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Accounting for Intangibles: Can Capitalization of R&D Improve Investment Efficiency?

This paper investigates the potential for accounting rules to mitigate under-investment induced by myopic managerial incentives. It exploits the difference within US GAAP requiring the capitalization of some research and development (R&D) costs in software development but proscribing the capitalization of R&D in other industries. We first investigate whether other hi-technology firms with no capitalization of R&D costs suffer higher levels of under-investment in myopic settings relative to software development firms. Second, we investigate whether the capitalization rule assists in mitigating under-investment within the software development industry, and whether this comes at the cost of over-investment in the presence of financial flexibility. Our findings are consistent with the mitigation of under-investment in the software development setting but we find no evidence of over-investment in the presence of high financial flexibility. Other hi-tech firms that cannot capitalize R&D costs suffer higher levels of under-investment relative to software development firms. Finally, we find that the ability to capitalize for the sample of software firms does reduce the probability of cutting R&D investment when managers are under earnings pressure. The findings in this paper are relevant to standard setters seeking to understand the costs imposed by (understandably) conservative accounting rules, and how verification of points of feasibility alongside less conservative accounting can prevent dysfunctional investment outcomes. This is the first study to consider whether the ability to (justifiably) capitalize the costs of internally generated intangibles can improve investment efficiency (the allocation of resources).

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The literature on real earnings management documents that US firms under pressure to achieve short-term performance targets[1] cut investments in intangibles such as research and development (R&D) to avoid the immediate expensing of related costs (Bushee, 1998; Roychowdhury, 2006; Edmans *et al.*, 2017).[2] Graham *et al.* (2005) and Dichev *et al.* (2013) report field evidence from interviews that managers are willing to engage in such behaviour even if such actions are value destroying, for example as seen in terms of negative long-run impacts on value creation in future patents (Bereskin *et al.*, 2018), and future firm performance (Cohen and Zarowin, 2010). Terry (2017) finds that such negative impacts also pertain at the aggregate economy level. Taken together, this evidence is consistent with under-investment due to myopic managerial behaviour or short-termism. These real effects are of concern for the sectors of the economy that rely on innovation as a strategic path to growth or to defend competitive positions.

While the above evidence indicates that the immediate expensing rule for investments in R&D comes at the potential ‘cost’ of inducing value-destroying behaviour, it is not clear whether this cost can be mitigated by an orthogonal accounting rule (capitalization contingent on the probability of future benefits to the firm). In a full expensing regime, cutting R&D yields a dollar-for-dollar impact on earnings. Capitalization, on the other hand, only increases earnings by the proportion of R&D spending that is capitalized, which in turn is contingent on reaching a threshold level of project feasibility. Given most firms have a portfolio of projects in varying stages of the pipeline, the likelihood of capitalization alleviating pressure on earnings would depend on the status of those projects and their eligibility for capitalization. There is no empirical evidence at the firm level on the question of whether capitalization would reduce the likelihood of cutting R&D spending.[3] There is also a broader unanswered question of whether a full

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[1] The incentive to do so can arise from capital market-related benefits to maintaining steady and increasing earnings patterns, bonus-related elements of managerial compensation schemes, or short horizons of managers’ retirement (e.g., Baber *et al.*, 1991; Dechow and Sloan, 1991; Burgstahler and Dichev, 1997; Barth *et al.*, 1999). Edmans *et al.* (2017) directly test the link between managers’ short-term concerns (using the amount of stock and options scheduled to vest in a given quarter) and their real investment decisions.

[2] While we focus on R&D, other accounts used for real activities management include price discounts, overproduction to reduce cost of sales, discretionary spending on advertising, and marketing investment in brands. In their survey, Hunter *et al.* (2012, p. 122) find that production and technology is the most common expenditure on intangibles, predominated by R&D. Hence, such expenditures play a major role in any budgeting decision.

[3] However, studies based on experimental methods show that capitalization of R&D spending can have real effects. For example, Cooper and Selto (1991) present evidence that under-investment is mitigated if managers are given the opportunity to capitalize and subsequently amortize costs of successful R&D investments, while Seybert (2010) shows that a capitalization regime encourages over-investment.

expensing versus a capitalization regime is more likely to move a firm towards optimal investment in R&D. While the empirical literature documenting cuts to R&D in times of pressure to meet earnings targets *implies* under-investment is the outcome under full expensing,[4] this has not been directly tested. Nor is it known whether capitalization would lead to over-investment.

The theoretical literature on short-termism and the real effects of accounting decisions predict that the short-term incentives of managers can lead to *either* under- or over-investment. One of the reasons managers can engage in short-termism with respect to intangibles is the high information asymmetry between management and investors with respect to the investment level, including managerial effort. In equilibrium, when the investment level is unobservable, the manager will under-invest (Stein, 1988, 1989). But there is an interaction effect between the observability of the investment level and its profitability (Bebchuk and Stole, 1993; Kanodia *et al.*, 2005; Kanodia and Sapra, 2016). When the investment level is unobservable, the equilibrium outcome is under-investment regardless of whether profitability is known. However, over-investment occurs when the investment level is known but profitability is not. Kanodia and Sapra (2016) call for empirical work on specific accounting issues to discover what the equilibrium outcomes are in practice. The R&D setting is an especially interesting one for this purpose given the difficulty in assessing the level of investment in R&D and its profitability.[5] The level of R&D spending is not always observable (Koh and Reeb, 2015) and managerial effort is mostly unobservable (Stein, 1988). A fully expensing regime does not offer any accounting signal of profitability, unlike a capitalization regime which can offer at least a noisy one.[6,7]

This paper investigates the previously unexplored real effects of expensing versus the capitalization of R&D. It addresses the question in the US setting, which offers contrasting treatments for R&D costs for two somewhat related industries: software development and other hi-technology (‘other hi-tech’) (Mohd, 2005).[8] Firms in the business of software development are required to capitalize ‘successful’ R&D spending, while those in ‘other hi-tech’ are proscribed from doing so. Focusing within one jurisdiction reduces confounding factors that might arise in international comparisons. We first investigate whether the

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[4] Under-investment is inferred because the real effects documented are value destroying *cuts* to R&D spending.

[5] Kanodia and Sapra (2016, pp. 634–35) argue that while non-financial disclosures may play a complementary role to financial ones, they cannot be substitutes. The capitalization of the portion of R&D that is expected to generate future economic benefits allows differentiating between successful and unsuccessful investments, which is important for predicting cash flows.

[6] Consistent with this, Oswald and Zarowin (2007) find that capitalization is more highly associated with future earnings relative to expensing.

[7] See Hunter *et al.* (2012) for a discussion of related standard-setting considerations.

[8] We use ‘other hi-tech’ firms as a contrasting sample for the reasons explained in Mohd (2005); that is, other hi-tech firms also invest heavily in R&D and like software development firms have relatively short product life cycles.

capitalization regime in the software development industry relative to the 'other hi-tech' industry, (i) mitigates under-investment when a firm is facing short-term earnings pressure, and / or (ii) exacerbates over-investment in the presence of financial flexibility (Biddle *et al.*, 2009). Second, in an analysis within the software development industry, we investigate whether the capitalization regime for software development costs mitigates the likelihood of a cut to R&D spending when managers are under pressure to meet earnings targets.

We employ an expectation model for R&D investment based on prior work in Berger (1993), Perry and Grinaker (1994), and Laplante *et al.* (2015). We extend this baseline expectation model with variables capturing the presence of short-term managerial incentives and financial flexibility. Our findings for the US software sample confirm prior experimental evidence that managers are less likely to cut investment in intangible assets to achieve short-term earnings goals, and less likely to under-invest if they are operating in a capitalization regime. In addition, we do not find any evidence that the ability to capitalize exacerbates over-investment in the presence of financial flexibility.

This paper is the first to investigate how the capitalization of R&D (software development costs) impacts under- or over-investment in these activities in the software development industry relative to full expensing of R&D investment in 'other hi-tech' firms. Our work contributes to the literature in two ways. First, we complement emerging research on the impact of accounting rules in general on investment efficiency (e.g., Biddle *et al.*, 2016). Our analyses based on software development and other hi-tech industries provide valuable insights on how accounting rules can induce or mitigate sub-optimal investment. Misallocation of capital can impose large costs on firms in the long run. Understanding how different accounting rules impact on investment decisions is therefore important to both users of financial information and standard setters. Second, prior literature specific to accounting for the costs of self-generated intangibles has primarily focused on the information effects pursuant to their capitalization, for example, on the value relevance of capitalized amounts, earnings quality, and forecast accuracy (e.g., Lev and Sougiannis, 1996; Aboody and Lev, 1998; Abrahams and Sidhu, 1998; Ahmed and Falk, 2006; Matolcsy and Wyatt, 2006; Oswald, 2008; Ciftci, 2010; Dinh *et al.,* 2016; Chen *et al.*, 2017; Russell, 2017)[9] or the effect on information asymmetry (Mohd, 2005), rather than on the question of investment efficiency. This study complements prior research by showing the impact of such an accounting rule for self-generated intangible assets on real investment decisions.

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[9] In her review paper, Wyatt (2008) states that while R&D has been shown to be value relevant, it faces problems of lower reliability compared to tangible assets and a larger variation related to the ability to signal future economic benefits. For France, Cazavan-Jeny and Jeanjean (2006) find a negative association of R&D capitalization with stock prices and returns.

From a standard-setter's perspective, we contribute to the ongoing debate on the accounting for intangible assets. In 2008, the Australian Accounting Standards Board (AASB) issued a discussion paper on the initial accounting for internally generated intangible assets that the International Accounting Standards Board (IASB) considered but did not add to its agenda at that time due to a lack of resources.[10,11] Since then, the IASB has primarily focused on goodwill and impairment but not R&D, and lately has shifted discussions towards extractive activities. In the IASB Work Plan 2017–2021, the Board highlights that significant resources would be required to address the challenges of accounting for R&D while working on extractive activities only is more effective and efficient.[12] With our study, we therefore aim to re-stimulate this discussion and provide academic insights about the potential benefits when capitalizing R&D.

INSTITUTIONAL BACKGROUND

Accounting for costs incurred in generating intangible assets such as R&D remains a controversial issue for standard setters and researchers. While accounting rules in the US require the immediate expensing of all R&D costs (SFAS 2[13] / ASC 730), costs incurred on software development (SFAS 86 / ASC 350-40) are required to be capitalized contingent on certain recognition criteria being met. SFAS 86 *Accounting for the Costs of Computer Software to Be Sold, Leased, or Otherwise Marketed* (which became mandatory from years beginning after 31 December 1985) specifies that once technological feasibility has been established for a computer software product, costs incurred internally in creating that product shall be capitalized and subsequently amortized. Prior to the release of SFAS 86, the FASB's position was that all software development costs should be expensed along with R&D costs in accordance with SFAS 2, issued in 1974. The differing treatment subsequently afforded to software development companies has been attributed by some to lobbying by the software industry, that full expensing understated the assets created by the industry (e.g., Burns and Peterson, 1982; Kaplan and Sandino, 2001). Burns and Peterson (1982) comment that the submission by the Association of Data Processing Services Organization (ADAPSO) claimed:

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[10] AASB (2008).

[11] Dedman *et al.* (2009) interpret the IASB's decision as in line with their UK evidence: although R&D capitalization and disclosures may sometimes be misleading, such an accounting rule paired with disclosures outside of the financial statements, the regulatory system in place, and market forces is working quite effectively.

[12] IASB (2016, p. 31).

[13] SFAS 2 *Accounting for Research and Development Costs* (FASB, 1974). In the years preceding, the treatment of R&D costs in practice varied across firms, from full expensing to capitalization with amortization.

> …. the FASB has not properly considered the nature of software product construction, has not properly evaluated the historical risk associated with software products, has rationalized away the importance of long-standing generally accepted accounting principles, and has issued a ruling which may cause significant distortion in the financial reports of companies engaged in the construction of software.

SFAS 86 relates specifically to software development costs and provides explicit examples of which costs are subject to capitalization, such as ‘coding and testing performed subsequent to establishing technological feasibility’ (SFAS 86, para. 5). Thereby, once a detailed program design or a working model has been completed, technological feasibility is established (SFAS 86, paras. 1 and 4). While the Standard prescribes capitalization, some consider that there is ample discretion in interpreting the recognition criteria. Ciftci (2010) even refers to it as an ‘accounting choice’. These difficulties in assessing technological feasibility, marketability, etcetera, are even more pronounced in the presence of multiple projects over several accounting periods (Walker and Oliver, 2005).

The release of SFAS 86 in 1985 addressed the treatment of development costs of software intended for external distribution (through sales, leases etc.), but not the treatment of costs incurred to develop software for internal use. This led to continued divergence in practice until the American Institute of Certified Public Accountants (AICPA) issued in 1998, a Statement of Position SOP 98-1, *Accounting for the Costs of Computer Software Developed or Obtained for Internal Use*, which proposed similar treatment for internal use software.

PRIOR RESEARCH AND HYPOTHESES DEVELOPMMENT

The literature on real earnings management from the more conservative US setting for R&D costs shows that firms cut these investments in the face of short-term managerial incentives to meet earnings targets. Several papers document that managers cut R&D spending to avoid negative impacts on earnings, maintain smooth patterns in earnings, avoid losses, meet analysts’ expectations, or boost firm performance during the CEO’s final years in office (Baber *et al.*, 1991; Dechow and Sloan, 1991; Perry and Grinaker, 1994; Burgstahler and Dichev, 1997; Bushee, 1998; Barth *et al.*, 1999; Roychowdhury, 2006; García Osma and Young, 2009; Edmans *et al.*, 2017). Field evidence in Graham *et al.* (2005) and Dichev *et al.* (2013) shows that managers engage in such behaviour in the knowledge that it is value destroying in the longer run. Recent work documents negative impacts at the firm level in terms of reduced value creation in future patents (Bereskin *et al.*, 2018), and future performance (Cohen and Zarowin, 2010). The negative impact also manifests at the aggregate economy level (Terry, 2017).

There is no empirical evidence on whether an orthogonal accounting rule requiring the capitalization of R&D costs can assist in mitigating incentives to cut these investments in the face of short-term pressure on earnings.[14,15] And it is not immediately obvious that this would be the case. In a full expensing regime, a one dollar cut to R&D increases earnings by the same amount. However, the increase in earnings under a capitalization regime is limited to the costs incurred beyond a threshold level of project feasibility and assurance of future benefits. Since firms vary in their portfolios of projects in the R&D pipeline, the likelihood of capitalization alleviating pressure on earnings would depend on the status of those projects.[16]

The theory literature on the effects of short-termism on investment predicts that short-term managerial incentives can lead to *either* under- or over-investment. One of the reasons managers can engage in short-termism with respect to intangibles is the high information asymmetry between management and investors with respect to the investment level, including managerial effort. The asymmetry leads investors to infer under-investment which in turn traps the manager into under-investment. In equilibrium, the manager will under-invest (Stein, 1988, 1989). But subsequent work shows that there is an interaction effect between the observability of the investment level and its profitability (Bebchuk and Stole, 1993; Kanodia *et al.*, 2005; Kanodia and Sapra, 2016). The under-investment result from Stein (1988, 1989) holds when the investment level is unobservable, regardless of whether profitability is known or not. However, when the investment level is known but profitability is not, the investor infers high profitability from higher investment levels. This scenario gives the manager incentives to over-invest.

Kanodia and Sapra (2016) call for empirical work on specific accounting issues to ascertain whether the observable equilibrium outcomes are consistent with the available theoretical predictions. The R&D setting is especially interesting since assessing the level of investment in R&D and its profitability is challenging. The level of R&D spending is not always observable or separately disclosed (Koh and Reeb, 2015) and managerial effort is mostly unobservable (Stein, 1988). Meanwhile, the productivity of the investment is much harder to ascertain; information about the productivity of R&D-type projects is likely to be limited due to the long lags and inherent uncertainty in such activity (Kothari *et al.*, 2002). While we do not receive any accounting signal in a full expensing regime, a capitalization regime can offer at least a noisy measure on the level of *successful*

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[14] We know only of experimental evidence that changing the accounting regime from expensing R&D to capitalizing alters participants' behaviour in a way that reduces suboptimal investment decisions; the participants in Cooper and Selto (1991) stopped cutting R&D and generating lower terminal present values once the accounting regime switched to capitalizing.

[15] A closely related working paper (Bhattacharya *et al.*, 2012) examines changes in investment efficiency in a German setting where the accounting rule for R&D changed in 2005 from full expensing in the pre-IFRS adoption period to allowing capitalization post-adoption. They find that the investment efficiency for their sample of German firms improved significantly in the post-IFRS period. However, in their empirical analyses they do not link the capitalization decision to managerial myopia and nor do they investigate the possibility of over-investment.

[16] We acknowledge also a possibility that the proportion capitalized may be influenced by incentives to manage earnings (Markarian *et al.*, 2008; Cazavan-Jeny *et al.*, 2011; Dinh *et al.*, 2016).

investment.[17] Consistent with this, Oswald and Zarowin (2007) find that capitalization is more highly associated with future earnings relative to expensing. Also consistent with capitalization providing signal value, Mohd (2005) finds that information asymmetry (bid-ask spreads) declined upon the introduction of rules for capitalization of successful R&D efforts in the US software development sector, as compared to the 'other hi-tech' sector where full expensing continued to be required.

Since the empirical setting offers noisy signals of both the level and profitability of investment in R&D, it is not obvious what the equilibrium outcome would be in practice in response to short-term managerial incentives.[18] In the absence of strong and unambiguous theory on the trade-off in these noisy signals, it is useful to examine how these effects play out in practice. But we draw on the available theory to conjecture that the two noisy signals push the information released by the manager towards optimal investment when there is no information asymmetry on either the level or profitability of investment as summarized in Figure 1.

We exploit the difference in the accounting treatment of firms in software development versus R&D costs in other high-tech industries in the US, to investigate whether a capitalization regime (i) mitigates under-investment in the face of earnings-based incentives or (ii) encourages over-investment in the presence of financial slack, and (iii) reduces the likelihood of cuts to R&D in the face of earnings-based incentives.

Based on experimental evidence (Cooper and Selto, 1991), we can also expect firms in a capitalization regime, such as software development, to be associated with lower under-investment relative to firms in a full expensing regime (Bushee, 1998). We use companies in the 'other hi-tech' sector as the contrasting sample. As previously discussed, Mohd (2005) contrasts the same two industry classifications in a study of whether the capitalization signal reduces information asymmetry. Likewise, Ciftci (2010) compares firms from the software industry with other hi-tech industries to find that the capitalization of software development costs does not improve earnings quality, but without addressing any real investment effects. Hence, our first hypothesis is stated as follows:

> H1: *Ceteris paribus*, a capitalization regime for R&D spending mitigates under-investment in intangibles (software development) when managers face earnings-based incentives.

While the focus on under-investment is predicated on capitalization serving to mitigate incentives for under-investment problems, it is plausible that the ability to

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[17] It is a noisy signal since only the costs incurred beyond the point of technical feasibility and the assurance of future benefits are capitalized. Further, the signal is only one of capitalized costs rather than value created. However, through that signal from managerial discretion, the quality of financial information is improved rather than diminished (Chambers *et al.*, 2003; Wyatt, 2005).

[18] Kanodia *et al.* (2005) show that in settings such as that of R&D, there is an optimal degree of imprecision in accounting measurement (of the investment) that is increasing in the information advantage of the manager. But it is not obvious how their result can be operationalized here.

Figure 1

THEORETICAL PREDICTIONS BASED ON THE INTERACTION BETWEEN THE OBSERVABILITY OF THE R&D INVESTMENT LEVEL AND ITS PROFITABILITY

PROFITABILITY **INVESTMENT LEVEL**	PUBLICLY **UN**KNOWN (R&D fully expensed and no other information signal on profitability)	PUBLICLY KNOWN (In practice, capitalized R&D is partially revealing of the proportion R&D spend that is successful, but not of the value created)
UNOBSERVABLE / IMPRECISE measurement (In practice, unobservable R&D spend / managerial effort / 'secret designs' are unobservable)	UNDER-INVESTMENT Stein, 1988/89 Bebchuk and Stole, 1993	UNDER-INVESTMENT Stein, 1988/89 Bebchuk and Stole, 1993 Kanodia and Sapra, 2016
OBSERVABLE / PRECISE measurement (In practice, R&D spend known but effort / 'secret designs' remain unobservable)	OVER-INVESTMENT Bebchuk and Stole, 1993 Kanodia and Sapra, 2016	OPTIMAL INVESTMENT

capitalize can exacerbate the opposite incentives for *over*-investment in the presence of financial flexibility or slack. That is, managers use their cash to invest in projects that are value-destroying and do not have positive net present values.[19] Experimental evidence in Seybert (2010) supports this expectation. The participants in that study were more likely to over-invest in R&D when they were concerned about their personal reputation and when they could capitalize R&D.

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[19] The underlying assumption here is that biased or untruthful capitalization protects the manager by a postponement in disciplining action. This is reflected in the conservative accounting treatment of R&D spending in industries outside of the software development sector in the US.

Consistent with the available theoretical models and experimental evidence, we expect managers of capitalizing firms to over-invest in software development if they have the flexibility to do so. More generally, Biddle *et al.* (2009) identify 'ex-ante firm-specific characteristics' that are likely to have an impact on a firm's investment decisions; they argue that low leverage and a high cash base offer financial flexibility, suggesting conditions enabling over-investment. Our second hypothesis is as follows:

> H2: *Ceteris paribus*, a capitalization regime for R&D spending exacerbates over-investment in intangibles (software development) in settings characteristic of high financial flexibility.

The real earnings management literature documents that managers of firms that are in danger of missing earnings-based targets will cut R&D in attempts to meet those targets. Field-based evidence confirms that managers do this despite recognizing the value-destroying effects of such actions. There is no empirical evidence on whether an orthogonal accounting rule requiring the capitalization of R&D costs of successful projects can assist in mitigating incentives to cut these investments in the face of short-term pressure on earnings. Since capitalization of R&D is unlikely to result in 100% of R&D spend being capitalized, it is unlikely to be as effective as cutting R&D spending to meet earnings targets. Nevertheless, the ability to offer investors a signal of success in the form of a capitalized R&D number may mitigate the cost of not meeting short-term earnings targets. We hypothesize as follows:

> H3: The probability of cutting R&D spending to meet earnings targets is lower under a capitalization regime (software development) than in a full expensing regime (other hi-tech).

MAIN ANALYSES

The research design described below relates to two samples selected as in Mohd (2005): (i) a sample of software development firms in the US that are required to capitalize software development costs under SFAS 86 / ASC 350-40, and (ii) a contrasting sample of other hi-technology firms that are not permitted to capitalize internally generated intangibles arising from R&D activities.[20] Our sample selection procedures are described in the corresponding section.

Expectation Model for Investment in R&D or Software Development

Our empirical model for the expected level of investment is based on the idea that investment in internally generated intangibles is a function of lagged investment

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[20] Self-selection bias is not an issue for our two samples of US firms. Only firms with software development costs may capitalize the related intangibles. We observe 97% of the US software sample capitalizing software development. Meanwhile, capitalization of R&D costs is not an option for the other hi-technology sample firms.

and financial opportunities. Drawing on the R&D expectation models in Berger (1993), Perry and Grinaker (1994), and Laplante *et al.* (2015), and the more general model in Biddle *et al.* (2009), we have the following specification:

$$INV_{it} = \beta_0 + \beta_1 INV_{it-1} + \beta_2 NETCASH_{it-1} + \beta_3 PROF'_{it-1} + \beta_4 SIZE_{it-1} + \beta_5 LEV'_{it} + \beta_6 TOBINSQ_{it} + \beta_7 CAPEX_{it} + \beta_8 AGE_{it} + \beta_9 OPCYCLE_{it} + \beta_{10} LOSS_{it} + \beta_{11} GNP_t + \varepsilon \quad (1)$$

The dependent variable INV_{it} represents investment in either software development spending in the software development sample (SW_{it}) or R&D spending in the other hi-technology sample (RD_{it}). The lagged value of INV_{it}, that is, INV_{it-1}, is included as an independent variable since prior studies find a strong correlation for R&D investment from period to period (e.g., Baber *et al.*, 1991; Berger, 1993; Perry and Grinaker, 1994).

The model includes firm size ($SIZE_{it}$)[21] measured by the natural logarithm of one plus total revenues as an independent variable to control for scale effects (since the model is to be estimated in levels), but also to capture the capacity of a firm to invest in intangibles. We also follow prior literature (Berger, 1993; Perry and Grinaker, 1994; Laplante *et al.*, 2015) to further capture the resources available or capacity to invest at the beginning of each period for budget allocation to intangibles, including: the lagged amount of cash and short-term investment less current liabilities ($NETCASH_{it-1}$); the lagged income before extraordinary items adjusted for the capitalization of development expenditures ($PROF'_{it-1}$); leverage adjusted for the capitalization of development expenditures minus the industry-median leverage (LEV'_{it}); and capital expenditures ($CAPEX_{it}$). Tobin's Q acts as a measure for growth opportunities ($TOBINSQ_{it}$) (Berger, 1993).[22] Finally, gross national product (GNP_t) captures technological progress in the economy which is expected to have an impact on the level of R&D investments (Berger, 1993). In addition, we follow Biddle *et al.* (2009) to capture the effect of different stages of the business cycle by including a measure of age (AGE_{it}), the length of operating cycle ($OPCYCLE_{it}$), and the frequency of losses ($LOSS_{it}$).

Our preliminary analyses on this model specification show that the lagged value of investment from the prior period (INV_{it-1}) is always the largest explanatory variable in the model.[23] To mitigate the possibility that the non-stationarity in the

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[21] We measure size by using the natural logarithm of one plus total revenues to avoid the problem of having zero values for revenues since the natural logarithm of zero is not defined.

[22] We also estimate our models using independent variables lagged one period, and the results are qualitatively unchanged.

[23] Results based on model (1) are available upon request. The model specifications overall do not change our results.

model leads to spurious results, we have taken a standard econometric approach to transform the non-stationary process into a stationary process for more reliable results. Specifically, we have transformed the expectation model (1) into the following specification with the change in the value of investment as the dependent variable ($DINV_{it}$) and an additional independent trend variable ($YTREND_t$) for detrending:

$$\begin{aligned}\boldsymbol{DINV_{it}} = {} & \beta_0 + \beta_1 NETCASH_{it-1} + \beta_2 PROF'_{it-1} + \beta_3 SIZE_{it-1} + \beta_4 LEV'_{it} \\ & + \beta_5 TOBINSQ_{it} + \beta_6 CAPEX_{it} + \beta_7 AGE_{it} + \beta_8 OPCYCLE_{it} \\ & + \beta_9 LOSS_{it} + \beta_{10} GNP_t + \boldsymbol{\beta_{11} YTREND_t} + \varepsilon \end{aligned} \tag{2}$$

Testing Hypotheses 1 and 2: Under- (Over-) Investment in Software Development versus Other Hi-Tech Sample, Given Managerial Incentives (Myopia or Financial Flexibility)

We compare the role of myopic incentives (in under-investment for Hypothesis 1) and financial flexibility (in over-investment for Hypothesis 2) between firms in the software industry versus firms in the other hi-tech industries. We conjecture that the under-investment problem will be more severe for firms that are not allowed to capitalize their R&D expenses (firms in other hi-tech industries) compared to firms that are required to capitalize (firms in the software industry) beyond the point of technical feasibility. On the other hand, we expect over-investment to be more pronounced if capitalization is present (software industry) in the presence of financial flexibility. We extend the expectation model (model (2)) to estimate the following two models separately for firms in the software industry and for firms in the other hi-tech industries:

$$\begin{aligned}DINV_{it} = {} & \beta_0 + \boldsymbol{\beta_M MYOPIA_{it}} + \beta_1 NETCASH_{it-1} + \beta_2 PROF'_{it-1} + \beta_3 SIZE_{it-1} \\ & + \beta_4 LEV'_{it} + \beta_5 TOBINSQ_{it} + \beta_6 CAPEX_{it} + \beta_7 AGE_{it} + \beta_8 OPCYCLE_{it} \\ & + \beta_9 LOSS_{it} + \beta_{10} GNP_t + \beta_{11} YTREND_t + \varepsilon \end{aligned} \tag{3}$$

$$\begin{aligned}DINV_{it} = {} & \beta_0 + \boldsymbol{\beta_F FINFLEX_{it}} + \beta_1 NETCASH_{it-1} + \beta_2 PROF'_{it-1} + \beta_3 SIZE_{it-1} \\ & + \beta_4 LEV'_{it} + \beta_5 TOBINSQ_{it} + \beta_6 CAPEX_{it} + \beta_7 AGE_{it} \\ & + \beta_8 OPCYCLE_{it} + \beta_9 LOSS_{it} + \beta_{10} GNP_t + \beta_{11} YTREND_t + \varepsilon \end{aligned} \tag{4}$$

where, $DINV_{it}$ is the change in spending on either software development ($SW_{it} - SW_{it-1}$) in the case of the software sample or R&D ($RD_{it} - RD_{it-1}$) in the case of the other hi-tech sample.

We proxy for myopic managerial incentives by identifying firm-years for which the previous year's earnings before extraordinary items is larger than the current year's earnings before extraordinary items plus the change in software development expenditures ($SW_{it} - SW_{it-1}$). The intuition is to capture earnings decline before software development investments when taking the prior year's level of investment as the minimum amount to be spent. If earnings remain below the prior year's earnings after having made the minimum investment in software development, $MYOPIA_{it}$ is set to one, and otherwise set to zero. For financial flexibility, we expect firm-years in the quartile with the lowest industry-adjusted leverage to have higher financial flexibility and hence, a higher likelihood of over-investment. The dummy variable $FINFLEX_{it}$ is set to one for these firms, and zero otherwise. We expect β_M in model (3) to be negative and significant, suggesting firms under-invest in a myopic setting. Meanwhile, if firms over-invest in the presence of financial flexibility, we would expect β_F estimated in model (4) to be positive and significant.[24]

We next estimate each of the above two models on both the software and hi-tech samples together rather than separately, by including a dummy variable $SOFTWARE_{it}$. The variable $SOFTWARE_{it}$, is set to one if a firm is operating within the software development industry, and zero if a firm is operating within one of the other hi-tech industries. We include interaction terms between $SOFTWARE_{it}$ and $MYOPIA_{it}$ or between $SOFTWARE_{it}$ and $FINFLEX_{it}$ in models (5) and (6), respectively:

$$\begin{aligned} DINV_{it} = {} & \beta_0 + \boldsymbol{\beta_M MYOPIA_{it}} + \boldsymbol{\beta_S SOFTWARE_{it}} + \boldsymbol{\beta_{MS} MYOPIA_{it} \times SOFTWARE_{it}} \\ & + \beta_1 NETCASH_{it-1} + \beta_2 PROF'_{it-1} + \beta_3 SIZE_{it-1} + \beta_4 LEV'_{it} + \beta_5 TOBINSQ_{it} \\ & + \beta_6 CAPEX_{it} + \beta_7 AGE_{it} + \beta_8 OPCYCLE_{it} + \beta_9 LOSS_{it} + \beta_{10} GNP_t \\ & + \beta_{11} YTREND_t + \varepsilon \end{aligned} \tag{5}$$

$$\begin{aligned} DINV_{it} = {} & \beta_0 + \boldsymbol{\beta_F FINFLEX_{it}} + \boldsymbol{\beta_S SOFTWARE_{it}} + \boldsymbol{\beta_{FS} FINFLEX_{it} \times SOFTWARE_{it}} \\ & + \beta_1 NETCASH_{it-1} + \beta_2 PROF'_{it-1} + \beta_3 SIZE_{it-1} + \beta_4 LEV'_{it} + \beta_5 TOBINSQ_{it} \\ & + \beta_6 CAPEX_{it} + \beta_7 AGE_{it} + \beta_8 OPCYCLE_{it} + \beta_9 LOSS_{it} + \beta_{10} GNP_t \\ & + \beta_{11} YTREND_t + \varepsilon \end{aligned} \tag{6}$$

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[24] Other proxies for measuring financial flexibility are discussed under subsequent sensitivity analyses.

Specifically, model (5) is estimated including firms in both the software industry and the other high-tech industries to test the first hypothesis. In estimating model (5), we expect β_M to be negative and significant, suggesting firms under-invest in a myopic setting but we expect β_{MS} to be positive and significant, suggesting that the under-investment behaviour is less pronounced for firms operating in the software industry compared to firms operating in other hi-tech industries. Meanwhile, model (6) is estimated including both software firms and other hi-tech firms to test the second hypothesis. In estimating model (6) we expect β_F to be positive and significant, suggesting firms over-invest in the presence of financial flexibility and we expect β_{FS} to be positive and significant, suggesting that the over-investment behaviour is more pronounced for firms operating in the software industry compared to firms operating in other hi-tech industries.

Testing Hypothesis 3: Probability of Cutting Software Development Spending

In testing Hypothesis 3, we follow Bushee (1998) to further explore the effect of the ability to capitalize successful software spending on myopic behaviour within the sample of software firms. We have characterized the myopia setting as one in which earnings have declined. A decline in earnings might be mitigated in one of at least two ways in our setting: (i) by capitalizing a larger proportion of the successful spending to reduce the decline in earnings and/or (ii) by cutting spending. We test the first possibility on average across the whole sample of software firms and then in three sub-samples based on the ability to negate a decline in earnings by cutting R&D spending. The latter is dependent on the relative amount of earnings decline to the previous year's software spending. Thus, we partition our software development sample into three segments: (a) Large Earnings Decline (LD) where the earnings decline (before the effects of capitalization and before extraordinary items) is greater than SW_{t-1}, that is, cutting all of last year's spending cannot fully reverse the decline in earnings; (b) Small Earnings Decline (SD), where the earnings decline is smaller than SW_{t-1}, that is, cutting some of last year's spending can fully reverse the decline in earnings; and (c) Earnings Increase (IN), where earnings stay the same or there is an increase in earnings.

We estimate the following probability (logit) model where the dependent variable SW_CUT_{it}, is a dummy variable set to one if a firm's total software development spending is lower in the current period (SW_{it}) relative to the previous period (SW_{it-1}). The main independent variable of interest is $CHANGESWCAP_{it}$, which is the change of capitalized software development costs from the previous period ($SWCAP_{it-1}$) to the current one ($SWCAP_{it}$). The control variables are the same as in model (1).

$$\Pr(SW\_CUT_{it}) = \beta_0 + \beta_1 CHANGESWCAP_{it} + \beta_2 NETCASH_{it-1} + \beta_3 PROF'_{it-1}$$

$$+ \beta_4 SIZE_{it-1} + \beta_5 LEV'_{it} + \beta_6 TOBINSQ_{it} + \beta_7 CAPEX_{it} + \beta_8 AGE_{it} + \beta_9 OPCYCLE_{it}$$

$$+ \beta_{10} LOSS_{it} + \beta_{11} GNP_t + \varepsilon \qquad (7)$$

We expect the coefficient β_1 on $CHANGESWCAP_{it}$ to be negative, suggesting that firms with increased amount of capitalized software development costs will be less likely to reduce investment in software development, that is, less likely to under-invest.

ADDITIONAL ANALYSES

Probability of Under- (Over-) Investment in Software Development in a Multinomial Design

To ascertain the *probability* of over- or under-investment, we first estimate the expectation model (model (1)) for software and other hi-tech firms together to obtain residuals (which represent deviations from the expected investment level). We then partition the sample into three groups based on the magnitude of the residuals. Specifically, we set up a categorical variable INV_RES_{it}, which is equal to one if the ranked residuals for the firm-year observation are in the bottom quartile (i.e., the most negative residuals representing under-investment). INV_RES_{it} is set to three if the ranked residuals for the firm-year observation are in the top quartile (i.e., the most positive residuals representing over-investment). INV_RES_{it} is set to two if the ranked residuals for the firm-year observations are in the middle two quartiles (representing close to optimal level of investment).

We use the categorical variable INV_RES_{it} as the dependent variable to estimate the multinomial logistic regression models for the under-investment setting (model (8)) and over-investment setting (model (9)). Specifically, we set INV_RES_{it} equal to two as the baseline so the multinomial logistic model estimates whether capitalizing software development cost influences the likelihood that a firm will under-invest ($INV\_RES_{it} = 1$) or over-invest ($INV\_RES_{it} = 3$) compared to firms with optimal (or close to optimal) level of investment.

$$\Pr(INV\_RES_{it}) = \beta_0 + \beta_M MYOPIA_{it} + \beta_S SOFTWARE_{it} + \beta_{MS}(MYOPIA_{it} \times SOFTWARE_{it}) + \varepsilon \tag{8}$$

$$\Pr(INV\_RES_{it}) = \beta_0 + \beta_F FINFLEX_{it} + \beta_S SOFTWARE_{it} + \beta_{FS}(FINFLEX_{it} \times SOFTWARE_{it}) + \varepsilon \tag{9}$$

Since model (8) examines the most negative residuals with the baseline in the software sample (middle two quartiles of ranked residuals), the coefficient β_M reflects the probability that companies will be more likely to under-invest in firm-years defined to be in a myopic setting (i.e., $\beta_M > 0$). The ability to capitalize for software development firms will reduce the likelihood that firms fall into the bottom quartile (i.e., under-invest); that is, we expect the coefficient on the interaction term to be negative ($\beta_{MS} < 0$).

Meanwhile, model (9) examines the most positive residuals with the baseline in the software sample (middle two quartiles of ranked residuals). Thus, the coefficient β_F is expected to be positive consistent with the prediction that companies will be more likely to over-invest in firm-years with higher financial flexibility. The over-investment is predicted to be exacerbated when capitalization ratios are higher. So, we expect the coefficient on the interaction term to be positive ($\beta_{FS} > 0$).

The Influence of Institutional Ownership

The second set of additional analysis addresses the concern that managers' myopic behaviour is mitigated by institutional ownership. Bushee (1998) finds that firms are less likely to engage in manipulating R&D spending when institutional ownership is high. Thus, we expect that the effect of capitalizing software development spending on mitigating the effect of myopic behaviour would be less pronounced when institutional ownership is high since the myopic incentives are also lower. To test our conjecture, we include an additional variable $PINSOWN_{it}$ in model (3) to control for the percentage of institutional ownership to ascertain the average effect of institutional ownership. As in Bushee (1998, p. 316), $PINSOWN_{it}$ is the percentage of institutional ownership 'at the end of the calendar quarter in which the firm's third fiscal quarter ends'. We next partition our sample based on the variable $PINSOWN_{it}$ into four quartiles and re-estimate the original model (3) separately for firms in the top quartile (highest percentage of institutional ownership) versus firms in the other three quartiles. This analysis is in line with Bushee (1998) and tests whether firms with the highest level of institutional ownership (quartile 4) do not suffer from myopic incentives as other firms do. For these firms, the ability to capitalize expenditure on software development may not add much incremental value since myopic behaviour might have already been controlled for by the presence of institutional owners. In contrast, in the absence of high percentage of institutional ownership (quartiles 1 to 3) the effect of capitalizing software development expenditures on mitigating myopic behaviour is expected to be more pronounced.

SAMPLE SELECTION AND DESCRIPTIVE STATISTICS

Table 1 provides information on the sample selection. Panel A describes the sample of firm-years in the software industry (SIC 7370-7374) following Mohd (2005). We start with 4,704 observations during the sample period, 2005–2012. After excluding inactive firm-years, observations with no software development costs, and missing values on test variables, we obtain 1,575 observations from 361 firms. With respect to other hi-tech industries (per Francis and Schipper (1999) cited in Mohd (2005) defined as SIC 283, 357, 360–368, 481, 7375–7379, 873), we start with 17,576 firm-years to obtain 4,031 observations from 731 firms.

Table 1

SAMPLE SELECTION

Panel A: Software industry	
	Number of firm-years (firms)
US software companies 2005–2012	4,704 (588)
SIC 7370–7374	
With available 10-Ks or 10-K SBs reports	2,641 (514)
thereof active	2,231 (496)
thereof with software development costs >0	2,200 (493)
less observations with missing values	–625 (132)
	1,575 (361)
thereof capitalizers	1,031 (240)
thereof expensers	544 (153)
Panel B: Other hi-tech industries	
	Number of firm-years (firms**)**
US companies 2005–2012	17,576 (2,197)
SIC 283, 357, 360-368, 481, 7375-7379, 873	
thereof active	8,609 (1,447)
thereof with R&D costs >0	8,321 (1,434)
less observations with missing values	–4,290 (1,409)
	4,031 (731)

Note: In Panel A of Table 1, there are 32 firms that have capitalized software development expenditures in some years but not all years. The number of firms that never capitalized their software development expenditures is 121 (153 minus 32).

Self-selection bias is not an issue for our analyses because only firms with software development costs may capitalize the related intangibles. In addition, virtually all software firm-years capitalize part of their software development costs.

We hand-collect the data on the capitalization of software development in the US software sample because this specific information cannot be retrieved from available databases. Compustat only provides data on the amount of total capitalized software (Compustat variable name *capsft*), which captures the ending balance of the capitalized software development at the balance date rather than the amount that is capitalized during that period. Nor does Compustat provide the total amount spent on software development in any one year, or the portion that is expensed.

In our manual data collection, we notice that the item *xrd* on Compustat can relate to various definitions of 'expensed R&D': 1) software development expense; 2) software development expenditure (software capitalization + software expense); 3) software-related research and development expense (e.g., product development and engineering); 4) research and development expense other than software development expense (i.e., 'pure' R&D). In order to ensure a clean amount of expensed software development costs, we differentiate between these different categories in our data collection. We use total software development expenditures as reported in the 10-K annual filings if available to capture the total amount invested in software development. If not, we calculate the latter by adding the expensed and the portion capitalized per year, by re-constructing the relevant

Table 2

DESCRIPTIVE STATISTICS

Panel A: Descriptive statistics on the software sample and the other hi-tech sample

Full software sample				Full other hi-tech sample			
Variables	Mean	SD	Median	Variables	Mean	SD	Median
$SWCAP_{it}$	5.303	15.782	0.000				
$SWEXP_{it}$	147.54	692.57	21.797				
SW_{it}	118.128	370.397	22.445	XRD_{it}	218.901	571.022	21.631
$NETCASH_{it-1}$	22.274	341.321	1.582	$NETCASH_{it-1}$	−438.040	2,126.779	4.578
$PROF'_{it-1}$	95.252	448.231	3.987	$PROF'_{it-1}$	293.063	1,051.920	0.000
$SIZE_{it}$	5.241	1.697	5.146	$SIZE_{it}$	5.076	2.692	4.845
LEV'_{it}	1.694	3.676	1.599	LEV'_{it}	1.756	3.132	1.513
$TOBINSQ_{it}$	2.593	4.617	1.931	$TOBINSQ_{it}$	2.577	4.308	1.613
$CAPEX_{it}$	33.562	101.523	5.402	$CAPEX_{it}$	241.717	756.377	4.447
AGE_{it}	10.472	10.231	9.000	AGE_{it}	14.931	13.678	12.000
$OPCYCLE_{it}$	4.264	0.678	4.327	$OPCYCLE_{it}$	4.899	0.993	4.971
$LOSS_{it}$	0.378	0.485	0.000	$LOSS_{it}$	0.505	0.500	1.000
Number of observations		N = 1,575		Number of observations		N = 4,031	

Panel B: Correlation matrix

		1	2	3	4	5	6	7	8	9	10	11	12	13
1	SW_{it}		N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
2	SW_{it-1}	0.993		N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
3	$SWCAPRATIO_{it}$	−0.392	−0.402		N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
4	$SWRD_{it-1}$	0.851	0.861	−0.182		−0.491	0.742	0.517	0.082	−0.066	0.620	0.256	0.063	−0.037
5	$NETCASH_{it-1}$	0.199	0.187	−0.113	0.235		−0.526	−0.371	−0.097	0.048	−0.747	−0.182	0.028	0.108
6	$PROF'_{it-1}$	0.619	0.621	−0.120	0.899	0.128		0.447	0.064	−0.054	0.733	0.286	**0.004**	−0.192
7	$SIZE_{it}$	0.444	0.440	**0.005**	0.574	**0.000**	0.403		0.156	−0.308	0.493	0.366	−0.073	−0.419
8	LEV'_{it}	0.045	**0.044**	**0.029**	0.070	−0.062	0.057	0.132		−0.087	0.092	0.042	**0.016**	−0.097
9	$TOBINSQ_{it}$	**−0.031**	**−0.034**	**−0.006**	**−0.040**	**0.005**	**−0.031**	−0.375	−0.099		−0.068	−0.067	**−0.011**	0.174
10	$CAPEX_{it}$	0.544	0.536	−0.062	0.810	0.156	0.837	0.489	0.062	−0.049		0.209	−0.050	−0.197

Table 2

CONTINUED

Panel B: Correlation matrix

		1	2	3	4	5	6	7	8	9	10	11	12	13
11	AGE_{it}	0.320	0.315	−0.210	0.293	−0.208	0.337	0.390	0.043	−0.048	0.328		0.057	−0.045
12	$OPCYCLE_{it}$	**−0.012**	**−0.010**	**0.025**	0.073	−0.059	**0.041**	**0.007**	0.102	**−0.0025**	**0.010**	0.093		0.026
13	$LOSS_{it}$	−0.134	−0.104	**−0.041**	−0.162	**−0.036**	−0.170	−0.299	−0.098	0.169	−0.176	−0.101	**−0.010**	

Note: Panel A of Table 2 shows descriptive statistics for both samples separately and Panel B of Table 2 shows the Pearson correlation coefficient (bold if significant at the 0.05 level or less) for the the US software sample (below the diagonal) and for the US other hi-tech sample (above the diagonal). Variables are defined in the Appendix.

TABLE 3

BASELINE MODEL IN SOFTWARE DEVELOPMENT AND IN OTHER HI-TECH INDUSTRIES

Dependent variable: $DINV_{it}$	Software	Other hi-tech	Software and other hi-tech
Intercept	−313.591***	−406.252***	−372.274***
	(−4.046)	(−3.405)	(−4.212)
$NETCASH_{it-1}$	0.010	0.007***	0.007***
	(1.459)	(2.583)	(3.077)
$PROF'_{it-1}$	−0.008	0.011**	0.010**
	(−0.415)	(2.169)	(2.153)
$SIZE_{it}$	7.353***	4.491***	4.877***
	(4.261)	(3.247)	(4.551)
LEV'_{it}	0.005	−0.035	−0.032
	(0.097)	(−1.209)	(−1.180)
$TOBINSQ_{it}$	0.591*	0.475**	0.537***
	(1.718)	(2.111)	(2.593)
$CAPEX_{it}$	0.054	0.013	0.016**
	(1.379)	(1.635)	(2.031)
AGE_{it}	−0.727***	−0.399**	−0.469***
	(−3.411)	(−2.151)	(−3.011)
$OPCYCLE_{it}$	1.239	1.875*	1.948**
	(0.525)	(1.791)	(2.071)
$LOSS_{it}$	−0.984	9.149	5.783
	(−0.522)	(1.402)	(1.318)
GNP_t	0.020***	0.027***	0.024***
	(3.886)	(3.319)	(4.062)
$YTREND_t$	−2.046	−4.676***	−3.803***
	(−1.521)	(−4.065)	(−4.277)
Industry fixed effects	Yes	Yes	Yes
Year fixed effects	No	No	No
Firm clustered SE	Yes	Yes	Yes
Observations	1,575	4,031	5,606
Adj. R-squared	0.153	0.026	0.034
Highest VIF	4.92	4.83	4.77

Note: Robust *t*-statistics are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Variables are defined in the Appendix.

journal entries from the balance and income statement.[25] All the other financial statement variables are obtained from Compustat while the institutional ownership data are downloaded from Thomson Reuters through the WRDS platform.

Panel A of Table 2 provides descriptive statistics for the software and the other hi-tech samples. All variables are winsorized at the 1st and 99th percentiles. Panel B of Table 2 provides the correlation matrix with the Pearson correlation coefficients for the software sample below the diagonal and for the other hi-tech sample above the diagonal. The coefficients do not show any signs of multicollinearity.

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[25] Note that we set *SWEXP* to be zero if we do not find any mention of the amount expensed in any part of the financial statements, including the footnotes. This assumes that the expensed amount is zero (or close enough to zero to not warrant mention in the accounts). In addition, we also notice that the item for software asset in Compustat may sometimes include both capitalized amounts of internally developed software and purchased software alike. Since our focus is on internally generated software, we collect the information separately.

Table 4

ASSOCIATION BETWEEN CHANGE IN INVESTMENT AND PRESENCE OF MYOPIC MANAGERIAL INCENTIVES IN SOFTWARE DEVELOPMENT AND IN OTHER HI-TECH INDUSTRIES

Dependent variable: $DINV_{it}$	Software	Other hi-tech	Software and other hi-tech	Software and other hi-tech interaction
Intercept	−309.160***	−430.008***	−388.782***	−388.221***
	(−4.095)	(−3.533)	(−4.325)	(−4.320)
$MYOPIA_{it}$	−2.425	−18.554***	−14.521***	−16.784***
	(−1.134)	(−4.200)	(−4.527)	(−4.283)
$SOFTWARE_{it}$				0.612
				(0.111)
$MYOPIA_{it} \times SOFTWARE_{it}$				8.485**
				(2.241)
$NETCASH_{it-1}$	0.010	0.007***	0.007***	0.008***
	(1.486)	(2.640)	(3.119)	(3.118)
$PROF'_{it-1}$	−0.009	0.012**	0.011**	0.011**
	(−0.543)	(2.341)	(2.305)	(2.315)
$SIZE_{it}$	7.271***	4.329***	4.719***	4.688***
	(4.248)	(3.188)	(4.471)	(4.446)
LEV'_{it}	0.011	−0.027	−0.025	−0.024
	(0.215)	(−0.894)	(−0.897)	(−0.865)
$TOBINSQ_{it}$	0.585*	0.386*	0.474**	0.476**
	(1.725)	(1.717)	(2.378)	(2.334)
$CAPEX_{it}$	0.056	0.013	0.016**	0.016**
	(1.486)	(1.574)	(1.966)	(1.969)
AGE_{it}	−0.701***	−0.365**	−0.439***	−0.442***
	(−3.362)	(−2.012)	(−2.869)	(−2.888)
$OPCYCLE_{it}$	1.323	2.041*	2.041**	2.063**
	(0.559)	(1.933)	(2.168)	(2.189)
$LOSS_{it}$	−0.296	15.879**	10.856**	10.742**
	(−0.139)	(2.086)	(2.115)	(2.100)
GNP_t	0.019***	0.028***	0.025***	0.025***
	(3.961)	(3.462)	(4.197)	(4.196)
$YTREND_t$	−1.975	−4.585***	−3.814***	−3.768***
	(−1.527)	(−4.011)	(−4.278)	(−4.238)
Industry fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	No	No	No	No
Firm clustered SE	Yes	Yes	Yes	Yes
Observations	1,575	4,031	5,606	5,606
Adj. R-squared	0.153	0.031	0.039	0.039
Highest VIF	4.93	4.83	4.77	4.95

Note: Robust *t*-statistics are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Variables are defined in the Appendix.

EMPIRICAL RESULTS—MAIN ANALYSES

Table 3 presents the results from estimating the baseline model (2) in our two samples: where capitalization beyond the point of technical feasibility is required (software development) versus not allowed (other hi-tech). The dependent variable is the change in either investment in software development (column 1) or R&D (column 2).

Under- (Over-) Investment in the Software Development versus the Other Hi-Tech Sample

Table 4 displays the results of the impact of myopic incentives on investment in our two samples. Again, the dependent variable is either the change in investment in software development (column 1) or R&D (column 2). The results suggest that the under-investment problem is significantly more severe for the other hi-tech group (a statistically significant coefficient on $MYOPIA_{it}$ of –18.554) compared to the software sample (an insignificant coefficient on $MYOPIA_{it}$ of –2.425). Columns 3 and 4 present the results with the combined sample. The variable $SOFTWARE_{it}$ is a dummy variable set to be one if a firm is a software development firm, and zero otherwise. The positive and significant coefficient of 8.485 on the interaction term $MYOPIA_{it}{\times}SOFTWARE_{it}$ in the last column suggests that the tendency to under-invest is mitigated for software development firms in the presence of myopic incentives. Results from Table 4 show that even though these software development firms also under-invest on average, they under-invest rather less compared to the other hi-tech firms. This is consistent with our expectations that myopic behaviour is more pronounced in the other hi-tech industry, where the capitalization of self-generated intangibles is proscribed in contrast to the case of software development firms. Thus, our first hypothesis is supported.

Table 5 presents results comparing the effect of financial flexibility on investment in the same two samples. The idea is to investigate if financial flexibility exacerbates any tendency to over-invest where capitalization is required (software development) versus not (other hi-tech). The coefficients on $FINFLEX_{it}$ are not individually significant in either set of regression results except for a marginally significant coefficient on $FINFLEX_{it}$ for the other high-tech sample. When looking at results from the combined sample as presented in column 4, we do not find any significant results either. Overall, these results do not offer any evidence that requiring capitalization exacerbates over-investment for the software sample compared to the other high-tech sample. Thus, our second hypothesis is not supported.

Probability of Cutting Software Development Spending

Table 6 presents results for the effect of a change in the degree of capitalization on the probability of cutting investment in software development (SW_CUT_{it}). A negative coefficient on the variable $CHANGESWCAP_{it}$ indicates that an increase in the degree of capitalization is associated with a lower probability of a cut in investment. Indeed, we observe a negative and highly significant coefficient (–0.049, *p*-value <0.05) on $CHANGESWCAP_{it}$ when estimating the regression on the full sample (column 1). When we partition the sample into three groups of small decrease in earnings, large decrease in earnings, and increase in earnings (i.e., SD, LD, and IN as described previously under testing Hypothesis 3), the magnitude of the coefficient on $CHANGESWCAP_{it}$ is the largest in the LD sample (–0.460, *p-value* < 0.01). This is the sample in which cutting all investment would not negate the decline in earnings. For the SD sample, the coefficient on

Table 5

ASSOCIATION BETWEEN CHANGE IN INVESTMENT AND FINANCIAL FLEXIBILITY IN SOFTWARE DEVELOPMENT AND IN OTHER HI-TECH INDUSTRIES

Dependent variable: $DINV_{it}$	Software	Other hi-tech	Software and other hi-tech	Software and other hi-tech interaction
Intercept	−312.084***	−407.564***	−372.380***	−372.849***
	(−4.038)	(−3.412)	(−4.214)	(−4.215)
$FINFLEX_{it}$	6.478	−7.164*	−3.572	−6.193
	(0.811)	(−1.842)	(−1.000)	(−1.643)
$SOFTWARE_{it}$				1.23
				(0.22)
$FINFLEX_{it} \times SOFTWARE_{it}$				8.88
				(1.12)
$NETCASH_{it-1}$	0.010	0.007**	0.007***	0.007***
	(1.482)	(2.577)	(3.074)	(3.073)
$PROF'_{it-1}$	−0.010	0.011**	0.010**	0.010**
	(−0.555)	(2.189)	(2.162)	(2.166)
$SIZE_{it}$	7.546***	4.241***	4.750***	4.714***
	(4.017)	(3.011)	(4.310)	(4.292)
LEV'_{it}	0.088	−0.045	−0.039	−0.039
	(0.729)	(−1.473)	(−1.364)	(−1.360)
$TOBINSQ_{it}$	0.574*	0.583**	0.577***	0.596***
	(1.698)	(2.257)	(2.784)	(2.715)
$CAPEX_{it}$	0.056	0.013	0.016**	0.016**
	(1.497)	(1.636)	(2.032)	(2.028)
AGE_{it}	−0.714***	−0.405**	−0.471***	−0.474***
	(−3.326)	(−2.173)	(−3.020)	(−3.026)
$OPCYCLE_{it}$	1.634	1.791*	1.884**	1.918**
	(0.721)	(1.705)	(2.002)	(2.040)
$LOSS_{it}$	−1.436	9.249	5.885	5.814
	(−0.711)	(1.418)	(1.341)	(1.324)
GNP_t	0.019***	0.027***	0.024***	0.024***
	(3.916)	(3.332)	(4.069)	(4.070)
$YTREND_t$	−1.931	−4.628***	−3.787***	−3.766***
	(−1.511)	(−4.041)	(−4.251)	(−4.263)
Industry fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	No	No	No	No
Firm clustered SE	Yes	Yes	Yes	Yes
Observations	1,575	4,031	5,606	5,606
Adj. R-squared	0.155	0.026	0.034	0.034
Highest VIF	4.92	4.83	4.77	4.95

Note: Robust *t*-statistics are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Variables are defined in the Appendix.

$CHANGESWCAP_{it}$ is smaller in magnitude and less significant (–0.086, *p*-value <0.05). The coefficient on $CHANGESWCAP_{it}$ is not statistically significant for the IN sample (–0.041, *p*-value >0.1). The results presented in Table 6 are consistent with Hypothesis 3 that capitalizing software development expenditure lowers the probability of experiencing cuts in investment. In addition to the average effect, we find that this effect is more pronounced for the LD sample in which cutting all investment would not negate the decline in earnings. However, if cutting software

Table 6

THE ASSOCIATION BETWEEN THE PROBABILITY OF DECLINE IN SOFTWARE DEVELOPMENT SPENDING AND CHANGES IN CAPITALIZATION IN THE SOFTWARE DEVELOPMENT SAMPLE

Dependent variable: Pr(SW_CUT_t)	(1) Full sample	(2) SD sample	(3) LD sample	(4) IN sample
Intercept	21.859***	25.887***	19.134	23.234***
	(4.953)	(3.209)	(1.443)	(3.761)
$CHANGESWCAP_{it}$	−0.049**	−0.086**	−0.460***	−0.041
	(−2.540)	(−2.393)	(−2.972)	(−1.596)
$NETCASH_{it-1}$	−0.000	0.000	0.000	−0.000
	(−0.536)	(1.072)	(0.262)	(−0.513)
$PROF'_{it-1}$	−0.001	−0.001	0.002	−0.001
	(−0.948)	(−0.530)	(1.146)	(−0.677)
$SIZE_{it}$	−0.148***	−0.187*	−0.142	−0.216***
	(−2.820)	(−1.817)	(−1.005)	(−2.694)
LEV'_{it}	−0.003	0.034	−0.056	−0.008
	(−0.146)	(0.992)	(−1.189)	(−0.360)
$TOBINSQ_{it}$	−0.013	−0.383***	0.018	−0.152
	(−0.272)	(−2.950)	(1.593)	(−1.425)
$CAPEX_{it}$	0.000	−0.001	0.005	0.001
	(0.110)	(−0.181)	(0.655)	(0.517)
AGE_{it}	0.057***	0.074***	0.052	0.048***
	(5.370)	(4.112)	(1.603)	(3.739)
$OPCYCLE_{it}$	−0.082	−0.483*	0.264	−0.155
	(−0.728)	(−1.785)	(1.231)	(−0.897)
$LOSS_{it}$	0.425***	0.053	0.421	0.452**
	(2.944)	(0.212)	(1.027)	(1.964)
GNP_t	−0.002***	−0.002***	−0.001	−0.002***
	(−4.973)	(−2.791)	(−1.579)	(−3.696)
$YTREND_t$	0.062	0.050	0.036	0.061
	(1.281)	(0.559)	(0.281)	(0.915)
Industry fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	No	No	No	No
Firm clustered SE	Yes	Yes	Yes	Yes
Observations	1,575	422	220	933
Pseudo Adj. R-squared	0.088	0.137	0.150	0.113

Note: Robust z-statistics are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. SD is small decrease in earnings, LD is large decrease in earnings, IN is increase in earnings. Variables are defined in the Appendix.

development expenditure is enough to cover the small earnings decline for the current year (SD sample), then the choice to capitalize does not have as large or as statistically significant an impact.

EMPIRICAL RESULTS: ADDITIONAL ANALYSES

Multinomial Analysis

We employ a multinomial specification to further test the effect of capitalization on the probability of under- (over-) investment. We first estimate the expectation model (model (2)) which represents the expected level of investment given the growth opportunities and resources available to invest. Panel A of Table 7 presents the regression results from the expectation model. The extreme residuals from this estimation are used to build categorical variables to represent under- and over-investment; the residuals are ranked into quartiles to construct the categorical variable INV_RES_{it}, the dependent variable in the multinomial tests. The quartile containing the most negative residuals is given the value of one ($INV\_RES_{it} = 1$) while the quartile with the most positive residuals is assigned a value of three, and the two middle quartiles are combined into a category with the value of two.

Results from the multinomial logistic models are presented in Panel B of Table 7. When examining under-investment ($INV\_RES_{it} = 1$) versus 'normal' investment, the coefficient on $MYOPIA_{it}$ is positive (0.396) and significant ($p < 0.01$), suggesting that firms with myopic incentives are more likely to be in the bottom quartile (i.e., under-investing). The coefficient on the interaction term $MYOPIA_{it} \times SOFTWARE_{it}$ is negative and significant (–0.341 with p-value < 0.05), suggesting that firms operating in the software industry are less likely to under-invest with the presence of myopic incentives compared to firms operating in the other hi-tech industries.

When examining over-investment ($INV\_RES_{it} = 3$) versus 'normal' investment, the coefficient on the interaction term $FINFLEX_{it} \times SOFTWARE_{it}$ is not significant, suggesting no evidence that the choice to capitalize for the subsample of software development companies leads to over-investment. Overall, the results from the multinomial analysis are consistent with our results in the main analysis.

The Role of Institutional Ownership

Finally, Table 8 presents results with respect to the effect of institutional ownership on the relationship between myopic behaviour and software development spending. The first column presents results from estimating model (3) on the sample of software firms with an added variable $PINSOWN_{it}$ to capture the average effect of institutional ownership. The coefficient on $PINSOWN_{it}$ is insignificant on the full sample of software firms. To further explore the effect of institutional ownership, recall that we partition the sample into quartiles based on the percentage of institutional ownership ($PINSOWN_{it}$) and results are presented in columns 2 and 3 of Table 8. Quartile 4 contains the firms with the highest percentage of institutional ownership. Consistent with our conjecture, the coefficient on $MYOPIA_{it}$ becomes insignificant in the group of firms with the highest percentage of institutional ownership (Quartile 4). That is, this group of firms on average does not cut R&D or under-invest, presumably because the institutions are holding them to account. This is consistent with the disciplining role of institutional ownership in settings characteristic of myopia. However, when looking at the rest of the sample (Quartiles 1 to 3), we continue to find a negative and significant effect of $MYOPIA_{it}$ on investment.

TABLE 7

MULTINOMIAL LOGISTIC REGRESSION FOR THE PROBABILITY OF OVER- / UNDER-INVESTMENT

Panel A: Expectation model

Dependent variable: $DINV_{it}$	(1) Expectation model
Intercept	−370.926*** (−4.249)
$NETCASH_{it-1}$	0.008*** (3.218)
$PROF'_{it-1}$	0.011** (2.553)
$SIZE_{it}$	4.554*** (4.502)
LEV'_{it}	−0.034 (−1.275)
$TOBINSQ_{it}$	0.614*** (2.667)
$CAPEX_{it}$	0.013* (1.869)
AGE_{it}	−0.413*** (−2.850)
$OPCYCLE_{it}$	1.378* (1.718)
$LOSS_{it}$	6.467 (1.483)
GNP_t	0.024*** (4.131)
$YTREND_t$	−3.768*** (−4.283)
Industry fixed effects	No
Year fixed effects	Yes
Firm clustered SE	Yes
Observations	5,606
Adj. R-squared	0.035

Panel B: Multinomial regression

Dependent variable: INV_RES_{it}	Under-investment myopia	Over-investment financial flexibility
Under-investment ($INV\_RES_{it} = 1$) versus normal investment ($INV\_RES_{it} = 2$)		
Intercept	−1.903*** (−4.948)	−1.757*** (−4.897)
$MYOPIA_{it}$	0.396*** (4.722)	
$FINFLEX_{it}$		−0.455*** (−2.951)
$SOFTWARE_{it}$	0.567 (1.002)	0.469 (0.858)
$MYOPIA_{it} \times SOFTWARE_{it}$	−0.341** (−2.077)	
$FINFLEX_{it} \times SOFTWARE_{it}$		0.224 (0.878)

Table 7

CONTINUED

Panel B: Multinomial regression		
Dependent variable: INV_RES_{it}	Under-investment myopia	Over-investment financial flexibility
Over-investment ($INV\_RES_{it} = 3$) versus normal investment ($INV\_RES_{it} = 2$)		
Intercept	−1.633**	−1.683**
	(−2.358)	(−2.417)
$MYOPIA_{it}$	−0.252***	
	(−3.014)	
$FINFLEX_{it}$		−0.348**
		(−2.388)
$SOFTWARE_{it}$	−0.041	−0.151
	(−0.048)	(−0.180)
$MYOPIA_{it} \times SOFTWARE_{it}$	−0.425**	
	(−2.256)	
$FINFLEX_{it} \times SOFTWARE_{it}$		0.060
		(0.208)
Industry fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Firm clustered SE	Yes	Yes
Observations	5,606	5,606
Pseudo R-squared	0.109	0.105

Note: Robust *z*-statistics are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Variables are defined in the Appendix.

SENSITIVITY ANALYSES

Alternative Proxy for Myopic Incentives

In our main analysis, we operationalize myopic incentives as managers facing earnings-based pressures (i.e., decline in earnings from the prior period). In sensitivity analyses, we use an alternative measure for managers' myopic incentives based on their compensation packages. Prior studies show that the structure of compensation for top management influences the alignment of interests between the top management and the shareholders (Jensen and Murphy, 1990; Hall and Liebman, 1998; Merchant and Van der Stede, 2007). Specifically, equity-based compensation in the form of stock options or restricted stock grants better aligns the top management's interests with that of shareholders.

We follow Leone *et al.* (2006) to measure cash compensation as salary plus bonus and measure equity-based compensation as the value of stock option grants plus restricted stock grants. Narayanan (1996) argues that cash-based compensation contracts tend to induce under-investment while equity-based compensation contracts tend to induce over-investment in the long run, suggesting more balanced compensation contracts with both cash and equity-based components are most likely to produce a more efficient level of investment. Thus, we take the percentage of cash compensation to total compensation (cash

Table 8

THE ROLE OF INSTITUTIONAL OWNERSHIP IN MITIGATING MYOPIC INCENTIVES IN THE SOFTWARE DEVELOPMENT INDUSTRY

Dependent variable: $DINV_{it}$	(1) Full sample	(2) Quartiles 1 to 3 *of* $PINSOWN_{it}$	(3) Quartile 4 *of* $PINSOWN_{it}$
Intercept	−252.699**	−261.532**	−397.554
	(−2.095)	(−1.984)	(−1.564)
$MYOPIA_{it}$	−5.227*	−9.557**	1.610
	(−1.715)	(−2.404)	(0.218)
$NETCASH_{it-1}$	−0.006	−0.013	0.038
	(−0.431)	(−0.923)	(1.667)
$PROF'_{it-1}$	0.001	0.002	0.069
	(0.096)	(0.229)	(1.642)
$SIZE_{it}$	7.433*	4.963	16.069***
	(1.882)	(1.582)	(3.213)
LEV'_{it}	−0.291	−0.336	−1.517
	(−0.983)	(−1.005)	(−1.066)
$TOBINSQ_{it}$	0.841	0.397	3.936**
	(1.440)	(0.901)	(2.014)
$CAPEX_{it}$	−0.008	−0.001	−0.149*
	(−0.132)	(−0.012)	(−1.963)
$PINSOWN_{it}$	−12.879		
	(−1.175)		
AGE_{it}	−0.039	−0.083	−0.846*
	(−0.195)	(−0.387)	(−1.806)
$OPCYCLE_{it}$	−6.726**	−4.868*	−8.876*
	(−2.547)	(−1.674)	(−1.715)
$LOSS_{it}$	1.926	1.536	8.405
	(0.734)	(0.672)	(0.650)
GNP_t	0.018**	0.019**	0.022
	(2.195)	(2.117)	(1.393)
$YTREND_t$	−4.120*	−4.281*	−2.760
	(−1.929)	(−1.745)	(−1.368)
Industry fixed effects	Yes	Yes	Yes
Year fixed effects	No	No	No
Firm clustered SE	Yes	Yes	Yes
Observations	596	149	447
Adj. R-squared	0.093	0.195	0.109

Note: Robust *t*-statistics are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Variables are defined in the Appendix.

compensation plus equity-based compensation) as a proxy to capture managers' myopic incentives ($CECOMP_{it}$). The compensation-related data are downloaded from the ExecuComp database through the WRDS platform.

Compensation-related management incentives can have short-term or long-term effects. For instance, the incentives arising from equity option grants may vary depending on the vesting period. Thus, in addition to estimating model (1) in differences form in our main analysis, we add two more years of lagged investment to test Hypothesis 1 on the tendency to under-invest.

The overall results are consistent with our main results. Columns 1 to 4 in Table 9 present results from estimating models (3) and (5) in differences form.

TABLE 9

ALTERNATIVE PROXY FOR MYOPIC INCENTIVES BASED ON COMPENSATION

	Dependent variable: $DINV_{it}$				Dependent variable: INV_{it}		
VARIABLES	(1) Software (model (3))	(2) Other hi-tech (model (3))	(3) Software and other hi-tech (model (3))	(4) Software and other hi-tech interaction (model (5))	(5) Software and other hi-tech interaction with one lag	(6) Software and other hi-tech interaction with two lags	(7) Software and other-hi-tech interaction with three lags
Intercept	−651.351***	−657.818**	−619.166***	−616.708***	−663.448***	−271.659*	−230.580
	(−3.349)	(−2.190)	(−2.942)	(−2.935)	(−3.295)	(−1.784)	(−1.517)
INV_{it-1}					0.818***	0.640***	0.631***
					(14.838)	(28.785)	(27.631)
INV_{it-2}						0.207***	0.197***
						(9.042)	(7.102)
INV_{it-3}							0.026
							(1.063)
$CECOMP_{it}$	3.177	−40.426**	−23.035*	−30.769*	−46.659**	−47.360***	−49.532***
	(0.265)	(−2.287)	(−1.892)	(−1.734)	(−2.549)	(−2.916)	(−3.042)
$SOFTWARE_{it}$				1.068	8.311	7.174	2.272
				(0.065)	(0.245)	(0.169)	(0.054)
$CECOMP_{it} \times SOFTWARE_{it}$				18.526	36.973	38.441	45.977*
				(0.933)	(1.565)	(1.615)	(1.921)
$NETCASH_{it-1}$	0.007	0.011**	0.009**	0.008**	0.009**	0.009***	0.008***
	(1.192)	(2.047)	(2.300)	(2.282)	(2.064)	(3.590)	(3.360)
$PROF'_{it-1}$	−0.017	0.014	0.007	0.007	0.045*	0.037***	0.036***
	(−0.879)	(1.260)	(0.823)	(0.825)	(1.845)	(6.198)	(6.041)
$SIZE_{it}$	18.901***	6.678*	9.027***	8.911***	30.101***	30.118***	29.553***
	(2.977)	(1.907)	(3.240)	(3.171)	(3.967)	(9.857)	(9.632)
LEV'_{it}	0.082	−0.004	0.005	0.004	−0.031	−0.031	−0.033
	(0.500)	(−0.110)	(0.149)	(0.113)	(−0.548)	(−0.196)	(−0.210)
$TOBINSQ_{it}$	10.266*	3.663	6.449**	6.294**	7.647**	9.375***	9.845***
	(1.924)	(1.315)	(2.333)	(2.271)	(2.386)	(4.133)	(4.199)
$CAPEX_{it}$	0.048	−0.001	0.012	0.012	0.019	0.025**	0.021**
	(1.336)	(−0.044)	(0.644)	(0.637)	(0.864)	(2.537)	(2.181)

Table 9

CONTINUED

VARIABLES	Dependent variable: $DINV_{it}$				Dependent variable: INV_{it}		
	(1) Software (model (3))	(2) Other hi-tech (model (3))	(3) Software and other hi-tech (model (3))	(4) Software and other hi-tech interaction (model (5))	(5) Software and other hi-tech interaction with one lag	(6) Software and other hi-tech interaction with two lags	(7) Software and other-hi-tech interaction with three lags
AGE_{it}	−1.332***	−0.788*	−0.883***	−0.891***	−0.277	−0.640**	−0.656**
	(−3.084)	(−1.961)	(−2.901)	(−2.924)	(−0.719)	(−2.441)	(−2.461)
$OPCYCLE_{it}$	4.237	6.414	5.181	5.191	3.549	4.112	3.178
	(0.625)	(1.119)	(1.202)	(1.203)	(0.647)	(0.854)	(0.659)
$LOSS_{it}$	1.258	27.388	18.630	18.681*	36.562**	38.493***	38.023***
	(0.238)	(1.599)	(1.647)	(1.651)	(2.189)	(5.149)	(5.073)
GNP_t	0.036***	0.043**	0.039***	0.039***	0.032***	0.004	0.002
	(3.295)	(2.172)	(2.812)	(2.821)	(2.619)	(0.457)	(0.239)
$YTREND_t$	−3.713	−8.352***	−6.223***	−6.207***	−6.414***		
	(−1.258)	(−3.064)	(−3.207)	(−3.216)	(−3.481)		
Observations	652	1,320	1,972	1,972	1,972	1,941	1,905
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Highest VIF	4.93	4.31	4.35	4.35	4.36	6.34	6.34
Adj. R-squared	0.198	0.037	0.053	0.053	0.960	0.961	0.962

Note: Robust *t*-statistics are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Variables are defined in the Appendix.

Similar to results in our main analyses, the coefficients on the variable $CECOMP_{it}$, which replaces $MYOPIA_{it}$ in the main analyses, are negative and significant for columns 2 to 4, suggesting that a higher percentage of cash-based compensation on average leads to under-investment. The coefficient on $CECOMP_{it}$ in column 1 (software development sample only) is not significant, providing no evidence of under-investment for the subsample of software development firms. The coefficient on the interaction term between $CECOMP_{it}$ and $SOFTWARE_{it}$ in column 4 is also not significant.

Given the long-term orientation of compensation contracts, especially the equity-based component, we present additional results in columns 5 to 7, including one to three years of lagged investment to see how that might affect our results. Interestingly, we find the coefficient on the interaction term between $CECOMP_{it}$ and $SOFTWARE_{it}$ becomes more significant when we increase the number of lagged investment from one to three years. The coefficient on the interaction term is positive and significant in column 7 when we include three years of lagged investment, suggesting that under-investment is mitigated for firms in the software development industry when they have a higher percentage of cash-based compensation.

Alternative Proxies for Financial Flexibility

We try two alternative proxies to capture financial flexibility. The first proxy is consistent with the financial slack measure developed by Biddle *et al.* (2009) to capture firms' ex-ante likelihood of under- or over-investment. Specifically, we take decile ranking (with one being the lowest and 10 being the highest) of a firm's cash balance (using either net cash or operating cash flows) and the negative of the leverage ratio and then take the average of the two ranks as a proxy for financial flexibility. The second proxy is constructed to measure a firm's industry-adjusted incremental borrowing power. Specifically, we first calculate a firm's incremental borrowing capacity if given the industry leverage ratio (either industry mean or median). Then, we use the sum of the incremental borrowing capacity calculated above and the operating cash flows as a measure of financial flexibility. Overall, our results remain the same.

Pre- versus Post-Adoption of SFAS 86

We use the adoption of SFAS 86 as a regulatory shock to conduct a test around this period. Specifically, our sample for this test includes firms in the software development and other hi-tech industries from 1983 to 1988. Following Mohd (2005), the pre-SFAS 86 period is defined as from 1983 to 1985 and the post-SFAS 86 period is defined as from 1986 to 1988. We then estimate our baseline model (2) by including a dummy variable for software firms, a dummy variable for the post-SFAS 86 period, and an interaction term between these two dummy variables. Unfortunately, we are not able to obtain data on the actual capitalized amount for the sample of software firms, so we have taken the R&D expense values from Compustat as a crude proxy for total R&D expenditures. For the sample of software firms, this proxy is most likely to be understated because it does not include any capitalized software development expenditures. We find that the sample of software firms has a significantly higher amount of R&D expense in the post-SFAS 86 period compared to the sample of other hi-tech firms. We interpret the results as supporting our conjectures. Despite the fact that the proxy used in this test for R&D expenditures is potentially understated (which potentially biases against finding results on improved level of investment for software firms), we still find that the sample of software firms invest more in R&D compared to the sample of other hi-tech firms.

CONCLUSION

Overall, we find strong support for the hypothesis that the capitalization of costs associated with successful software development under US accounting rules does mitigate the likelihood of under-investment in the face of myopic incentives. Further, firms that capitalize such costs do not appear to over-invest in the presence of financial flexibility, relative to those firms that cannot capitalize. Our results are consistent with the notion that capitalizing development expenditures mitigates the problem of under-investment for the US software sample where capitalization is adopted almost ubiquitously (almost all firms capitalize some portion of software development costs).

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APPENDIX: VARIABLE DEFINITIONS

Variable	Definition
Main dependent and independent variables	
INV	= placeholder for investment in *SW* or *RD*
DINV	= $INV_t - INV_{t-1}$
INV_RES	= categorical variable that equals one if residuals are at the bottom quartile, two if residuals are in the middle two quartiles, and three if residuals are in the top quartile of the investment expectation model
MYOPIA	= dummy variable that equals one if $E_{it-1} > E_{it} + (SW_{it} - SW_{it-1})$, and zero otherwise (with E as earnings before extraordinary items)
FINFLEX	= dummy variable that equals one if LEV'_{it} is in the lowest quantile of the sample, and zero otherwise
SW	= total amount of software development costs in the current period (capitalized amount plus expensed amount)
SWCAP	= amount of software development costs capitalized in the current period
SWEXP	= amount of software development costs expensed in the current period
SWCAPRATIO	= the proportion of software development costs capitalized in the current period
SW_CUT	= dummy variable that equals one if $(SW_t - SW_{t-1}) < 0$, and zero otherwise
CHANGESWCAP	= change in the amount of software development costs capitalized in the current period relative to the previous period, calculated as $(SWCAP_t - SWCAP_{t-1})$
RD	= amount of research and development costs in the current period
Control variables	
SOFTWARE	= dummy variable that equals one if a firm is a software development firm, and zero otherwise
NETCASH	= cash and short-term investments minus current liabilities
PROF'	= income before extraordinary items adjusted for capitalization of software development or R&D, respectively
SIZE	= the natural logarithm of one plus total revenues
LEV'	= industry-adjusted leverage (total assets divided by total equity, both adjusted for capitalization of software development or R&D, respectively less industry median)
TOBINSQ	= (total assets + number of shares outstanding stock price – total equity) / total assets
CAPEX	= capital expenditures
AGE	= the difference between the first year in which the firm appears in CRSP and the current year

OPCYCLE = the log of receivables to sales plus inventory to COGS multiplied by 360
LOSS = an indicator variable that takes the value of one if income before extraordinary items is negative, and zero otherwise
GNP = gross national product
YTREND = year trend
PINSOWN = percentage of institutional ownership