invariant, firm-specific effects. The firm-invariant, time-effects ϑ_t, on the other hand, remain the same for all firms, but vary over time. They mainly capture economy-wide factors that the firm cannot control, such as interest rates and inflation. The idiosyncratic term υ_{it} satisfies the white-noise assumptions.

Equation (1) is a linear specification of the effect of R&D activity, debt, and firm size on agency costs. In this framework, R&D activity, debt, and firm size exert the same effect on agency costs for all firms regardless of their respective levels. This specification is an empirical issue. That is, it is an empirical issue if debt, firm size, and R&D activity explain agency costs in a linear fashion. We extend this view by specifying a non-linear relationship between debt, R&D activity, firm size, and agency costs and examine whether the non-linear relationship provides a more adequate characterization of the data. A simple specification that captures that non-linearity (Griffith et al., 1993) uses a polynomial model that includes the squared terms of R&D activity (*R&D SQ*), debt (*DEBT SQ*), and firm size (*SIZE SQ*) in equation (1)[4]: Accordingly, the revised specification is as follows:

[4] The quadratic specification is advantageous over the piecewise specification in that the turning point is endogenous instead of being specified in advance (McConnell and Serveas 1990).

$$AC_{it} = \lambda AC_{it-1} + \beta_1 R\&D_{it-1} + \beta_2 DEBT_{it-1} + \beta_3 SIZE_{it-1} + \beta_4 SDEBT_{it-1}$$

$$+ \gamma_1 R\&D\ SQ_{it-1} + \gamma_2 DEBT\ SQ_{it-1} + \gamma_3 SIZE\ SQ_{it-1} + \vartheta_i + \vartheta_t + \upsilon_{it} \qquad (2)$$

This specification displays a certain degree of flexibility in the effect of firm size, R&D activity, and debt on agency costs. Since the quadratic form is linear in the parameters, it is straightforward to estimate the model and to provide a direct interpretation of the parameter estimates.

The quadratic specification in equation (2) implies that the marginal effects of R&D activity, debt, and firm size on agency costs are, respectively, given by

$$\beta_1 + 2\gamma_1 R\&D_{it-1}, \qquad (3)$$

$$\beta_2 + 2\gamma_2 DEBT_{it-1}, \text{ and} \qquad (4)$$

$$\beta_3 + 2\gamma_3 SIZE_{it-1}. \qquad (5)$$

These effects are not constant, but linearly depend on their respective levels.

Furthermore, we hypothesize that the relationship between agency costs and debt first decreases and then increases (U-shape), while the relationship between agency costs and R&D activity as well as the relationship between agency costs and firm size first increases and then decreases (inverted U-shape). Since asset turnover inversely measures agency costs, these hypotheses, in turn, imply: 1) an inverted U-shaped relationship between asset turnover and debt; 2) a U-shaped relationship between asset turnover and firm size; and 3) a U-shaped relationship between asset turnover and R&D activity. The traditional approach to testing U-shaped or inverted U-shaped relationships relies on the signs of the estimates of linear and quadratic terms. A U-shaped relationship exists for a negative coefficient on the linear term and a positive coefficient on the quadratic term. In contrast, an inverted U-shaped relationship exists for a positive coefficient on the linear term and a negative coefficient on the quadratic term. Thus, the hypotheses are validated if the coefficients on the linear and the quadratic terms exhibit different signs, which are individually and jointly significant.

Lind and Mehlum (2010) argue, however, that this criterion alone is weak, since the true relationship may be convex (concave), but monotonic on the available data range, which implies a false quadratic U-shaped (inverted U-shaped) relationship. Lind and Mehlum (2010) develop an exact test that avoids false inference of the true non-linear relationship by extending the work of Sasabuchi (1980). The procedure tests the presence of a U-shape (inverted U-shape) on some interval value by testing the composite hypothesis that the slope of the relationship is positive (negative) at the left-hand side of the interval and negative (positive) at the right end side.[5]

Specifically, from equation (2), the data support a U-shaped relationship between *ATR* and *R&D,* if we can reject the combined null hypothesis

$$H_0 : \hat{\beta}_1 + \hat{\gamma}_1 R\&D_L \geq 0 \text{ and/or } \hat{\beta}_1 + \hat{\gamma}_1 R\&D_H \leq 0 \quad (6)$$

in favor of the combined alternative

$$H_1 : \hat{\beta}_1 + \hat{\gamma}_1 R\&D_L < 0 \text{ and } \hat{\beta}_1 + \hat{\gamma}_1 R\&D_H > 0 . \quad (7)$$

Similarly, the data support a U-shaped relationship between *ATR* and *SIZE*, if we can reject the combined null hypothesis

$$H_0 : \hat{\beta}_3 + \hat{\gamma}_3 SIZE_L \geq 0 \text{ and/or } \hat{\beta}_3 + \hat{\gamma}_3 SIZE_H \leq 0 \quad (8)$$

in favor of the combined alternative

$$H_1 : \hat{\beta}_3 + \hat{\gamma}_3 SIZE_L < 0 \text{ and } \hat{\beta}_3 + \hat{\gamma}_3 SIZE_H > 0 . \quad (9)$$

[5] A discussion of the test can be found in Haans, et al (2016). Further applications of the test can be found in Arcand, et al. (2015) and Byoun (2011). We observe, incidentally, that testing the significance of a quadratic specification does not tell us whether a quadratic relationship is true but only whether is a good representation among others. There may be other functional forms that fit the data better.

Conversely, the data support an inverted U-shaped relationship between *ATR* and *DEBT*, if we can reject the combined null hypothesis

$$H_0 : \hat{\beta}_2 + \hat{\gamma}_2 DEBT_L \leq 0 \text{ and/or } \hat{\beta}_2 + \hat{\gamma}_2 DEBT_H \geq 0 \tag{10}$$

in favor of the combined alternative

$$H_1 : \hat{\beta}_2 + \hat{\gamma}_2 DEBT_L > 0 \text{ and } \hat{\beta}_2 + \hat{\gamma}_2 DEBT_H < 0 . \tag{11}$$

The subscripts *L* and *H* refer to the minimum (lowest) and maximum (highest) of the observed data range. To assure at most one extreme point on the data interval, Lind and Mehlum (2010) require that the non-linear relationship possesses at most one extreme point. The test for H_0 uses the likelihood ratio principle developed by Sasabuchi (1980), known as an intersection-union test. Lind and Mehlum (2010) also propose the Fieller (1954) method (see, i.e., Cox, 1990) to compute the confidence interval for the estimated extreme value or threshold point $\beta_i / 2\lambda_i$ for *i* = 1,2,3.Lind and Mehlum (2010) argue that the Fieller method is superior to the delta method.

The lagged dependent variable produces the dynamic nature of the models and the possibility that the change in the level of agency costs takes place gradually (i.e., managers cannot adjust instantaneously the actual level of agency costs to their desired level). Florackis and Ozkan (2009) postulate a dynamic agency-cost adjustment, whereby managers behave as though they know the optimal level of agency costs. That is,

$$AC_{it} - AC_{it-1} = \delta(AC_{it}^{*} - AC_{it-1}) \tag{12}$$

where AC_{it}^{*} equals the desired level of agency costs, $(AC_{it}^{*} - AC_{it-1})$ equals the desired change in agency costs, and $\delta = 1 - \lambda$ equals the speed of adjustment. The speed of adjustment captures the extent to which deviations from the desired level of agency costs are eliminated in each period. If $\delta = 1$, the speed of adjustment is infinitely high, and managers can adjust the level of agency costs immediately, so that agency costs always equal the desired level: $AC_{it}^{*} = AC_{it-1}$. At the other extreme, when $\delta = 0$, the speed of adjustment equals zero, managers do not change the existing level of agency costs (i.e., they prefer to do nothing), because the adjustment costs are too high: $AC_{it} = AC_{it-1}$. A positive and below unity coefficient suggests that managers possess an optimal level of agency costs and revise it over time. On the other hand, a coefficient greater than one implies that managers do not have any optimal level of agency costs that they want to attain.

2.2 Estimation method

Estimation of dynamic panel models such as in equations (1) and (2) associate with at least three critical concerns, resulting from the fact that panel data experience problems of unobservable heterogeneity and endogeneity. Unobservable heterogeneity refers to omitted variables that affect the dependent variable but correlate with the explanatory variables. The analyst usually addresses unobservable heterogeneity through the individual fixed effects (FE), which differ for every firm but remain constant over time.

Second, the presence of the lagged dependent variable as a regressor implies that the standard ordinary least squares (OLS) estimator generates biased and inconsistent estimates and gives an upward biased estimate of the coefficient on the lagged dependent variable. This occurs because the lagged dependent variable and ϑ_i are necessarily correlated, even if the idiosyncratic component of the error term is serially uncorrelated, which creates an endogeneity problem. Removing the firm-specific fixed effects by taking the first differences does not resolve the problem, because the first difference transformation introduces a correlation between the lagged dependent variable and the differenced error term. In this case, the FE estimator gives seriously downward biased estimates for the coefficient on the lagged dependent variable.[6]

The third concern regards the set of regressors in equations (1) and (2). It is highly unlikely that we can treat the right-hand-side variables as strictly exogenous, since shocks that affect managerial decisions with respect to agency costs also likely affect profitability, debt, and R&D activity, among others. The dependent variable can also explain some of the right-hand-side variables. That is, the right-hand side variables could be determined simultaneously with the level of agency costs. Finally, all variables are likely measured with error, and in our case, this is particularly relevant because Kuha and Temple (2003) show that measurement error flatten the curvature of the estimated quadratic functions.

Researchers recently developed several estimators for dynamic panel data, where many individuals (firms) are observed for a small number of time periods (years), the case of "large *N*, small *T*". Flannery and Hankins (2013) provide a detailed overview. They include, among others, the bias-corrected least-squares dummy-variable estimator (LSDVC) for dynamic models developed by Kiviet (1995) and adapted by Bruno (2005a, 2005b) to unbalanced panels, the dynamic panel fractional (DPF) estimator for dynamic panel models with a fractional dependent variable developed by Loudermilk (2007) and adapted by Elsas and Florysiak (2015) to unbalanced panels, and the long

[6] Bond (2002) shows that OLS and FE estimates of the lagged dependent variable are likely biased in opposite directions. The pooled OLS estimator, which is standard in many empirical finance applications, ignores unobservable, time-invariant effects, resulting in overestimation of the lagged dependent variable and, consequently, in underestimation of the speed of adjustment. This upward bias is known as the finite sample bias (Nickell, 1981; Kiviet, 1995). The fixed-effects estimator, which considers the unobservable individual effects (in our case, firm-specific characteristics such as managerial abilities), applies the within transformation that introduces a correlation between the within transformed lagged dependent variable and the within transformed error term. This correlation causes the FE estimate to underestimate the lagged dependent variable and, consequently, overestimate the speed of adjustment. Such a downward bias is referred to as the dynamic panel bias (Nickell, 1981; Kiviet, 1995).

differencing (LD) estimator developed by Hahn, et al. (2007) and modified by Huang and Ritter (2009).

A common potential disadvantage of these estimators, however, is the assumption of strictly exogenous regressors. Endogeneity is a central issue in corporate finance empirics (Roberts and Whited, 2012), which leads to biased and inconsistent parameter estimates that make reliable inference virtually impossible. In the presence of endogeneity, the system GMM estimator (Blundel and Bond, 1998) remains the best choice (Flannery and Hankins, 2013).[7] This methodology specifically addresses three econometric issues: (1) the presence of unobserved firm-specific effects; (2) the autoregressive process in the data; (3) and the potential endogeneity of the explanatory variables. The Blundell and Bond (1998) two-step system GMM estimator extends the difference GMM estimator of Arellano and Bond (1991) and alleviates the finite sample bias due to weak instruments in the difference GMM estimator. Arellano and Bover (1995) and Blundell and Bond (1998) suggest that variables in levels may be weak instruments in equations in differences and argue that the Arellano and Bond (1991) difference GMM estimator can be improved by including equations in levels in the estimation procedure, where the instruments are the first differences of the variables. The system GMM estimator exploits additional moment conditions by combining the equations in first differences (Arellano and Bond, 1991) with equations in levels and uses lagged levels as instruments for the equations in first differences and lagged first differences as instruments for the equations in levels. The consistency of the GMM estimator, however, depends on the validity of the instruments. Arellano and Bond (1991) and Blundell and Bond (1998) provide many tests to assess the validity of the instruments, including the Hansen test of over-identifying restrictions,

---

[7] The system GMM estimator, however, is biased for a highly persistent dependent variable. The findings of Florackis and Ozkan (2009) suggest that this is not the case with *ATR*.

which tests the overall validity of the instruments, and the tests for first- and second-order serial correlation in the differenced residuals.

3. Empirical results

3.1 Sample characteristics and descriptive analysis

We use firm-level accounting data from 81 ICT firms that survived over 1990-2013. We obtain our data from the Standard and Poor's COMPUSTAT Annual North America database (Economic Sector Code: 8000). The data constitute a slightly unbalanced panel, and comprise six sectors of the ICT industry: 1) Telecommunication Equipment (ISC 8030); 2) System Software (ISC 8140) and Application Software (ISC 8130); 3) Semiconductors (ISC 8230) and Semiconductor Equipment (ISC 8220); 4) Computer Hardware (ISC 8050) and Computer Storage and Peripherals (ISC 8052); 5) Electronic Manufacturing Services (ISC 8200) and Consulting Services (ISC 8120); 6) Electronic Equipment and Instruments (ISC 8150), where ISC is the COMPUSTAT industry sector code.

Semiconductors and Semiconductor Equipment, the largest category, comprises 23% of the sample. Electronic Equipment and Instruments, and Electronic Manufacturing Services and Consulting Services comprise 22% and 20% of the sample, respectively. Telecommunication Equipment, and System Software and Application Software each comprise 12% of the sample, while Computer Hardware and Computer Storage and Peripherals comprise 10% of the sample. In line with Myers and Majluf’s (1984) argument, all variables reflect book value. In part, this decision is forced by data limitation (see Titman and Wessels, 1988).

At the theoretical level, however, book-based measures may better reflect management decisions (Almazan and Molina, 2005), since market-based measures depend on several factors that managers cannot control, such as stock price movements (Welch, 2004). Furthermore, information obtained from corporate financial statements may enjoy more credibility (Lemma and Negash, 2014;

Lang et al., 1996; Opler and Titman, 1994), or more relevancy than information from the market. For instance, the cost of financial distress relates more to the book value of debt than the market value (see Kim, et al., 2006). We drop firm-year observations, when *DEBT* and *R&D* take on values greater than one. That means the deletion of 5 firm-year observations on *DEBT* and 10 firm-year observations on *R&D*. After the removal of these fifteen firm-year observations, the BACON (Blocked Adaptive Computationally-efficient Outlier Nominator) algorithm (Billor, et al., 2000; Weber, 2010) did not detect any irregular firm-year observation based on the 85th percentile of the chi-square distribution.[8]

We also use *SIZE SQ*, *R&D SQ*, and *DEBT SQ* as quadratics of *SIZE*, *R&D*, and *DEBT*. Table 1 reports descriptive statistics for both the dependent variable and key explanatory variables. They include the mean, median, standard deviation, minimum and maximum values, and the 25- and 75-percentile values.

The average *ATR* in our sample is 1.02, indicating that, on average, net sales and total assets move in an approximately one- to-one proportion. More specifically, sales, on average, are 1.02 times total assets, which is below the averages of 1.20, 1.43, and 4.76 reported by Florackis and Ozkan (2009), Singh and Davidson (2003), and Ang, et al. (2000), respectively, for their samples. The *ATR* averages in our sub-samples vary from 0.77 in the semiconductor and semiconductor equipment sector to 1.32 percent in the computer hardware, and computer storage and peripherals sector. The average *DEBT* is 0.368, indicating that debt finances 36.8 percent of total assets, while *SDEBT* is 64.9 percent of total debt. *R&D* is 9.81 percent of net sales, and *PROF* is 4.46 percent of assets. Total assets and net sales average $8,667 million and $7,248 million, respectively. The

[8] The BACON algorithm chooses a subset *m* of observations from the multivariate dataset and consecutively adds more observations based on their Mahalanobis distance from the basic subset, if this distance is not larger than a chosen percentile of a chi-square distribution. This procedure continues until the subset of non-outliers stops changing and the remaining observations are marked as outliers. We used the user-written Stata command *bacon* (Weber, 2010).

average *DEBT* is relatively modest compared to the corresponding figure of 55 percent reported by Rajan and Zingales (1995). This means that our ICT firms generally rely more on internal financial resources (i.e., equity capital and retained earnings) than debt financing.

Figures 1, 2, 3, 4, and 5 display the mean of *ATR*, *DEBT*, *SIZE*, *R&D*, and *SDEBT* over the sample by year, indicating that the sample contains substantial time variation. Two general patterns are noteworthy. First, *ATR*, *DEBT*, and *SDEBT* decline after the prosperous decade of the 1990s, with only *DEBT* reversing the trend recently. Second, the last decade of the last century and the beginning of the first decade of this century witness a staggering growth of R&D activity. Importantly, our sample experienced two significant events in the ICT sector. One, the dot-com crash saw A*TR* and *R&D* decline significantly from their highs. Two, the global financial crisis and Great Recession saw *DEBT* and *SDEBT* showing a significant plunge. Interestingly, *DEBT* and *SDEBT* move in opposite directions during the crisis. In contrast, only *SIZE* displays a positive trend throughout the period.

We check all variables for multicollinearity, where finding no strong correlation between the explanatory variables (see Table 2) lessens the threat of multicollinearity. A positive correlation exists between *PROF* and *GROWTH*, which is not surprising. Our profitability measure, however, is pre-tax and pre-dividend. A profitable firm without any positive net present value projects to invest in may pay out all profit as dividends without adding any retained earnings to its balance sheet. Our profitability measure, thus, proxies for the cash flow generating ability of the firm, whereas actual firm growth captures whether the firm can find new profitable investment opportunities holding constant the level of profitability. Not surprisingly, there is a negative correlation between *DEBT* and *SDEBT*, a positive correlation between *SIZE* and *DEBT*, as expected, and a negative correlation between *R&D* and *DEBT*, which is consistent with the findings of Aghion et al (2004). Gujarati and

Porter (2009) explain that a serious problem only exists if the correlation coefficients between explanatory variables exceed 0.8. Furthermore, the VIF test results report values substantially less than 2. Gujarati and Porter (2009) argue that VIFs greater than 10 indicate multicollinearity.

3.2 Two-step system GMM results

Table 3 reports the results of four dynamic panel-data specifications, using the Blundell and Bond (1998) two-step system GMM estimator[9] with the Windmeijer (2005) correction for the finite sample bias associated with the estimator.[10] Throughout the empirical analysis, we follow the literature and include (but do not report) time effects (year dummies) to control for macroeconomic and global effects (e.g., changes in the state of the economy, interest rates and prices, accounting standard modifications, and other regulations). We lag all explanatory variables by one period to reduce the potential of endogeneity bias (i.e., the correlation between the explanatory variables and the error term)[11] and to ensure that managers can access in a timely manner the data for decision making. We opt for a parsimonious approach concerning the set of instruments. That is, we reduce the number of internal instruments by restricting their lag length and using the "collapse" version of the two-step

[9] Among the GMM estimators, the econometric literature distinguishes between the one- and two-step estimators, which are asymptotically equivalent if the idiosyncratic error term is normally distributed with mean zero and constant variance (Blundell and Bond, 1998). The one-step GMM estimator, built under the strong assumption of a known weighting matrix, is efficient under the restrictive assumptions of homoskedasticity and no autocorrelation of the error term. On the other hand, the presence of heteroskedasticity and serial correlation causes efficient GMM estimation to require the two-step GMM, which adopts a consistent estimate of the weighting matrix from the one-step estimation residuals. See, for technical details, Davidson and MacKinnon (2004).

[10] Though asymptotically more efficient, the two-step GMM presents estimates of the standard errors that tend to be severely downward biased. This problem is solved by the finite-sample correction to the two-step covariance matrix derived by Windmeijer (2005) that makes the two-step estimates more efficient than the one-step estimates, especially in the case of the system GMM (Roodman, 2009). Results are obtained by using the user-written Stata command *xtabond2* (Roodman, 2005).

[11] In virtually all empirical studies in corporate finance, the explanatory variables are scaled either by total assets or by net sales. Since our dependent variable is defined by the ratio of sales to total assets, this creates among the explanatory variables ratios that have at the denominator a common variable (i.e., sales for R&D activity, assets for debt to assets and size. These explanatory variables are obviously affected by the dependent variable. For this reason, we used lags of the explanatory variables and treat the explanatory variables as endogenous (except the squared terms and the year dummies, which we treat as exogenous).

system GMM, which makes the number of instruments linear in *T* instead of quadratic. Roodman (2009) observes that the use of numerous instruments may bias the coefficient estimates towards those from non-IV estimators and may lead to implausible high p-values for the Hansen test. Moreover, Roodman (2009) suggests the rule of thumb that the number of instruments should be lower than the number of panel-data units (firms).

Model 1 in Column 2 reports the results of the linear specification of equation (1). The results imply that firm size and R&D activity significantly aggravate agency costs, while short-term debt as well as total debt significantly alleviate agency conflicts within the firm. Specifically, the evidence supports the hypothesis that asset turnover negatively associates with firm size, which is consistent with Fama and Jensen's (1983) argument that agency costs increase with firm size as monitoring becomes more difficult. The evidence also supports the hypothesis that asset turnover negatively associates with R&D activity, which is consistent with the findings of Fleming et al (2005). Finally, the evidence supports the hypothesis that asset turnover positively associates with total debt and short-term debt, which is consistent with the view that debt holders play a monitoring role of managerial conduct. Ang et al. (2000) and Fleming et al. (2005) also report that debt significantly affects asset turnover. The finding that both debt and short-term debt significantly reduce agency costs, however, is noteworthy, because it differs from the recent literature and provides evidence for the first time regarding U.S. firms. Truong and Heaney (2013) and Florackis and Ozkan (2009) use both debt and short-term debt in their asset turnover regressions, but neither finds that both effects prove significant. Truong and Heaney (2013) find that total debt exerts a positive, but insignificant, effect on agency cost (Australia firms) while short-term debt exerts a negative and significant effect on agency costs, while Florackis and Ozkan (2009) find that both total debt and short-term debt exert a negative effect on agency costs (U.K. firms), but only short-term debt proves significant.

Model 2 in Column 3 reports the results of the non-linear specification of equation (2). The results strongly support our hypotheses of heterogeneous effects across different levels of debt, R&D activity, and firm size. Total debt exerts a positive and significant effect on asset turnover while the square of total debt exerts a negative and significant effect. Short-term debt exerts a positive and significant effect on asset turnover, and the size of the coefficient exceeds the corresponding coefficient in Model 1. The Lind and Mehlum test [12] of the non-linear relationship between debt and asset turnover rejects the null of monotonicity in favor of an inverted U-shaped relationships with a turning point at 0.517.

The positive and significant coefficient of total debt conforms to the view that debt holders monitor managers, thus, reducing agency costs. The negative and significant coefficient on the square of total debt, however, suggests that debt monitoring becomes ineffective above a critical threshold, whereby agency costs increase. Short-term debt, on the other hand, maintains a positive effect on asset turnover and, thus, continues to reduce agency costs.

Firm size exerts a negative and significant effect on asset turnover while the square of firm size exerts a small positive and significant effect. The Lind and Mehlum test for the non-linear relationship between size and asset turnover rejects the null of monotonicity in favor of a U-shaped relationships with a turning point at 8.564.

R&D activity also exerts a negative and significant effect on asset turnover while the square of R&D activity exerts a positive and significant effect. The Lind and Mehlum test statistic for the non-linear relationship between R&D activity and asset turnover rejects the null of monotonicity in favor of a U-shaped relationships with a turning point at 0.231.

[12] The Lind and Mehlum test is performed using the Stata command *utest* (Lind and Mehlum, 2010).

Models 3 and 4 augment the linear and quadratic specifications in equations (1) and (2) by including firm growth opportunities (*GROWTH*) and profitability (*PROF*) as additional explanatory variables. From an agency perspective, we conjecture that the presence of profits lessens the monitoring activity by debt holders and creates opportunities for managers to expropriate shareholders wealth, resulting in increase in agency costs, while growth opportunities signal that managers possess stronger incentives not to engage in underinvestment and asset substitution, resulting in decrease in agency costs. This notion is further strengthened by Jensen's (1986) free-cash-flow hypothesis, which predicts that firms with more investment opportunities have less need for the monitoring effect of debt to control their free cash flow.

The findings suggest that in both Model 3 and Model 4 profitability negatively (positively) associates with asset turnover (agency costs), while firm growth positively (negatively) associates with asset turnover (agency costs). Firm growth, however, is only significant in Model 4. This result corroborates the agency theory arguments that increases in profitability lessen the monitoring by debt holders and encourages managers to take advantage of free cash flow, resulting in an increase in agency costs.[13]

The coefficient estimates in Model 3 maintain approximately the sign and size of Model 1. Asset turnover (agency costs) decreases (increase) when firm size increases and R&D expenditure increases, and increases (decrease) when total debt increases and short-term debt increases. All the findings are significant at conventional levels. In Model 4, both the linear and quadratic terms are significant, and as in Model 2, the quadratic effects exert the opposite sign of the linear effects. The differences between the estimated coefficients of the two quadratic specifications (Model 2 and

---

[13] We also run the regressions with three other measures of profitability (return on equity, return on sales and return on investment) and find qualitatively same results.

Model 4) are moderate, which we consider a further indication of the validity of the non-linear approach. The collinearity between the linear and the quadratic terms is high, which could raise issues of significance of the estimates. However, stability of the results is strong, implying that the collinearity between the linear and the quadratic terms is not inflating the standard errors.

The Lind and Mehlum test confirms that the findings of a U-shaped relationship between asset turnover and firm size and between asset turnover and R&D activity as well as the finding of an inverted U-shape relationship between debt and asset turnover continue to hold.[14] In both Model 2 and Model 4, the points where the effect of a change of *DEBT* on *ATR* turns from positive to negative and the effect of change of *R&D* and *SIZE* on *ATR* turn from negative to positive fulfil the requirement of falling in the range of the observed data. In fact, the findings of Model 4 imply that approximately 76 percent of the sample observations on *DEBT* and *SIZE* fall on their negative slopes (below their respective implied estimates of the threshold), while approximately 94 percent of the sample observations on *R&D* fall on their positive slope (below the turning point). In comparison, from Model 2, the percentages of sample observations on *DEBT* and *SIZE* below their implied estimate of the threshold are 77 and 75 percent, respectively, while the percentage of observations on *R&D* is unchanged at 94 percent.

The finding of the existence of a turning point in the relationship between debt and asset turnover deserves further notice because, as described in Table 1, the average value of debt, from Table 1, is 0.368. This value falls below the extreme point of the 0.512 (Model 4) and 0.517 (Model 2) as well as below the lower bound on their respective confidence bands. Consequently, we can conclude that the average U.S. firm in the ICT sample, while operating in the decreasing agency

[14] We do not report the lower and upper bound estimates of the slopes of the U-shaped and inverted U-shaped quadratic specifications for economy of space. They are available upon request. The slope estimates are correctly signed in all cases and are significant at the 1 percent level.

costs region, does not operate at a level of debt that minimizes agency costs.[15] That is, the average ICT firm in the sample does not operate with an optimal capital structure. On the other hand, the average values of firm size and R&D activity in the ICT sample are, from Table 1, 6.219 and 0.095, respectively. These averages fall below the turning points of *SIZE* and *R&D*, respectively, 8.683 and 0.241 (Model 4) and 8.564 and 0.231 (Model 2) as well as below the lower bound on their confidence bands, which implies that the average firm in the ICT sample still operates in the region of increasing agency costs.

The results strongly support the dynamic specification hypothesis of the agency costs model, as the lagged dependent variable exerts a highly significant effect in all four regressions. Consistent with Floracki s and Ozkan (2009), we do not reject the dynamic nature of agency costs.[16] This confirms the existence of dynamism in the agency costs decisions in that managers adjust the agency costs of their behavior to achieve their desired level. Agency costs persist, and mean revert, confirming the Florackis and Ozkan (2009) conjecture that managers behave as though they want to achieve their optimal level of agency costs.

The estimated coefficient on the lagged dependent variable is significant at the 1-percent level in all four specifications and significantly differs from zero and from unity, indicating that the dynamics of agency costs lies between "perfect contractual possibilities" (Florackis and Ozkan, 2009) and "no recontracting possibilities" (Florakis and Ozkan, 2009). The adjustment speed, given by 1 minus the estimated coefficient on the lagged dependent variable, increases when considering quadratic terms. In the linear specifications, the adjustment speeds are 0.47 (Model 1) and 0.44

---

[15] Modigliani and Miller (1963) demonstrate that optimal capital structure minimizes agency costs and maximizes firm value.

[16] Thus, the static versions appear to omit an important explanatory variable. The OLS and FE regression results based on the static versions of the agency costs model are available from the authors.

(Model 3), implying that it takes managers 2.12 (Model 1) and 2.77 (Model 3) years to move agency costs to the desired level. In contrast, in the quadratic specifications, the speed of adjustments are 0.58 (Model 2) and 0.46 (Model 4), implying that it takes managers 1.72 (Model 2) and 2.17 (Model 4) years to attain the desired level.

This finding suggests that managers face substantial adjustment costs when they wish to adjust to the desired level of agency costs (Florackis and Ozkan, 2009). Thus, the value of the estimated coefficient of the lagged dependent variable implies that it takes from less than two years to about two and a half years to complete the adjustment. This, in turn, suggests that agency costs persist and accumulate over time.

Finally, for all four models, we perform two specification tests: 1) the AR(1) and AR(2) first and second-order serial-correlation tests; as well as 2) the Hansen test of over-identifying restrictions. We observe that in all cases, the Hansen test does not reject the null hypothesis of over-identified restrictions, suggesting valid instruments, and the serial correlation test fails to reject the null of no second-order autocorrelation but rejects the null of no first-order autocorrelation. In short, we cannot reject the model identification and the validity of the instruments. We also report two Wald tests of joint significance of the coefficients in Table 3. Wald test 1 rejects the null hypothesis that all regression coefficients are jointly zero, and Wald test 2 rejects the null hypothesis that the coefficients of the quadratic terms are jointly zero, consistently supporting the validity of the quadratic specification. Additional evidence on the appropriateness of the quadratic specification is provided by the Verardi and Debarsy (2012) semi-parametric approach, based on the Robinson (1988) double residual methodology. Specifically, we implement the test for equivalence between a parametric polynomial model and a non-parametric model proposed by Hardle and Mammen (1993). We conduct the test three times, corresponding to each the three quadratic modes. The null hypothesis each time assumes that the polynomial adjustment of degree 2 is appropriate. The results of the Hardle and Mammen (1993) test indicate that no statistical difference exists between the second-degree parametric polynomial and the non-parametric estimation, implying that we can represent our data through a parametric model with polynomial functions of second degree in firm size, debt, and R&D activity.[17]

4. Robustness checks

Our robustness checks mainly relate to four concerns. First, a concern exists about the correlation between *DEBT* and *SDEBT*, as total debt is the numerator of *DEBT* and the denominator of *SDEBT*. Thus, as a first test of robustness, we re-estimate the four versions of the models excluding *SDEBT* to control for the possibility that the *SDEBT* effect on agency costs is embedded in *DEBT*. Table 4 presents the two-step GMM results, which indicate that removing *SDEBT* does not lead to the failure of the main hypotheses, particularly the inverted U-shaped relationship between *DEBT* and *ATR*. When we remove *SDEBT*, however, the estimates of the lagged dependent variable are substantially higher in all four versions, resulting in a lower speed of adjustment. Thus, the adjustment toward the desired level of agency costs occurs more quickly when we account for short-term debt. We infer that *SDEBT* simultaneously reduces agency costs and increases the speed of adjustment.

Second, a concern exists that one sector may drive our results, such as the telecommunication or the semiconductor sectors. To address this concern, we construct six restricted datasets derived by dropping one industry at a time from the original sample.[18] Table 5 reports the two-step system GMM results based on six restricted samples using the extended quadratic specification (Model 4),

---

[17] The semi-parametric Robinson (1988) model and the Hardle and Mammen (1993) test are estimated using the Stata command *semipar* (Verardi and Debarsy, 2012). The p-values for the Hardle and Mammen (1993) tests, using the wild bootstrap with 500 simulations, are all greater than 0.30.

[18] We do not have enough time-series observations to run each sector separately.

which is our preferred model. Thus, Model 9 excludes the telecommunications sector (ISC 8030); Model 10 excludes the computer software sector (ISC 8140 and 8130); Model 11 excludes the semiconductors sector (ISC 8230 and 8220); Model 12 excludes the computer hardware sector (ISC 8050 and 8052); Model 13 excludes electronic manufacturing and consulting services (ISC 8200 and 8120); and Model 14 exclude the electronic instruments and equipment (ISC 8150).

The comparison between the overall sample results in Model 4 and the results for the different sub-samples, which we view with caution because of the smaller number of observations, highlights the strong similarity between the sub-samples estimates and the estimates of the full sample. The coefficients of the lagged dependent variables are relatively stable, ranging from a minimum of 0.418 in Model 13 to a maximum of 0.557 in Model 11. This not only compares favorably with the estimate of Model 4, but also leaves no doubt regarding the importance of modeling agency costs as a dynamic process. The estimates of the lagged dependent variable show that the ICT sector adjusts more quickly when we exclude the electronic manufacturing services (ISC 8200) and consulting services (ISC 8120) industry. In comparison, when we exclude *SDEBT*, the (unreported) estimates of the lagged dependent variable in the sub-samples range from 0.610 to 0.698, implying a speed of adjustment of 0.31 and 0.30, respectively, confirming our earlier finding that the adjustment toward the desired level of agency costs occurs more quickly when we account for short-term debt.

Consistent with the results of Model 4, the signs of the coefficient estimates on *PROF* and *GROWTH* are negative and positive, respectively. Profitability is significant in all sub-samples except the last one, while firm growth is only significant in the third and fourth sub-samples and, marginally, in the fifth one. In contrast, the linear and quadratic terms are significant and opposite in sign in all six subsamples, and the Lind and Mehlum (1993) test strongly supports our earlier conclusion of inverted U-shaped relationship between debt and asset turnover and U-shaped relationship between firm size and R&D activity and asset turnover, and are consistent with those obtained from the full sample. We take this strong similarity as evidence that the full sample regressions results are not driven by any industry of the ICT sector. The coefficient on short-term debt seems exceptionally stable across subsamples, varying from 0.351 (Model 14) to 0.427 (Model 10).

Third, a concern exists that the results may reflect the two main historical events that mark our sample period: the so-called dot-com crisis of 2000-2001 and the financial crisis and Great Recession of 2007-2008. Table 6 reports for economy of space only the results of Model 4 (with *SDEBT*) and Model 8 (without *SDEBT*). In Models 15 and 16, we remove the years of the dot-com crisis (2000-2001), whereas in Models 17 and 18, we drop the years of the Great Recession (2007-2008).

Finally, a last concern exists that the results may reflect a particular year. Table 7 presents the estimates of Models 3 and 4,[19] where we drop the last four and first four years to ensure that the estimates are not driven by a particular year. Table 7 displays the findings without the first four years of data in Models 19 and 20, and without the last four years of data in Models 21 and 22.

The estimates in Tables 6 and 7 support the previous findings and the importance of the quadratic terms in the model specification. Thus, overall, the robustness checks provide assurance that our main results remain robust to sample definition, model specification, and time-period of estimation.

---

[19] We do not report the regression outputs for Models 1 and 2 for economy of space, but they are available from the authors.

5. Conclusions

This paper examines the importance of firm-specific characteristics, such as firm size, debt, R&D activity, and short-term debt structure in explaining agency costs. We examine these issues with a sample of U.S. ICT firms from 1990 to 2013. We adopt a dynamic partial-adjustment model and conduct the analysis using the GMM estimation procedure that controls for endogeneity and firm-specific fixed effects. Most work in this area assumes a linear relationship between agency costs and firm-specific characteristics. We question this assumption and provide strong evidence that firm size, R&D activity, and debt affect agency costs in a non-linear and non-monotonic fashion. Specifically, to the best of our knowledge, this is the first empirical work that documents a robust and consistent non-linear link between firm size, debt, and R&D activity and agency costs that includes an extreme point.

Firm size and R&D activity relate to agency costs by an inverted U-shaped relationship, suggesting that two levels of firm size and R&D spending exist, one below the threshold, and one above the threshold that may produce the same level of agency costs. The average firm in our ICT sample operates in the region below the thresholds (i.e., on the upward slope). In contrast, debt relates to agency costs by a U-shaped relationship. This supports the view that debt holders successfully monitor the conduct of managers, but only up to a certain point. More debt is not always better, and too much can be as bad as too little. The average firm in our ICT sample operates in the region of the downward slope (i.e., in the region of declining agency costs), but has not reached the point where capital structure minimizes agency costs.

The dynamic analysis, in common with Florackis and Ozkan (2009), provides strong empirical evidence that agency costs are highly persistent and converge toward an optimal level. Consistent with the agency cost literature, we provide evidence that short-term debt helps mitigate agency costs. In addition, our findings indicate that short-term debt helps accelerate the speed of adjustment of agency costs toward their optimal level. Extensive additional analysis confirms the robustness of our results.

References

Aghion, P., Bond, S., Klemm, A., and Marinescu, I. (2004). Technology and financial structure: Are innovative firms different? *Journal of the European Economic Association* 2, 277-288.

Almazan, A., and Molina, C. A. (2005). Intra-Industry Capital Structure Dispersion. *Journal of Economics and Management Strategy* 14, 263-297.

Altman, E. (1984). A further empirical investigation of the bankruptcy cost question. *Journal of Finance* 39, 1067-1089.

Amihud, Y., and Lev, B. (1981). Risk reduction as a managerial motive by conglomerate managers. *Bell Journal of Economics* 12, 605-617.

Amihud, Y., Kamin, Y. J., and Ronen, J. (1983). 'Managerialism', 'ownerism' and risk. *Journal of Banking and Finance* 7, 189-196.

Ang, J., Cole, R., and Lin, J. (2000). Agency costs and ownership structure. *Journal of Finance* 55, 81-106.

Arcand, J.-L., Berkes, E., Panizza, U. (2015). Too much finance? *Journal of Economic Growth* 20, 105-148.

Arellano, M., and Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *Review of Economic Studies* 58, 277-297.

Arellano, M., and Bover, O. (1995). Another look at the instrumental variable estimation of error-components models. *Journal of Econometrics* 68, 29-51.

Armstrong, C. S., Guay, W. R., and Weber, J. P. (2010). The role of information and financial reporting in corporate governance and contracting. *Journal of Accounting and Economics* 50, 179- 234.

Baker, H. K., and Powell, G. (2005). *Understanding Financial Management: A Practical Guide*. Wiley-Blackwell

Bazzi, S., and Clemens, M. (2013). Blunt instruments: avoiding common pitfalls in identifying the causes of economic growth. *American Economic Journal: Macroeconomics* 5, 152-186.

Billor, N., Hadi, A. S., and Vellemann, P. F. (2000). BACON: Blocked adaptive computationally-efficient outlier nominators. *Computational Statistics and Data Analysis* 34, 279-298.

Blundell, R., and Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econome*trics 87, 115-143.

Bond, S. R. (2002). Dynamic panel data models: a guide to micro data methods and practice. *Portuguese Economic Journal* 1, 141-162

Brockman, P., Martin, X., and Unlu, E. (2010). Executive compensation and the maturity structure of corporate debt. *Journal of Finance* 67, 1123-1161.

Brown, J. R., and Petersen, B. C. (2009) Why has the investment-cash ow sensitivity declined so sharply? Rising R&D and equity market developments. *Journal of Banking and Finance* 33, 971-984.

Bruno, G. S. F. (2005a). Approximating the bias of the LSDV estimator for dynamic unbalanced panel data models. *Economics Letters* 87, 361-366.

Bruno, G. S. F. (2005b). Estimation and inference in dynamic unbalanced panel data models with a small number of individuals. *The Stata Journal* 5, 473-500.

Byoun, S. (2011). Financial flexibility and capital structure decision. Available at SSRN: http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1108850

Carpenter, R. E., and Petersen, B. C. (2002) Capital market imperfections, high-tech investment, and new equity financing. *Economic Journal* 112, 54-72.

Chen, L. (2017). Managerial incentives, R&D investments and cash flows. *Managerial Finance* 43, 898-913.

Cherensky, S. S. (1994). Shareholders, managers, and corporate R&D spending: An agency cost model. *Santa Clara High Technology Law Journal* 10, 299-346.

Childs, P. D., Mauer, D. C., and Ott, S. H. (2005). Interactions of corporate financing and investment decisions: The effects of agency conflicts. *Journal of Financial Economics* 76, 667-690.

Core, J. E., Holthausen, R. H., and Larcker, D. F. (1999) Corporate governance, chief executive officer compensation and firm performance. *Journal of Financial Economics* 51, 371-406.

Cox, C. (1990). Fieller's theorem, the likelihood and the delta method. *Biometrics* 46, 709-718.

Dang, V. A., Kim, M., and Shin, Y. (2015). In search of robust methods for dynamic panel data models in empirical corporate finance. *Journal of Banking and Finance* 53, 84-98.

Datta, S., Iskandar-Datta, M., and Raman, K. (2005). Managerial stock ownership and maturity structure of corporate debt. *Journal of Finance* 60, 2333-2350.

Davidson, R., and MacKinnon, J. G. (2004). *Econometric Theory and Methods*. Oxford University Press, New York.

Demsetz, H. (1983). The structure of ownership and the theory of the firm. *Journal of Law and Economics* 26, 375-390.

Demsetz, H., and Lehn, K. (1985). Managerial ownership of voting rights: Causes and consequences. *Journal of Political Economy* 93, 1155-77.

Diamond, D. W. (1984). Financial intermediation and delegated monitoring. *Review of Economic Studies* 51, 393-414.

Diamond, D. W. (1991). Debt maturity structure and liquidity risk. *Quarterly Journal of Economics* 106, 709-737.

D'Mello, R., and Miranda, M. (2010). Long-term debt and overinvestment agency problem. *Journal of Banking and Finance* 34, 324-335

Doukas, J. A., Kim, C., and Pantzalis, C. (2000). Security analysis, agency costs and company characteristics, *Financial Analysts Journal* 56, 54-63.

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

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

Fama, E. F., and Jensen, M. C. (1983). Agency problems and residual claims. *Journal of Law and Economics* 26, 327-349.

Fieller, E. C. (1954). Some problems in interval estimation. *Journal of the Royal Statistical Society, Series B* 16, 175-185.

Flannery, M. J. (1986). Asymmetric information and risky debt maturity choice. *Journal of Finance* 41, 19-37.

Flannery, M. J., and Hankins, K. W. (2013). Estimating dynamic panel models in corporate finance. *Journal of Corporate Finance* 19, 1-19.

Flannery, M. J., and Rangan, K. P. (2006) Partial adjustment toward target capital structures. *Journal of Financial Economics* 79, 469-506.

Fleming, G., Heaney, R., and McCosker, R. (2005). Agency costs and ownership structure in Australia. *Pacific Basin Finance Journal* 13, 29-52.

Florackis, C. (2008). Agency costs and corporate governance mechanisms: Evidence for UK firms. *International Journal of Managerial Finance* 4, 37-59.

Florackis, C., and Ozkan, A. (2009). Managerial incentives and corporate leverage: Evidence from the United Kingdom. *Accounting and Finance* 49, 531–553.

Frydman, C., and Jenter, D. (2010). CEO compensation. *Annual Review of Financial Economics* 2, 75-102.

Gompers, P. A., and Lerner, J. (2001). The venture capital revolution. *Journal of Economic Perspectives* 15, 45-62.

Gompers, P. A.; and Lerner, J. (2003). The really long-run performance of initial public offerings: The pre-Nasdaq evidence. *Journal of Finance* 58, 1355-1392.

Griffith, W., Hill, C., and Judge, G. (1993). *Learning and Practicing Econometrics*. New York: John Wiley and Sons.

Grossman, S., and Hart, O. (1982). Corporate financial structure and managerial incentives. In: J. J. McCall, ed., *The Economics of Information and Uncertainty* (University of Chicago Press, Chicago, IL), 107–140.

Grossman, S., and Hart, O. D. (1986). The costs and benefits of ownership: A theory of vertical and lateral integration. *Journal of Political Economy* 94, 691-719.

Gujarati, D. N., and Porter, D. C. (2009). *Basic econometrics* (5th ed.). Boston: McGraw-Hill.

Hahn, J., Hausman, J., and Kuersteiner, G. (2007). Long difference instrumental variables estimation for dynamic panel models with fixed effects. *Journal of Econometrics* 140, 574–617.

Haans, R., Pieters, C., and He, Z. (2016). Thinking about U: Theorizing and testing U- and inverted U-shaped relationships in strategy research. *Strategic Management Journal* 37, 1177-1195

Hardle, W., and Mammen, E. (1993). Comparing nonparametric versus parametric regression fits. *Annals of Statistics* 21, 1926–1947.

Hart, O., and Moore, J. (1995). Debt and seniority: An analysis of the role of hard claims in constraining management. *American Economic Review* 85, 567−58.

Hart, O., and Moore, J. (1998). Default and renegotiation: A dynamic model of debt. *Quarterly Journal of Economics* 113, 1-41.

Harvey, C., Lins, K., and Roper, A. (2004). The effect of capital structure when expected agency costs are extreme. *Journal of Financial Economics* 74, 3-30.

Henry, D. (2010). Agency costs, ownership structure and corporate governance compliance: A private contracting perspective. *Pacific Basin Finance Journal* 18, 24–46.

Hsiao, C., Pesaran, M. H., and Tahmiscioglu, A. K. (2002). Maximum likelihood estimation of fixed effects dynamic panel data models covering short time periods. *Journal of Econometrics* 109, 107-150.

Hirshleifer, D. (1993). Managerial reputation and corporate investment decisions. *Financial Management* 22, 145-160.

Holmström, B. (1999). Managerial incentive problems: A dynamic perspective. *The Review of Economic Studies* 66, 169-182.

Huang R., and Ritter J. R. (2009). Testing theories of capital structure and estimating the speed of adjustment. *Journal of Financial and Quantitative Analysis* 44, 237-271.

Jelinek, K., and Stuerke, P. S. (2009). The nonlinear relation between agency costs and managerial equity ownership: Evidence of decreasing benefits of increasing ownership. *International Journal of Managerial Finance* 5, 156-178.

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

Jensen, M. C. (1993). The modern industrial revolution, exit, and the failure of internal control systems. *Journal of Finance* 48, 831-880.

Jensen, M. C., and Meckling, W. H. (1976). Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of Financial Economics* 3, 305−360.

Jensen, M. C., and Smith, C. W., Jr. (2000). Stockholder, manager, and creditor interests: Applications of agency theory. In E. I. Altman and M. G. Subrahmanyam, *eds., Recent Advances in Corporate Finance.* . Homewood, IL: Richard D. Irwin, 1985. (Reprinted in *Theory of the Firm: Governance, Residual Claims, and Organizational Forms*, Harvard University Press).

Jenter, D., and Lewellen, K. (2015). CEO Preferences and Acquisitions. *Journal of Finance* 70, 2813-2851.

Johnson, S. A. (2003). Debt maturity and the effects of growth opportunities and liquidity risk on leverage. *Review of Financial Studies* 16, 209-236.

Kim, S. I., Mathur, I., and Nam, J. (2006). Is operational hedging a substitute for or a complement to financial hedging? *Journal of Corporate and Finance* 12, 834-853.

Kiviet, J. F. (1995). On bias, inconsistency, and efficiency of various estimators in dynamic panel data models. *Journal of Econometrics* 68, 53-78.

Knyazeva, D. (2007). Corporate governance, analyst following, and firm behavior. Working paper, New York University.

Kothari, S. P., Laguerre, T. E., and Leone, A. J. (2002). Capitalization versus expensing: Evidence on the uncertainty of future earnings from capital expenditures versus R&D outlays. *Review of Accounting Studies* 7, 355-382.

Lang, L., Ofek, E., and Stulz, R. M. (1996). Leverage, investment and firm growth. *Journal of Financial Economics* 40, 3–29.

Laperche, B. (2007). Knowledge-capital and innovation in multinational corporations. *Journal of Technology and Globalisation* 3, 4-41.

La Porta, R., Lopez-de-Silanes, F., Shleifer, A., and Vishny, R. W. (2002). Investor protection and corporate valuation. *Journal of Finance* 57, 1147-1170.

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

Lemma, T. T., and Negash, M. (2014). Determinants of the adjustment speed of capital structure: Evidence from developing economies. *Journal of Applied Accounting Research* 15, 64-99.

Lind, J. T., and Mehlum, H. (2010). With or Without U? – The appropriate test for a U-shaped relationship. *Oxford Bulletin of Economics and Statistics* 72, 109-118.

Lummer, S. L., and McConnell, J. J. (1989). Further evidence on the bank lending process and the capital markets response to bank loan agreements. *Journal of Financial Economics* 21, 99-122.

McConnell, J. J., and Servaes, H. (1990). Additional evidence on equity ownership and corporate value. *Journal of Financial Economics* 27, 595-612.

McKnight, P. J., and Weir, C. (2009). Agency costs, corporate governance mechanisms and ownership structure in large UK publicly quoted companies: A panel data analysis. *The Quarterly Review of Economics and Finance* 49, 139-58.

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

Nickell, S. (1981). Biases in dynamic models with fixed effects. *Econometrica* 49, 1417-1426.

Opler, T. C., and Titman, S. (1994). Financial distress and corporate performance. *Journal of Finance* 49, 1015-1040.

Ozkan, A. (2001). Determinants of capital structure and adjustment to long run target. *Journal of Business Finance and Accounting* 28, 175- 98

Porter, M. E. (1990). *The Competitive Advantage of Nations*. New York, The Free Press.

Rajan, R. J., and Zingales, L. (1995). What do we know about capital structure? Some evidence from international data. *Journal of Finance* 50, 1421-1460.

Rajan, R., and Winton, A. (1995). Covenants and collateral as incentives to monitor, *Journal of Finance* 50, 1113-1146.

Roberts, M. R., and Whited, T. M. (2012). Endogeneity in empirical corporate finance. In G. Constantinides, M. Harris, and R. Stulz, eds., *Handbook of the Economics of Finance* vol. 2, Elsevier.

Robinson, P. M. (1988). Root-N-consistent semiparametric regression. *Econometrica* 56, 931-954.

Roodman, D. (2009). How to do xtabond2: An introduction to difference and system GMM in Stata. *Stata Journal* 9, 86–136.

Sasabuchi, S. (1980). A test of a multivariate normal mean with composite hypotheses determined by linear inequalities. *Biometrika* 67, 429-39.

Shleifer A, and Vishny, R. W. (1989). Management entrenchment: The case of managers' specific investments. *Journal of Financial Economics* 25: 123-139.

Shleifer, A., and Vishny, R. W. (1992). Liquidation values and debt capacity: A market equilibrium approach. *Journal of Finance* 47, 1343-1366.

Shleifer, A., and Vishny, R. W. (1997). A survey of corporate governance. *Journal of Finance* 52, 737-783.

Singh, M. and Davidson, W. N. (2003). Agency costs, ownership structure and corporate governance mechanisms, *Journal of Banking and Finance* 27, 793-816.

Smith, C. W., and Stulz, R. (1985). The determinants of firms' hedging policies. *Journal of Financial and Quantitative Analysis* 20, 391-405.

Stulz, R. M. (1990). Managerial discretion and optimal financing policies. *Journal of Financial Economics* 26, 3−27.

Stulz, R. M., 2002. Does financial structure matter for economic growth? In A. Demirguc-Kunt and R. Levine, eds., *Financial Structure and Economic Growth: Cross-Country Comparisons of Banks, Markets, and Development*. MIT Press, Cambridge, MA, 143–188.

Titman, S. (1984). The effect of capital structure on a firm's liquidation decision. *Journal of Financial Economics* 13, 137-151.

Titman, S., and Wessels, R. (1988). The determinants of capital structure choice. *Journal of Finance* 43, 1-19.

Truong, T. T., and Heaney, R. (2013). The determinants of equity agency conflicts between managers and shareholders: Evidence from Australia. *Journal of Multinational Financial Management* 23, 314-326.

Verardi, V., and Debarsy, N. (2012). Robinson's square root of N consistent semiparametric regression estimator in Stata. *Stata Journal* 12, 726-735.

Weber, S. (2010). BACON: An effective way to detect outliers in multivariate data using Stata (and Mata) *Stata Journal* 10, 331-338.

Welch, I., 2004. Capital structure and stock returns. *Journal of Political Economy* 112, 106-131.

Williams, J. (1987). Perquisites, risk and capital structure. *Journal of Finance* 42, 29-49.

Windmeijer, F. (2005). A finite sample correction for the variance of linear efficient two-step GMM estimators. *Journal of Econometrics* 126, 25-51.

Zhang, H., and Li, S. (2008), The impact of capital structure on agency costs: Evidence from UK public companies. In C.-F. Lee, ed., *Proceedings of the 16th Annual Conference on Pacific Basin Finance, Economics, Accounting and Management*, Brisbane, Australia, 1-18.

Table 1. Descriptive Statistics

Variable	Mean	St. Dev	Min	25%	Median	75%	Max
ATR	1.021	0.511	0.014	0.667	0.940	1.248	3.783
DEBT	0.368	0.193	0.000	0.218	0.342	0.502	0.914
SDEBT	0.698	0.225	0.070	0.540	0.729	0.885	1.000
SIZE	6.219	2.783	0.310	4.035	6.035	8.426	11.867
R&D	0.095	0.086	0.000	0.037	0.074	0.137	0.776
PROF	0.046	0.125	-1.541	0.014	0.057	0.104	0.531
GROWTH	0.100	0.234	-1.054	-0.016	0.074	0.104	1.729

Notes: This table reports the descriptive statistics of the dependent variable and the main independent variables. Summary statistics include the mean and standard deviation, the minimum and maximum values, and the 25^{th}, 50^{th}, and 75^{th} percentiles. The data are collected over the 24-year period from 1990 to 2013 from the COMPUSTAT Annual North America database. The sample contains 81 U.S. firms that belong to the COMPUSTAT Economic Sector 8000. The data constitute a slightly unbalanced panel, and comprise six sectors of the ICT industry: 1) Telecommunication Equipment (ISC 8030); 2) System Software (ISC 8140) and Application Software (ISC 8130); 3) Semiconductors (ISC 8230) and Semiconductor Equipment (ISC 8220); 4) Computer Hardware (ISC 8050) and Computer Storage and Peripherals (ISC 8052); 5) Electronic Manufacturing Services (ISC 8200) and Consulting Services (ISC 8120); 6) Electronic Equipment and Instruments (ISC 8150), where ISC is the COMPUSTAT industry sector code. *GROWTH* is firm growth rate, computed as the logarithmic first difference of total assets (COMPUSTAT item no. 6). *PROF* is computed as the return on assets, using income before extraordinary items (COMPUSTAT item no. 18) divided by total assets (COMPUSTAT item no. 6). *SIZE* is log of total assets (COMPUSTAT item no. 6). *ATR* is net sales (COMPUSTAT item no. 12) divided by total assets (COMPUSTAT item no. 6). *DEBT* is the sum of long-term debt (COMPUSTAT item no. 9) and short-term debt (COMPUSTAT item no. 12) divided by total assets (COMPUSTAT item no. 6). *R&D* is R&D expenditure (COMPUSTAT item no. 46) divided by net sales (COMPUSTAT item no. 12). *SDEBT* is the proportion of short term debt (COMPUSTAT item 12) in *DEBT*.

Table 2. Pearson Correlation Matrix

	ATR	*DEBT*	*SDEBT*	*SIZE*	*R&D*	*PROF*	*GROWTH*
ATR	1.000						
DEBT	**0.177**	1.000					
SDEBT	**0.296**	**-0.418**	1.000				
SIZE	**-0.393**	**0.343**	**-0.285**	1.000			
R&D	**-0.420**	**-0.267**	0.017	**0.104**	1.000		
PROF	**0.055**	**-0.143**	**0.149**	**0.136**	-0.265	1.000	
GROWTH	-0.017	**-0.054**	0.082	0.049	-0.082	**0.506**	1.000

Notes: See Table 1. This table reports the Pearson correlation coefficients between the main independent variables. Values in bold are significant at the 5 percent level and above.

Table 3. Parameter estimates of the dynamic agency costs adjustment model: Full sample

Independent Variables	Model 1	Model 2	Model 3	Model 4
ATR(t-1)	0.526	0.423	0.556	0.543
	(6.45)	(5.36)	(6.21)	(7.61)
SIZE(t-1)	-0.048	-0.161	-0.038	-0.188
	(-4.77)	(-3.72)	(-3.60)	(-4.92)
SIZE SQ(t-1)		0.009		0.012
		(3.23)		(4.36)
DEBT(t-1)	0.847	3.431	0.614	3.154
	(4.12)	(4.04)	(2.95)	(3.29)
DEBT SQ(t-1)		-3.31		-3.205
		(-3.77)		(-3.14)
R&D(t-1)	-0.556	-2.412	-0.659	-2.050
	(-2.10)	(-3.54)	(-2.50)	(-3.15)
R&D SQ(t-1)		5.215		4.258
		(3.40)		(2.91)
SDEBT(t-1)	0.281	0.402	0.255	0.411
	(3.02)	(3.64)	(2.60)	(3.34)
GROWTH(t-1)			0.041	0.060
			(1.42)	(2.20)
PROF(t-1)			-0.370	-0.301
			(-3.12)	(-3.24)
Wald test 1 (p-value)	0.000	0.000	0.000	0.000
Wald test 2 (p-value)		0.000		0.000
AR(1) (p-value)	0.000	0.000	0.000	0.000
AR(2) (p-value)	0.872	0.432	0.549	0.528
Hansen test (p-value)	0.292	0.595	0.130	0.503
Lind-Mehlum test on *R&D*				
Overall test		3.37		2.87
p-value		0.000		0.000
Turning point (min)		0.231		0.241
95% Fieller CI		0.19 0.29		0.18 0.34
Lind-Mehlum test on *SIZE*				
Overall test		2.23		2.68
p-value		0.013		0.003
Turning point (min)		8.564		8.683
95% Fieller CI		7.72 10.86		7.77 10.44
Lind-Mehlum test on *DEBT*				
Overall test		3.38		4.38
p-value		0.000		0.000
Turning point (max)		0.517		0.512
95% Fieller CI		0.48 0.58		0.46 0.56

Table 3. Parameter estimates of the dynamic agency costs adjustment model: Full sample (continued)

Note: See Table 1. This table presents the estimates of the four versions of the dynamic adjustment models using the two- step system GMM in the xtabond2 package for Stata 14 (Roodman, 2009a). All variables are lagged one year. *SIZE SQ*, *DEBT SQ*, and *R&D SQ* are the squared values of *SIZE*, *DEBT*, and *R&D*, respectively. Figures in parentheses are t-statistics based on the robust Windmeijer (2005) finite-sample corrected standard errors. Wald test 1 reports the p-values of the chi-square test of the null hypothesis that all parameters of the model are jointly zero. Wald test 2 reports the p-values of the chi-square-test of the null hypothesis that the parameters of lagged growth and lagged size are jointly zero. Year dummies are included but not reported. All explanatory variables are treated as endogenous (except the year dummies, and the squared variables) and are instrumented. The "collapse" option is used in all four specifications. For the equation in differences, levels dated t-2, t-3, and t-4 are used as instruments, whereas for the equation in levels, differences dated t-1 are used. The Arellano-Bond test for AR(1) is the test for first-order autocorrelation in the differenced residuals and is distributed as N(0,1) under the null hypothesis of no first-order autocorrelation. The Arellano-Bond test for AR(2) is the test for second-order autocorrelation in the differenced residuals and is distributed as N(0,1) under the null hypothesis of no first-order autocorrelation. The Hansen test is a test of over-identifying restrictions, that is, tests of the validity of the instruments. The Hansen test statistics are asymptotically chi-square distributed under the null, with degrees of freedom equal to the number of instruments minus the number of parameters. The Lind and Mehlum test is a test of non-linearity. The t-statistics and the corresponding p-values are reported. Also reported are the turning points and their respective Fieller confidence intervals. The lower and upper bound estimates of the slopes (not reported to save space) are significant at the 5 percent level or better and of opposite signs.

Table 4. Parameter estimates of the dynamic agency costs adjustment model excluding SDEBT: full sample

Independent Variables	Model 5	Model 6	Model 7	Model 8
ATR(t-1)	0.581	0.508	0.676	0.626
	(8.62)	(7.95)	(11.31)	(10.91)
SIZE(t-1)	-0.042	-0.224	-0.035	-0.200
	(-4.17)	(-4.89)	(-3.98)	(-5.09)
SIZE SQ(t-1)		0.013		0.012
		(4.47)		(5.05)
DEBT(t-1)	0.501	4.561	0.488	2.600
	(3.32)	(3.69)	(3.04)	(2.62)
DEBT SQ(t-1)		-4.823		-2.902
		(-3.54)		(-2.57)
R&D(t-1)	-0.687	-1.986	-0.636	-1.998
	(-2.37)	(-2.60)	(-2.38)	(-3.35)
R&D SQ(t-1)		4.441		4.271
		(2.47)		(3.14)
GROWTH(t-1)			0.067	0.080
			(2.36)	(3.33)
PROF(t-1)			-0.445	-0.296
			(-3.25)	(-3.01)
Wald test 1 (p-value)	0.000	0.000	0.000	0.000
Wald test 2 (p-value)		0.000		0.000
AR(1) (p-value)	0.000	0.000	0.000	0.000
AR(2) (p-value)	0.762	0.432	0.928	0.731
Hansen test (p-value)	0.293	0.595	0.288	0.566
Lind-Mehlum test on *R&D*				
Overall test		2.46		3.10
p-value		0.007		0.000
Turning point (min)		0.223		0.234
95% Fieller CI		0.17 0.33		0.18 0.31
Lind-Mehlum test on *SIZE*				
Overall test		3.54		4.55
p-value		0.000		0.000
Turning point (min)		8.158		7.750
95% Fieller CI		7.62 9.06		7.15 8.41
Lind-Mehlum test on *DEBT*				
Overall test		3.36		2.50
p-value		0.000		0.006
Turning point (max)		0.472		0.447
95% Fieller CI		0.44 0.51		0.41 0.52

Note: See Table 3. This table presents the estimates of the four versions of the dynamic adjustment models using the two- step system GMM in the xtabond2 package for Stata 14 (Roodman, 2009a) after removing *SDEBT* .

Table 5. Parameter estimates of the dynamic agency costs adjustment model for different sub-samples

Indep. Variables	Model 9	Model 10	Model 11	Model 12	Model 13	Model 14
ATR(t-1)	0.475	0.495	0.557	0.512	0.418	0.536
	(7.37)	(7.78)	(6.13)	(6.60)	(4.40)	(6.97)
SIZE(t-1)	-0.211	-0.176	-0.161	-0.191	-0.112	-0.236
	(-3.82)	(-4.65)	(-3.29)	(-4.22)	(-3.36)	(-4.42)
SIZE SQ(t-1)	0.013	0.011	0.010	0.012	0.006	0.015
	(3.45)	(4.01)	(2.82)	(4.02)	(2.66)	(4.18)
DEBT(t-1)	3.014	3.659	3.552	3.077	2.836	3.042
	(2.98)	(3.58)	(2.74)	(3.10)	(2.62)	(3.65)
DEBT SQ(t-1)	-3.000	-3.731	-3.583	-3.309	-2.872	-3.035
	(-2.85)	(-3.43)	(-2.66)	(-3.02)	(-2.69)	(-3.77)
R&D(t-1)	-2.026	-1.844	-2.614	-1.793	-2.584	-1.872
	(-3.60)	(-3.72)	(-3.92)	(-3.56)	(-2.93)	(-2.63)
R&D SQ(t-1)	4.043	3.303	5.533	3.440	4.949	4.149
	(3.31)	(3.21)	(3.32)	(3.16)	(2.84)	(2.52)
SDEBT(t-1)	0.364	0.427	0.363	0.364	0.396	0.351
	(2.74)	(3.49)	(2.48)	(2.96)	(2.90)	(2.55)
GROWTH(t-1)	0.021	0.038	0.107	0.054	0.038	0.034
	(0.72)	(1.32)	(2.74)	(2.26)	(1.72)	(1.17)
PROF(t-1)	-0.270	-0.359	-0.452	-0.298	-0.263	-0.190
	(-2.65)	(-4.57)	(-4.40)	(-3.31)	(-3.63)	(-1.58)
Wald test 1(p-value)	0.000	0.000	0.000	0.000	0.000	0.000
Wald test 2 (p-value)	0.000	0.000	0.000	0.000	0.000	0.000
AR(1) (p-value)	0.000	0.000	0.000	0.000	0.000	0.000
AR(2) (p-value)	0.669	0.382	0.684	0.576	0.641	0.479
Hansen test (p-value)	0.815	0.915	0.736	0.477	0.496	0.661
Lind-Mehlum test on *R&D*						
Overall test	3.26	3.13	3.25	3.10	2.82	2.30
p-value	0.000	0.000	0.000	0.000	0.002	0.011
Turning point (min)	0.251	0.279	0.236	0.261	0.261	0.226
95% Fieller CI	0.19 0.34	0.21 0.41	0.18 0.34	0.20 0.37	0.21 0.34	0.15 0.38
Lind-Mehlum test on *SIZE*						
Overall test	2.69	2.86	2.06	3.44	1.83	3.49
p-value	0.003	0.002	0.019	0.000	0.033	0.000
Turning point (min)	8.137	8.112	7.948	7.824	8.854	7.870
95% Fieller CI	7.49 9.62	7.35 9.66	7.02 11.21	7.21 8.73	7.16 15.77	7.21 8.84
Lind-Mehlum test on *DEBT*						
Overall test	3.21	3.24	2.51	2.91	2.62	3.65
p-value	0.000	0.000	0.006	0.001	0.004	0.000
Turning point (max)	0.490	0.504	0.495	0.464	0.493	0.501
95% Fieller CI	0.45 0.54	0.46 0.56	0.44 0.59	0.42 0.52	0.42 0.55	0.43 0.56

Note: See Table 3. This table reports the two-step system GMM results based on six restricted samples using the extended quadratic specification (Model 4), which is our preferred model. Thus, Model 9 excludes the telecommunications sector (ISC 8030); Model 10 excludes the computer software sector (ISC 8140 and 8130); Model 11 excludes the semiconductors sector (ISC 8230 and 8220); Model 12 excludes the computer hardware sector (ISC 8050 and 8052); Model 13 excludes electronic manufacturing and consulting services (ISC 8200 and 8120); and Model 14 exclude the electronic instruments and equipment (ISC 8150).

Table 6. Parameter estimates of Model 4 dropping the 2000-2001 years and the 2007-2008 years

Independent Variables	Model 15	Model 16	Model 17	Model 18
ATR(t-1)	0.575	0.496	0.630	0.532
	(5.80)	(5.34)	(8.02)	(5.41)
SIZE(t-1)	-0.164	-0.171	-0.139	-0.139
	(-3.61)	(-4.62)	(-2.92)	(-3.04)
SIZE SQ(t-1)	0.010	0.010	0.009	0.009
	(3.41)	(3.74)	(2.88)	(2.94)
DEBT(t-1)	2.949	3.818	2.102	2.924
	(2.11)	(4.02)	(2.35)	(2.67)
DEBT SQ(t-1)	-3.11	-3.874	-2.222	-2.941
	(-2.03)	(-3.83)	(-2.30)	(-2.60)
R&D(t-1)	-1.901	-2.208	-2.204	-2.472
	(-2.75)	(-2.99)	(-3.56)	(-3.64)
R&D SQ(t-1)	4.243	4.789	4.336	4.856
	(2.64)	(2.77)	(2.96)	(3.14)
SDEBT(t-1)		0.335		0.415
		(3.01)		(3.05)
GROWTH(t-1)	0.061	0.057	0.084	0.059
	(1.61)	(1.47)	(2.61)	(1.83)
PROF(t-1)	-0.278	-0.338	-0.393	-0.341
	(-2.10)	(-2.63)	(-2.70)	(-2.60)
Wald test 1(p-value)	0.000	0.000	0.000	0.000
Wald test 2 (p-value)	0.000	0.000	0.000	0.000
AR(1) (p-value)	0.000	0.000	0.000	0.000
AR(2) (p-value)	0.285	0.183	0.459	0.686
Hansen test (p-value)	0.283	0.418	0.430	0.684
Lind-Mehlum test on *R&D*				
Overall test	2.63	2.74	2.90	3.08
p-value	0.004	0.003	0.002	0.001
Turning point (min)	0.224	0.231	0.254	0.255
95% Fieller CI	0.17 0.31	0.18 0.32	0.21 0.39	0.20 0.36
Lind-Mehlum test on *SIZE*				
Overall test	2.69	2.27	2.62	2.47
p-value	0.003	0.011	0.004	0.006
Turning point (min)	8.324	8.563	7.723	7.943
95% Fieller CI	7.38 9.87	7.61 10.9	6.72 9.10	6.76 9.81
Lind-Mehlum test on *DEBT*				
Overall test	1.93	3.52	2.23	2.48
p-value	0.026	0.000	0.012	0.006
Turning point (max)	0.473	0.492	0.473	0.497
95% Fieller CI	0.43 1.10	0.45 0.55	0.41 0.59	0.44 0.59

Note: See Table 3. This table reports the results of Model 4 (with *SDEBT*) and Model 8 (without *SDEBT*) under additional modifications. In Models 15 and 16, we remove the years of the dot-com crisis (2000-2001), whereas in Models 17 and 18, we drop the years of the Great Recession (2007-2008).

Table 7. Parameter estimates of Models 3 and 4 dropping the first and last four years

Independent Variables	Model 19	Model 20	Model 21	Model 22
ATR(t-1)	0.736	0.488	0.654	0.522
	(8.90)	(5.96)	(6.67)	(6.23)
SIZE(t-1)	-0.027	-0.237	-0.028	-0.143
	(-2.87)	(-5.17)	(-3.78)	(-3.36)
SIZE SQ(t-1)		0.015		0.009
		(5.15)		(3.11)
DEBT(t-1)	0.491	2.734	0.422	2.392
	(2.52)	(2.38)	(2.55)	(2.24)
DEBT SQ(t-1)		-2.828		-2.403
		(-2.41)		(-2.14)
R&D(t-1)	-0.462	-1.653	-0.654	-1.720
	(-2.75)	(-2.64)	(-2.27)	(-3.19)
R&D SQ(t-1)		3.567		3.156
		(2.58)		(2.93)
SDEBT(t-1)	0.177	0.341	0.176	0.329
	(1.79)	(2.36)	(1.74)	(2.41)
GROWTH(t-1)	0.059	0.042	0.057	0.040
	(2.29)	(1.77)	(2.06)	(1.46)
PROF(t-1)	-0.405	-0.186	-0.443	-0.291
	(-2.53)	(-1.94)	(-5.70)	(-3.55)
Wald test 1(p-value)	0.000	0.000	0.000	0.000
Wald test 2 (p-value)		0.000		0.000
AR(1) (p-value)	0.000	0.000	0.000	0.000
AR(2) (p-value)	0.681	0.554	0.854	0.917
Hansen test (p-value)	0.309	0.254	0.109	0.539
Lind-Mehlum test on *R&D*				
Overall test		2.56		2.87
p-value		0.005		0.002
Turning point (min)		0.231		0.272
95% Fieller CI		0.16 0.34		0.18 0.41
Lind-Mehlum test on *SIZE*				
Overall test		4.63		2.55
p-value		0.000		0.005
Turning point (min)		7.739		7.708
95% Fieller CI		7.12 8.41		6.87 9.46
Lind-Mehlum test on *DEBT*				
Overall test		2.39		1.99
p-value		0.000		0.023
Turning point (max)		0.483		0.497
95% Fieller CI		0.40 0.55		0.42 0.84

Note: See Table 3. This table presents the estimates of Models 3 and 4 where we drop the last four and first four years to ensure that the estimates are not driven by a particular year. In Models 19 and 20 we remove the first four years, and in Models 21 and 22 we remove the last four years.

Figure 1: Mean *ATR*

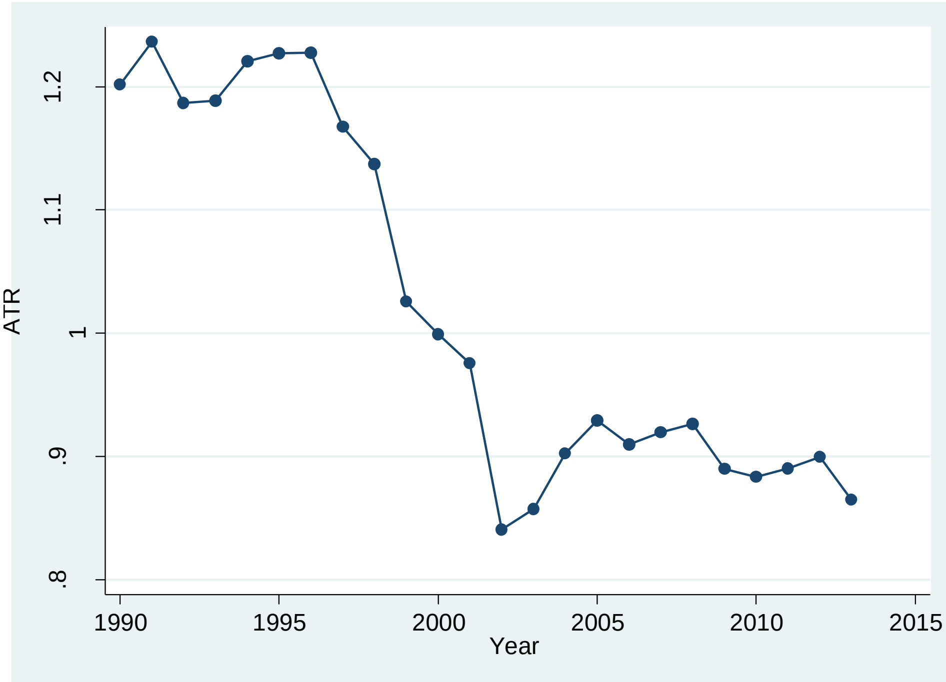

Figure 2: Mean *DEBT*

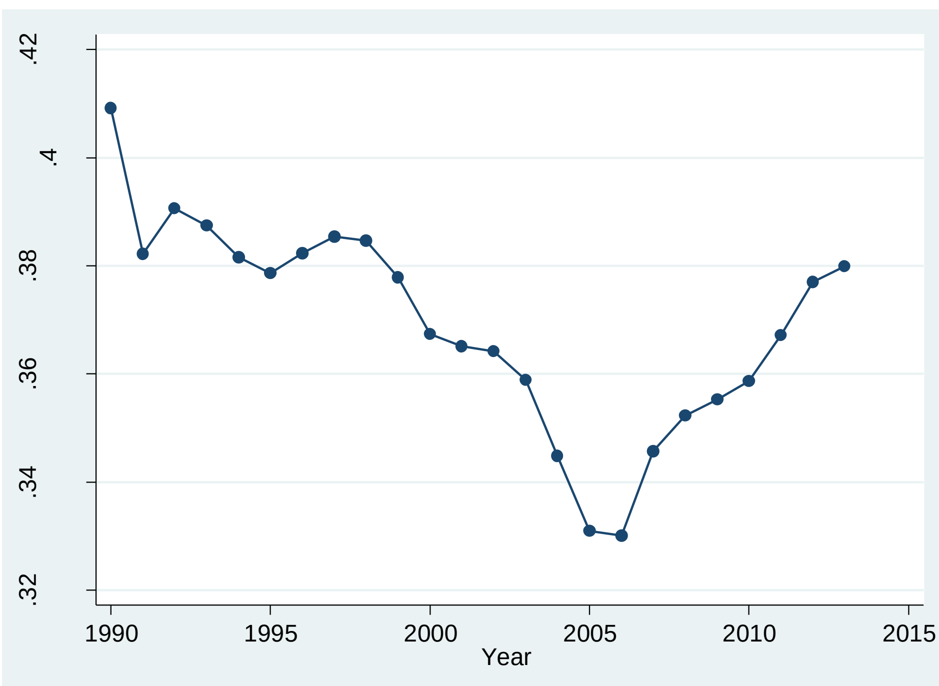

Figure 3: Mean *SIZE*

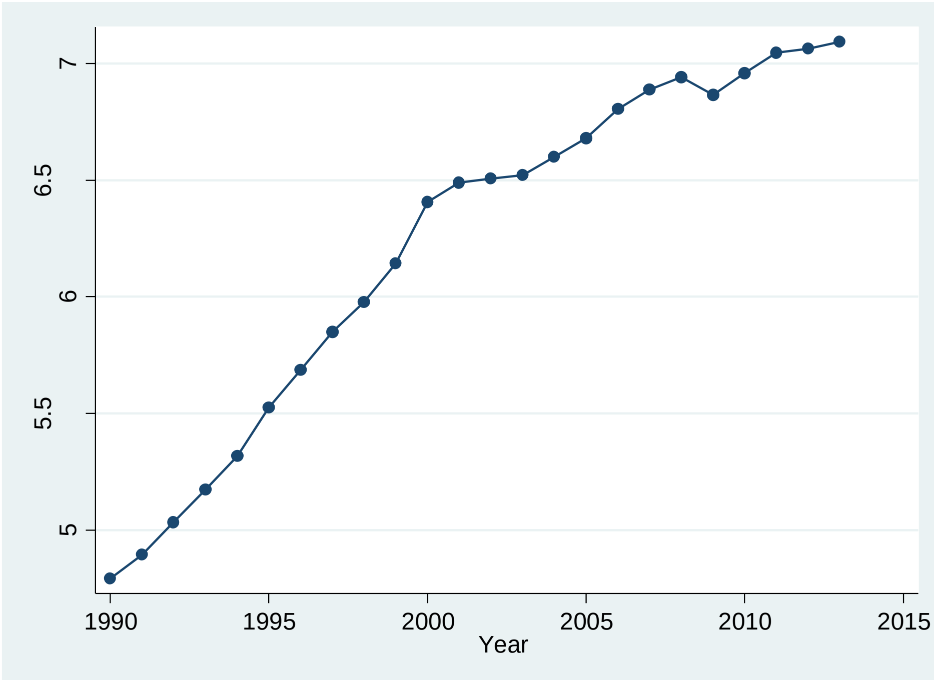

Figure 4: Mean *R&D*

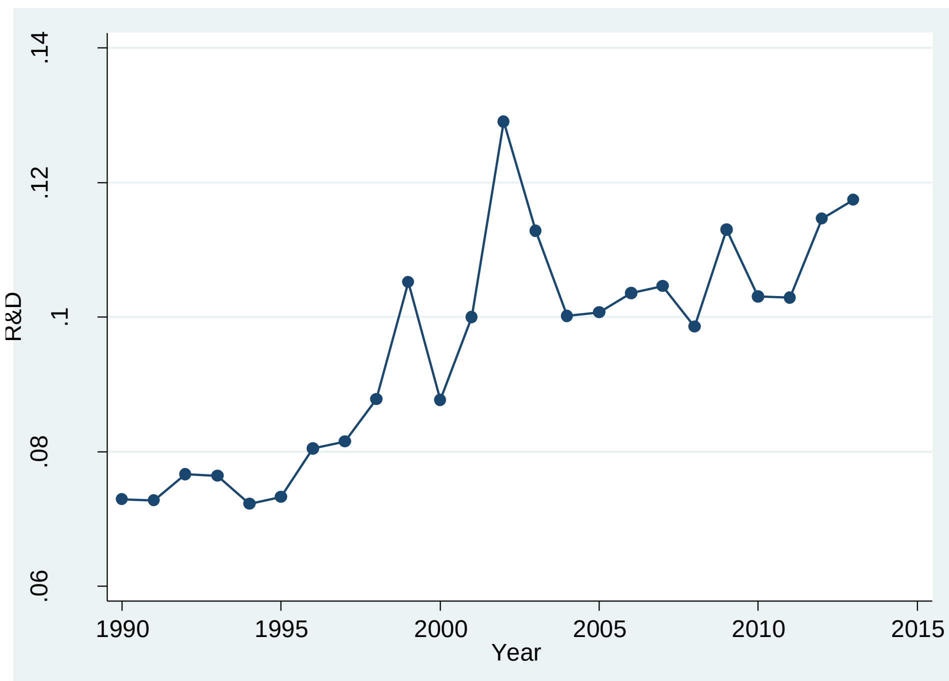

Figure 5: Mean *SDEBT*

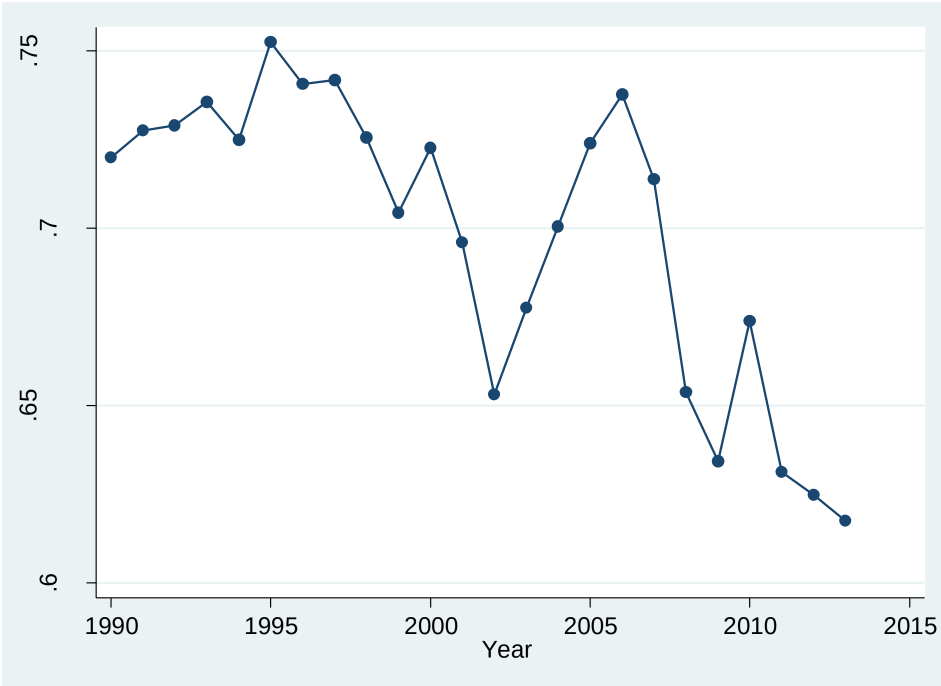

Figure 6: Mean Short-Term Debt Ratio

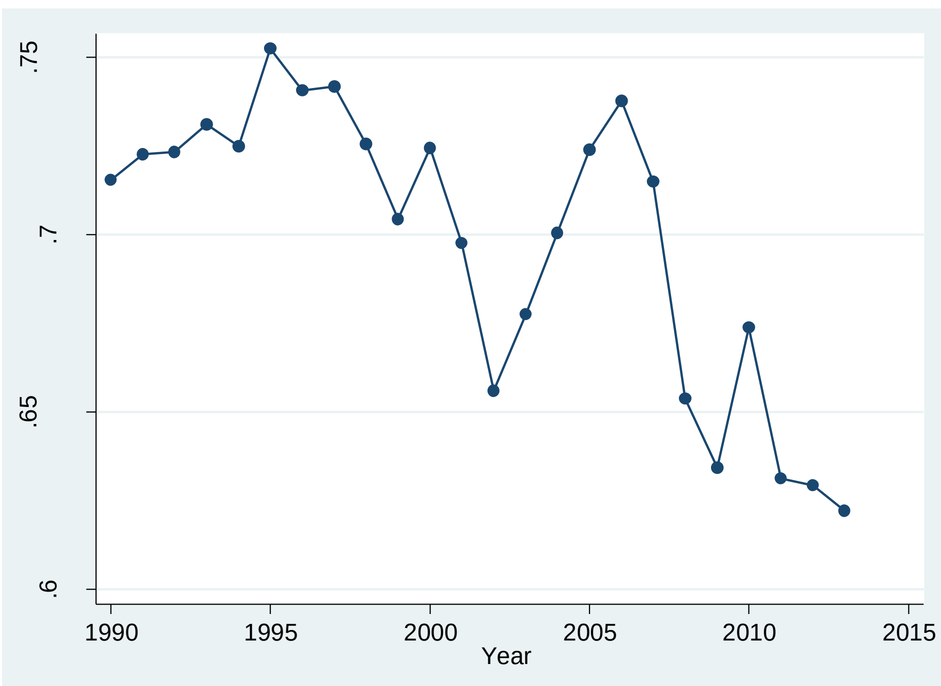

Figure 7: Mean Short-Term Debt to Assets