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Decoupling management inefficiency: Myopia, hyperopia and takeover likelihood

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ABSTRACT

Using combinations of accounting and stock market performance measures, we advance a comprehensive multidimensional framework for modelling management performance. This framework proposes "*poor*" management, "*myopia*", "*hyperopia*" and "*efficient*" management, as four distinct attributes of performance. We show that these new attributes align with, and extend, existing frameworks for modelling management short-termism. We apply this framework to test the management inefficiency hypothesis using UK data over the period 1988 to 2017. We find that takeover likelihood increases with "*poor*" management and "*myopia*", but declines with "*hyperopia*" and "*efficient*" management. Our results suggest that managers who focus on sustaining long-term shareholders' value, even at the expense of current profitability, are less likely to be disciplined through takeovers. By contrast, managers who pursue profitability at the expense of long-term shareholder value creation are more likely to face takeovers. Finally, we document the role of bidders as enforcers of market discipline.

1. Introduction

Management performance is perhaps one of the most explored latent variables in empirical accounting, corporate finance and business management research. Prior studies (see, for example, Wiersma, 2017; Bennouri, Chtious, Nagati, & Nekhili, 2018; Paniagua, Rivelles, & Sapena, 2018) use measures of accounting profitability, including return on assets (ROA), return on equity (ROE) and return on capital employed (ROCE), as empirical proxies of management or firm performance, while others (see, for example, Li, Qiu, & Shen, 2018; Bennouri et al., 2018; Owen & Temesvary, 2018) use market-based measures such as average abnormal returns (AAR), stock price growth and Tobin's Q, for the same purpose. The implications of these choices have not been documented, but, as we will show, in some cases the choice can lead to inconclusive or even contradictory findings (Danbolt, Siganos, & Tunyi, 2016; Espahbodi & Espahbodi, 2003). Besides the lack of consensus about how this latent variable should be operationalised, current research tradition implicitly views management performance in a simple unidimensional manner—efficient or poor management (Rappaport, 2005). Here, firms that report *high* ROA, ROCE or AAR are considered *efficient*, while their counterparts reporting *low* values are considered *poor*. All other firms are calibrated along this two-dimensional scale, which provides an indication of relative performance. In this paper, we depart from this tradition by proposing a comprehensive multidimensional framework for modelling management performance that consists of four distinct attributes of performance: (i) *poor* management; (ii) short-termism, or *myopia*; (iii) long-termism, or *hyperopia*; and (iv) *efficient* management, instead of the unidimensional scale (*poor—efficient*) implicit in prior studies. Our framework extends the traditional framework but relies on the same proxies of financial (e.g., ROA, ROCE) and market-based (AAR) measures of performance that have been recurrently used in the literature. It recognises that these measures proxy for distinct performance attributes and, hence, are complements, not substitutes.

To demonstrate the applicability of our framework, we draw on a related issue that has been extensively explored with inconclusive findings—the role of the market for corporate control (MCC) as a disciplinary mechanism. The inefficient management hypothesis of takeovers (Brar, Giamouridis, & Liodakis, 2009; Cremers, Nair, & John, 2009; Danbolt et al., 2016) suggests that takeovers play a key role in the correction of management inefficiency by targeting underperforming or *poor* management. In essence, the hypothesis suggests that takeover likelihood should decline with management performance, with *poor* management most likely, and *efficient* management least likely, to

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receive takeover bids. Having evidenced the need for a more comprehensive multidimensional framework, we extend the literature on the inefficient management hypothesis by exploring the relation between our new attributes, *myopia* and *hyperopia*, and takeover likelihood. For this, we draw from the earnings management literature and contribute to the debate on the consequences of earnings management by (1) linking earnings management and management inefficiency, and (2) identifying a market mechanism (MCC) that partly corrects these inefficiencies.

Prior research has extensively documented managements' fixation on achieving short-term earnings targets, even at the cost of long-term shareholder value creation (Graham, Harvey, & Rajgopal, 2006; Healy & Wahlen, 1999). Healy and Wahlen (1999), for example, find that, besides applying judgement in financial reporting, managers reduce long-term investments by freezing hiring, closing underperforming units and delaying critical maintenance projects, amongst others, in order to meet short-term earnings targets set by them or their analysts. In a survey of 401 senior financial executives of US companies, Graham et al. (2006) also find that 80% of respondents would decrease "discretionary" spending, such as R&D, advertising and maintenance, to meet their earnings target. The pervasive nature of such managerial short-termism is, perhaps, driven by pay-for-performance reward systems (Duru, Iyengar, & Zampelli, 2012; Lambert & Larcker, 1987). A few studies have examined whether the takeover market discourages management short-termism in spite of the incentive to adopt a myopic approach (Atanassov, 2013; Faleye, 2007; Meulbroek, Mitchell, Mulherin, Netter, & Poulsen, 1990). For example, Meulbroek et al. (1990) document a decline in R&D investments in US firms that adopt antitakeover amendments, while Faleye (2007) finds that US firms with classified boards are associated with lower R&D spending. Similarly, Atanassov (2013) finds that US firms incorporated in states that pass anti-takeover laws experience a decline in innovation in the post-passage period. While these studies show that a decline in the threat of takeovers (e.g., by adopting classified boards or operating under the protection of anti-takeover amendments) reduces the tendency or incentive for management to be myopic, they do not provide any insights on the consequences of management myopia. Our study fills this gap by exploring whether the MCC potentially disciplines management myopia—which our framework considers to be a form of management inefficiency.

Theoretically, the role of the takeover market in enforcing managerial discipline is possibly weakened by the existence of other, perhaps more efficient, disciplinary mechanisms, including industry competition, corporate monitoring by boards, competition within the managerial labour market, threat of bankruptcies, and capital flight from poorly performing to well-performing firms. This suggests that takeovers are, perhaps, an expensive and imprecise solution to the problem of management inefficiency (Herzel & Shepro, 1990). Consistent with this view, several prior studies find no empirical support for the inefficient management hypothesis (Agrawal & Jaffe, 2003; Franks & Mayer, 1996; Powell, 1997). Notwithstanding, some empirical evidence supports the existence of a thriving MCC, where underperforming firms get acquired and/or underperforming managers get replaced through takeovers (Barnes, 1999; Lang, Stulz, & Walkling, 1989; Powell & Yawson, 2007). We argue that the mixed and inconclusive findings from prior research are largely a consequence of limitations in the current conceptualisation of the management inefficiency construct—i.e., how management performance is measured.

Prior empirical studies indiscriminately use accounting and market measures of performance (e.g., ROA, ROCE, ROE, Tobin's Q and AAR) to proxy for management performance (Agrawal & Jaffe, 2003; Danbolt et al., 2016; Powell & Yawson, 2007). These studies consider performance as a unidimensional variable along a linear scale with two extremes—efficient performance and poor performance—and implicitly assume that each manager's performance can be calibrated along this unidimensional scale. We decouple the arguably complex construct of management inefficiency within the context of the MCC by proposing that "*poor*" management, "*myopia*" and "*hyperopia*" are distinct attributes of inefficient management. In this sense, as opposed to simply describing management as "good" or "poor", we propose that managers can be categorised as "*efficient*", "*myopic*", "*hyperopic*" or "*poor*". Our rationale for this new multidimensional framework is summarised below and fully discussed in Section 2.

It is widely accepted that accounting measures, such as ROA, ROCE and ROE, amongst others, best measure *past* performance, whilst stock market variables, such as abnormal returns, measure *future* prospects (Lambert & Larcker, 1987; Rappaport, 1986). Using simple combinations of accounting and stock market measures, we are able to identify four distinct categories of management performance: (i) *efficient* (high accounting and high stock market performance); (ii) *myopia* (high accounting but low stock performance); (iii) *hyperopia* (low accounting but high stock market performance); and (iv) *poor* (low accounting and low stock market performance). We validate this framework by showing that firms classified as *myopic* are more likely to reduce R&D in the next period when compared to their *hyperopic* counterparts. We also show that *myopic* firms are associated with positive discretionary accruals (evidence of accrual earnings management), while their *hyperopic* counterparts are associated with negative discretionary accruals. We use our multidimensional framework to shed new light on the inefficient management hypothesis of takeovers.

In summary, we make two main contributions to the extant literature. First, we develop and validate a simple yet comprehensive multidimensional framework for modelling management performance. This method integrates management horizon (short-termism versus long-termism) with performance and uses readily available firm-level information to construct proxies. Prior studies primarily use a decline in R&D expenditure as a measure of management myopia (e.g., Faleye, 2007; Holden & Lundstrum, 2009; Meulbroek et al., 1990; Wahal & McConnell, 2000), but, as documented by Boubaker, Chourou, Saadi, and Zhong (2017), a significant proportion of firms do not report any investment in R&D. Indeed, we find that UK firms report R&D spending in only 30% of firm-years between 1988 and 2017. Further, firms which outsource R&D or acquire innovation will be misclassified as *myopic* firms due to low investment in in-house R&D projects. A few studies have used firms' ability to meet analysts' earnings forecasts, a decline in capital expenditure, and discretionary accruals due to earnings management as evidence of firm *myopic* behaviour (Boubaker et al., 2017; Wahal & McConnell, 2000). The problems with such measures are evident. For example, earnings forecasts rely on analysts following, which is biased towards large firms, and capital expenditure will naturally vary with firm lifecycle and industry. Our measures yield consistent results with some of these other measures. For example, firms we classify as *myopic* in one period report significantly lower levels of R&D investment in the next period, when compared to their *hyperopic* counterparts. Additionally, our *myopic* firms, unlike their *hyperopic* counterparts, are more likely to engage in accrual-based earnings management. Importantly, being less data-intensive than alternative measures, our simple framework can more easily be applied to a wider set of firms.

Second, we contribute to the merger and acquisition (M&A) literature by explaining the inconsistent findings in prior studies on the disciplinary role of takeovers—the management inefficiency hypothesis. This hypothesis has been explored in several prior studies, with inconclusive findings. For instance, Palepu (1986) and Danbolt et al. (2016) find that takeover likelihood decreases with a firm's stock market returns, but increases with a firm's accounting return. Brar et al. (2009) show that takeover likelihood increases with accounting return. Espahbodi and Espahbodi (2003) find that takeover likelihood has a negative but insignificant relation with abnormal returns, and a positive but insignificant relation with ROE. Together, these studies suggest that, consistent with the hypothesis, takeover likelihood declines with stock market performance, but, inconsistent with the hypothesis, takeover likelihood also increases with accounting performance. We further discuss these inconsistencies in more detail in Section 2.1. Our framework, which proposes performance as a multidimensional construct, enables us to shed light on this conundrum. By using our framework, we show that takeover likelihood increases with *poor* management and management *myopia*, but generally declines with management *hyperopia*. We find that *efficient* managers are least prone to face takeover bids for their firms. The results suggest that managers who perform poorly both in the accounting and market sense, as well as managers who focus on generating short-term profits for investors at the expense of long-term shareholder value, are more likely to be disciplined through takeovers. By contrast, managers who focus on creating long-term value, even at the expense of current profitability, are less likely to be disciplined through takeovers. This provides new evidence on the management inefficiency hypothesis and explains the apparent inconsistencies in prior research. It also provides new insights on the consequences of earnings management by highlighting the role of the MCC in discouraging management *myopia*.

The rest of the paper is structured as follows. We develop our multidimensional framework and discuss our hypotheses in Section 2. We discuss our empirical methods, data and sample in Section 3, and discuss our empirical results in Section 4. Our concluding remarks are presented in Section 5.

2. Review of literature and hypotheses development

2.1. Theory and evidence on the disciplinary role of takeovers

The MCC theory suggests that, in an active takeover market, various management teams compete for the rights to manage a firm's resources in a manner that maximises shareholder value (Jensen & Ruback, 1983; Manne, 1965). Consistent with this theory, the inefficient management hypothesis of takeovers suggests that managers who deviate from the best interest of their shareholders are replaced by more efficient management teams (Jensen & Ruback, 1983; Manne, 1965; Palepu, 1986). Empirical evidence on the inefficient management hypothesis and the existence of the MCC is generally mixed and inconclusive. Prior studies either find no support for or evidence against the inefficient management hypothesis (Agrawal & Jaffe, 2003; Berger & Ofek, 1996; Franks & Mayer, 1996).[1] Notwithstanding, some contradictory empirical evidence supports the existence of a thriving MCC (Asquith, 1983; Lang et al., 1989).

More recently, the management inefficiency hypothesis has been directly tested in the takeover prediction literature. The evidence from this literature is also inconclusive. In support of the management inefficiency hypothesis, some studies find that targets have lower accounting performance (Barnes, 1999; Cremers et al., 2009) and lower stock market performance (Danbolt et al., 2016; Powell & Yawson, 2007) when compared to non-targets. Others find no significant difference between targets and non-targets in terms of accounting profitability and stock market performance (e.g., Ambrose & Megginson, 1992; Espahbodi & Espahbodi, 2003). Yet, some studies report mixed results from the same sample (Brar et al., 2009; Danbolt et al., 2016; Palepu, 1986).[2] In a nutshell, therefore, there is as yet no consensus on this age-old conundrum: are takeovers initiated to discipline inefficient management? We examine this question by proposing a recalibration of the scales for measuring management performance in this context.

2.2. Measuring and calibrating management performance

Management or firm performance is perhaps one of the most studied concepts in business research, with several studies investigating antecedents or determinants of performance. Yet, there is no consensus on how performance should be measured (Miller, Washburn, & Glick, 2013). The extant accounting, finance and business literature uses accounting measures, such ROA, ROCE and ROE, as well as market measures, such as AAR, to proxy for performance. Some studies use hybrid measures, such as Tobin's Q, price to earnings ratio (PE) and market to book values (MTB), to proxy for performance, although such measures have been argued to proxy for market misvaluation rather than performance (Dybvig & Warachka, 2015). While it is generally accepted that these pure accounting and market measures reasonably capture the underlying concept of management performance, their use sometimes leads to researcher dilemma when empirical results are not consistent across market and accounting measures (Brar et al., 2009; Espahbodi & Espahbodi, 2003; Palepu, 1986).

A review of the literature shows that most researchers, at least in their discussions, calibrate management performance along a two-dimensional scale, with "good" and "poor" performance as extremes. This is particularly prevalent in the M&A literature. Specifically, prior studies testing the management inefficiency hypothesis (e.g., Agrawal & Jaffe, 2003; Barnes, 1999; Cremers et al., 2009; Danbolt et al., 2016; Palepu, 1986; Powell, 2001; Powell & Yawson, 2007), implicitly assume that management performance can be classified along a scale of *efficient* (outperform) or *poor* (underperform) relative to some benchmark (e.g., a sample of matched firms, the industry or the entire market). Further, these studies indiscriminately use different accounting and stock market variables, such as ROA, ROE, ROCE, AAR and Tobin's Q, amongst others, as proxies of management quality or firm performance. This narrow definition of management performance means that some studies report conflicting results when two measures of performance have opposite effects on takeover likelihood. For example, Palepu (1986) finds that takeover likelihood has a positive but insignificant relation with return on equity (ROE), but a negative and significant relation with average excess stock market returns. Espahbodi and Espahbodi (2003) also find that takeover likelihood has a negative but insignificant relation with abnormal returns, and a positive but insignificant relation with ROE. Danbolt et al. (2016) find that takeover likelihood is positively related to ROA (insignificant), but declines with average excess return.

Whilst it is generally hypothesised that poor management performance can lead to takeovers, there is no consensus on what constitutes "poor management performance". The mixed findings in the existing literature appear to be a result of the use of different performance proxies (both accounting and market-based) across different studies. In general, firms are described as being poorly managed when their accounting and/or stock market performance is lower than a benchmark,

[1] Additionally, these studies find that targets earn negative but insignificant abnormal returns, zero returns and positive abnormal returns in the period prior to acquisitions (Jensen & Ruback, 1983). Berger and Ofek (1996) also find that a firm's return on equity ratio does not affect its probability of being acquired. From an extensive literature review and an empirical study looking at both target accounting and stock market performance, Agrawal and Jaffe (2003) conclude that there is little evidence to support the assertion that underperforming firms are more likely to become takeover targets.

[2] In Table 1 (p.74), Danbolt et al. (2016) show that UK targets have significantly higher mean ROCE (11.8%) compared to non-targets (6.8%). The difference is significant at the 1% level. Table 2 (p.75) in Danbolt et al. (2016) shows that takeover likelihood is negatively related to average excess return (AER) (coefficient of −3.552, *p-value* of 0.000) but positively related to ROCE (coefficient of 0.087, *p-value* of 0.171). While the AER results are consistent, the ROCE results are inconsistent with the management inefficiency hypothesis. Table 3 (p.436) of Brar et al. (2009) presents descriptive statistics for their European sample. They find that targets have higher profitability (ROE and operating margin) when compared to non-targets. Their targets have an operating margin of 8.1% compared to −12.7% for non-targets (the difference is significant at the 5% level). Again, the results on the relation between accounting profitability (ROE and operating profit margin) are inconsistent with the hypothesis.

and well managed otherwise.

While market-based performance measures (i.e., measures based on stock prices) are thought to estimate the present value of all future cash flows that will accrue to a particular stock as a result of the manager's actions (Lambert & Larcker, 1987), accounting measures have been criticised for their inability to reflect the future consequences of current managerial actions (Rappaport, 1986). The two measures of management performance can, perhaps, be considered as complements rather than substitutes, as accounting measures mainly gauge management's historical performance, whilst market measures assess management's future prospects. Indeed, Lambert and Larcker (1987) argue that accounting regulations may limit the ability of accounting performance to reflect future cash flows that a firm may generate as a result of current management actions; hence, there are benefits in combining accounting and market measures when evaluating management performance. In our dataset, we find that, in the case of UK firms between 1988 and 2017, the correlation coefficient (rho) between accounting (ROCE) and market measures (AAR) of firm performance is −0.05, suggesting that these two measures are complements, not substitutes, in modelling management performance.

Much of the evidence in the M&A literature points to the possibility that bidders show a preference for targets with potential for profitability. There is overwhelming evidence that, on average, targets are profitable firms—as shown by their accounting performance (Brar et al., 2009; Danbolt et al., 2016; De & Jindra, 2012; Palepu, 1986). The evidence also suggests that, despite current profitability, targets have a lower prospect for future growth or a limited ability to generate future cash flows (Danbolt et al., 2016). This is corroborated by findings that targets face declining sales growth and declining stock returns prior to receiving a bid (Brar et al., 2009; Danbolt et al., 2016; Palepu, 1986; Powell & Yawson, 2007). In this sense, current empirical tests of the management inefficiency hypothesis are, perhaps, too general to provide meaningful insights.

As shown in Fig. 1, management can achieve one of four different combinations of accounting and stock market performance. Managers who are able to achieve both high accounting and stock market performance are clearly efficient (*efficient*). Their counterparts who achieve low accounting as well as low stock market performance are also clearly inefficient (*poor*). We argue that a combination of high accounting and low stock market performance is indicative of management short-termism (*myopia*), as these managers achieve high current earnings (accounting performance) from past activities at the expense of long-term shareholder value (stock market returns). Conversely, we argue that a combination of low accounting and high stock market performance is indicative of management long-termism (*hyperopia*).

		Accounting Performance (A) [ROA, ROCE, ROE, NPM]	
		HIGH H_A	LOW L_A
Stock Market Performance (M) [Abnormal Returns]	HIGH H_M	efficient $H_A + H_M$	hyperopia $L_A + H_M$
	LOW L_M	myopia $H_A + L_M$	poor $L_A + L_M$

Fig. 1. Calibrating management performance.
The figure demonstrates the classification of firms into four performance categories based on combinations of their accounting and stock market performance. Accounting performance is proxied by the return on capital employed (ROCE), although other measures, including return on assets (ROA), return on equity (ROE) and net profit margin (NPM), yield a similar result. Stock market performance is proxied by the average daily abnormal return computed using the market model. A firm's performance in a particular year is classified as HIGH if it is greater than the industry median; otherwise, it is classified as LOW. H_A and H_M denote HIGH accounting and HIGH market performance, respectively, while L_A and L_M denote LOW accounting and LOW market performance, respectively.

Therefore, with regards to our framework, we conceptualise our categories as follows: (1) *Poor* management are managers who achieve relatively low accounting and low stock market returns. That is, they report low earnings from past activities and also have poor future prospects or opportunities for generating positive net cash flows. (2) *Myopic* management are managers who achieve relatively high accounting but low stock market returns. Such managers report high earnings from past activities, usually at the expense of future prospects. (3) *Hyperopic* management are managers who achieve relatively low accounting but high stock market returns. While these managers achieve low earnings from past activities, they have good future prospects. (4) *Efficient* management are managers who achieve relatively high accounting and high stock market returns. These managers achieve high earnings from past activities and also exhibit good future prospects. The difference between *poor* and *myopic* management lies with their past earnings or accounting performance, i.e., poor management have low accounting performance, while myopic management have high accounting performance. Similarly, the difference between hyperopic and efficient management lies with their accounting performance. Poor management and efficient management have no similarities in terms of performance (accounting or stock market). Similarly, in terms of performance, myopic management are starkly different from hyperopic management.

Prior studies, such as Palepu (1986), Barnes (1999), Powell (2001), Agrawal and Jaffe (2003), Powell and Yawson (2007), Cremers et al. (2009) and Danbolt et al. (2016), implicitly assume the existence of the first and fourth attributes (i.e., *efficient* and *poor*), but ignore the second and third attributes (i.e., *myopia* and *hyperopia*). Clearly, we need to validate the existence of the second and third attributes, which we do by exploring the earnings management behaviour of firms in these categories.

2.3. Management inefficiency and takeover likelihood: Hypotheses

In this section, we develop two testable hypotheses that will allow us to use our new framework to shed new light on the management inefficiency hypothesis. Consistent with the objective of the firm (Jensen & Meckling, 1976; Manne, 1965), efficient managers are those who are able to maximise shareholder wealth both in the short and long run (i.e., the firm's present value). They can create short- and long-term value by maximising current profitability using strategies that do not jeopardise future earnings. Additionally, they are less likely to be swayed by the pressures of meeting earnings targets typically put forward by myopic corporate stakeholders, such as daily traders and short-term investors. Consequently, firms run by efficient managers are not only more likely to have higher historical accounting performance, but also higher stock market performance (*efficient*), to reflect the firms' future prospects. Consequently, their strong performance bestows such managers with the financial backing, reputational clout and stakeholder (board and shareholders') support required to fend off unwanted takeovers. By contrast, their counterparts who achieve low accounting performance and low stock market performance (*poor*) are unlikely to have the support required to retain their independence. Consistent with the undervaluation hypothesis of takeovers (Palepu, 1986), these firms will constitute an under-priced asset to any bidder with the strategy and managerial capacity to reverse the firms' fortunes. We therefore hypothesise that managers who perform below (above) average over the two attributes—accounting and market performance—are more (less) likely to be exposed to takeovers (hypothesis 1). Our first hypothesis is formally stated below:

H1. Takeover likelihood declines (increases) with efficient (poor) management.

Our second hypothesis focuses on our two new attributes. Prior research suggests that portfolio managers focus on short-term earnings and portfolio tracking error rather than traditional discounted cash flow analysis, whilst financial analysts fixate on current earnings rather than fundamental analysis in investment decision-making (Rappaport, 2005). It is, therefore, not surprising that managers, in their bid to satisfy the investment community, prioritise short-term earnings over the creation of long-term value for their shareholders (Graham et al., 2006; Rappaport, 2005). This focus on earnings could see managers decrease discretionary expenditure or investment in projects that yield long-term value (such as recruitment, training and development, marketing and advertisement, R&D and product development, and the maintenance of assets and replacement of major equipment) in order to achieve short-term earnings targets set by them or their analysts (Graham et al., 2006). For managers to maximise long-term value, their primary commitment must be to continuing or long-term shareholders and not to day traders, momentum investors and other short-term oriented investors (Rappaport, 2005). Short-termism, or myopia, can, therefore, be described as a distinct attribute of management inefficiency, where managers achieve short-term performance at the expense of long-term performance.

The flip side to managerial short-termism is a situation where managers focus on creating long-term value for shareholders at the expense of short-term profitability—management long-termism or hyperopia. Whether this is another attribute of inefficiency is subject to debate. The view taken in the mainstream finance literature is that the maximisation of long-term shareholder value is the primary objective of a firm (Jensen & Meckling, 1976). Arguably, a firm with a *hyperopic* management team is likely to have a higher stock market value than it would have with a myopic management team. This high stock market value reflects future prospects, particularly the future cash flows to be enjoyed as a consequence of current managerial actions. The inefficient management hypothesis suggests that inefficiently managed firms are acquired by bidders who believe they can generate higher future cash flows given current firm resources (Danbolt et al., 2016; Palepu, 1986). Consistent with this hypothesis, therefore, it is unlikely that firms with *hyperopic* management teams will be targeted by bidders seeking opportunities to generate higher future cash flows. Further, such firms are likely to command a high price in comparison to current profits, making it difficult for bidders to justify the usual high takeover premiums (Danbolt & Maciver, 2012; Franks & Harris, 1989). We therefore predict that firms with *hyperopic* management teams are less likely to be takeover targets, while firms with myopic management teams are more exposed to takeovers.

H2. Takeover likelihood increases (declines) with management myopia (hyperopia).

3. Empirical methods

3.1. Developing the empirical framework

We start by developing measures for our four attributes of management performance; *poor*, *myopia*, *hyperopia* and *efficient*. As we will discuss, our data is obtained from Thomson DataStream, so we note DataStream variable codes in parentheses. We use accounting and market measures of performance to capture two measures of management performance—historical (accounting) and future (market). Consistent with prior studies (e.g., Brar et al., 2009; Danbolt et al., 2016; Palepu, 1986), the return on capital employed (ROCE) and the average daily abnormal stock return (AAR) over the last year are used to measure management performance. ROCE is computed as the ratio of net operating income before tax and depreciation, or EBITDA, (WC01250) to total capital employed (WC03998). This ratio measures management's success in utilising resources efficiently in the generation of profits through regular business operations in the previous period. The market measure of management performance is the average daily abnormal return (AAR)—a measure of a firm's stock market performance. Daily abnormal returns (DAR) is computed from daily return index (RI) data using the OLS market model (Brown & Warner, 1985) in Eq. (1) below.

$$DAR_{it} = R_{it} - (\widehat{\alpha}_i + \widehat{\beta}_i R_{mt}) \tag{1}$$

DAR for a firm *i* at time *t* is given by the difference between the firm's actual stock return (R_{it}) and expected stock return ($\widehat{\alpha}_i + \widehat{\beta}_i R_{mt}$) at time *t*. The simple return for each firm *i* on day *t* (denoted R_{it}) and the market *m* on day *t* (denoted R_{mt}) are first computed. The daily return of the FTSE All-Share (R_{mt}) is used as a proxy for the daily market returns. Next, $\widehat{\alpha}_i$ and $\widehat{\beta}_i$ are estimated by using data in the previous period, *t-1* (i.e., 260 trading days). Each firm's daily stock returns in the previous period are regressed on its daily market returns, and the coefficients of the regression model are used as estimates of $\widehat{\alpha}_i$ and $\widehat{\beta}_i$ in the current period. The *DAR* over the 260 days are averaged to obtain the average abnormal return (*AAR*) for each year.

Next, we derive industry-year medians of ROCE and AAR. Each firm's ROCE and AAR are classified as "high" if they are greater than or equal to its two-digit SIC code industry median in that year, and "low" if otherwise.[3] These classifications of "high" and "low" are used to calibrate four attributes of management performance, with each firm-year observation attributed to only one of these four categories (see Fig. 1). That is, *efficient* refers to managers who are able to achieve "high" accounting (ROCE) and "high" stock market performance (AAR); *myopia* to those who achieve "high" accounting but "low" stock performance; *hyperopia* to those who achieve "low" accounting but "high" stock market performance; and *poor* to those who achieve "low" accounting and "low" stock market performance.[4]

3.2. Validating the framework

We first seek to establish that our attributes are valid and distinct from each other. Here, we use multiple analysis of variance (MANOVA) to compare the vector of mean firm characteristics of firm-years in our four categories. We also use one-way analysis of variance (ANOVA) to compare firm-years in our four categories across several characteristics. Our objective is to see whether the firms within each of the four categories are similar to each other but different from firms in the other three categories. We consider an extensive set of firm characteristics, including measures of liquidity, leverage, sales growth, free cash flow, age, size and tangibility, amongst others.

Firms classified by our framework as *poor* or *efficient* are clearly underperforming and outperforming (respectively) in comparison to their counterparts. We have suggested *myopia* and *hyperopia* as two new attributes capturing management horizon. The extant UK and US literature argues that a reduction in R&D investment is symptomatic of management short-termism through real earnings management (Healy & Wahlen, 1999; Graham et al., 2006; Osma & Young, 2009; Athanasakou, Strong, C, & Walker, 2011). Hence, our next validation

[3] Our use of two-digit SIC codes is consistent with Botsari and Meeks (2008) and Cohen and Zarowin (2010). We use median values, as our financial variables, particularly ROCE, are skewed. In robustness checks, we use mean values, and our results remain qualitatively similar.

[4] In robustness checks, we explore other measures of accounting performance, including operating profit margin (OPM), return on assets (ROA) and return on equity (ROE). We also compute market performance (abnormal returns) as the simple excess firm monthly stock returns over the market returns. Further, we use the industry median instead of the industry mean as the benchmark in arriving at our four attributes of management performance. In untabulated results, our key findings remain qualitatively the same. We do not report these due to space limitations.

test explores whether the firms classified as *myopic* (and *hyperopic*) in our framework are more likely to reduce (and increase) R&D investments in the next period, respectively. We estimate the following OLS model (Eq. (2)) for R&D investment (RDI), controlling for firm characteristics, as well as industry and year fixed effects:

$$RDI_{it} = \alpha + \beta * Performance_{it-1} + \gamma * Controls_{it-1} + \varepsilon_{it} \tag{2}$$

R&D investment (RDI) is measured as the ratio of R&D expenditure (WC01201) to total assets (WC02999). The independent variable of interest is *performance*, measured using our four dummy variables: *poor*, *myopia*, *hyperopia* and *efficient*. A negative coefficient for *myopia* and positive for *hyperopia* will support our contention that these categories capture firms that are respectively more and less likely to invest in R&D. In all models, we lag all our independent variables by one period to address potential reverse causality issues. Another potential source of endogeneity in our case is self-selection bias, as only 30% of firm-years in our sample appear to engage in R&D between 1988 and 2017. In our model, we use the Heckman Two-Stage method (Heckman, 1979) to correct for selection bias. In the first stage, we estimate the likelihood of reporting R&D (i.e., R&D > 0) conditional upon observed firm characteristics using a probit model. This allows us to compute the Inverse Mills ratio (the non-selection hazard), which we use as an additional control variable in the second stage.[5] The other control variables in the model (stage 1) include variables that have been shown in prior studies to impact firm-level R&D investments, including Tobin's Q, firm size, liquidity, leverage, sales growth, level of tangible assets and firm age. See Appendix 1 for details on variable construction.

While a reduction in R&D is symptomatic of real earnings management behaviour, it does not provide conclusive evidence of real earnings management. Second, our use of RDI as the dependent variable in Eq. (2) can lead to simultaneity bias (endogeneity), which might not be fully addressed by the use of lags. Hence, our second proxy for real earnings management behaviour through the reduction of discretionary expenditures (primarily R&D) comes from the real earnings management literature. We do not explore other real earnings management strategies (specifically, abnormal cash flows from operations and abnormal production costs) due to the limited evidence on their pervasiveness in the UK context (Athanasakou et al., 2011; Athanasakou, Strong, & Walker, 2009). Cohen and Zarowin (2010) argue that firms that manage earnings upwards are likely to have abnormally low levels of discretionary expenses. Hence, we explore whether firm-year observations classified as *myopia* (*hyperopia*) under our framework report significantly negative (positive) abnormal discretionary expenses. We follow Dechow, Kothari, and Watts (1998), Roychowdhury (2006) and Cohen and Zarowin (2010) to estimate the levels of abnormal discretionary expenses for each firm-year observation in our sample.

$$\frac{DISX_{it}}{Assets_{it-1}} = \beta_1 \frac{1}{Assets_{it-1}} + \beta_2 \frac{SALES_{it-1}}{Assets_{it-1}} + \varepsilon_{it} \tag{3}$$

We first estimate total discretionary expenses (DISX) as the sum of R &D expenditures (WC01201) and selling, general and administrative (SG&A) expenditures (WC01101). Consistent with Cohen and Zarowin (2010), we model total discretionary expenditure as a function of lagged sales ((WC01001) and estimate Eq. (3) to derive expected or normal levels of discretionary expenses. All terms in the equation are scaled by lagged total assets (*Assets*, WC02999). Abnormal discretionary expenditure (AbDISX) is derived as the residual of this equation. Given revenue levels, firms that manage earnings upwards (i.e., firms with myopic management) are likely to report abnormally low discretionary expenses (Cohen & Zarowin, 2010). We use this estimate of abnormal discretionary expenses to retest Eq. (2) while controlling reverse causality and self-selection biases.

Finally, we draw on literature which suggests that myopic managers will manage earnings upwards through accrual management channels (Jones, 1991; Dechow, Sloan, & Sweeney, 1995; Peasnell, Pope, & Young, 2000, 2005; Chen, Rhee, Veeraraghavan, & Zolotoy, 2015). In essence, we explore whether firm-year observations classified as *myopia* (*hyperopia*) under our framework report significantly positive (negative) discretionary accruals. For completeness, we also explore levels of discretionary accruals in *poor* and *efficient* firms. Peasnell et al. (2000) suggest that, in the UK context, the Jones (1991) and modified-Jones (Dechow et al., 1995) models are powerful tools for detecting revenue and bad debt manipulations. Hence, we use the Jones (1991) model as modified by Dechow et al. (1995) to estimate discretionary accruals.[6] The model suggests that total accruals is a combination of discretionary accruals (*DA*) and non-discretionary accruals (*NDA*), with *DA* being used by managers to potentially inflate earnings. Total accruals is defined as the change in current assets (*CA*, WC02201) minus cash (*Cash*, WC02001) minus the change in current liabilities (*CL*, WC03101) minus depreciation (*DEP*, WC01148).[7]

$$Total\ Accruals_{it} = \Delta CA_{it} - \Delta Cash_{it} - \Delta CL_{it} - DEP_{it} \tag{4}$$

TA and *NDA* are estimated as in Eqs. (5) and (6).

$$\frac{Total\ Accruals_{it}}{Assets_{it-1}} = \beta_1 \frac{1}{Assets_{it-1}} + \beta_2 \frac{(\Delta REV_{it} - \Delta REC_{it})}{Assets_{it-1}} + \beta_3 \frac{PPE_{it}}{Assets_{it-1}} + \varepsilon_{it} \tag{5}$$

$$\frac{NDA_{it}}{Assets_{it-1}} = \widehat{\beta}_1 \frac{1}{Assets_{it-1}} + \widehat{\beta}_2 \frac{(\Delta REV_{it} - \Delta REC_{it})}{Assets_{it-1}} + \widehat{\beta}_3 \frac{PPE_{it}}{Assets_{it-1}} \tag{6}$$

All terms in Eqs. (5) and (6) are scaled by lagged total assets (*Assets*, WC02999). REV, REC and PPE are firm-specific measures of total revenues (WC01001), total receivables (WC02051) and property, plant and equipment (WC02051), respectively. ΔREV_{it} and ΔREC_{it} measure the firm-specific one-year change in total revenues and total receivables, respectively. The difference between reported total accruals and estimated *NDA* is *DA*—which is computed as the residual in model (5).

Following evidence (Hunt, Moyer, & Shevlin, 1996) that managers do not use depreciation accruals to smooth earnings, Botsari and Meeks (2008) suggest that depreciation and amortisation are not credible long-term tools for earnings management due to visibility, rigidity and predictability. Hence, consistent with Botsari and Meeks (2008), we also compute current accruals by excluding depreciation from the computation of total accruals in Eq. (4). As in Eq. (7), current accruals is defined as the change in current assets (*CA*, WC02201) minus cash (*Cash*, WC02001) minus the change in current liabilities (*CL*, WC03101). Similarly, as shown in Eq. (8), given that we have excluded depreciation from our computation of total accruals in Eq. (4), we also exclude property, plant and equipment (PPE) from our estimation of total accruals in Eq. (5). Additionally, we estimate the relation between our estimates of discretionary accruals (*DA*), i.e., current and total discretionary accruals, and our attributes of management performance using Eq. (9).

$$Current\ Accruals_{it} = \Delta CA_{it} - \Delta Cash_{it} - \Delta CL_{it} \tag{7}$$

$$\frac{Current\ Accruals_{it}}{Assets_{it-1}} = \beta_1 \frac{1}{Assets_{it-1}} + \beta_2 \frac{(\Delta REV_{it} - \Delta REC_{it})}{Assets_{it-1}} + \varepsilon_{it} \tag{8}$$

$$DA_{it} = \alpha + \beta * Performance_{it} + \gamma * Controls_{it} + \varepsilon_{it} \tag{9}$$

The independent variable of interest is *performance*, measured using our four dummy variables: *poor, myopia, hyperopia* and *efficient*. We

[5] Indeed, in our analysis, we find that the Inverse Mills ratio is significant, hence justifying this analysis.

[6] Our results do not materially change and remain robust when we use the unmodifed version of the model.

[7] Following Botsari and Meeks (2008), no adjustment is made for the current portion of long-term debt due to data unavailability.

expect to find a positive relation between DA and *myopia*, but not for *hyperopia*, consistent with myopic managers managing earnings upwards.

3.3. Modelling takeover likelihood

In our final set of analyses, we use the framework to retest the management inefficiency hypothesis as set out in hypotheses 1 and 2. Consistent with prior literature (Brar et al., 2009; Cremers et al., 2009; Danbolt et al., 2016; Palepu, 1986; Powell, 2001; Tunyi & Ntim, 2016), we test the relation between a firm's takeover likelihood and our attributes of management performance, controlling for established determinants of takeover likelihood. The base logit regression model is given as follows (Eq. (10)):

$$\Pr[Target_{it} = 1] = F(\alpha + \beta * Performance_{it-1} + \gamma * Controls_{it-1} + \varepsilon_{it}) \tag{10}$$

Target takes a value of one if a firm (*i*) is the subject of a takeover bid for control in a period (*t*), and a value of zero otherwise. The model classifies each firm as a takeover target or non-target by computing its odds of being a target in period *t* conditional upon its observed characteristics in period *t-1*. The independent variable of interest is *performance*, measured using our four dummy variables: *poor*, *myopia*, *hyperopia* and *efficient*. The *controls* are variables shown in prior studies to influence a firm's takeover likelihood. Prior research (Ambrose & Megginson, 1992; Brar et al., 2009; Cremers et al., 2009; Danbolt et al., 2016; Palepu, 1986; Powell, 2001) suggests that takeover likelihood is a function of a firm's size (SIZE), level of free cash flow (FCF), available tangible assets (TANG), age (AGE), degree of undervaluation (TBQ), the presence of a mismatch between its level of growth and available resources (SGW, LIQ, LEV, GRD), industry concentration (HHI), the occurrence of other takeovers in the firm's industry (IDD), the presence of block holders (BLOC), the circulation of merger rumours (RUM), trading volume (TVOL) and market sentiment (SENT). These control variables, their underlying rationale and selected proxies are summarised in Appendix 1.

Our analysis here is also prone to endogeneity concerns (omitted variable bias and reverse causality). We partly mitigate omitted variable bias by including several control variables and controlling for firm and year fixed effects (panel regression). Also, in Eq. (10), we lag our independent variables by one period to partly control for possible reverse causality. To further mitigate reverse causality, we use a two-stage estimation approach (Newey, 1987), with the industry average of R&D investment (*mRDI*) as an instrumental variable for both *myopia* and *hyperopia*. Our instrumental variable meets the relevance condition (i.e., it is strongly correlated with performance per our attributes)[8] and the exclusion restriction (i.e., industry-level R&D investment has no bearing on firm-level takeover likelihood). In the first stage we run the following probit regression models (Eqs. (11) and (12)) to generate predicted values for *myopia* and *hyperopia*.

$$\Pr[Myopia_{it} = 1] = F(\alpha + \beta * mRDI_{jt} + \gamma * Controls_{it} + \varepsilon_{it}) \tag{11}$$

$$\Pr[Hyperopia_{it} = 1] = F(\alpha + \beta * mRDI_{jt} + \gamma * Controls_{it} + \varepsilon_{it}) \tag{12}$$

In the second stage we use predicted values for our key performance attributes (i.e., $\widehat{myopia}$ and $\widehat{hyperopia}$) to rerun Eq. (10).

3.4. Data and sample

Our sample consists of 3522 firms listed on the London Stock Exchange between 1988 and 2017. To mitigate survivorship bias, all live and dead firms are included. However, financial firms (i.e., firms with SIC codes 60–69) are excluded as they follow unique reporting practices (Botsari & Meeks, 2008). Firm financial information is obtained from Thomson DataStream. Firm-year observations with insufficient financial information (i.e., no total assets reported) are excluded from further analysis. This generates an unbalanced panel of 39,723 firm-year observations. Notice that only 30% of firm-year observations report R&D expenditures. This suggests that the use of R&D in empirical analysis (e.g., as a proxy for *myopia*) results in a significant reduction in the usable sample.

Data for 3342 M&A announcements (and their deal characteristics) for UK listed takeover targets for the sample period is obtained from Thomson One. We also obtain data on deal characteristics, including the method of payment (cash versus stock), origin of the bidder (domestic versus cross-border), acquisition motive (control versus stake), bid outcome (successful versus failed) and bid attitude (hostile versus friendly). DataStream codes are used to link the two databases, whilst using the June approach (Soares & Stark, 2009) to maintain appropriate lags in the model (i.e., takeover probability in the current period is a function of firm characteristics in the previous period). The June approach recognises that although most UK firms have a December year end, their financial data (which bidders are assumed to use in their acquisition decisions) is only published several (up to six) months later. In our main analyses, we focus on bids that, if successful, will give the bidder control (i.e., > 50% shareholding) of the target.

4. Results and discussions

4.1. Descriptive statistics

Table 1 presents descriptive statistics for variables used in the study.[9] The mean *ROCE* and *AAR* for the sample are 3.3% and 0%, respectively. The results for *ROCE* are arguably low perhaps, because *ROCE* is negatively skewed. The median *ROCE* for UK firms between 1988 and 2017 is a more realistic 10.8%. In untabulated results, we find that the correlation coefficient between *ROCE* and *AAR* is −0.05 (*p-value* of 0.000). While the *p-value* is significant at the 1% level, the magnitude of the coefficient is small, indicating a low possibility of multicollinearity. The low correlation coefficient between *ROCE* and *AAR* supports our view that the two measures provide different types of performance-related information and are, hence, complements rather than substitutes.

In Table 2, we group the firms in our sample under the proposed four attributes. Over 39.3% of the firm-year observations in the sample are classified as having *efficient* management teams, and only 15.1% are classified as having *poor* management teams. This suggests that 45.7% of firms cannot be clearly identified as having either efficient or inefficient management teams. Our framework allows us to classify these under two categories: *myopia* (26.1% of observations) and *hyperopia* (19.7% of observations).

4.2. Results from validation tests

We conduct a number of tests to validate this framework. In our first test, we explore whether the attributes (i.e., *poor, myopic, hyperopic* and *efficient*) are valid and distinct from each other (i.e., whether firms under each category are integrally different from firms in other categories). We use conventional one-way multivariate analysis of variance (MANOVA) to compare the vector of means of firm characteristics (Tobin's Q, liquidity, leverage, sales growth, growth-resource mismatch dummy, industry disturbance dummy, free cash flow, tangible assets, size, age, industry concentration, block-holders, rumours, momentum and trading volume) for the four categories of management performance. These variables are fully defined in Appendix 1. In untabulated

[8] We explore this in untabulated results.

[9] All continuous and unbounded variables are winsorised at the 1st and 99th percentile.

Table 1
Descriptive statistics of variables.

The table reports summary statistics for variables used in the study. The main dependent variables include *Target* (a dummy variable identifying firms subject to takeover bids), research & development to total asset ratio (RDI), abnormal discretionary expenses (abDISX), current discretionary accruals (dCACC) and total discretionary accruals (dTACC). The independent variables include the return on capital employed (ROCE), average abnormal returns (AAR), Tobin's Q (TBQ), liquidity (LIQ), leverage (LEV), sales growth (SGW), growth-resource mismatch dummy (GRD), industry disturbance dummy (IDD), free cash flow (FCF), proportion of tangible assets (TANG), firm size (SIZE), firm age (AGE), Herfindahl-Hirschman Index (HHI), block holders dummy (BLOC), rumour dummy (RUM), price momentum (MOM), trading volume (TVOL) and market sentiment (SENT). The variables are fully defined in Appendix 1.

	N	Mean	Median	Standard deviation	Skewness	25th percentile	75th percentile
Target	38,246	0.048	0.000	0.214	4.217	0.000	0.000
RDI	11,896	0.071	0.020	0.191	20.370	0.004	0.070
abDISX	32,527	−0.002	−0.017	1.698	−4.149	−0.152	0.106
dCACC	30,385	0.000	−0.001	1.816	−61.436	−0.059	0.053
dTACC	30,156	0.002	0.000	1.703	−61.331	−0.054	0.057
ROCE	39,468	0.033	0.108	0.746	−3.614	−0.019	0.220
AAR	34,066	0.000	0.000	0.003	0.028	−0.001	0.001
TBQ	35,963	1.968	1.372	2.209	5.287	1.008	2.038
MTB	35,034	1.709	1.016	2.407	4.228	0.594	1.797
LIQ	39,694	0.161	0.085	0.201	1.996	0.027	0.208
LEV	39,547	0.436	0.216	1.484	3.408	0.011	0.565
SGW	34,937	0.293	0.081	1.261	8.775	−0.031	0.245
GRD	35,790	0.247	0.000	0.432	1.171	0.000	0.000
IDD	39,580	0.294	0.000	0.456	0.905	0.000	1.000
FCF	32,270	−0.066	0.011	0.335	−4.975	−0.084	0.072
TANG	39,228	0.294	0.241	0.254	0.823	0.073	0.445
SIZE	39,712	17.789	17.596	2.311	0.219	16.289	19.155
AGE	36,593	2.774	2.773	1.212	−0.282	1.946	3.829
HHI	38,226	0.122	0.070	0.150	2.812	0.039	0.125
BLOC	39,723	0.355	0.000	0.446	0.634	0.000	1.000
RUM	39,723	0.006	0.000	0.079	12.563	0.000	0.000
MOM	35,816	0.131	0.176	1.187	−0.149	−0.673	0.972
TVOL	36,075	0.211	0.091	0.347	3.314	0.003	0.264
SENT	36,009	0.103	0.145	0.163	−0.854	−0.035	0.220

Table 2
Four attributes of management performance.

The table shows the development of a framework for calibrating performance. Accounting performance is proxied by the return on capital employed (ROCE), computed as the ratio of profit before interest and tax (PBIT) to the sum of total equity and long-term debt. Stock market performance is proxied by average daily abnormal return (AAR) computed using the market model. Performance (Accounting and Market) in each year is classified as "low" or "high" if the firm's ratio (ROCE or AAR) is lower or higher, respectively, than the industry average in that year. *Efficient* takes a value of one if a firm reports high accounting and high market performance, and a value of zero otherwise. *Myopia* takes a value of one if a firm reports high accounting and low market performance, and a value of zero otherwise. *Hyperopia* takes a value of one if a firm reports low accounting and high market performance, and a value of zero otherwise. *Poor* takes a value of one if a firm reports low accounting and low market performance, and a value of zero otherwise. We classify all firms in our sample into these four mutually exclusive categories and record the number of observations for each category.

Accounting performance	Market performance	Management performance	Number of observations	Percentage of sample
High	High	*Efficient*	15,615	39.3
High	Low	*Myopia*	10,365	26.1
Low	High	*Hyperopia*	7730	19.5
Low	Low	*Poor*	6013	15.1

results, we find that the key MANOVA test statistics (including Wilks' lambda, Pillai's trace, Lawley-Hotelling trace and Roy's largest root) are all statistically significant with *p-values* of < 0.000. This suggests integral differences in our four attributes. The results are robust to the choice of firm characteristics.

In Table 3, we explore this further through a one-way analysis of variance (ANOVA) with standard Bonferroni correction of the level of significance (panel A). Given that several of our variables are skewed (see Table 1), we also use the non-parametric alternative, Dunn's test of differences in medians (Dunn, 1964), in panel B. This allows us to compare the means and medians of our 18 firm-level variables across the four attributes of management performance. In panel A, we find that the distribution of eight of our variables (including average abnormal returns, Tobin's Q, liquidity, free cash flow, size, block holders, momentum and trading volume) are unique across each attribute and statistically different from those of the other three attributes. Similarly, in panel B, when we compare median values, we find that firms in the four categories are distinct in terms of market to book values, leverage, tangible assets, size, presence of block holders and momentum.

Our next validation test explores the relation between firm-level R&D investments and our attributes, in a multivariate setting in which we control for other firm characteristics. Given that R&D is a discretionary expenditure, managers can vary its level with a direct impact on reported profit. A cut in R&D will increase current profitability with an adverse impact on long-term cash flows (Boubaker et al., 2017; Faleye, 2007; Holden & Lundstrum, 2009). A negative (positive) relation between R&D investments and our *myopia* (*hyperopia*) measure will be consistent with our view that this measure captures management short-termism (long-termism). We do not have any expectations in terms of the relation between R&D investments and our *poor* (and *efficient*) measures. Our results from Eq. (2) are presented in Table 4, models 1 to 4. To directly explore real earnings management through a reduction of R&D and/or SG&A, we also use abnormal discretionary expenses, computed as the residual in Eq. (3), as an alternative dependent variable in Eq. (2). These results are presented in models 5 to 8. All models correct for selection bias using the Heckman Two-Stage approach.[10] All independent variables are lagged by one period and all models control for industry and year effects.

The results from models 2 and 6 suggest a negative and statistically significant relation between management short-termism and R&D investment (model 2) or abnormal discretionary expenses (model 6). That

[10] The coefficient of the Inverse Mills Ratio (non-selection hazard) is significant in all models, suggesting selection bias in the sample.

Table 3
Firm characteristics across attributes of management performance.

Panel A of the table presents one-way ANOVA results (with Bonferroni correction of the level of significance) for piecewise comparisons of the means of the respective variable distributions across the four categories of management performance (*poor, myopic, hyperopic* and *efficient*, denoted respectively by the letters P, M, H and E, for conciseness). Panel B presents results for differences in median (Dunn's test) across the four categories. The variables include the return on capital employed (ROCE), average abnormal returns (AAR), Tobin's Q (TBQ), liquidity (LIQ), leverage (LEV), sales growth (SGW), growth-resource mismatch dummy (GRD), industry disturbance dummy (IDD), free cash flow (FCF), proportion of tangible assets (TANG), firm size (SIZE), firm age (AGE), Herfindahl-Hirschman Index (HHI), block holders dummy (BLOC), rumour dummy (RUM), price momentum (MOM), trading volume (TVOL) and market sentiment (SENT). The variables are fully defined in Appendix 1. Six (6) comparisons (i.e., one-way ANOVA tests) are conducted in each case (M&E, H&E, P&E, M&H, P&M and P&H). The results of significance testing (at the 10% level) are summarised in the last column. Here, the cases with a statistically significant difference are noted. We use "All pairs" to indicate a statistically significant difference across all six cases. We also use "ex" to indicate any exclusions or cases where the difference is not statistically significant.

	Panel A: differences in mean				
	Poor (*P*)	*Myopia* (*M*)	*Hyperopia* (*H*)	*Efficient* (*E*)	Significance tests (at 10% level)
ROCE	−0.258	0.183	−0.277	0.202	*All ex P&H, M&E*
AAR	−0.002	−0.001	0.002	0.001	*All pairs*
TBQ	2.303	1.926	2.115	1.780	*All pairs*
MTB	1.938	1.606	1.935	1.578	*All ex P&H, M&E*
LIQ	0.183	0.127	0.211	0.150	*All pairs*
LEV	0.428	0.467	0.306	0.483	*All ex P&M, M&H*
SGW	0.389	0.286	0.281	0.264	*P&M, P&H, P&E*
GRD	0.244	0.245	0.247	0.251	*None*
IDD	0.292	0.298	0.296	0.291	*None*
FCF	−0.220	0.012	−0.269	0.023	*All pairs*
TANG	0.281	0.305	0.274	0.302	*All ex P&H, M&E*
SIZE	17.199	18.340	16.856	18.114	*All pairs*
AGE	2.680	2.875	2.647	2.804	*All ex P&H*
HHI	0.131	0.122	0.131	0.115	*All ex P&H*
BLOC	0.295	0.418	0.254	0.387	*All pairs*
RUM	0.004	0.008	0.004	0.007	*All ex P&H, M&E*
MOM	−0.409	−0.271	0.348	0.573	*All pairs*
TVOL	0.152	0.225	0.176	0.245	*All pairs*

	Panel B: differences in median				
	Poor (*P*)	*Myopia* (*M*)	*Hyperopia* (*H*)	*Efficient* (*E*)	Significance tests (at 10% level)
ROCE	−0.031	0.159	−0.017	0.166	*All ex M&E*
AAR	−0.001	−0.001	0.001	0.001	*All ex P&M*
TBQ	1.307	1.496	1.164	1.390	*All ex P&E*
MTB	0.893	1.125	0.798	1.072	*All pairs*
LIQ	0.084	0.075	0.099	0.088	*All ex P&E*
LEV	0.209	0.264	0.135	0.226	*All pairs*
SGW	0.035	0.092	0.038	0.100	*All ex P&H*
GRD	0.000	0.000	0.000	0.000	*None*
IDD	0.000	0.000	0.000	0.000	*None*
FCF	−0.087	0.030	−0.092	0.040	*All ex P&H*
TANG	0.220	0.259	0.207	0.249	*All pairs*
SIZE	16.987	18.086	16.739	17.890	*All pairs*
AGE	2.565	2.890	2.565	2.833	*All ex P&H*
HHI	0.070	0.071	0.070	0.068	*M&E*
BLOC	0.000	0.110	0.000	0.000	*All pairs*
RUM	0.000	0.000	0.000	0.000	*All ex P&H, M&E*
MOM	−0.404	−0.243	0.432	0.634	*All pairs*
TVOL	0.042	0.115	0.049	0.120	*All ex M&E*

is, firms classified as suffering from *myopia* in the current period tend to reduce discretionary expenses, particularly R&D investment, in the next period. Conversely, our results from models 3 and 6 suggest that firms classified as *hyperopic* in the current period tend to grow R&D investment (model 3) or discretionary expenditures (model 7) in the next period. This finding is consistent with the extant literature, which documents a positive relation between short-termism and firm-level R&D investments (Graham et al., 2006; Wahal & McConnell, 2000). More importantly, it provides some empirical evidence of the tendency for our categories to correctly classify firms in terms of management horizon. Notwithstanding, we find similarities between our *poor* and *hyperopic*, as well as *myopic* and *efficient*, attributes. That is, firms classified as *poor* (*efficient*) also report higher (lower) R&D investments and abnormal discretionary expenses.

Our final validation test focuses on accrual earnings management. Prior research suggests that short-termist managers seeking to meet earnings targets can use a variety of accrual earnings management strategies (e.g., revenue recognition and bad debt manipulation, amongst others) to inflate reported earnings (Cohen & Zarowin, 2010; Dechow et al., 1995). We use the modified-Jones model, as specified in Eqs. (4) to (8), to compute total and current discretionary accruals. Following Cohen and Zarowin (2010), we expect firms classified as *myopic (hyperopic)* to report positive (negative) discretionary accruals. For completeness, we also report results for our *poor* and *efficient* attributes, but have no expectations for these two attributes. In Table 5, we compare the mean and median discretionary accruals for firms across the four attributes.

Our results from Table 5 show that observations classified as *myopia* report positive discretionary accruals (both total and current), while those classified as *hyperopia* report negative discretionary accruals. The difference in mean and median discretionary accruals for the two categories (i.e., (2)–(3)) is significant at the 10% level. This suggest that firm-year observations we classify under the *myopia* category are more likely to be associated with upward accrual earnings management when compared to their *hyperopia* counterparts, who appear to manage earnings downward. When we explore differences in discretionary accruals reported by the other categories, we find statistically significant differences between *poor* and *myopia*, and between *hyperopia* and *efficient*. As in Table 4, we do not find significant differences between our *poor* and *hyperopia* or between our *myopia* and *efficient* attributes, in terms of levels of discretionary accruals.

Our regression results in Table 6 confirm that, after controlling for firm, industry and year characteristics, levels of current discretionary accruals decline with *poor* and *hyperopia* but increase with *myopia* and *efficient*. These results are robust to different model specifications, including the use of the original (unmodified) Jones (1991) model to compute discretionary accruals, as well as the use of total discretionary accruals instead of current discretionary accruals. While the results suggest some similarities between firms in our *poor* and *hyperopia*, as well as *myopia* and *efficient* attributes, in terms of R&D investments and discretionary accruals, our results in the next section will demonstrate that firms within these attributes face distinct takeover risks.

4.3. Management performance and takeover likelihood

We apply our framework to retest the management inefficiency hypothesis. Prior studies generally test this hypothesis by investigating whether targets underperform (relative to non-targets) prior to takeovers (Agrawal & Jaffe, 2003; Powell & Yawson, 2007) and also by investigating whether takeover likelihood increases with firm performance (Ambrose & Megginson, 1992; Palepu, 1986; Powell & Yawson, 2007; Tunyi & Ntim, 2016). We first replicate traditional tests to demonstrate how the lack of a comprehensive framework for calibrating management performance leads to inconclusive results.

In untabulated results, targets have a mean *ROCE* of 9.2% compared to the 2.8% for non-targets. The difference of 6.4 percentage points is statistically significant at the 1% level (*p-value* of 0.000).[11] These results

[11] In untabulated results, we find that these results are generally robust to deal characteristics. Even when one focuses on a subsample of M&As which are

Table 4
R&D and attributes of management performance.
The table presents regression results for Eq. (2), specified below;
$RDI_{it} = \alpha + \beta * Performance_{it-1} + \gamma * Controls_{it-1} + \varepsilon_{it}$ (2)
Research & development expenditure to total asset ratio (*RDI*) is the dependent variable in models (1) to (4). The dependent variable in models (5) to (8) is abnormal discretionary (R&D and SG&A) expenditures, computed as the residual in Eq. (3) specified below:
$\frac{DISX_{it}}{Assets_{it-1}} = \beta_1 \frac{1}{Assets_{it-1}} + \beta_2 \frac{SALES_{it-1}}{Assets_{it-1}} + \varepsilon_{it}$ (3)
The independent variable of interest is firm performance (*performance*), measured using our four dummy variables: *poor*, *myopia*, *hyperopia* and *efficient*. For example, *myopia* takes a value of one if a firm reports high accounting and low market performance, and a value of zero otherwise. The *Controls* in the model include one-period lags of Tobin's Q (TBQ), liquidity (LIQ), leverage (LEV), sales growth (SGW), proportion of tangible assets (TANG), firm size (SIZE) and age (AGE). Models are estimated using the Heckman Two-Stage approach to control for non-selection hazard (self-selection bias). In the first stage, a probit model is used to compute each firm's likelihood of reporting R&D > 0 as a function of its characteristics (TBQ, LIQ, LEV, SGW, SIZE, TANG, AGE) in that year. The predicted probability is used to compute the non-selection hazard (*Mills*, Inverse Mills Ratio), which is included as an additional control in the second stage model. The *p-values* are presented in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	R&D investment				Abnormal discretionary expenses			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Poor	0.036***				0.026**			
	(0.000)				(0.039)			
Myopia		−0.013***				−0.034***		
		(0.000)				(0.000)		
Hyperopia			0.028***				0.066***	
			(0.000)				(0.000)	
Efficient				−0.023***				−0.018*
				(0.000)				(0.062)
Mills	−0.102***	−0.085***	−0.081***	−0.100***	−0.208***	−0.186***	−0.180***	−0.208***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
TBQ	0.010***	0.011***	0.011***	0.010***	0.047***	0.048***	0.049***	0.047***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LIQ	0.106***	0.121***	0.120***	0.109***	−0.052	−0.040	−0.043	−0.051
	(0.000)	(0.000)	(0.000)	(0.000)	(0.122)	(0.234)	(0.200)	(0.132)
LEV	0.000	0.001	0.001	0.000	0.004	0.004	0.004	0.004
	(0.769)	(0.613)	(0.676)	(0.773)	(0.321)	(0.297)	(0.335)	(0.325)
SGW	0.002	0.002	0.002	0.002	0.006	0.006	0.006	0.006
	(0.145)	(0.103)	(0.138)	(0.152)	(0.116)	(0.110)	(0.137)	(0.118)
SIZE	−0.018***	−0.018***	−0.017***	−0.019***	−0.051***	−0.049***	−0.047***	−0.051***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
TANG	0.062***	0.051***	0.049***	0.060***	0.028	0.015	0.010	0.026
	(0.000)	(0.000)	(0.000)	(0.000)	(0.488)	(0.714)	(0.804)	(0.513)
AGE	−0.012***	−0.012***	−0.011***	−0.012***	−0.030***	−0.028***	−0.027***	−0.030***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.427***	0.398***	0.369***	0.443***	1.272***	1.211***	1.148***	1.284***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Industry	YES	YES	YES	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES	YES	YES
Obs.	30,655	30,655	30,655	30,655	30,500	30,500	30,500	30,500

do not support the management inefficiency hypothesis that targets underperform (compared to non-targets) prior to takeovers. They are, nonetheless, consistent with the findings of several studies, including Agrawal and Jaffe (2003) and Danbolt et al. (2016). The results obtained using market measures of performance are in stark contrast. Consistent with the predictions of the management inefficiency hypothesis, targets report significantly lower *AAR* in the year prior to acquisitions compared to their non-target counterparts. On average, targets achieve negative *AAR* of −4.02% per year compared to abnormal returns of −1.06% per year earned by non-targets. The difference in mean of three percentage points is statistically significant at the 5% level (*p-value* of 0.033). These results are generally robust to deal characteristics, industry differences and differences across years.

This inconclusive evidence on the management inefficiency hypothesis persists in a multivariate analytical setting in which we regress takeover likelihood on standard accounting and market measures of performance.[12] The results for panel logit (fixed effects) regressions are presented in Table 7 (model 1).[13] The dependent variable is takeover likelihood (dummy) and the predictor variables are measures of management performance; the control variables are defined in Appendix 1. All independent variables in the models are lagged by one period to partly control for endogeneity (reverse causality bias). The variables of interest are *ROCE* (accounting measure of management performance) and *AAR* (market measure of management performance). Consistent with the results from the univariate analysis, the results show that takeover likelihood declines with *AAR* and increases with *ROCE* after controlling for other determinants of takeover likelihood. These results are also robust to bid characteristics (untabulated), mirror the findings of prior studies (Danbolt et al., 2016; Palepu, 1986) and are consistent with other studies exploring the management inefficiency hypothesis (e.g., Franks & Mayer, 1996; Agrawal & Jaffe, 2003. These results are

(*footnote continued*)
most likely to be disciplinary in nature (i.e., hostile bids and bids for control), the results do not change—on average, targets achieve higher accounting performance than non-targets.

[12] Pearson and Spearman correlation coefficients, as well as variance inflation factors (VIF) for the independent variables in the regression model, are first computed to ensure that there are no issues of multicollinearity. We find that price momentum (MOM) and average abnormal return (AAR) are correlated with a rho of 0.4. We therefore do not include MOM in our regressions.

[13] Our choice of a fixed effects model specification in Table 7 is validated by our results from the Hausman specification tests (Chi square and *p-values*) shown in the table. All Hausman Chi squares are significant at the 1% level.

Table 5

Discretionary accruals and management performance.

This table reports differences in mean and median discretionary accruals (current and total) reported by firms classified under the four attributes, (1) *poor*, (2) *myopia*, (3) *hyperopia*, (4) *efficient*, and (5) the full sample (*All firms*). The table also reports differences of means and medians between groups. Total discretionary accruals are estimated as the residual of the Modified-Jones model (Eq. (5)), while current discretionary accruals are estimated as the residual of an adjusted (for PPE) Modified-Jones model (Eq. (8)):

$$\frac{Total\ Accruals_{it}}{Assets_{it-1}} = \beta_1 \frac{1}{Assets_{it-1}} + \beta_2 \frac{(\Delta REV_{it} - \Delta REC_{it})}{Assets_{it-1}} + \beta_3 \frac{PPE_{it}}{Assets_{it-1}} + \varepsilon_{it} \quad (5)$$

$$\frac{Current\ Accruals_{it}}{Assets_{it-1}} = \beta_1 \frac{1}{Assets_{it-1}} + \beta_2 \frac{(\Delta REV_{it} - \Delta REC_{it})}{Assets_{it-1}} + \varepsilon_{it} \quad (8)$$

REV, *REC* and *PPE* are firm-specific measures of total revenues, total receivables and property, plant & equipment, respectively. ΔREV_{it} and ΔREC_{it} measure the firm-specific 1-year change in total revenues and total receivables, respectively. Total accrual (TA) is computed as the difference between operating income and cash flows from operations. We do the regression analysis across *industry-year* subgroups. The *p-values* are presented in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	Current discretionary accruals		Total discretionary accruals	
	Mean	Median	Mean	Median
(1) Poor	0.002	−0.007	−0.007	−0.002
(2) Myopia	0.030	0.000	0.007	0.003
(3) Hyperopia	−0.018	−0.006	−0.006	−0.000
(4) Efficient	−0.018	0.000	0.004	0.000

Differences	Current discretionary accruals		Total discretionary accruals	
	Mean	Median	Mean	Median
(1)–(2)	−0.028	−0.007***	−0.014***	−0.005***
	(0.300)	(0.000)	(0.000)	(0.000)
(2)–(3)	0.048*	0.006***	0.013***	0.003***
	(0.068)	(0.000)	(0.000)	(0.000)
(1)–(3)	0.020	−0.013	−0.001	−0.002
	(0.227)	(0.632)	(0.622)	(0.165)
(2)–(4)	0.047	0.000	0.002	0.003*
	(0.116)	(0.699)	(0.132)	(0.061)
(3)–(4)	−0.001	−0.006***	−0.010***	−0.000***
	(0.981)	(0.000)	(0.000)	(0.000)

inconclusive, as they neither support nor refute the management inefficiency hypothesis.

Next, we replace traditional measures of performance (ROCE and AAR) in model 1 with proxies for *poor* (model 2), *myopia* (model 3), *hyperopia* (model 4) and *efficient* (model 5) management. We find that, consistent with our first hypothesis, takeover likelihood increases with *poor* management (model 2), but declines with *efficient* management (model 5). This suggests that managers that achieve high accounting and high stock market performance (i.e., efficient managers) are less likely to be targeted by takeovers when compared to managers that achieve low accounting and low stock market performance. This result is also consistent with the predictions of the management inefficiency hypothesis (Brar et al., 2009; Danbolt et al., 2016; Palepu, 1986; Tunyi & Ntim, 2016). The results also show that, consistent with our second hypothesis, takeover likelihood increases with *myopia* (model 3) but declines with *hyperopia* (model 4). In model 8, we include *poor*, *myopia* and *hyperopia* in the model, with *efficient* acting as the reference category. The results show that *poor* and *myopic* firms (but not *hyperopic* firms) have relatively higher takeover likelihood when compared to *efficient* firms. Overall, the results suggest that managers who focus on achieving short-term accounting earnings at the expense of long-term shareholder value (as measured by their stock market performance) are susceptible to takeovers, whereas managers who focus on creating long-term value for their shareholders, even at the expense of generating short-term profitability, are less likely to be disciplined through takeovers. Our conclusions are robust to the inclusion of other control variables, such as price momentum, trading volume and market sentiment.

As opposed to our earlier results (Tables 4–6),[14] the results here (Table 7) show that firms in the weaker performance categories (*poor* and *myopia*), as well as firms in the stronger categories (*hyperopia* and *efficient*), share similarities in terms of takeover likelihood. However, the coefficients in models 2 and 3 (Table 7) suggest that firms with *myopic* management are more likely to face takeovers compared to firms with *poor* management. Similarly, models 4 and 5 suggest that firms with *efficient* management are less likely to face takeovers compared to firms with *hyperopic* management teams. These results are further confirmed when we explore marginal effects (untabulated). The difference in takeover likelihood between *poor* and *myopic* firms may at first appear puzzling, as we would expect *poor* firms to be more exposed to takeovers. One possible explanation for this observation is that, given that both *poor* and *myopic* firms have poor market returns, rational acquirers are likely to show preference for the category of firms that has some potential for profitability (i.e., *myopic* firms).

Even though we have lagged our independent variables by one period and also used the June approach (Soares & Stark, 2009) to match our dependent and independent variables, our results are prone to reverse causality issues. In essence, one could argue reverse causality – takeover threat forces managers to perform optimally. To the extent that optimal performance is consistent with a preference for a long-term orientation towards investments, as opposed to a myopic view, we would expect a negative (positive) relation between takeover likelihood and *myopia* (*hyperopia*). Our results are inconsistent with such a view. In this context, our results in Table 7[15] rather suggest that a low threat of takeover incentivises managers to improve performance and vice versa. This is counterintuitive. Nonetheless, besides using lagged values of explanatory variables in all our analyses, we also apply a two-stage

[14] The results show that firms in the *poor* and *hyperopia* attributes, as well as those in the *myopia* and *efficient* attributes, bear similarities in terms of R&D investments and levels of estimated discretionary accruals.

[15] That is, a positive relation between takeover likelihood and *poor* (as well as *myopia*) and a negative relation between takeover likelihood and *efficient* (as well as *hyperopia*).

Table 6
Discretionary accruals and management performance.

The table reports panel regression results (with firm and year fixed effects) from Eq. (9), which explores whether attributes of *performance* (*poor, myopia, hyperopia* and *efficient*) explain variations in levels of discretionary accruals (*DA*) across firms.

$DA_{it} = \alpha + \beta * Performance_{it} + \gamma * Controls_{it} + \varepsilon_{it}$ (9)

The dependent variable is current discretionary accruals. The control variables in the model are fully discussed in Appendix 1. The *p-values* are presented in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Poor	−0.012***			
	(0.000)			
Myopia		0.005***		
		(0.004)		
Hyperopia			−0.016***	
			(0.000)	
Efficient				0.009***
				(0.000)
TBQ	0.001	0.000	0.000	0.001
	(0.232)	(0.493)	(0.866)	(0.215)
LIQ	−0.082***	−0.082***	−0.081***	−0.082***
	(0.000)	(0.000)	(0.000)	(0.000)
LEV	−0.002***	−0.002***	−0.002***	−0.002***
	(0.001)	(0.001)	(0.001)	(0.001)
SGW	0.003***	0.003***	0.003***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)
GRD	−0.000	−0.000	−0.000	0.000
	(0.971)	(0.969)	(0.950)	(1.000)
IDD	−0.003*	−0.003*	−0.003	−0.003*
	(0.079)	(0.079)	(0.102)	(0.085)
FCF	−0.042***	−0.040***	−0.043***	−0.043***
	(0.000)	(0.000)	(0.000)	(0.000)
TANG	−0.067***	−0.066***	−0.067***	−0.067***
	(0.000)	(0.000)	(0.000)	(0.000)
SIZE	0.004**	0.003**	0.003*	0.004***
	(0.010)	(0.048)	(0.062)	(0.004)
AGE	−0.001	−0.000	−0.000	−0.001
	(0.758)	(0.858)	(0.851)	(0.736)
HHI	−0.016**	−0.017**	−0.014*	−0.017**
	(0.040)	(0.034)	(0.084)	(0.037)
BLOC	−0.006***	−0.005**	−0.007***	−0.006***
	(0.007)	(0.017)	(0.002)	(0.004)
Constant	−0.030	−0.020	−0.012	−0.045*
	(0.235)	(0.436)	(0.641)	(0.083)
Obs.	23,165	23,165	23,165	23,165
R-squared	0.013	0.012	0.014	0.013
Firms	2758	2758	2758	2758

approach to mitigate reverse causality bias in our analysis. Our focus is on our new constructs, *myopia* and *hyperopia*. In the first stage, we use mean industry R&D as an instrument to generate predicted values for *myopia* and *hyperopia*. We use these predicted values (i.e., $\widehat{myopia}$ and $\widehat{hyperopia}$) in place of the actual values used in models 3 and 4. The results are presented in models 6 and 7. We find that our results are robust to reverse causality or simultaneity bias.[16]

4.4. Switching and takeover likelihood

We expect firms to switch from one category to another over time, consistent with variability in management performance. Hence, we explore how frequently firms switch between the four categories, whether these switches are driven by management efforts to adopt a more long-term orientation (i.e., investment in R&D, reduction in discretionary accruals), and how the takeover market responds to such efforts. To explore the drivers and effects of switching from one year to another, we assume an ordinal scale for performance, where *poor* is ranked lowest (1), followed by *myopia* (2), then *hyperopia* (3) and *efficient* (4). We then identify three categories of firms: *improve* (firms that switch from lower to higher ranked categories), *maintain* (firms that do not change category) and *decline* (firms that switch from higher to lower ranked categories) from one year to the next. We expect to observe substantial movement (*improve*) from underperforming categories (*poor* and *myopia*) into the outperforming category (*efficient*) as management responds to external pressures, such as those from the takeover market. In response to such pressures, we expect to also observe comparatively lower levels of switching (*decline*) from the outperforming category (*efficient*) into the underperforming categories (*poor*, *myopia* and *hyperopia*). Results on how frequently firms switch categories are presented in Table 8.

Indeed, we find significant switching, particularly for our *poor* (64.1%), *myopic* (61.7%) and *hyperopic* (60.8%) categories. That is, about 35.9%, 38.3% and 39.2% of observations in our *poor*, *myopic* and *hyperopic* categories *maintain* their attributes from one year to the next. By contrast, only 44.5% of observations in our *efficient* category switch to other categories from one year to the next (i.e., 55.5% *maintain* this category). These results suggest that, as expected, managers are more eager to move out of the *poor* and *myopia* categories (i.e., *improve*) when compared to the *efficient* category (i.e., *decline*). We find that a majority of observations (41.8%) switching from *poor* move into the *hyperopia* category. Similarly, almost half (44%) of firms switching from the *myopia* category move into the *efficient* category.

Next, we specifically explore whether the adoption of a more long-term approach (e.g., as evidenced by increased investment in R&D or the accumulation of lower discretionary accruals) partly explains the switch from underperforming to better performing categories (*improve*). We may therefore observe that firms switching up from *poor* (i.e., *improve*) are associated with higher R&D investments or lower accumulated discretionary accruals in the previous period. To explore this issue, we run logit regression models to estimate the likelihood of *improve*, *maintain* and *decline*, as a function of lagged R&D investments and lagged current discretionary accruals. Our results are reported in Table 9.

The results (models 1 and 2) from Table 9 show that an increase in R&D investments, as well as a decrease in discretionary accruals in one period, increases the likelihood of switching up (*improve*) in the next period. Also, as in model 5, a decrease in R&D investments in the current period increases the likelihood of switching down (*decline*) in the next period. Firms that grow their levels of discretionary accruals (i.e., model 4) appear to stay within their current category. Overall, the results suggest that firms achieve improved performance (i.e., *improve*) partly by taking a long-term view (e.g., by investing in R&D or reducing discretionary accruals). These results are robust when we use abnormal discretionary expenses in place of R&D investments in the models. We explore the implications of a switch (*decline, maintain, improve*) on a firm's takeover likelihood in Table 10.

The results from models 1 and 2 suggest that takeover likelihood of *poor* firms increases if they do not switch (*maintain*), and decreases insignificantly if they switch up (*improve*). From models 3–5, we find that takeover likelihood of *myopic* firms increases slightly if they switch down to *poor* (i.e., *decline*) and significantly if they do not switch (i.e., *maintain*), but their takeover likelihood falls substantially if they switch up into our *hyperopia* or *efficient* categories (i.e., *improve*). The results suggests that, compared to *poor*, the takeover likelihood of *myopic* firms is more sensitive to their performance over time. Looking at models 6–10, takeover likelihood of *hyperopic* firms declines when they *maintain*, with the effects of *decline* and *improve* being not statistically significant. Models 9 and 10 show that takeover likelihood for *efficient* firms increases when they *decline* and decreases when they *maintain*. Overall, our results broadly suggest that firms that switch from underperforming to outperforming categories face lower levels of takeover risk and vice versa. Additionally, firms in underperforming categories (specifically, *myopia*) who do not switch up face higher takeover risks,

[16] Notice that the results for *poor* and *efficient* (untabulated) are also robust to reverse causality or simultaneity bias. We do not present them for conciseness.

Table 7
Takeover likelihood and management performance.

The table reports results from panel fixed effects logit models (Eq. (10)) estimating a firm's takeover likelihood as a logit function of firm characteristics.

$Pr[Target_{it} = 1] = F(\alpha + \beta * Performance_{it-1} + \gamma * Controls_{it-1} + \varepsilon_{it})$ (10)

The dependent variable in the model (*Target*) takes a value of one if a firm (*i*) is the subject of a takeover bid for control in a period (*t*) and a value of zero otherwise. In model (1), *performance* is proxied by a firm's return on capital employed (ROCE) and average abnormal return (AAR). Models (2) to (5) use *poor, myopia, hyperopia* and *efficient* as proxies of *performance* (see Table 2 for full definitions of these proxies). Models (6) and (7) are two-stage panel fixed effects models controlling for potential endogeneity using mean two-digit SIC industry R&D investment (RDI) as an instrumental variable for *myopia* and *hyperopia*. $\widehat{Myopia}$ and $\widehat{Hyperopia}$ are predicted values of myopia and hyperopia, respectively. The control variables in the model are fully discussed in Appendix 1. The *p-values* for model coefficients are presented in parentheses. *Chi2* represents Hausman chi-square. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level of significance, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Poor		0.142*						0.279***
		(0.080)						(0.003)
Myopia			0.320***					0.365***
			(0.000)					(0.000)
Hyperopia				−0.218**				0.008
				(0.013)				(0.937)
Efficient					−0.314***			
					(0.000)			
$\widehat{Myopia}$						3.334***		
						(0.000)		
$\widehat{Hyperopia}$							−0.663**	
							(0.048)	
ROCE	0.089*							
	(0.096)							
AAR	−16.179*							
	(0.085)							
TBQ	−0.022	−0.003	−0.019	−0.008	−0.012	−0.029	0.008	−0.026
	(0.402)	(0.904)	(0.440)	(0.729)	(0.634)	(0.313)	(0.726)	(0.309)
LIQ	−0.104	−0.097	−0.066	−0.089	−0.081	0.140	−0.104	−0.067
	(0.721)	(0.738)	(0.821)	(0.760)	(0.781)	(0.668)	(0.724)	(0.816)
LEV	0.039**	0.035*	0.036**	0.036**	0.035*	0.040**	0.036*	0.035*
	(0.034)	(0.052)	(0.050)	(0.049)	(0.058)	(0.037)	(0.051)	(0.058)
SGW	−0.048*	−0.046*	−0.051**	−0.050**	−0.045*	−0.050	−0.045*	−0.049**
	(0.057)	(0.063)	(0.043)	(0.047)	(0.071)	(0.185)	(0.069)	(0.049)
GRD	−0.086	−0.084	−0.101	−0.085	−0.097	−0.060	−0.079	−0.098
	(0.187)	(0.195)	(0.121)	(0.188)	(0.137)	(0.385)	(0.231)	(0.132)
IDD	−0.179***	−0.182***	−0.177***	−0.180***	−0.180***	−0.129*	−0.152**	−0.176***
	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)	(0.051)	(0.017)	(0.005)
FCF	−0.272	−0.139	−0.214	−0.227	−0.057	−0.011	−0.163	−0.142
	(0.158)	(0.468)	(0.259)	(0.232)	(0.768)	(0.960)	(0.387)	(0.468)
TANG	0.264	0.245	0.235	0.242	0.248	0.495	0.328	0.253
	(0.408)	(0.442)	(0.462)	(0.448)	(0.437)	(0.164)	(0.319)	(0.427)
SIZE	0.420***	0.437***	0.390***	0.428***	0.405***	0.388***	0.452***	0.380***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
AGE	0.392***	0.385***	0.403***	0.386***	0.402***	0.497***	0.399***	0.409***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
HHI	−1.518***	−1.560***	−1.473***	−1.485***	−1.604***	−1.361***	−1.407***	−1.515***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.001)	(0.000)
BLOC	0.754***	0.765***	0.730***	0.735***	0.782***	0.652***	0.737***	0.745***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
RUM	−0.405**	−0.404**	−0.407**	−0.411**	−0.392*	−0.383*	−0.381*	−0.395*
	(0.046)	(0.046)	(0.046)	(0.043)	(0.054)	(0.063)	(0.061)	(0.053)
TVOL	0.203**	0.206**	0.202**	0.200*	0.213**	0.189*	0.186*	0.212**
	(0.047)	(0.045)	(0.049)	(0.050)	(0.038)	(0.085)	(0.076)	(0.039)
SENT	0.277*	0.262*	0.182	0.266*	0.176	0.313*	0.262*	0.159
	(0.069)	(0.084)	(0.232)	(0.079)	(0.249)	(0.051)	(0.086)	(0.296)
Chi2	862***	1048***	848***	983***	890***	891***	857***	819***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Obs.	13,663	13,702	13,702	13,702	13,702	11,976	13,153	13,702
Firms	1557	1558	1558	1558	1558	1405	1533	1558

while their counterparts in outperforming categories (*hyperopia* and *efficient*) who do not *decline* experience lower takeover risks.

4.5. Additional analyses and robustness checks

We conduct two additional analyses in this section. First, we briefly explore whether acquirers provide market discipline, as suggested by the management inefficiency hypothesis. Second, we explore an alternative explanation for our main finding, i.e., whether valuation rather than performance explains the differences in takeover likelihood across the different categories. We also summarise the robustness checks we have conducted.

Consistent with prior studies testing the inefficient management hypothesis (Agrawal & Jaffe, 2003; Brar et al., 2009; Danbolt et al., 2016), our analyses so far have focused on target firms. Here, we extend these analyses by exploring whether the action by bidders—the targeting of *poor* management and management *myopia*—can be considered as discipline, as suggested by the management inefficiency hypothesis. If bidders are to act as enforcers of market discipline, then they themselves should be well-performing prior to making bids. An alternative view is that bidding firms are also subject to *myopia* and are focused on acquiring high profit-making opportunities through

Table 8
Percentage of firm-year switches between attributes.
The table records the percentage of firm-years switching from one attribute of management performance (*poor, myopia, hyperopia* and *efficient*) to another. In the table, firms switch *from* (Switch from:) attributes in the second row *to* (Switch to:) attributes in the second column. The diagonal (in bold) shows the percentage of firm-year observations that do not switch categories from one year to the next.

		Switch from:			
		Poor	*Myopia*	*Hyperopia*	*Efficient*
Switch to:	*Poor*	**35.9**	8.6	30.9	4.6
	Myopia	9.1	**38.3**	11.3	35.1
	Hyperopia	41.8	9.2	**39.2**	4.9
	Efficient	13.2	44.0	18.6	**55.5**

takeovers. If this is the case, then the acquisition of targets will not constitute the correction of management inefficiency, but rather participation in the "earnings game". We find that bidders have an average ROCE of 11.5% in the five years before the bid. This plummets to 0.9% in the bid year (perhaps due to significant merger costs), before increasing to an average of 13.5% over the five years after the bid. The AAR generated by bidders before and after the bid are close to zero. In Table 11 we explore whether the probability of making a bid increases with bidder management *hyperopia* and *efficiency*.

The results from Table 11 suggest that the likelihood of making a takeover bid increases with management *hyperopia* (*p-value* of 0.089) and declines with *poor* management (*p-value* of 0.044). We do not find evidence that *myopic* firms are more likely to make bids. Given that bidder management are, on average, well-performing prior to bids and less likely to be classified as *poor* or *myopic*, their decision to acquire underperforming firms can, perhaps, be indicative of the role of acquisitions in providing market discipline.

Second, we explore whether valuation rather than performance explains the differences in takeover likelihood across the different categories. Our main result suggests that *poor* and *myopic* firms are more exposed to takeovers compared to their *hyperopic* and *efficient* counterparts. If categories of firms with low stock market returns (i.e., *poor* and *myopic* firms) are simply undervalued firms, while their counterparts with high market returns (i.e., *hyperopic* and *efficient* firms) are relatively overvalued firms, then our results are consistent with the misevaluation hypothesis (Dong, Hirshleifer, Richardson, & Teoh, 2006; Rhodes-Kropf, Robinson, & Viswanathan, 2005; Shleifer & Vishny, 2003). That is, undervalued firms are more exposed to takeovers compared to their overvalued counterparts (as established by Shleifer & Vishny, 2003; Rhodes-Kropf et al., 2005; Dong et al., 2006, amongst others).

We argue that this is not the case, and these categories do not simply proxy for valuation. To evidence this, we group *poor* and *myopic* firms into one category (PM) and *hyperopic* and *efficient* firms into another (HE). We compare the mean and median MTB and TBQ of these two

Table 9
R&D investments, discretionary accruals and the likelihood of switching.
The table reports logit regressions results on the likelihood of switching (dependent variable: *improve, maintain* or *decline*) across attributes (independent variables): (1) *poor,* (2) *myopia,* (3) *hyperopia* and (4) *efficient*. *Improve* indicates a switch from a lower to a higher attribute from one year to the next e.g., a switch from (1) *poor* to (2) *myopia*, and so forth. *Decline* indicates a switch from a higher to a lower attribute. *Maintain* indicates no switch. We explore whether the levels of R&D investment (RDI) and current discretionary accruals (C. Accruals) in the previous year (i.e., lagged values) explain the likelihood of switching. The control variables in the model are fully discussed in Appendix 1. The *p-values* are presented in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	Improve		Maintain		Decline	
	(1)	(2)	(3)	(4)	(5)	(6)
RDI	0.625***		−0.023		−0.579***	
	(0.001)		(0.893)		(0.005)	
C. Accruals		−0.557***		0.344***		0.174
		(0.000)		(0.006)		(0.195)
TBQ	−0.206***	−0.196***	0.029**	0.036***	0.114***	0.110***
	(0.000)	(0.000)	(0.015)	(0.000)	(0.000)	(0.000)
LIQ	0.083	0.203*	−0.051	0.018	−0.013	−0.205*
	(0.573)	(0.052)	(0.710)	(0.857)	(0.929)	(0.053)
LEV	−0.014	−0.011	0.026	0.011	−0.024	−0.004
	(0.496)	(0.352)	(0.154)	(0.284)	(0.263)	(0.710)
SGW	−0.022	−0.010	−0.025	−0.014	0.051***	0.028*
	(0.301)	(0.552)	(0.212)	(0.368)	(0.010)	(0.065)
GRD	−0.040	−0.064*	0.066	0.017	−0.036	0.048
	(0.503)	(0.091)	(0.233)	(0.634)	(0.549)	(0.204)
IDD	−0.038	−0.015	0.079	0.056	−0.052	−0.052
	(0.594)	(0.701)	(0.242)	(0.135)	(0.464)	(0.197)
FCF	−0.344***	−0.519***	−0.021	0.262***	0.307***	0.198***
	(0.002)	(0.000)	(0.832)	(0.000)	(0.004)	(0.008)
TANG	0.026	−0.092	0.082	0.193**	−0.132	−0.127
	(0.884)	(0.301)	(0.619)	(0.021)	(0.458)	(0.159)
SIZE	−0.049***	−0.042***	0.057***	0.042***	−0.014	−0.002
	(0.001)	(0.000)	(0.000)	(0.000)	(0.332)	(0.829)
AGE	0.014	−0.036**	0.027	0.003	−0.051*	0.028
	(0.614)	(0.038)	(0.286)	(0.839)	(0.061)	(0.112)
HHI	−0.189	0.007	0.662**	0.468***	−0.447	−0.462***
	(0.571)	(0.965)	(0.042)	(0.005)	(0.190)	(0.007)
BLOC	−0.058	−0.142*	−0.059	0.026	0.097	0.097
	(0.631)	(0.064)	(0.595)	(0.717)	(0.429)	(0.223)
Constant	0.181	0.517	−2.408*	−2.102***	−0.136	−0.556
	(0.857)	(0.280)	(0.052)	(0.000)	(0.894)	(0.248)
Obs.	8636	21,593	8647	21,593	8638	21,586
Industry	YES	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES

Table 10
Impact of switching on takeover likelihood.

The table reports logit regressions results on the impact of switching on takeover likelihood (*Target*) across the four attributes (1) *poor,* (2) *myopia,* (3) *hyperopia* and (4) *efficient*. The dependent variable (*Target*) takes a value of one if a firm receives a bid, and a value of zero otherwise. *Improve* indicates a switch from a lower to a higher attribute from one year to the next e.g., a switch from (1) *poor* to (2) *myopia*, and so forth. *Decline* indicates a switch from a higher to a lower attribute. *Maintain* indicates no switch. In models (1) and (2), for example, we explore how the takeover likelihood for firms classified as poor changes if they switch (or not) from one attribute to the next. The control variables in the models are fully discussed in Appendix 1. The *p-values* are presented in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	Poor firms		Myopic firms			Hyperopic firms			Efficient firms	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Decline			0.207			0.100			0.425***	
			(0.133)			(0.440)			(0.000)	
Maintain	0.200*			0.335***			−0.315**			−0.411***
	(0.097)			(0.000)			(0.035)			(0.000)
Improve		−0.192			−0.388***			0.236		
		(0.111)			(0.000)			(0.136)		
TBQ	0.018	0.018	−0.101**	−0.114**	−0.115***	−0.015	−0.017	−0.015	−0.039	−0.038
	(0.605)	(0.600)	(0.020)	(0.011)	(0.010)	(0.621)	(0.576)	(0.625)	(0.171)	(0.179)
LIQ	0.461	0.461	0.102	0.187	0.200	−0.496	−0.464	−0.481	−0.353	−0.354
	(0.139)	(0.139)	(0.746)	(0.553)	(0.525)	(0.173)	(0.203)	(0.188)	(0.225)	(0.225)
LEV	0.029	0.030	0.040*	0.039*	0.038*	0.009	0.009	0.010	0.053**	0.053**
	(0.415)	(0.414)	(0.069)	(0.077)	(0.086)	(0.837)	(0.847)	(0.821)	(0.022)	(0.022)
SGW	0.024	0.024	−0.017	−0.024	−0.022	0.019	0.018	0.019	−0.030	−0.030
	(0.447)	(0.447)	(0.726)	(0.630)	(0.649)	(0.574)	(0.600)	(0.577)	(0.464)	(0.465)
GRD	0.015	0.015	−0.031	−0.048	−0.040	−0.097	−0.099	−0.101	0.094	0.095
	(0.914)	(0.913)	(0.743)	(0.616)	(0.673)	(0.535)	(0.527)	(0.521)	(0.267)	(0.262)
IDD	−0.572***	−0.574***	−0.259***	−0.251***	−0.251***	−0.079	−0.076	−0.070	−0.342***	−0.346***
	(0.000)	(0.000)	(0.003)	(0.004)	(0.004)	(0.587)	(0.603)	(0.632)	(0.000)	(0.000)
FCF	0.312	0.311	0.008	−0.084	0.038	−0.067	−0.116	−0.147	0.645*	0.631*
	(0.201)	(0.203)	(0.980)	(0.774)	(0.898)	(0.800)	(0.658)	(0.574)	(0.054)	(0.059)
TANG	0.852***	0.853***	0.655***	0.626***	0.644***	0.888***	0.920***	0.880***	0.240	0.242
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.114)	(0.112)
SIZE	0.158***	0.158***	0.049**	0.043**	0.046**	0.133***	0.133***	0.137***	0.092***	0.092***
	(0.000)	(0.000)	(0.022)	(0.044)	(0.029)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
AGE	−0.098*	−0.098*	−0.115***	−0.114***	−0.114***	−0.088	−0.088	−0.093	−0.142***	−0.142***
	(0.087)	(0.087)	(0.001)	(0.002)	(0.002)	(0.147)	(0.145)	(0.125)	(0.000)	(0.000)
HHI	−3.531***	−3.537***	−2.535***	−2.442***	−2.427***	−3.658***	−3.660***	−3.579***	−2.196***	−2.208***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
BLOC	0.234	0.235	0.178**	0.146*	0.162*	0.204	0.193	0.201	0.220***	0.222***
	(0.127)	(0.127)	(0.037)	(0.087)	(0.057)	(0.223)	(0.250)	(0.229)	(0.007)	(0.007)
RUM	0.775	0.773	0.638**	0.677**	0.679**	0.426	0.412	0.368	0.208	0.210
	(0.154)	(0.155)	(0.016)	(0.011)	(0.011)	(0.592)	(0.604)	(0.643)	(0.548)	(0.544)
TVOL	0.055	0.055	0.085	0.091	0.095	0.309*	0.318*	0.293	−0.112	−0.112
	(0.788)	(0.791)	(0.459)	(0.431)	(0.412)	(0.091)	(0.081)	(0.110)	(0.305)	(0.305)
SENT	0.110	0.109	0.739***	0.647***	0.616**	−0.036	0.011	−0.002	0.243	0.243
	(0.783)	(0.784)	(0.002)	(0.008)	(0.011)	(0.937)	(0.980)	(0.997)	(0.259)	(0.259)
Constant	−4.703***	−4.511***	−2.607***	−2.594***	−2.342***	−4.450***	−4.327***	−4.512***	−3.618***	−3.204***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Industry	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Obs.	3611	3611	7781	7781	7781	3675	3675	3675	9456	9456

categories. If our categories simply proxy for valuation, then we would expect that HE firms should have significantly higher MTB and TBQ when compared to their PM counterparts. On the contrary, we find that the mean and median MTB of PM firms are higher than those of HE firms. As shown in Table 12 (panel A), the mean (median) MTB of PM is 1.727 (1.043), while the mean (median) MTB of HE is 1.694 (0.991). The difference in mean MTB (0.033) is not statistically significant (*p-value* of 0.205), while the difference in median MTB (0.053) is statistically significant (*p-value* of 0.000). The results are similar when we use TBQ as a proxy for valuation. The mean (median) TBQ for PM firms is 2.064 (1.433) as compared to 1.887 (1.318) for HE firms. Here, the differences in mean and median TBQ are both statistically significant at the 1% level (*p-value* of 0.000). The results suggest that *poor* and *myopic* firms have relatively higher valuations than their *hyperopic* and *efficient* counterparts.

We further explore these results in a multivariate setting where we control for other firm variables. Here, we generate a dummy variable (PM_HE) which takes a value of one if a firm is in the HE category (i.e., *hyperopic* and *efficient* firms) and a value of zero if the firm is in the PM category (i.e., *poor* and *myopic* firms). We run panel fixed effects regression models where the dependent variables are MTB (models 1 and 2) and TBQ (models 3 and 4) and the main independent variable is PM_HE. The model controls for other firm characteristics.

We find that as PM_HE increases by one unit (i.e., a move from PM to HE), other things remaining equal, MTB reduces by about 27.3% (model 2) and TBQ reduces by about 33.0% (model 4). The coefficient of PM_HE is negative and significant at the 1% level in all models. Consistent with findings from panel A, the results suggest that firms in the PM category have relatively higher valuations. Hence, it is unlikely that our categories and results capture valuation. Our findings that PM

Table 11
Determinants of bid likelihood.

The table shows panel logit regression summary results for models which predict firm takeover likelihood as a function of firm financial characteristics. The model is adapted from Eq. (10), specified as follows:

$$\Pr[Bidder_{it} = 1] = F(\alpha + \beta * Performance_{it-1} + \gamma * Controls_{it-1} + \varepsilon_{it}) \quad (10)$$

Here, the dependent variable *(Bidder)* takes a value of one if a firm (*i*) initiates a takeover bid for control in a period (*t*) and a value of zero otherwise. *Poor, myopia, hyperopia* and *efficient* are used as proxies of *performance* in models (1) to (4) (see Fig. 1 for full definitions of these proxies). For conciseness, only the coefficient of the main independent variable (*performance*) and its *p-value* are presented. The control variables (suppressed from each model) are fully discussed in Appendix 1. These include Tobin's Q (TBQ), liquidity (LIQ), leverage (LEV), sales growth (SGW), growth-resource mismatch dummy (GRD), industry disturbance dummy (IDD), free cash flow (FCF), tangible assets (TANG), firm size (SIZE), firm age (AGE), industry concentration (HHI) and block holders dummy (BLOC). The *p-values* for model coefficients are presented in parenthesis. ***, **, * indicate statistical significance at the 1%, 5% and 10% level of significance, respectively.

	Poor	Myopia	Hyperopia	Efficient
	(1)	(2)	(3)	(4)
Poor	−0.253**			
	(0.044)			
Myopia		0.029		
		(0.690)		
Hyperopia			0.190*	
			(0.089)	
Efficient				−0.017
				(0.814)
Industry	YES	YES	YES	YES
Year	YES	YES	YES	YES
Obs.	8222	8222	8222	8222
Firms	604	604	604	604

firms have relatively higher valuations but lower abnormal returns is consistent with the value versus growth puzzle (Fama & French, 1998), i.e., high MTB firms or growth firms (in this case PM firms) earn lower returns than low MTB firms or value firms (in this case HE firms).

An alternative way of ruling out the valuation argument is to explore whether our results hold when we use MTB in place of AAR in deriving our four categories. If our results simply capture valuation, we expect to obtain similar or stronger results if using MTB rather than AAR to classify firms into the four categories, then explore whether this classification affects takeover likelihood. Our findings are presented in Table 13. Here, we suppress the coefficients of control variables to save space. We do not find that our results are supported when we use MTB rather than AAR to categorise firms; while the signs are consistent with our main results, the coefficients are no longer statistically significant. This conclusion does not change when we use TBQ in place of MTB. This further suggests that our results are not driven by misvaluation.

The findings in this study are robust to a number of methodological choices and endogeneity issues. We have discussed these issues alongside our results. We provide a brief summary here. First, we recognise that alternative proxies for accounting and stock market performance have been used in the literature. In our robustness checks we have explored alternative measures of accounting performance, including operating profit margin (OPM), return on assets (ROA) and return on equity (ROE). In our main analysis, we compute AAR using the market model. In robustness checks, we have also used the single-index model, where we assume each firm has an alpha of 0 and a beta of 1. Our results remain qualitatively similar. Second, in arriving at our categories, we identify industry groups using the two-digit SIC codes, which is consistent with the literature (Botsari & Meeks, 2008; Cohen & Zarowin, 2010). We have explored alternative industry definitions, including three- and four-digit SIC codes. When using these alternatives, we obtain more extreme values and encounter several missing values, particularly when computing discretionary accruals using cross-sectional regressions (across industry-year subgroups). Nonetheless, our main results remain qualitatively robust. Finally, given that financial variables are skewed (see Table 1), we use industry medians as the benchmark to classify firms into our categories. We have explored industry means as an alternative, and the results remain robust. These additional results are available upon request.

Table 12
Firm valuation versus management performance.

This table explores whether the categories of management performance proxy for valuation, i.e., whether *poor* and *myopic* firms (PM) are low valuation (undervalued) firms, while *hyperopic* and *efficient* firms (HE) are high valuation (overvalued) firms. Panel A presents differences of mean and median market to book (MTB) values and Tobin's Q (TBQ) of two groups: PM (*poor* and *myopic* firms) versus HE (*hyperopic* and *efficient* firms). Panel B presents results for panel fixed effects regressions where the dependent variable is MTB (models 1 and 2) and TBQ (models 3 and 4). The main independent variable is PM_HE, a dummy variable which takes a value of one if a firm is classified as *hyperopic* or *efficient*, and a value of zero if the firm is classified as *poor* or *myopic*. Models 1 and 3 have no additional control variables. Models 2 and 4 control for liquidity (LIQ), leverage (LEV), sales growth (SGW), free cash flow (FCF), tangible fixed assets (TANG), firm size (SIZE), firm age (AGE), industry concentration (HHI) and the presence of block holders (BLOC). The coefficients of control variables in models 2 and 4 are suppressed to save space. All variables are fully defined in Appendix 1. The *p-values* for model coefficients are presented in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level of significance, respectively.

	Panel A: difference in means and medians			
	Poor and myopia (PM)	Hyperopia and efficient (HE)	Difference (HE-PM)	(*p-value*)
Mean MTB	1.727	1.694	−0.033	(0.205)
Median MTB	1.044	0.991	−0.053***	(0.000)
Mean TBQ	2.064	1.888	−0.176***	(0.000)
Median TBQ	1.433	1.318	−0.115***	(0.000)

	Panel B: panel regression			
	MTB		TBQ	
	(1)	(2)	(3)	(4)
PM_HE	−0.115***	−0.274***	−0.183***	−0.331***
	(0.000)	(0.000)	(0.000)	(0.000)
Controls	NO	YES	NO	YES
Constant	1.772***	10.044***	2.068***	11.853***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	35,034	24,356	35,963	25,113
R-squared	0.001	0.082	0.003	0.152
Fixed effects	YES	YES	YES	YES
Firms	3204	2858	3391	2995

5. Summary and conclusion

Performance, in the context of firms and their managers, is perhaps one of the most studied issues in accounting, corporate finance and business management research. Nonetheless, there is no comprehensive framework for assessing performance. Different studies use different

Table 13
Valuation, accounting performance and takeover likelihood.

The table reports results from panel fixed effects logit models (Eq. (10)) estimating a firm's takeover likelihood as a logit function of firm characteristics.

$\Pr[Target_{it} = 1] = F(\alpha + \beta * Performance_{it-1} + \gamma * Controls_{it-1} + \varepsilon_{it})$ (10)

Here, the dependent variable (*Target*) takes a value of one if a firm (*i*) is the subject of a takeover bid for control in a period (*t*), and a value of zero otherwise. We use MTB values (in place of AAR) and ROCE to classify firms in four categories: *poor*, *myopia*, *hyperopia* and *efficient*. See Fig. 1 for details on the classification procedure. We use the measures derived using MTB as our main independent variable. The control variables in the model are fully discussed in Appendix 1 and include measures of liquidity (LIQ), leverage (LEV), sales growth (SGW), growth-resource mismatch dummy (GRD), industry disturbance dummy (IDD), free cash flow (FCF), proportion of tangible assets (TANG), firm size (SIZE), firm age (AGE), Herfindahl-Hirschman Index (HHI), block holders dummy (BLOC), a rumour dummy (RUM), trading volume (TVOL) and market sentiment (SENT). The coefficients of control variables are suppressed to save space. The *p-values* for model coefficients are presented in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level of significance, respectively.

	(1)	(2)	(3)	(4)
Poor	0.109 (0.109)			
Myopia		0.048 (0.511)		
Hyperopia			−0.041 (0.536)	
Efficient				−0.084 (0.166)
Controls	YES	YES	YES	YES
Obs.	14,185	14,185	14,185	14,185
Firms	1595	1595	1595	1595

measures, ranging from accounting (e.g., ROA, ROE, ROCE) and stock market (e.g., abnormal returns such as AAR) to hybrid measures (e.g., MTB or Tobin's Q). In this study, we argue that these measures are complements rather than substitutes, and this is supported by our finding that, in a UK sample of listed firms from 1988 to 2017, the correlation coefficient (rho) between ROCE and AAR is −0.05. It is widely agreed that accounting measures capture historical performance (e.g., over the last year), while market measures are forward looking. Assuming that these measures (accounting and market) are complements rather than substitutes, we use simple combinations to develop a performance assessment framework, which suggests that *myopia* and *hyperopia* are additional distinct attributes of management performance besides the classic attributes of *efficient* and *poor* management. We show how simple accounting and market variables can be used to operationalise these four attributes. To validate the framework, we draw on prior literature suggesting that myopic firms are associated with declines in R&D investments (a strategy for real earnings management), as well as positive discretionary accruals (accrual earnings management). We show that firms subject to *myopia* (*hyperopia*), as per our framework, are substantially more likely to cut (grow) R&D investments in the following period. We also show that *myopic* (*hyperopic*) firms are associated with significant positive (negative) discretionary accruals. We use this new calibration to re-examine a contentious issue—the inefficient management hypothesis of takeovers.

Prior studies using either accounting or market-based measures of performance provide inconsistent results with regard to whether the inefficient management hypothesis of takeovers holds (with takeover probability *decreasing* with market performance but *increasing* with the level of accounting earnings). Our framework, combining accounting and market-based measures of performance to identify management quality, resolves this conundrum. Consistent with the inefficient management hypothesis, the results reveal that management teams that underperform in terms of both accounting profitability and stock market performance are susceptible to takeovers. However, management teams that focus on short-term profits at the expense of long-term shareholder value (*myopia*) are even more likely to be disciplined by the takeover market. Management teams that focus on long-term value creation, even at the expense of short-term profitability (*hyperopia*), are not disciplined by the takeover market. We also find that well-performing management teams are least susceptible to takeovers. Additionally, we explore the extent to which firms switch from one attribute to the other, and how this impacts their takeover likelihood. Here, we find that firms that switch from underperforming to outperforming categories face lower levels of takeover risk and vice versa. Further, firms in underperforming categories that do not switch up face higher takeover risks, but their counterparts in outperforming categories that do not switch down experience lower takeover risks. Finally, we explore whether bidders play an important role in enforcing market discipline. We do not find evidence that bidders are myopic. Indeed, we find that firms we classify as *hyperopia* and *efficient* are more likely to initiate takeover deals than their *poor* and *myopia* counterparts. These results provide new insights on the disciplinary role of the takeover market.

Our findings have implications for the notion of management or firm performance. Our results suggest that performance, at least in the context of M&As, is better understood as a *multidimensional construct*, with *poor*, *myopia*, *hyperopia* and *efficient* representing four distinct attributes of performance. In practice, such a multidimensional framework for assessing performance could be useful in the design of optimal managerial reward systems or contracts. It also provides a simple tool for identifying firms that are most likely and least likely to manage earnings. In research, several studies have explored how different variables or strategic choices (e.g., corporate governance, capital or ownership structure, corporate social responsibility, diversification, executive compensation, etc.) influence firm performance across different contexts. A shift from a univariate to a multivariate framework for measuring performance opens up new avenues to revisit and rethink these research issues.

The study also, perhaps, has implications for the pervasive “earnings game”, in which managers fixate on short-term earnings targets even at the expense of long-term value creation. The results suggest that if managers achieve such targets by sacrificing long-term value-generating projects, they may be doing so at their own peril—increasing the probability of their firm becoming a takeover target.

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Appendix 1. Variables in the regression models

Prediction hypotheses	Rationale for use in takeover likelihood modelling	Proxy (sign) & DataStream codes	Relevant references
Misvaluation	Bidders seek to profit from takeovers by buying undervalued targets for cash at a price below fundamental value, or by paying equity for targets that, even if overvalued, are less overvalued than the bidder.	***Tobin's Q*** TBQ (−): Market value of assets (MVA) to replacement cost of assets (RCA), where MVA is the sum of book value of debt (BVD) and market value of equity (MVE). BVD is total assets (WC02999) minus shareholder equity (WC03995). MVE is number of shares outstanding (NOSH) multiplied by share price in pounds (UP/100). RCA is proxied by the book value of total assets (WC02999). ***Market to book value*** In additional tests, we have used the market to book (MTB) value as an alternative proxy. It is defined as market value of equity (MVE) divided by book value of equity (WC02999-WC03255).	Danbolt et al. (2016); Dong et al. (2006).
Growth-resource mismatch (Sales growth, Liquidity and Leverage)	Takeovers are pursued to generate synergies by correcting for mismatches between a firm's growth opportunities (measured by sales growth) and its available resources (measured by the firm's leverage versus liquidity positions). As in Palepu (1986), four variables are used to proxy this hypothesis.	***Liquidity*** LIQ (±): Cash and short-term investments (WC02001) to total assets (WC02999). ***Leverage*** LEV (±): Total debt (WC03255) to total assets (WC02999). ***Sales growth*** SGW (±): Change in total revenues (WC01001) as a ratio of previous year's total revenues (WC01001). ***Growth-Resource dummy*** GRD (+): Dummy that takes a value of one if a firm has high growth and low resources or vice versa, and a value of zero otherwise.	Palepu (1986).
Industry disturbance	A firm's takeover likelihood will increase with the announcement of a merger bid in that industry, as other industry players seek to consolidate in order to compete effectively.	***Industry disturbance dummy*** IDD (+): Dummy is one if any merger is completed within a firm's two-digit SIC industry in the year prior to the bid, and a value of zero otherwise.	Palepu (1986).
Free cash flow	Management which hoards or misappropriates excess free cash flows are likely to face a challenge for corporate control. Besides the opportunity to correct management inefficiency, the bidding firm is attracted by the excess free cash flow in the target firm, as this free cash flow can be used to reduce the net cost of acquisition.	***Free cash flow*** FCF (+): Ratio of net cash flow from operating activities (WC04860) minus capital expenditures (WC04601) scaled by total assets (WC02999).	Powell and Yawson (2007); Powell (1997).
Real property	Tangible fixed assets proxy for debt capacity and provide financial slack to enable a firm to raise debt capital in times of need. These assets can reduce a bidder's implicit takeover cost as they can be divested to raise finance needed to complete the transaction.	***Tangible assets*** TANG (+): Ratio of property, plant and equipment (WC02501) to total assets (WC02999).	Powell (1997); Ambrose and Megginson (1992).
Firm size	Several size-related transaction costs are associated with acquiring a target and, therefore, the number of viable bidders for a target decreases as its size increases.	***Size*** SIZE (−): Natural log of total assets (WC02999).	Powell (1997); Powell and Yawson (2007).
Firm age	Firm endowments are generally low when firms are born, but increase over time as firms invest in research and development. Older firms are more endowed and knowledgeable about themselves. Hence, the probability of firm survival (takeover) within an industry increases (decreases) as firms grow older.	***Firm age*** AGE (+): Number of years since date of incorporation (WC18273)	Pakes and Ericson (1998); Agarwal and Gort (2002); Bhattacharjee, Higson, Holly, and Kattuman (2009).
Industry concentration	Competition in product markets (i.e., low industry concentration) is especially costly for inefficiently managed firms as it leads to their elimination, possibly through takeovers.	***Herfindahl-Hirschman index*** HHI (−): Sum of the squared market shares derived from total revenues (WC01001) of all listed firms in the two-digit SIC industry.	Danbolt et al. (2016); Powell and Yawson (2007).
Block holders	The presence of large shareholders facilitates takeovers as they can reduce the bidder's takeover costs by splitting the gains on their own shares with the bidder.	***Presence of block holders*** BLOC (+): Dummy is one if a firm has a significant (i.e., at least 5%) strategic shareholder (NOSHST), and zero otherwise.	Cremers et al. (2009).
Merger rumours	Several takeovers are preceded by M&A rumours.	***Rumours*** RUM (+): Dummy is one if a firm is a rumoured target in a specific year (as recorded in Thomson One), and zero otherwise.	Danbolt et al. (2016)

Price momentum and trading volume	Market anticipation and merger rumours can lead to active trading in firms with a high likelihood of receiving takeover bids. Active trading is evident through price momentum (rapid increase in share prices over a short space of time) and an increase in the volume of shares traded.	***Price momentum*** MOM (+): t-statistic of the trend line on daily share prices (UP) for the 90 days leading up to June 30 each year.	Brar et al. (2009); Danbolt et al. (2016)
		Trading volume TVOL (+): Total number of shares traded daily (VO) in the 90 days leading up to June 30 each year as a ratio of the shares outstanding (NOSH).	
Market sentiment	Market conditions shape the timing of acquisitions. Takeovers are more likely to be initiated in periods of overall market growth.	***Market sentiment*** SENT (+): Dummy is one if FTSE All-Share index (RI) reports a positive return in the year, and zero otherwise.	Brar et al. (2009); Danbolt et al. (2016)

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