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Takeover Vulnerability and Pre-Emptive Earnings Management

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Abstract We explore whether firms that are vulnerable to takeovers pre-emptively manage earnings in anticipation of such events. We find a positive relationship between firms' vulnerability to takeovers and their propensity to manage earnings, mainly through the manipulation of real activities. We consider two motivations for firms' pre-emptive earnings management behavior; (1) to deter future takeovers and (2) to optimize M&A outcomes. Concerning the former, we document evidence consistent with entrenched managers using real earnings management to deter or delay future takeovers. Concerning the latter, we find evidence suggesting that, contingent on receiving takeover bids, vulnerable firms that pre-emptively manipulate real activities extract comparatively higher merger premiums. Overall, our findings suggest that managers of vulnerable firms pre-emptively manage earnings to purposefully delay the timing and optimize the outcomes of prospective takeovers.

Keywords: Takeovers; Takeover vulnerability; Earnings management; Takeover deterrent; Merger premiums

1. Introduction

The press frequently alludes to managers' awareness of their firms' vulnerability to potential takeovers. For example, in a media interview, the CEO of Infineon, Reinhard Ploss noted the following;

> There is one risk [takeover]: we are busy in highly attractive markets. That is a strength, but maybe we should be aware that people [acquirers] might be interested in Infineon [target] because of that market position.
>
> The Financial Times, 31 August 2015

How do managers react to this threat of takeovers? While takeovers might benefit target shareholders (Danbolt et al., 2016), target managers often lose their jobs and pecuniary benefits (Mikkelson & Partch, 1997). Hence, when faced with takeover threats, managers might take pre-emptive measures such as engaging in open market share repurchases (Billett & Xue, 2007), increasing dividend payout (Driver et al., 2020), adopting golden parachutes

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(Buchholtz & Ribbens, 1994), and selling their firms' crown jewels (Billett & Xue, 2007), amongst others, to protect their interest or optimize their shareholders' outcomes.[1]

Even though earnings management (EM) is costly and risky (Cohen & Zarowin, 2010; Graham et al., 2005; Kim et al., 2020; Kothari et al., 2016),[2] prior research suggests that managers engage in real activities manipulation (REM) and accruals EM (AEM) ahead of major *scheduled* corporate events such as seasoned equity offerings (SEOs) (Cohen & Zarowin, 2010), initial public offerings (IPOs) (Teoh et al., 1998), management buyouts (Botsari & Meeks, 2008) and stock-financed mergers (Erickson & Wang, 1999; Higgins, 2013). Several studies exploring EM around takeovers focus on acquiring managers' opportunistic EM behavior (see, Botsari & Meeks, 2008; Erickson & Wang, 1999; Higgins, 2013; Mao & Renneboog, 2015, among others).[3] While a few studies show that managers reduce EM activities following the enactment of takeover protection regulation (Ge & Kim, 2014; Sul, 2020; Zhao & Chen, 2008; Zhao et al., 2012), it is still unclear whether managers *pre-emptively* engage in EM in anticipation of takeovers and how such pre-emptive EM affect takeover outcomes.

Building on extant research, we contend that managers might seek to thwart impending takeovers or optimize outcomes of subsequent M&As (e.g., the premium paid by the acquirer) by managing earnings upwards and, consequently, driving up their firms' stock price. Indeed, EM might have some advantages over other strategies such as increasing dividend payouts, repurchasing shares or selling off crown jewels, particularly in institutional settings wherein the use of defensive strategies and frustrating actions are frowned upon.[4] Notably, in contrast to the other tactics, EM is potentially stealthy, reversible, not under the jurisdiction of any regulation and can pass off for operational strategy instead of outright fraud or frustrating actions. Against this background, we, therefore, investigate whether managers engage in EM in response to takeover threats and whether such EM (if it indeed exists), (1) deters future takeovers or (2) optimizes M&A outcomes. Throughout our study, we refer to this type of EM as 'pre-emptive EM' to reflect its cause (as a response to firms' vulnerability to takeovers) and purpose (as a tactic to deter or delay takeovers or optimize M&A outcomes).

Our empirical analysis employs a large sample of 1208 takeover deals involving UK publicly listed targets matched to a set of firms listed on the London Stock Exchange between 1987 and 2016 (i.e., 2933 unique firms with over 24,454 firm-year observations). Our focus on UK firms is significant for the following reasons. First, although the UK has the second most active market for corporate control after the US (Agyei-Boapeah et al., 2019), embedded takeover defences such as poison pills and staggered boards that characterize the US market are non-existent. Second, listing regulations, Companies law and corporate governance regulations prevent listed UK firms from pursuing frustrating actions. Thus, to the extent that EM could serve as a viable response to external takeover threats, we expect the relationship between EM and target firms' M&A exposure to be stronger in the UK compared to the US market.

We document several novel findings and, in the process, contribute to various strands of the EM and M&A literature. Firstly, we find a positive relationship between vulnerability

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[1] Billett & Xue discuss the case of Sears, Roebuck & Co. reported in The Wall Street Journal (WSJ) (1988). Sears took aggressive actions, including repurchasing shares and selling its corporate headquarters, which was then the World's tallest building (a crown jewel) after it was rumored to be a target of an impending takeover.

[2] While any benefits from EM are likely to be transitory (Cohen & Zarowin, 2010; Gunny, 2010; Kothari et al., 2016), REM, in particular, might have long-lasting adverse effects on future cash flows (Graham et al., 2005).

[3] These studies assume that, because acquirers initiate M&As, they can purposefully manage earnings before making a bid. However, takeover targets, being the recipient of bids, are often unaware of their timing and hence have limited opportunities to manage earnings before a bid announcement (Erickson & Wang, 1999).

[4] See, for example, Rule 21 of the UK Takeover Code on restrictions on frustrating action.

to takeovers and EM in the ensuing period. Vulnerable firms manage earnings upwards by mainly employing REM strategies, specifically, overproduction and aggressive reduction of discretionary expenses. Further, vulnerable firms use REM and AEM as complements rather than as substitutes, with their use of AEM increasing when takeovers become more imminent. This suggests that vulnerable firms generally deploy during-the-year REM in the first instance, then, if necessary, complement this with year-end AEM to address any shortfalls. This finding contributes to the EM literature by showing that firms manage earnings pre-emptively when faced with takeover threats. It complements prior studies documenting EM behavior ahead of scheduled events (e.g., IPOs, SEOs and management buyouts) (Cohen & Zarowin, 2010; Mao & Renneboog, 2015; Teoh et al., 1998) and around takeover protection regulation (Ge & Kim, 2014; Sul, 2020; Zhao & Chen, 2008; Zhao et al., 2012). It contributes to the M&A literature by documenting EM in target firms before takeovers.[5]

Secondly, we explore the consequences of firms' pre-emptive EM behavior. Specifically, we examine whether pre-emptive EM can enable potential targets to (i) deter takeovers, and (ii) extract higher premiums from subsequent merger deals. Concerning the former, we find evidence suggesting that pre-emptive REM, when underlined by agency problems, potentially reduces the likelihood that perpetrating firms will receive takeover bids. These results are broadly consistent with the extant studies showing that vulnerable firms use different strategies to mitigate their takeover risk (Billett & Xue, 2007; Buchholtz & Ribbens, 1994; Driver et al., 2020). Our work, therefore, contributes to this strand of the literature by highlighting the takeover deterrent effect of EM.

Finally, we uncover evidence suggesting that, contingent on receiving bids, firms that pre-emptively manage earnings extract comparatively higher bid premiums from would-be acquirers. This finding is in line with the signaling theory and contributes to the debate on whether firms manage earnings for opportunistic (Roychowdhury, 2006) or signaling reasons (Gunny, 2010). Prior studies show that the stock market systematically reacts positively to EM (Botsari & Meeks, 2008; Cohen & Zarowin, 2010; Erickson & Wang, 1999; Mao & Renneboog, 2015; Teoh et al., 1998), suggesting that EM has a signaling value. However, these studies also find that this positive reaction is only transitory, as firms generally experience a reversal in the medium to long term (Cohen & Zarowin, 2010; Gunny, 2010; Kothari et al., 2016). To the extent that stock markets are efficient, these findings, perhaps, obfuscate inferences on whether opportunistic or signaling motives underline EM. Our research design enables us to focus on another source of information besides the stock market – acquiring managers – and eliminates the need to explore potential reversals in the medium to long term. Within this context, we find evidence consistent with managers using EM for both opportunistic (i.e., to deter or delay takeovers) and signaling reasons (to optimize merger premiums). Collectively, our findings have important policy and managerial implications as they highlight the signaling role of EM and its use by managers to maximize value for their shareholders when faced with takeover threats.

The rest of the paper is organized as follows. Section 2 discusses the prior literature. Section 3 discusses the data and empirical models. Our results are discussed in Section 4, and concluding remarks are presented in Section 5.

[5]Contrary to Anagnostopoulou and Tsekrekos (2013, 2015), who find evidence that 'seeking-buyer' firms manage earnings (AEM) downwards before takeovers, we document evidence of upwards EM (REM) in vulnerable firms. Moreover, in contrast to these studies, we provide more generalizable evidence from a large panel dataset.

2. Related Literature and Hypotheses

2.1. Earnings Management Strategies and Motives

EM involves the exercise of judgment in financial reporting or operating activities to alter financial reports to either mislead some stakeholders about firms' underlying economic performance or influence contractual outcomes that depend on these financial reports (Roychowdhury, 2006). Drawing from an agency theory perspective, several studies show that firms engage in opportunistic EM to meet or beat targets and thus, promote managerial interests (Graham et al., 2005; Roychowdhury, 2006). From a signaling perspective, other studies suggest that managers use EM activities to signal private information, which benefits investors (Subramanyam, 1996). More recently, the debate has focused on specific EM (AEM and REM) strategies used by firms and how these strategies influence different firm outcomes (Cohen & Zarowin, 2010; Gunny, 2010; Roychowdhury, 2006; Zang, 2012). While AEM involves the use of managerial discretion in the choice and application of accounting methods (Dechow et al., 1995; Jones, 1991), REM involves the manipulation of real transactions and business activities to distort reported earnings (Graham et al., 2006; Gunny, 2010; Roychowdhury, 2006).[6]

With tighter accounting and governance regulations, AEM, particularly the use of aggressive accounting choices, has become easily detectable, thus opening perpetrating firms to severe scrutiny (Cohen et al., 2008; Gunny, 2010). Also, the applicability of AEM is constrained by the nature of business operations and AEM activity in previous years (Barton & Simko, 2002; Cohen & Zarowin, 2010). Importantly, AEM occurs at year-end, leaving managers uncertain about what financial reports will show (Gunny, 2010). On the other hand, REM is not under the purview of current auditing systems and is less subject to external scrutiny (Kim & Sohn, 2013). Given that REM, must take place before year-end (Zang, 2012), managers might be inclined to resort to year-end AEM only when opportunities for during-the-year REM have been exhausted.

While prior research suggests that REM might be relatively more costly (Cohen & Zarowin, 2010; Kothari et al., 2016), the evidence on the consequences of different EM strategies is mixed. For example, one stream of the literature contends that REM negatively impacts future cash flows, the cost of capital, bond ratings and hence, long term firm value (Graham et al., 2005; Kim & Sohn, 2013; Kim et al., 2020). In contrast, other studies (Cohen et al., 2008; Cohen & Zarowin, 2010; Kothari et al., 2016) show that stock markets respond positively to REM, at least over the short run.[7] We contribute to this ongoing debate by exploring EM choices in firms facing takeover threats.

2.2. Takeover Vulnerability and Earnings Management Behavior

The market for corporate control (henceforth, MCC) theory explains the firm-level drivers of takeover activity and provides evidence that managers can assess their exposure to future takeovers (Brar et al., 2009; Danbolt et al., 2016; Palepu, 1986; Tunyi & Ntim, 2016). It is plausible that managers take action when faced with such an external threat. Indeed, prior studies show that managers react to takeover threats by repurchasing shares and increasing dividend payout (Billett & Xue, 2007; Driver et al., 2020; Jenson, 1984). Here, we argue that managers

[6]REM could, for example, be achieved by curbing discretionary expenses such as R&D and selling, general and advertising expenditures (Cohen & Zarowin, 2010), overproduction to reduce the cost of goods sold (Roychowdhury, 2006), sale of profitable assets (Herrmann et al., 2003), timing securitization activities (Dechow & Shakespear, 2009) and deferring expenditures on essential maintenance and investments in new projects (Graham et al., 2006), amongst others.

[7]Consistent with a signaling motive of REM, Gunny (2010), for example, finds that REM allows firms to attain current-period benefits that, in turn, enable them to achieve improved future performance.

might also be inclined to manage earnings when exposed to takeovers threats, whether for agency or signaling reasons.

From an agency perspective, managers facing takeover threats might become short-termist and prioritize short-run gains over long-run business interests. From a signaling perspective, by seeking to drive-up share prices through EM, these managers might want to address the source of their heightened vulnerability to takeovers, e.g., underperformance or undervaluation (Danbolt et al., 2016; Palepu, 1986; Powell, 2001). The resulting increase in prices (Erickson & Wang, 1999; Higgins, 2013; Mao & Renneboog, 2015) might weaken a would-be acquirer's bargaining position, thereby discouraging takeover bids and reinforcing managerial entrenchment within prospective targets. In sum, vulnerable firms are likely to manage earnings upwards as EM potentially has direct consequences on the prospect and outcomes of any subsequent takeovers. Therefore, such EM is pre-emptive in nature, as it (1) precedes the event and (2) potentially allows managers to influence subsequent M&A outcomes. Our baseline hypothesis is stated as follows.

Hypotheses 1 (H1). Firms that are vulnerable to takeovers manage earnings in response i.e., pre-emptive earnings management.

Our second hypothesis (H2) examines the potential takeover deterrent effect of pre-emptive EM. The takeover market might enforce managerial discipline by allowing for the replacement of inefficient management teams (Jensen, 1986; Mikkelson & Partch, 1997). Besides the financial consequences, such replacements might have adverse effects on the reputation and future career prospects of the affected managers. Therefore, managers of vulnerable firms have an incentive to take actions that reduce their exposure to takeovers, particularly when motivated by agency (entrenchment) motives.

A spike in a prospective target's share price ahead of a takeover, even if temporary, can discourage or delay a deal by reducing the gains to the acquirer. Entrenched managers can seek to deter takeovers by using EM to temporarily drive up prices in order to discourage or delay impending takeovers and retain their status and pecuniary benefits. To the extent that EM acts as an ad-hoc takeover defence strategy, we might observe that vulnerable firms that manage earnings upwards are less likely to receive future bids in the short term, with the relationship stronger in firms with higher agency problems. We state our second hypothesis as follows.

Hypotheses 2 (H2). Pre-emptive earnings management, when perpetrated by entrenched managers, deters future takeovers.

Target shareholders enjoy significant windfalls or premiums from acquisitions (Danbolt et al., 2016). Hence, evidence in support of H2 will be consistent with managerial entrenchment through EM. However, an alternative view is that when defences are ineffective in blocking the takeover (e.g., by delaying takeovers), they serve the interest of shareholders by raising the bid premium (Brennan, 1999; Holl & Kyriazis, 1997; Kadyrzhanova & Rhodes-Kropf, 2011). Brennan (1999), for example, finds that voluntary profit forecast disclosures made by UK managers after receiving takeovers bids did not influence the outcome of the bid (i.e., failure or success) but allowed firms to secure a higher offer price. Nonetheless, Schoenberg and Thornton (2006) argue that reacting to takeover bids is ineffective as the capacity of management to use defensive measures to entrench themselves or boost the bid premium is limited once an offer has been received. This highlights the need for managers to be more proactive and pre-emptive in planning for future takeovers.

EM can potentially signal managers' private information about the availability of future growth opportunities (Bartov et al., 2002; Kasznik & McNichols, 2002), perhaps forcing a would-be acquirer to offer a higher premium in recognition of the firm's prospects. Prospective target firms can, therefore, optimize their M&A outcomes (e.g., M&A premium) by managing earnings upwards ahead of takeovers. Therefore, we focus on merger (offer) premiums as an important M&A outcome that captures the acquirer's assessment of the target. Our final hypothesis is stated as follows.

Hypotheses 3 (H3). Pre-emptive earnings management improves target firms' merger outcomes, specifically offer premiums.

2.3. Vulnerability and Earnings Management Choices

Firms generally deploy REM and AEM either as complements or substitutes (Achleitner et al., 2014; Zang, 2012). In our context, vulnerable firms seeking to pre-emptively manage earnings might prefer REM to AEM for several reasons. Firstly, because accounting discretion is limited, AEM cannot be pursued indefinitely in the same direction without reversing accruals brought forward from previous periods (Baber et al., 2011). Given uncertainties around the timing of takeovers, vulnerable firms might be reluctant to use AEM. Concerning H1, we might, thus, observe that vulnerable firms use more REM than AEM, perhaps, increasing the level of AEM when takeovers become more imminent.

Secondly, if managers achieve desired levels of EM through REM in the course of the year, then they may not need to engage in AEM at the end of the year (Zang, 2012). In this case, we will again find that our results for H1 are more robust for REM than AEM. Thirdly, vulnerable firms might particularly face greater auditor scrutiny because they might exhibit going-concern problems (e.g., sustained underperformance, falling share prices, amongst others) that heightens auditors' substantive procedures. Finally, to the extent that vulnerable firms manage earnings, in our test of H1, we might find more robust results for REM than AEM.

Fourthly, while AEM might be constrained and scrutinized (Cohen et al., 2008; Gunny, 2010), REM-type activities (e.g., reducing discretionary expenses, laying-off employees and delaying vital maintenance) can be reversed later on, albeit at a cost. Hence, concerning H1, we expect firms to use more REM than AEM when faced with takeover threats. Finally, any substantial pre-bid AEM is likely to be spotted by the acquirer during due diligence, thus potentially adversely impacting offered premiums. In our tests of H3, we might, therefore, observe a stronger relationship between levels of pre-bid REM and subsequent offer premiums.

3. Data and Methodology

3.1. Sample and Data

Our sample consists of 2,933 firms listed on the London Stock Exchange (main market) between 1987 and 2016. To mitigate survivorship bias, we include all firms (live and dead) that were listed over that period, only excluding financial firms (SIC code 60–69) due to their unique reporting practices (Botsari & Meeks, 2008). Following Boone et al. (2010), we also exclude all firms from 2-digit SIC code industry-years with less than ten observations to ensure that the coefficients of our industry-year cross-sectional EM regressions are robust.

The firm-level data used in this study is drawn from Thomson Eikon (Datastream). Firm-year observations with insufficient financial information are excluded from the sample. This screening process generates an unbalanced panel of 37,937 firm-year observations, for which we compute relevant variables. For any observation to be included in our final dataset, it must have the data required to estimate our key variable – vulnerability. Over 24,454 firm-year observations meet this criterion. We winsorise our continuous variables at the 1st and 99th percentiles to eliminate outliers.

Next, we collect M&A deal information from Thomson One. This includes details of the identity of targets and acquirers, offer premiums, method of payment, location of acquirers, whether the deal was hostile or friendly and whether other competing bids were received, amongst others. We focus on UK listed firms that are targets of takeovers announced between 1st July 1988 and 30th June 2018. Consistent with prior studies on takeover likelihood modeling (Danbolt et al., 2016; Powell, 2001), we restrict our M&A sample to bids which, if completed, will give the bidder control (over 50% shareholding in the target).[8]

Following prior UK studies (Danbolt et al., 2016; Tunyi et al., 2019), we recognize that most (UK) firms will only publish their financial results for the previous year ($t-1$) by the end of June in the current year (t). This implies that any bid announcements made between 1st July year (t) and 30th June year ($t+1$) can be attributed to financial results for year-end December year ($t-1$). We, therefore, match the data from the two databases (Thomson One and Datastream) using Datastream codes and bid announcement dates (month-year). In essence, we adjust for the 6-month lag (between the financial year-end and the release of financial reports) by considering the month and year of the announcement, when matching firm financial data to M&A announcements. Our matching strategy implies that we can only consider a maximum of one bid for each target in each year. For firms receiving multiple bids within a year, we retain only the deal with the highest deal value. Our final dataset consists of 1208 takeover deals involving UK publicly listed targets matched to an unbalanced panel data set of 2933 unique firms listed on the London Stock Exchange (Main market) between 1987 and 2016 (i.e., 24,454 firm-year observations). We use the final dataset to estimate our proxies for vulnerability and EM. We discuss the derivation of these variables below. Meanwhile, descriptive statistics of our main variables are provided in Table 1 and Appendix A1. provides full variable definitions.

3.2. Measure of Vulnerability to Takeovers

Prior research has established that a firm's takeover likelihood can reasonably be estimated ex-ante using only publicly available information (Cremers et al., 2009; Danbolt et al., 2016; Palepu, 1986; Tunyi et al., 2019). This suggests that firms are plausibly aware of their exposure to future takeovers and hence, as we hypothesize, might engage in pre-emptive EM. In line with the literature (Billett & Xue, 2007; Cremers et al., 2009; Danbolt et al., 2016; Palepu, 1986; Powell, 2001), our measure of vulnerability is a firm's takeover likelihood derived from its financial characteristics in the previous period. The use of a one-period lag allows us to mitigate look-ahead bias and partly address reverse causality concerns. Our base regression model is the logit model given as follows:

$$\textit{Takeover Likelihood}_{it} = \frac{1}{1 + e^{-Z_{it-1}}} \tag{1}$$

where $\textit{Takeover Likelihood}_{it}$ is the probability that firm i will receive a takeover bid in the current period (t), and Z_{it-1} is a vector of firm i's characteristics in the previous period ($t-1$). The dependent variable in Equation (1) is binary and takes the value of one if a firm (i) is the subject of a takeover bid in period t, and a value of zero otherwise.

Following the literature (Danbolt et al., 2016; Palepu, 1986; Powell, 2001; Tunyi, 2019; Tunyi et al., 2019), we populate our vector of firm characteristics (Z_{it-1}) using measures of abnormal returns, profitability, Tobin's q, sales growth, liquidity, leverage, growth-resource mismatch, industry disturbance, firm size, free cash flow, tangible assets, firm age and block holders to capture firm characteristics. These variables are fully defined in Appendix A1. For brevity, we

[8] As we do not analyze bidders in this study, the bidder can be public or private, as well as be a UK firm or a foreign firm.

Table 1. Descriptive statistics.

Variables	N (1)	Mean (2)	SD (3)	p25 (4)	p50 (5)	p75 (6)
Panel A: Main variables						
Target	24,454	0.049	0.217	0.000	0.000	0.000
Vulnerability	24,454	0.051	0.028	0.028	0.051	0.071
REM	21,928	0.004	0.503	– 0.174	0.025	0.236
REMprod	21,928	– 0.002	0.226	– 0.089	0.000	0.103
REMdisx	24,335	0.001	0.390	– 0.112	0.020	0.164
REMcfo	24,333	– 0.002	0.339	– 0.077	– 0.005	0.051
AEM	23,211	– 0.003	0.394	– 0.054	0.000	0.057
Premium	1115	43.767	38.091	21.210	37.860	58.900
Panel B: Control variables – Firm financial characteristics						
Abnormal returns	24,454	0.000	0.003	– 0.001	0.000	0.001
Profitability	24,454	0.006	0.284	– 0.029	0.070	0.134
Tobin's *q*	24,454	1.902	1.953	1.000	1.350	2.020
Market to book	24,454	1.601	2.146	0.560	0.987	1.766
Sales growth	24,454	0.266	0.977	– 0.036	0.075	0.240
Liquidity	24,454	0.151	0.181	0.030	0.085	0.196
Leverage	24,454	0.189	0.194	0.025	0.151	0.283
Debt issue	20,936	1.011	5.250	– 0.251	0.000	0.374
Growth-resource	24,454	0.151	0.358	0.000	0.000	0.000
Disturbance	24,454	0.729	0.445	0.000	1.000	1.000
Firm size	24,454	18.141	2.239	16.615	17.923	19.511
Free cash flow	24,454	– 0.035	0.236	– 0.057	0.018	0.070
Tangible assets	24,454	0.282	0.254	0.066	0.215	0.431
Firm age	24,454	2.339	1.034	1.609	2.398	3.296
Block holders	24,454	0.223	0.252	0.000	0.130	0.420
Z–Score	20,630	80.121	339.054	3.348	9.099	20.637
Net operating assets	24,264	1.740	6.032	0.255	0.499	1.075
Panel C: Control variables – Corporate governance characteristics						
Audit quality	24,454	0.027	0.158	0.000	0.001	0.005
Gender diversity	12,169	0.068	0.102	0.000	0.000	0.143
Board independence	12,169	0.384	0.226	0.250	0.429	0.556
Director experience	12,160	54.498	4.514	51.800	54.667	57.429
Board tenure	12,160	5.813	3.597	3.356	5.000	7.411
Audit committee	12,169	0.962	0.190	1.000	1.000	1.000
Panel D: Control variables – M&A characteristics						
Cash payment	1208	0.762	0.426	1.000	1.000	1.000
Crossborder	1208	0.288	0.453	0.000	0.000	1.000
Bid attitude	1208	0.913	0.282	1.000	1.000	1.000
Competing bids	1208	0.099	0.299	0.000	0.000	0.000
Diversifying bids	1208	0.563	0.496	0.000	1.000	1.000
Panel E: Other variables (including instruments)						
Merger intensity	17,819	1.092	0.920	0.000	1.099	1.792
Industry rumors	24,454	0.022	0.038	0.000	0.010	0.030
LTIP	13,388	0.073	0.106	0.000	0.000	0.135
Concentration	24,454	0.238	0.198	0.102	0.188	0.301
Sentiment	23,136	0.091	0.160	0.010	0.138	0.209

Note: The table presents the descriptive statistics for key variables used in the study. All continuous variables are winsorised at the 1st and 99th percentile to eliminate outliers. Full variable definitions are available in Appendix A1.

do not discuss the selection of these predictor variables in detail here, as these have been discussed at length in previous studies (Cremers et al., 2009; Danbolt et al., 2016; Palepu, 1986; Powell, 2001; Tunyi, 2021; Tunyi et al., 2019).

We estimate a firm's vulnerability to takeovers using a two-stage process. The first stage involves estimating coefficients of our takeover likelihood model (Equation (1)) using firm-level characteristics from one period ($t-1$) matched to an indicator variable for takeover bids in the next period (t). In the second stage, we use the derived coefficients and firm-level characteristics in period t to estimate a firm's likelihood of receiving a takeover bid in period $t+1$ conditional on observed characteristics in period t. We use a recursive approach (Danbolt et al., 2016) to estimate our sample firms' takeover likelihood in each year from 1995 to 2016. In essence, to start, we use data from the period 1987–1994 to generate model coefficients, which we deploy to estimate takeover likelihood for individual firms in 1995. We then expand the estimation window by one year and estimate takeover likelihood for firms in 1996 using coefficients generated using data from 1987–1995. We continue this recursive process until our data is exhausted. Finally, we use the estimated values of takeover likelihood for each firm at the start of each period as our measure of vulnerability for the current year.

3.3. Measures of Earnings Management

We focus on overproduction and the reduction of discretionary expenses as the primary channels for REM (Zang, 2012). Following prior studies (Zang, 2012), our measures of overproduction (REMprod) and abnormal discretionary expenses (REMdisx) are the residuals from the industry-year cross-sectional regressions modeling production costs and discretionary expenses using sales.[9] We compute a summary measure (REM) by summing our estimates of REMprod and REMdisx (Roychowdhury, 2006; Zang, 2012). The literature is ambiguous on the extent to which abnormal cash flows from operations (CFO) indicates REM.[10] For completeness, we include abnormal CFO, similarly estimated from sales, as a third channel. Our measure of AEM is discretionary accruals estimated as the residual from the modified-Jones model (Dechow et al., 1995). Here, total accruals is modeled as a function of property, plant and equipment and the difference between change in sales and change in receivables. For brevity, all our EM models are fully presented in Appendix A1 and further discussed in our online appendices.

4. Results and Discussions

4.1. Vulnerability to Takeovers vs Actual Takeovers

We start by exploring the explanatory and predictive power of our vulnerability measure. In column 2 of Table 2, we present pooled logit coefficient estimates (marginal effects) of our base logit model (Equation (1)) computed from the full sample. In columns 4 to 7, we present descriptive statistics of the coefficients derived from year-by-year (32) pooled regressions. The results from Table 2 suggest that our predictor variables have some explanatory power in the expected direction (column 1). For example, we find that, over the pooled sample, consistent with the literature, takeover likelihood declines with abnormal returns, Tobin's q and firm age but increases with free cash flow (Danbolt et al., 2016; Loderer & Waelchli, 2015; Palepu, 1986; Powell, 2001). We also find that the relationship between firm size and takeover likelihood is non-linear, as suggested by prior studies (Tunyi, 2019).

In panel B of Table 2, we report results from various goodness-of-fit tests and compare these to results from a null model (the equivalent of a random selection strategy) that only controls

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[9] we multiply REMdisx by negative 1 so that higher values are indicative of higher levels of REM.

[10] Roychowdhury (2006) contends that price discounts and overproduction negatively impact abnormal CFO while a reduction of discretionary expenses positively impacts the same.

Table 2. Estimating firm vulnerability to future takeovers.

Panel A: Regression coefficients and descriptive statistics

	Logit regression coefficients: Pooled sample			Descriptive statistics of yearly regression coefficients			
Variables	Pred. (1)	Margins (2)	*P*-value (3)	Mean (4)	SD (5)	Min (6)	Max (7)
Abnormal returns	–	– 1.894***	(0.000)	– 49.486	73.702	– 210.146	145.630
Profitability	–	– 0.000	(0.964)	– 0.010	0.361	– 1.008	0.859
Tobin's *q*	–	– 0.005***	(0.000)	– 0.232	0.230	– 0.619	0.086
Sales growth	+/–	– 0.003*	(0.098)	– 0.245	0.454	– 1.848	0.289
Liquidity	+/–	– 0.013	(0.210)	– 0.188	1.303	– 2.673	2.193
Leverage	+/–	0.008	(0.357)	– 0.087	0.909	– 2.201	1.478
Growth-resource	+	– 0.000	(0.916)	– 0.012	0.415	– 1.109	0.607
Disturbance	+	0.003	(0.325)	0.087	0.456	– 0.938	0.875
Firm size	+	0.136***	(0.000)	3.642	2.166	– 0.426	7.412
Firm size#Firm size	–	– 0.004***	(0.000)	– 0.094	0.058	– 0.197	0.012
Free cash flow	+	0.040***	(0.002)	0.910	1.698	– 2.043	5.583
Tangible assets	+	0.008	(0.190)	0.193	0.869	– 1.348	2.223
Firm age	–	– 0.007***	(0.000)	– 0.252	0.324	– 1.549	0.035
Block holders	+	0.006	(0.430)	0.016	0.894	– 2.474	1.975
Observations		24,802					
Firm FE		Yes					
Year FE		Yes					
χ^2		460	(0.000)				
Pseudo R^2		0.057					

Panel B: Within sample performance diagnostics: Goodness-of-fit of prediction versus null model

	Prediction	*vs*	Null
McFadden's R^2	6.2%		3.5%
Maximum Likelihood R^2	2.4%		1.2%
McKelvery and Zaroina's R^2	23.2%		8.9%
Cragg and Uhler's R^2	7.4%		4.1%
Efron's R^2	2.6%		1.4%
Area under ROC curve	69.9%		50.0%

Note: The table presents the regression results for Equation (1) which estimates each firm's takeover likelihood from a vector of its characteristics. The dependent variable takes a value of one if a firm receives a takeover bid in the next period and a value of zero otherwise. All predictor variables are fully defined in Appendix A1. The marginal effects presented in column 2 are generated from the entire sample (1987–2016). *P*-values are presented in parentheses. We present descriptive statistics for coefficients generated from yearly regressions in columns 3 to 6. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

for year and 2-digit SIC code industry fixed effects. These preliminary results indicate that our model has a higher discriminatory ability (in-sample) than a null model. Specifically, our pseudo R^2 values are higher than the null model's. Additionally, the area under the ROC curve for our model is 69.9% (*p*-value of 0.000), which is higher than the benchmark of 50%. While these results compare favorably against other UK studies (Danbolt et al., 2016; Powell, 2001), pseudo R^2 are notoriously unreliable measures of logit model performance. Hence, we turn our attention to out-of-sample tests.

Prior studies (see, for example, Brar et al., 2009; Danbolt et al., 2016; Powell, 2001) consider the proportion of actual targets (i.e., firms that receive takeover bids within one calendar year of prediction) within the quintile (or decile) of firms with the highest takeover likelihood as a measure of out-of-sample performance. This strategy implicitly imposes a, perhaps, unnecessary timing restriction on model performance, i.e., within one calendar year (Tunyi, 2021). To mitigate this bias, we extend the period to observe the extent to which vulnerable firms receive bids over the next three and five years.[11]

Starting from 1995, in each year, we rank firms by their vulnerability and generate quintiles (Q1 to Q5), where Q1 (Q5) represents the 20% or quintile of firms with the lowest (highest) vulnerability. We then count the number of firms in each quintile that receive a bid within one year (i.e., actual targets). If vulnerability captures future takeover risk, we expect to see comparatively more actual targets in Q5. We extrapolate this to explore the extent to which firms in Q5 are the subject of takeover bids over the next three and five years.

As in panel A of Table 3, we find that as we move from the quintile of firms that are least vulnerable (Q1) to those that are most vulnerable (Q5), the number and percentage of actual targets increases monotonically. For example, only 2.2% of firms in Q1 receive a bid within one year (column 3), whereas up to 7.3% of firms in Q5 receive a bid over the same period. More importantly, vulnerability in one year appears to result in takeovers in future years. For example, over 17.5% of firms in Q5 receive a bid within three years (column 5), increasing to 24.3% within five years (column 7). The results suggest that, consistent with prior studies (Danbolt et al., 2016), our measure of vulnerability, to a reasonable extent, captures firms' exposure to future takeovers.[12] This is critical to our empirical tests. However, the timing of takeovers remains uncertain, as we show that firms predicted to receive bids might not receive these bids within the first year or even the first three years. We, therefore, want to explore the extent to which firms manage earnings in anticipation of future bids.

4.2. Vulnerability and Earnings Management

In panel B of Table 3, we compare the mean and median values of our measures of EM for firms across different levels of vulnerability. In column 1, we present statistics for our full sample. In columns 2 to 6, we present statistics across the five quintiles. If vulnerable firms pre-emptively manage earnings, we expect to observe significant differences in EM behaviors across levels of vulnerability, with Q5 firms reporting significantly higher values of EM compared to Q1. Our reliance on Q1 and Q5, though consistent with the literature (Danbolt et al., 2016), means we only use 40% of our data in this analysis. To generate more generalizable results, we also use the (2-digit SIC code) industry-year median vulnerability as a benchmark to identify firms with low and high exposure to takeovers. Here, we should similarly observe comparatively higher EM in firms with higher–than–median vulnerability to takeovers.

Consistent with H1, we find that our measures of REM and its constituents (REMprod and REMdisx) generally increase as we move from Q1 to Q5. Similarly, firms with lower–than–median vulnerability report negative mean REM (including REMprod and REMdisx) values while their counterparts with high vulnerability report positive values. The differences in mean and median REM (including REMprod and REMdisx) between Q5 and Q1 and between low and high vulnerability firms are statistically significant at the 10% level. Our results for REMcfo are significant but not in the direction we expect. Perhaps, our REMcfo measure is subject to the ambiguity concern raised by prior studies (Roychowdhury, 2006; Zang, 2012). Further, we do not see any statistically significant differences in AEM across different levels of vulnerability.

We continue our analysis of the relationship between vulnerability and EM under an OLS regression framework in which we explicitly control for other antecedents of firms' EM behavior.

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[11] If EM by vulnerable firms deters acquirers from making takeover bids as we predict in H2, then the results of this out-of-sample test will be biased downwards.

[12] To the extent that our model is poorly specified and incapable of correctly ascribing takeover likelihood, we bias our findings negatively and are likely to improve rather than impair our results with a more optimal model.

Table 3. Vulnerability, actual takeovers and earnings management.

Panel A: Vulnerability and future (actual) takeovers

		Within 1 Year		Within 3 Years		Within 5 Years	
Quintile Variables	Total (1)	Bids (2)	%. (3)	Bids (4)	%. (5)	Count (6)	% (7)
Q1	4899	107	2.2%	326	6.7%	515	10.5%
Q2	4888	196	4.0%	533	10.9%	768	15.7%
Q3	4896	241	4.9%	670	13.7%	937	19.1%
Q4	4888	307	6.3%	771	15.8%	1079	22.1%
Q5	4883	357	7.3%	855	17.5%	1187	24.3%
Total	24,454	1208	4.9%	3155	12.9%	4486	18.3%

Panel B: Vulnerability and earnings management: Univariate analysis

		Vulnerability quintiles						Median vulnerability		
Quintile Variables	All (1)	Q1 (2)	Q2 (3)	Q3 (4)	Q4 (5)	Q5 (6)	Q5-Q1 (7)	Low (8)	High (9)	Diff. (10)
Means of earnings management proxies										
REM	0.004	– 0.046	– 0.026	0.013	0.041	0.037	0.083***	– 0.026	0.035	0.060***
REMprod	– 0.002	– 0.010	– 0.012	0.000	0.011	0.002	0.012**	– 0.009	0.007	0.016***
REMdisx	0.001	– 0.044	– 0.019	0.011	0.024	0.031	0.075***	– 0.023	0.024	0.047***
REMcfo	– 0.002	0.049	0.005	– 0.008	– 0.021	– 0.035	– 0.084***	0.018	– 0.022	– 0.039***
AEM	– 0.003	– 0.012	– 0.001	0.007	0.002	– 0.013	– 0.001	– 0.003	– 0.003	– 0.000
Medians of earnings management proxies										
REM	0.025	0.003	0.007	0.028	0.041	0.047	0.044***	0.012	0.041	0.029***
REMprod	0.000	0.000	0.000	0.000	0.000	0.002	0.002*	0.000	0.001	0.001*
REMdisx	0.020	0.006	0.007	0.019	0.029	0.036	0.030***	0.011	0.031	0.020***
REMcfo	– 0.005	0.000	0.000	– 0.003	– 0.008	– 0.020	– 0.020***	– 0.000	– 0.013	– 0.013***
AEM	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.000

Note: Panel A of the table assesses the out-of-sample predictive ability of the proxy for vulnerability. We rank all firms in each year by their vulnerability measure, then split them into 5 equal groups (quintiles). Q1 (Q5) represents the 20% of firms with lowest (highest) vulnerability. We then explore whether firms in each quintile receive takeover bids within the next year (within 1 year), 3 years (within 3 years) and 5 years (within 5 years). ‘Total’ indicates the number of firms in each quintile. ‘Bids’ indicates the number of actual targets in each quintile. ‘%’ (percentage) indicates the proportion of firms in each quintile (‘Total’) that receive ‘Bids’ each year. Panel B of the table presents the means and medians of measures of earnings management (EM) across quintiles of vulnerability. Q5-Q1 presents the difference in mean and median of EM proxies. All variables are fully defined in Appendix A1. For mean differences, statistical significance is based on p-values from difference of means (t) test. For median differences, we use p-values of chi-square (continuity corrected) from a difference of median test. P-values are untabulated for brevity. ***, ** and * indicate statistically significant difference at the 1%, 5% and 10% levels, respectively.

Our baseline model is specified in Equation (2) below:

$$EM_{it} = \beta_0 + \beta_1\ Vulnerability_{it-1} + \sum \beta_k\ Controls_{it-1} + v_j + v_t + \epsilon_{it} \tag{2}$$

The dependent variables (EM) in Equation (2) are measures of REM and AEM. The main independent variable is 'vulnerability.' Following prior studies (Gunny, 2010; Zang, 2012), we control for firm characteristics that may influence EM behavior including profitability, firm size, market to book, level of debt issue, leverage, free cash flow and the level of block holding, insolvency risk (Z–Score), net operating assets and audit quality. Additionally, we control for industry (j) and year (t) fixed effects to capture macroeconomic and industry-level effects.[13] The independent and control variables in Equation (2) are lagged by one period to address reverse causality concerns. Significance levels are based on Rogers standard errors adjusted for heteroskedasticity and clustered at firm-level. All variables are fully defined in Appendix A1. Our results are presented in Table 4.

In column 1, consistent with our prediction in H1 and the results from the univariate analysis, we find a positive and statistically significant relationship between vulnerability and REM at the 1% level (i.e., coefficient of 1.073 and p-value of 0.000). A standard deviation (i.e., 0.028 units) increase in vulnerability is associated with a 3.05% increase in REM in the next period. Regarding the specific channels, a standard deviation increase in vulnerability is associated with a 1.71% (1.49%) increase in REMprod (REMdisx). Consistent with findings in Table 3, our results for REMcfo are significant, albeit in the opposite direction. Mirroring the results from Table 3, in column 5, we do not find evidence that firms broadly use AEM strategies when vulnerable to takeovers. The AEM coefficient is small, negative (i.e., -0.091) and not significant at the 10% level (i.e., p-value of 0.569).[14]

Prior research suggests that firms might deploy REM and AEM strategies as substitutes or complements (Achleitner et al., 2014; Zang, 2012). We have previously argued that vulnerable firms are more likely to choose REM over AEM. Consistent with this view, our evidence in Table 3 and columns 1 to 5 of Table 4 suggest that vulnerable firms manage earnings using REM but not AEM strategies. To further understand firms' use of REM *vs* AEM when faced with vulnerability, we use the approach in Achleitner et al. (2014). Specifically, we re-estimate our results in column 1 for different levels of AEM by interacting vulnerability and AEM in Equation (2) to explore whether firms use these EM strategies as substitutes or complements. As in column 6 of Table 4, we find a positive and significant interaction effect, suggesting that vulnerable firms use AEM and REM as complements (Achleitner et al., 2014). Vulnerable firms, perhaps, use REM during the year and adjust their year-end AEM activity to address any shortfalls in the level of during-the-year REM already achieved.

[13] In untabulated robustness checks available in our online appendices, we re-estimate the model using a panel regression specification and also control for firm-level governance characteristics (including board size, CEO duality, board gender diversity, board independence, director experience, board tenure and the presence of an audit committee). Our governance data is patchy and largely missing for over 50% of our sample. Our results are robust to these additional controls and alternative model specification.

[14] In untabulated analyses (online appendices), we re-estimate our AEM results using alternative measures of AEM. Botsari and Meeks (2008) contend that working capital accruals are relatively more opaque and more open to manipulation when compared to depreciation. Secondly, J.-B. Kim et al. (2003) argues that discretionary accruals computed using Jones-type models (Dechow et al., 1995; Jones, 1991) are potentially biased due to measurement errors. We follow Botsari and Meeks (2008) and DeFond and Park (2001) to estimate alternative measures of AEM which we use to re-estimate our main results. Our conclusions are robust to these alternatives. That is, the relationship between vulnerability and AEM is statistically insignificant. F statistics in Table 4 are significant across all models and variance inflation factors (VIF) are below standard thresholds. The adjusted R^2 values are arguably low but in line with those reported in related large-sample studies (Achleitner et al., 2014; Gunny, 2010). In additional tests (online appendices), the adjusted R^2 values slightly improve after controlling for corporate governance characteristics.

Table 4. Vulnerability and earnings management: Real *vs* accrual.

		Specific REM channels				Trade-offs
Variables	REM (1)	REMprod (2)	REMdisx (3)	REMcfo (4)	AEM (5)	REM (6)
Vulnerability	1.073***	0.602***	0.521***	– 0.385**	– 0.091	0.956***
	(0.000)	(0.000)	(0.000)	(0.020)	(0.569)	(0.000)
Vulnerability#AEM						1.597***
						(0.008)
AEM						– 0.051
						(0.222)
Profitability	– 0.011	– 0.075***	0.073***	– 0.115***	0.011	0.033
	(0.684)	(0.000)	(0.001)	(0.000)	(0.555)	(0.384)
Firm size	0.018***	0.011***	0.006***	0.005***	– 0.005***	0.017***
	(0.000)	(0.000)	(0.000)	(0.003)	(0.007)	(0.000)
Market to book	– 0.037***	– 0.013***	– 0.023***	– 0.002	– 0.000	– 0.032***
	(0.000)	(0.000)	(0.000)	(0.358)	(0.935)	(0.000)
Debt issue	– 0.001	– 0.000	– 0.001*	– 0.000	0.000	– 0.003***
	(0.211)	(0.961)	(0.081)	(0.924)	(0.990)	(0.002)
Leverage	– 0.002	– 0.067***	0.055**	– 0.005	0.020	0.004
	(0.944)	(0.000)	(0.013)	(0.712)	(0.296)	(0.887)
Free cash flow	0.020	– 0.077***	0.131***	– 0.216***	0.066**	– 0.100**
	(0.662)	(0.000)	(0.000)	(0.000)	(0.017)	(0.020)
Block holders	– 0.048**	– 0.005	– 0.042***	0.019**	– 0.029	– 0.060***
	(0.025)	(0.600)	(0.007)	(0.047)	(0.210)	(0.003)
Z score	– 30.093**	– 7.746	– 33.053***	12.393**	15.699	– 17.113
	(0.016)	(0.200)	(0.000)	(0.014)	(0.194)	(0.151)
Net operating assets	0.003***	0.001***	0.002***	– 0.001*	– 0.002	0.002***
	(0.000)	(0.000)	(0.001)	(0.092)	(0.550)	(0.003)
Audit quality	0.070*	0.022	0.062*	– 0.026	0.007	0.077**
	(0.066)	(0.122)	(0.067)	(0.375)	(0.648)	(0.017)
Constant	– 0.343***	– 0.181***	– 0.151***	– 0.063**	0.104***	– 0.327***
	(0.000)	(0.000)	(0.000)	(0.042)	(0.003)	(0.000)
Observations	17,076	17,076	17,547	17,498	17,082	17,893
R-squared	0.062	0.049	0.066	0.046	0.011	0.054
Adj.R^2	0.060	0.047	0.064	0.044	0.009	0.051
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
F stat	17.03	15.63	14.69	12.48	1.898	14.10
Prob > F	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Highest VIF	2.070	2.070	2.080	2.080	2.080	2.120

Note: This table presents the coefficient estimates from OLS regressions exploring the relationship between vulnerability to takeovers and earnings management (EM) and the trade-off between real and accrual EM by vulnerable firms. The base model is specified in Equation (2). The model controls for firm characteristics that influence the EM decision, as well as industry and year fixed effects. All independent variables in columns 1 to 5 are lagged by one year. Column 6 explores contemporaneous relationships. All variables are fully defined in Appendix A1. *P*-values (from robust standard errors) are presented in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

4.3. Pre-Emptive Earnings Management and Future Takeovers

Haven documented evidence suggesting that firms manage earnings when vulnerable to takeovers, we now explore the motivations of this pre-emptive EM. To test our second hypothesis (H2), we first empirically examine the relationship between pre-emptive EM and the likelihood of receiving bids in the next year. Then, we capture 'pre-emptive' EM as the interaction between vulnerability and EM. This interaction reflects the extent to which vulnerability to takeovers amplifies EM behavior. Our model is specified as follows:

$$Prob(Target = 1)_{it} = \beta_0 + \beta_1\, Vulnerability_{it-1} * EM_{it-1} + \beta_2\, Vulnerability_{it-1} + \beta_3 EM_{it-1} + \sum \beta_k\, Controls_{it-1} + v_j + v_t + \epsilon_{it} \quad (3)$$

In Equation (3), the dependent variable is a binary variable that takes a value of one if a firm is a takeover target in the next period and a value of zero otherwise. Our main independent variable is the interaction effect between vulnerability and EM (i.e., our measure of pre-emptive EM). We have previously established a link between vulnerability and actual takeovers in the next one, three and five years (see Table 3). Hence, in Equation (3), a negative interaction effect will suggest that EM plays a defensive role by attenuating the relationship between vulnerability and actual takeovers. The model controls for several other determinants of takeover likelihood. These variables are fully defined in Appendix A1. We estimate the model through probit regressions with industry (j) and year (t) fixed effects to also capture macroeconomic and industry-level factors that might impact takeover decisions. The results from this analysis, estimated using our full sample, are presented in columns 1 to 2 of Table 5. Here, we do not find evidence to support the view that pre-emptive EM deters, delays or discourages takeovers across the entire sample. Specifically, we do not find a significant negative interaction effect.

In developing our hypothesis, we noted that the hypothesized relationship is likely to be driven by managerial entrenchment (agency) motives. The literature (see, for example, Berger et al., 1997) uses the sensitivity of executive compensation to firm performance to capture the level of managerial entrenchment. Specifically, entrenched managers are defined as those whose compensation is not sensitive to performance (Berger et al., 1997). Long term incentive plans (LTIPs), which comprises equity-based remuneration, were introduced in the UK in 1995 (i.e., covers the period of our study) and have become commonplace in the UK since 2002 (Goergen & Renneboog, 2011). From an optimal contracting theoretical perspective, equity-based compensation of top executives, such as LTIPs, promotes the adoption of long-term corporate investment policies, and hence, the maximization of shareholder value (Feito-Ruiz & Renneboog, 2017). LTIPs, therefore, align the interest of managers and shareholders, and hence reduce agency problems within companies (Feito-Ruiz & Renneboog, 2017).

Following prior studies, we use the ratio of the value of LTIPs to total managerial compensation, averaged over all board members, to model the level of managerial entrenchment within each firm (Feito-Ruiz & Renneboog, 2017). We identify firms with high and low entrenchment by comparing their ratio to their 2-digit SIC code industry-year median. Firms with a ratio of LTIPs to total compensation below (above) the industry-year median are classified as firms with high (low) entrenchment problems. We also designate firms with high entrenchment problems as 'Entrenched' firms.

In columns 3 to 4 of Table 5, we explore the extent to which managerial entrenchment impact the takeover deterrent effect of pre-emptive EM by interacting our measure of pre-emptive EM with the measure of 'Entrenched,' i.e., a three-way interaction effect. A negative three-way interaction effect will suggest that the takeover deterrent effect of pre-emptive EM is stronger for firms with high entrenchment problems. We find a significant negative three-way interaction effect for REM (p-value of 0.027, column 3) but not for AEM (p-value of 0.830, column 4).

To further elucidate the results in column 3 of Table 5, we re-estimate Equation (3) across sub-samples of firms with high (low) entrenchment problems. Our results in columns 5 and 6 show that pre-emptive REM plays a takeover deterrent role in our sample firms with high entrenchment problems, but not for others. Specifically, we find a significant negative relationship between pre-emptive REM and future takeover likelihood in our sub-sample of firms with high but not those with low entrenchment problems. While this finding supports H2, it also suggests that, except

Table 5. Pre-emptive earnings management and future takeovers.

	Full sample		Three-way interaction		Entrenchment	
					High	Low
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Vulnerability#REM#Entrenched			– 9.959**			
			(0.027)			
Vulnerability#AEM#Entrenched				– 1.526		
				(0.830)		
Vulnerability#REM	0.569		2.368		– 7.567**	0.778
	(0.597)		(0.492)		(0.012)	(0.816)
Vulnerability#AEM		– 0.229		0.904		
		(0.830)		(0.897)		
Vulnerability#Entrenched			5.267**	3.938*		
			(0.041)	(0.093)		
REM#Entrenched			0.482*			
			(0.093)			
AEM#Entrenched				0.031		
				(0.938)		
Vulnerability	– 1.092	– 0.067	– 1.846	– 1.713	2.880	– 2.494
	(0.375)	(0.964)	(0.559)	(0.564)	(0.529)	(0.526)
REM	– 0.066		– 0.186		0.323*	– 0.103
	(0.355)		(0.404)		(0.094)	(0.627)
AEM		0.057		0.061		
		(0.528)		(0.874)		
Entrenchment			– 0.438**	– 0.354**		
			(0.016)	(0.035)		
Abnormal returns	– 4.834	– 1.013	3.577	– 5.427	12.994	– 8.729
	(0.473)	(0.881)	(0.753)	(0.612)	(0.386)	(0.618)
Profitability	0.032	0.050	0.056	0.077	0.083	0.011
	(0.308)	(0.129)	(0.393)	(0.202)	(0.353)	(0.908)
Tobin's *q*	– 0.026*	– 0.017	– 0.045	– 0.045	– 0.023	– 0.080**
	(0.092)	(0.222)	(0.185)	(0.131)	(0.614)	(0.037)
Sales growth	0.011	0.003	0.054*	0.019	0.070**	0.009
	(0.564)	(0.851)	(0.063)	(0.501)	(0.040)	(0.874)
Liquidity	– 0.126	– 0.162	– 0.002	– 0.138	0.022	– 0.233
	(0.321)	(0.161)	(0.993)	(0.480)	(0.938)	(0.403)
Leverage	0.065	0.054	– 0.010	0.015	– 0.426*	0.430*
	(0.529)	(0.592)	(0.955)	(0.927)	(0.099)	(0.081)
Growth-resource	0.026	0.028	0.048	0.044	0.008	0.067
	(0.544)	(0.506)	(0.509)	(0.517)	(0.937)	(0.503)
Disturbance	0.092**	0.094**	0.212***	0.231***	0.203*	0.242**
	(0.023)	(0.021)	(0.007)	(0.003)	(0.073)	(0.030)
Firm size	1.296***	1.083***	0.492	0.644	0.660	0.248
	(0.000)	(0.000)	(0.224)	(0.110)	(0.307)	(0.650)
Firm size#Firm size	– 0.033***	– 0.028***	– 0.012	– 0.016	– 0.016	– 0.007
	(0.000)	(0.000)	(0.241)	(0.124)	(0.343)	(0.624)
Free cash flow	0.209*	0.125	0.236	0.129	0.444	0.193
	(0.098)	(0.362)	(0.317)	(0.543)	(0.151)	(0.621)
Tangible assets	0.144*	0.089	0.087	0.078	0.120	– 0.002
	(0.065)	(0.259)	(0.549)	(0.568)	(0.534)	(0.992)
Firm age	– 0.074***	– 0.068***	– 0.044	– 0.110***	– 0.096*	– 0.018
	(0.000)	(0.001)	(0.265)	(0.003)	(0.091)	(0.738)
Block holders	0.021	0.021	0.190	0.111	– 0.017	0.428**
	(0.815)	(0.803)	(0.163)	(0.384)	(0.923)	(0.040)
Constant	– 13.882***	– 11.932***	– 7.430**	– 8.431**	– 9.299	– 5.022
	(0.000)	(0.000)	(0.046)	(0.023)	(0.113)	(0.321)

(*Continued*)

Table 5. Continued.

Variables	Full sample (1)	(2)	Three-way interaction (3)	(4)	Entrenchment High (5)	Low (6)
Observations	19,307	20,477	8731	9726	4494	3880
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
χ^2	332.1	340.8	155.7	195.9	95.85	92.31
Prob (χ^2)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Highest VIF	1.350	1.390	1.390	1.430	1.460	1.470
Pseudo R^2	0.053	0.050	0.076	0.078	0.081	0.078

Note: This table presents the probit regression estimates from Equation (3) which explores the takeover deterrent effect of earnings management (EM). Columns 1 and 2 presents coefficient estimates of Equation (3) based on our entire sample. Columns 3 and 4 present coefficient estimates of Equation (3) when interacted with the entrenchment indicator. Columns 5 and 6 presents coefficient estimates of Equation (3) from two sub-samples; high and low entrenchment firms. We define high (low) entrenchment as a sub-sample of firms in which the value of compensation made up of long term incentive plans (LTIP) as a proportion total compensation (averaged across all board members) is less (greater) than the 2-digit SIC code industry-year median value. The model controls for firm characteristics that influence takeover likelihood, as well as industry and year fixed effects. All variables are fully defined in Appendix A1. *P*-values are presented in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

for firms with relatively high entrenchment problems, vulnerable firms pre-emptively manage earnings not to deter takeovers altogether but to potentially influence other M&A outcomes.

4.4. Pre-Emptive Earnings Management and Merger Premiums

Our third hypothesis (H3) predicts that pre-emptive EM allows firms to optimize merger outcomes by extracting higher merger premiums. To test this prediction, we run the following OLS model in which we regress opening period firm characteristics on the deal premium (for offers announced during the year), while controlling for deal characteristics, as well as industry (j) and year (t) fixed effects. As before, our measure of pre-emptive EM is the interaction between 'vulnerability' and our EM proxies:

$$\begin{aligned} Premium_{it} = \beta_0 + \beta_1\, Vulnerability_{it-1} * EM_{it-1} + \beta_2\, Vulnerability_{it-1} \\ + \beta_3 EM_{it-1} + \sum \beta_k\, Controls_{it-1} + v_j + v_t + \epsilon_{it} \end{aligned} \quad (4)$$

The dependent variable in Equation (4) is merger premium which is the premium based on offer price relative to the target stock price four weeks before the announcement. The main independent variable is the interaction between vulnerability and EM. The model controls for the last observable firm characteristics (including profitability, firm size, market to book, debt issue, leverage, free cash flow, block holders), as well as deal characteristics (including method of payment, whether the deal is cross border versus domestic bids, hostile versus friendly, single bidder versus competing bidders, and focus versus diversifying).

Our estimates of Equation (4) are reported in Table 6. We observe a positive interaction effect (p-value of 0.048) in column 1 but not in column 2 (p-value of 0.243). These results suggest that pre-emptive REM (but not AEM) is associated with higher merger premiums. To explore how vulnerability shapes this EM–premium relationship, we partition our sample into two sub-samples of low and high vulnerability and re-estimate a simple model with no interaction effect. The results are presented in columns 3 and 4 of Table 6. In column 3, we find a negative but statistically insignificant relationship between REM and premium within our sub-sample of firms with low vulnerability (p-value of 0.195). However, in column 4 (sub-sample of firms with high vulnerability), REM has a positive and statistically significant (p-value of 0.025) association with merger premiums. The latter is economically significant. Specifically, within the sub-sample firms with high vulnerability to takeovers, a standard deviation (i.e., 0.497 units) increase in REM is associated with a 290% increase in subsequent merger premiums. Overall, the results suggest that consistent with H3, vulnerable firms drive up subsequent merger premiums by pre-emptively managing earnings using REM strategies.

4.5. Additional Analyses and Robustness Checks

4.5.1. Are firms responding to takeover pressures or poor performance?

Our main results suggest that vulnerable firms manage earnings in anticipation of impending bids. A concern with this conclusion is that we might be capturing the impact of poor performance on EM behavior. If poorly performing firms manage earnings and are more vulnerable to takeovers, then the documented relationship between vulnerability and EM, even after controlling for firm performance (profitability) across all our models (see Table 4), might be spurious. Therefore, we conduct additional tests to allay this concern further.

Firstly, if our results are driven by poor performance, we should find that the results hold for underperforming firms and do not hold (or are weaker) for well-performing firms. We, therefore, split our sample along dimensions of high and low performance and re-estimate our results across these two sub-samples. Our sub-sample results are presented in Table 7. To identify high and low performance, we rank firms in each industry-year by the return on capital employed (ROCE) and identify the firms belonging to the top (20% of firms with highest ROCE) and bottom (20% of firms with the lowest ROCE) quintiles.

In columns 1 and 2 of Table 7, we explore the link between vulnerability and REM for sub-samples of underperforming (low ROCE) and well-performing firms (high ROCE), respectively. Our main results hold across the two sub-samples. Moreover, the test of difference in coefficients (i.e., 1.507 in column 1 and 1.177 in column 2) reveals that the coefficient difference is not significant at the 10% level (p-value of 0.632). This suggests that our results are unlikely to be driven by poor performance.

For robustness, we further deploy alternative classification strategies, as well as other measures of performance, including Tobin's q and abnormal returns (AAR). Specifically, we re-estimate our results in columns 1 and 2 of Table 7 for sub-samples of loss-making firms (net profit < 0) *versus* profit-making firms (net profit > 0) and firms with performance (i.e., ROCE, Tobin's q and AAR) greater than their industry-year median *versus* those with performance less than their industry-year median. In untabultaed results, we find that our results hold across all sub-samples and measures of performance. Specifically, irrespective of the level of performance, REM increases with vulnerability to takeovers.[15] Overall, the results from these checks suggest that vulnerability rather than poor performance drives the EM behavior we have documented.

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[15] In untabulated analyses (online appendices), we run quantile regressions to strengthen our findings even further. If our results merely capture poorly performing firms that are more likely to manage earnings, we should observe that our results are positive and significant at certain levels of EM and insignificant or negative at others. Quantile regressions allow us to test the sensitivity of the coefficient of vulnerability at different levels or quantiles of EM. The results suggest that the documented relationship is consistently positive at all levels or quantiles of EM. Therefore, it is unlikely that the results we observe are an artefact of poor performance. Additionally, in unreported results, we have explored pairwise correlations between measures of performance (ROA, ROCE, Tobin's q and AAR) and REM and find the correlation coefficients (rho) to be close to zero, suggesting that performance is unlikely to explain the vulnerability–EM relationship in our sample.

Table 6. Target earnings management and merger premiums.

	All firms		Vulnerability	
			Low	High
Variables	(1)	(2)	(3)	(4)
Vulnerability#REM	136.966** (0.048)			
Vulnerability#AEM		123.109 (0.243)		
Vulnerability	29.021 (0.547)	4.684 (0.919)		
REM	– 5.992 (0.278)		– 6.415 (0.195)	5.852** (0.025)
AEM		– 14.839*** (0.000)		
Profitability	0.146 (0.987)	– 3.261 (0.688)	1.749 (0.903)	– 0.399 (0.973)
Firm size	– 1.917*** (0.003)	– 1.890*** (0.004)	– 2.871*** (0.000)	0.227 (0.851)
Market to book	– 0.602 (0.340)	– 0.629 (0.276)	– 0.872 (0.382)	– 1.041 (0.230)
Debt issue	– 0.016 (0.932)	– 0.090 (0.593)	0.194 (0.646)	– 0.030 (0.887)
Leverage	– 1.505 (0.841)	– 1.753 (0.815)	– 13.868 (0.210)	12.216 (0.246)
Free cash flow	– 16.869 (0.219)	– 13.912 (0.322)	– 18.890 (0.373)	– 24.544 (0.194)
Block holders	– 10.576* (0.086)	– 11.036* (0.069)	– 22.975** (0.029)	2.149 (0.809)
Cash payment	8.599*** (0.000)	9.785*** (0.000)	6.376* (0.062)	9.642*** (0.001)
Cross border	4.753** (0.043)	4.153* (0.085)	6.597* (0.063)	3.117 (0.360)
Bid attitude	6.568** (0.039)	5.383* (0.082)	6.658 (0.104)	8.023* (0.070)
Competing bids	19.955*** (0.000)	18.973*** (0.000)	20.931*** (0.000)	18.937*** (0.000)
Diversifying bids	– 1.339 (0.507)	– 1.307 (0.518)	– 2.351 (0.467)	– 1.410 (0.607)
Constant	73.014*** (0.000)	73.121*** (0.000)	97.792*** (0.000)	29.002 (0.248)
Observations	1291	1349	538	737
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
F stat	5.177	5.143	3.660	3.656
Prob > F	(0.000)	(0.000)	(0.000)	(0.000)
Highest VIF	2.680	2.620	2.890	3.020
Adj.R^2	0.125	0.112	0.139	0.131

Note: This table presents the coefficient estimates from OLS regressions exploring the relationship between pre-emptive EM and subsequent merger premiums. The model is specified in Equation (4). The model controls for target firm characteristics that influence merger premiums, deal characteristics, as well as industry and year fixed effects. All variables are fully defined in Appendix A1. *P*-values (from robust standard errors) are presented in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Our second test focuses on a unique sub-sample of firms – suspect firms – that have a strong incentive to manage earnings to meet and beat targets (Gunny, 2010; Roychowdhury, 2006; Zang, 2012). These firms are typically characterized by low accounting performance (ROA), a net income marginally greater than zero and low levels of profit growth. To allay concerns

Table 7. Vulnerability and earnings management; Additional tests.

	Performance (ROCE)		Suspect firms		The impact of merger intensity			
Dependent variable	REM		REM		REM	AEM	REM	AEM
Sub-sample	Low ROCE (Q1)	High ROCE (Q5)	Suspects	Non-suspects	All	All	All	All
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Vulnerability	1.507***	1.177***	1.282***	1.112***			0.039	– 0.199
	(0.007)	(0.004)	(0.006)	(0.000)			(0.879)	(0.306)
Merger intensity					0.016**	– 0.003	– 0.048***	– 0.014**
					(0.012)	(0.333)	(0.002)	(0.037)
Vulnerability # Merger intensity							1.128***	0.176**
							(0.000)	(0.047)
Profitability	0.102**	– 0.086	0.069	– 0.027	– 0.012	0.002	– 0.033	0.005
	(0.045)	(0.260)	(0.509)	(0.352)	(0.709)	(0.947)	(0.319)	(0.822)
Firm size	0.005	0.020***	0.023***	0.019***	0.022***	– 0.007***	0.022***	– 0.007***
	(0.351)	(0.000)	(0.000)	(0.000)	(0.000)	(0.006)	(0.000)	(0.007)
Market to book	– 0.041***	– 0.024***	– 0.017*	– 0.040***	– 0.040***	0.000	– 0.040***	– 0.000
	(0.000)	(0.000)	(0.052)	(0.000)	(0.000)	(0.889)	(0.000)	(0.942)
Debt issue	0.000	– 0.003	0.000	– 0.001	– 0.000	0.000	– 0.001	0.000
	(0.983)	(0.176)	(0.977)	(0.147)	(0.840)	(0.929)	(0.486)	(0.885)
Leverage	– 0.004	– 0.069	0.075	– 0.015	0.004	0.027	– 0.022	0.027
	(0.963)	(0.297)	(0.318)	(0.629)	(0.907)	(0.267)	(0.547)	(0.281)
Free cash flow	0.009	– 0.023	0.005	0.019	0.060	0.081**	0.025	0.081**
	(0.899)	(0.817)	(0.963)	(0.702)	(0.272)	(0.013)	(0.652)	(0.018)
Block holders	0.110	– 0.095*	– 0.006	– 0.054**	– 0.038	– 0.034	– 0.045	– 0.042
	(0.108)	(0.076)	(0.928)	(0.019)	(0.182)	(0.295)	(0.113)	(0.195)
Z score	– 12.962	– 32.433	– 8.217	– 33.244**	– 43.803***	19.795	– 48.154***	21.126
	(0.669)	(0.181)	(0.813)	(0.013)	(0.004)	(0.215)	(0.002)	(0.199)
Net operating assets	0.003**	– 0.001	0.004	0.003***	0.004***	– 0.002	0.004***	– 0.003
	(0.015)	(0.688)	(0.170)	(0.000)	(0.000)	(0.518)	(0.000)	(0.513)
Audit quality	0.118*	– 0.062	0.122**	0.046	0.081*	0.014	0.095**	0.007
	(0.059)	(0.637)	(0.031)	(0.332)	(0.081)	(0.505)	(0.047)	(0.749)
Constant	– 0.138	– 0.427***	– 0.405***	– 0.374***	– 0.319***	0.032	– 0.393***	0.172***
	(0.200)	(0.000)	(0.000)	(0.000)	(0.000)	(0.563)	(0.000)	(0.001)

(*Continued*).

Table 7. Continued.

	Performance (ROCE)		Suspect firms		The impact of merger intensity			
Dependent variable	REM		REM		REM	AEM	REM	AEM
Sub-sample	Low ROCE (Q1)	High ROCE (Q5)	Suspects	Non-suspects	All	All	All	All
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Observations	2,625	3,567	2,760	14,316	12,693	12,679	12,227	12,213
R-squared	0.119	0.060	0.048	0.069	0.069	0.016	0.080	0.019
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-stat	5.357	4.895	2.975	16.58	14.37	1.948	15.94	1.864

Note: This table presents the coefficient estimates from OLS regressions exploring the relationship between vulnerability to takeovers and earnings management (EM) across different sub-samples. The table also explores the impact of merger intensity on EM and the vulnerability–EM nexus. The base model is specified in Equation (2). The model controls for firm characteristics that influence the EM decision, as well as industry and year fixed effects. All independent variables are lagged by one year. All variables are fully defined in Appendix A1. *P*-values (from robust standard errors) are presented in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

that our results might be driven by firms' predisposition to manage earnings (i.e., suspect firms) rather than their vulnerability to takeovers, in Table 7, we re-estimate our results for sub-samples of the suspect (column 3) and non-suspect (column 4) firms.[16] We find that our main findings are consistent across the two sub-samples. The difference in the coefficient of vulnerability in columns 3 and 4 is not statistically significant (*p*-value of 0.736).

Our third test focuses on firms operating in industries where mergers are commonplace. Mergers occur in waves and are shaped by external factors such as stock market valuation, economic growth, capital availability and macro-level liquidity, amongst others (Gort, 1969). Prior studies contend that firms are more likely to receive takeover bids during periods of high takeover activity or high merger intensity (Danbolt et al., 2016; Tunyi, 2019). If high merger intensity increases the unconditional likelihood of takeovers and reduces uncertainty around the timing of potential takeovers, then in support of our hypotheses, we should observe that (1) firms in merger-active industries engage in more EM, and (2) vulnerable firms, in particular, increase their EM activity even further when merger activity within their industry increases. Hence, we can strengthen our findings by empirically showing that (1) merger intensity has a positive relationship with EM, and (2) the vulnerability–EM relationship is stronger in periods when external takeover pressure or industry merger intensity increases. This will provide evidence that vulnerable firms manage earnings in response to takeover threats rather than some other factor we have not considered.

To avoid look-ahead bias, we estimate 'merger intensity'[17] as the natural log of the number of takeover bids announced in a firm's 2-digit SIC code industry in the *previous* year.[18] Our measure of merger intensity takes into account research suggesting that mergers cluster by industry (Danbolt et al., 2016; Palepu, 1986).[19] Moreover, managers are aware of M&A activity within their industry in the previous year, and following our argument, might ramp up their pre-emptive EM activity in response. Our results are presented in columns 5 to 8 of Table 7.

We find a positive relationship between merger intensity and REM in column 5. This suggests that firms engage in REM when takeover pressure or industry merger intensity increases. Our results for AEM are again statistically insignificant. In columns 7 and 8, we find that merger intensity positively moderates the vulnerability–REM and the vulnerability–AEM relationships (i.e., *p*-values of 0.000 and 0.047, respectively). Our AEM–merger intensity results are particularly interesting as they suggest that the relationship between vulnerability and AEM might persist under certain conditions. On the whole, the results indicate that under immense takeover pressure, when takeovers plausibly become more imminent, vulnerable firms become more aggressive in their EM activity. Since there is more certainty on the timing of potential bids, these firms might seek to increase EM levels by deploying both during-the-year REM and year-end AEM. Overall, these results suggest that takeover pressure, rather than some other factor we have not accounted for, drives the EM behavior we observe.

4.5.2. The causal effect of vulnerability: instrumental variable analyses

So far, we have demonstrated that consistent with H1, takeover vulnerability in one period is associated with EM in the ensuing period (see Table 4). To directly evidence causation, we

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[16]Following Roychowdhury (2006), Gunny (2010) and Zang (2012), but mindful of the UK institutional context, we identify suspect firms as (1) firms with a small net profit to asset ratio (ROA) of between 0 and 0.005, or (2) a small positive net income less than £500,000, or (3) a small growth in net income of between zero and £500,000. All other firms are classified as non-suspect firms.

[17]This is our proxy for merger activity or external takeover pressure within an industry.

[18]Our results are consistent when we use alternative industry definitions such as 4-digit SIC code industries.

[19]Merger activity within an industry incentivises other firms within that industry to engage in mergers in order to retain their competitive positions

employ a two-stage least squares (2SLS) instrumental variable approach and utilize two plausibly exogenous instruments for vulnerability. The first instrument draws from prior research suggesting that several takeovers are preceded by rumors (Danbolt et al., 2016; Jindra & Walkling, 2004; Pound & Zeckhauser, 1990). Specifically, consistent with Danbolt et al. (2016), we argue that firms are more likely to be merger targets if there are more merger rumors within their industry. The number of merger rumors in the UK in any one industry-year are few. Hence, we consider rumors over an extended period of five years. This approach also takes into account the fact that the timing of takeovers is uncertain. To enhance our regression coefficients, we scale the total number of rumors over the previous five years in each (2-digit SIC code) industry-year by 100.

Our second instrument builds on the economic disturbance theory of takeovers (Gort, 1969; Palepu, 1986), which suggests that acquisitions cluster by industry. We, therefore, consider the median vulnerability of peer firms (excluding the focal firm) within each (2-digit SIC code) industry-year in the previous year ($t-1$) as our second instrument.[20] The two instruments are plausibly exogenous to the focal firm as it neither influences the number of merger rumors in its industry nor the vulnerability of its peers. Importantly, there is, perhaps, no theoretical link between both instruments and firm-level EM except through their influence on the firms' vulnerability. We conduct tests for instrument validity and report the results alongside our 2SLS estimation results in Table 8.

The first stage OLS regression estimates for our 2SLS model are presented in column 1 of Table 8. As expected, we find a positive and statistically significant relationship between our instruments (industry rumors and median vulnerability) and our measure of vulnerability. The *p*-value of the regression coefficients are zero (i.e., 0.000) in both cases. Our under-identification tests suggest that the instruments are indeed relevant (Kleibergen-Paap rk LM statistic of over 400 in both cases, with *p*-value of 0.000). Further, the null hypothesis that these are weak instruments is rejected as all F-statistics (Cragg-Donald Wald F stat and Kleibergen-Paap rk Wald F stat) are significantly larger than the benchmarks proposed by Staiger et al. (1997), Stock and Yogo (2002) and Stock et al. (2002). We also test for over-identification, obtaining a *p*-value for our Hansen J statistic of greater than 10%, thus rejecting the null of over-identification. In sum, our tests for instrument validity suggest that the instruments meet accepted thresholds and are, perhaps, correctly excluded from our second stage regressions.

In columns 2 and 3 of Table 8, we present the results of the second-stage regressions, which include predicted values of vulnerability (obtained from the 1st stage) and exclude our instruments. Our main results are again confirmed. Specifically, we find a positive and statistically significant (*p*-value of 0.011) relationship between the predicted value of vulnerability and our measure of REM (i.e., column 2), and a negative but statistically insignificant (*p*-value of 0.277) relationship between vulnerability and AEM (i.e., column 3). This finding suggests that consistent with our hypothesis (H1), vulnerability to takeovers induces or causes REM.

4.5.3. Addressing potential endogenous sample selection

Our second hypothesis explores the takeover deterrent effect of pre-emptive EM (see Table 5). Firms that do and do not receive takeovers are likely very different across various characteristics other than the use of EM. In Table 5, we run our analysis across the entire sample of firms with available data (over 20,000 firm-year observations), of which just about 5% receive a bid. For robustness, we run the same analysis using a sample of firms that receive takeover bids and their propensity score-matched control sample. To generate the matched sample, we run a probit

[20] Notice that our results are consistent when we use the median-vulnerability in other earlier years up to ($t-6$). Our results are also consistent when we use alternative industry definitions e.g., 4-digit SIC codes.

Table 8. Vulnerability and earnings management: Two-stage least squares.

	First stage	Second stage	
	Vulnerability	REM	AEM
Variables	(1)	(2)	(3)
Industry rumors	0.027***		
	(0.000)		
Peer vulnerability	0.441***		
	(0.000)		
Vulnerability		1.599**	– 0.281
		(0.011)	(0.277)
Profitability	0.018***	– 0.026	0.018
	(0.000)	(0.406)	(0.378)
Firm size	– 0.001***	0.019***	– 0.006***
	(0.000)	(0.000)	(0.005)
Market to book	– 0.001***	– 0.036***	– 0.000
	(0.000)	(0.000)	(0.847)
Debt issue	0.000***	– 0.001	0.000
	(0.000)	(0.128)	(0.663)
Leverage	0.010***	– 0.006	0.022
	(0.000)	(0.842)	(0.282)
Free cash flow	0.025***	0.007	0.075***
	(0.000)	(0.881)	(0.008)
Block holders	– 0.001	– 0.046**	– 0.030
	(0.129)	(0.033)	(0.199)
Z–Score	– 0.346	– 28.353**	16.651
	(0.516)	(0.029)	(0.189)
Net operating assets	0.000***	0.003***	– 0.002
	(0.000)	(0.000)	(0.558)
Audit quality	– 0.015***	0.079**	0.006
	(0.000)	(0.049)	(0.726)
Constant	0.030***	– 0.384***	0.125***
	(0.000)	(0.000)	(0.009)
Observations	18,704	16,094	16,095
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Adj. R^2	0.296	0.063	0.012
F stat	186.74		
$Prob > F$	(0.000)		
F test of excluded instruments		266.28	266.86
p-value		0.000	0.000
Under identification test			
Kleibergen-Paap rk LM stat		408.895	408.457
$\chi^2 p$-value		0.000	0.000
Weak identification test			
Cragg-Donald Wald F stat		302.630	303.607
Kleibergen-Paap rk Wald F stat		266.281	266.862
Over identification test			
Hansen J statistic		1.476	0.091
$\chi^2 p$-value		0.224	0.763

Note: The table presents results from two-stage least squares (2SLS) regression analysis testing H1. The first stage of the 2SLS estimation is presented in column 1 while the second stage is presented in columns 2–3. The independent variables in the second stage regressions are lagged by 1 period. All predictor variables are fully defined in Appendix A1. *P*-values are presented in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

model where the dependent variable is an indicator variable which takes a value of one if a firm receives a takeover bid in the current year and a value of zero if a firm does not receive a bid in any one year over the next five years. The model includes explanatory variables such as abnormal returns (to capture performance), Tobin's q (to capture valuation), market value (to capture size), tangible assets and firm age. These variables have been shown to explain firm takeover likelihood (Danbolt et al., 2016; Loderer & Waelchli, 2015; Palepu, 1986; Powell, 2001). Observations are also matched by year to take account of merger waves (Gort, 1969).

We conduct several tests to ascertain the quality of the propensity score matching procedure. First, in untabulated results, we find that all variables in our probit model are statistically significant in the expected direction. Secondly, at six blocks, we find that the mean propensity score is not different for the treated and control firms across each block. Thirdly, we find that the balancing property is satisfied. Fourthly, we find that the standardized mean and median differences (i.e., percentage bias) in characteristics between the treated and control groups are low. The standardized mean and median differences for the matched sample are 2.0 (mean) and 2.1 (median) against 8.7 (mean) and 6.9 (median) in the unmatched sample. Finally, we find that Rubin's B and Rubin's R for our sample are 7.7 and 0.9, respectively, well in line with recommended thresholds (Rubin, 2001). We use the nearest neighbor (one-to-one) matching algorithm, matching each firm that receives a bid (treatment) to one firm from the control sample (control) that has the closest propensity of receiving a bid. Finally, we run our regression analysis (specified in Equation (3)) on the matched sample. Our results from this analysis are presented in Table 9.

In columns 1 and 2, we explore the relationship between pre-emptive EM and future takeovers in the matched sample of firms. Here, the number of observations is about 1500 compared to over 20,000 in our entire sample analysis (Table 5). In column 1, we do not find evidence that pre-emptive REM plays a defensive role (*p*-value of 0.878). However, we find a significant negative relationship between pre-emptive AEM and future takeovers (*p*-value of 0.034) in column 2. These results suggest that pre-emptive AEM might, indeed, play a defensive or deterrent role. As in Table 5, we explore the impact of managerial entrenchment on this relationship by using a three-way interaction. Consistent with Table 5, we find that the three-way interaction effect is negative and significant for REM but not for AEM. This result suggests that managerial entrenchment might amplify the takeover deterrent effect of pre-emptive REM. As in Table 5, we elucidate our three-way interaction results on pre-emptive REM by running the analysis across sub-samples of firms with high and low entrenchment problems. Here, we find that pre-emptive REM has a negative impact on future takeovers in the sub-sample of firms with high entrenchment problems (*p*-value of 0.000 in column 5) but not for those with low entrenchment problems (*p*-value of 0.558 in column 5). Overall, these results are consistent with our view that pre-emptive EM potentially deters, delays or discourages future takeovers. Our results suggest that pre-emptive AEM plays a deterrent effect on its own, while pre-emptive REM, when deployed by entrenched managers, potentially deters, delays or discourages takeovers.

4.5.4. Mitigating selection bias in the premium equation

Our evidence in Table 6 suggests that offer premiums increase with the level of pre-emptive REM but appear to be unaffected by the level of pre-emptive AEM. Merger premiums are, however, only observed for firms that receive takeover bids. This raises an issue of potential selection bias due to the non-random selection of firms into the acquisition sub-sample. We address this potential selection bias by re-estimating our results using Heckman's two-stage approach with three instruments; industry concentration, market sentiment and merger intensity (within a firm's industry). In the first stage, we estimate a selection model (whether or not a firm receives a bid in the current period) using all the sample firms and our instruments.

Our first instrument – industry concentration – is supported by prior research, which suggests that high competition within an industry (i.e., low industry concentration) leads to firm exit,

Table 9. Pre-emptive earnings management and future takeovers: Propensity Score Matching.

	Full sample		Three-way interaction		Entrenchment	
					High	Low
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Vulnerability#REM#Entrenched			− 51.223***			
			(0.002)			
Vulnerability#AEM#Entrenched				− 79.854		
				(0.248)		
Vulnerability#REM	0.833		8.976		− 80.917***	5.849
	(0.878)		(0.464)		(0.000)	(0.558)
Vulnerability#AEM		− 34.440**		45.735		
		(0.034)		(0.405)		
Vulnerability#Entrenched			− 7.277	− 7.896		
			(0.558)	(0.532)		
REM#Entrenched			2.912***			
			(0.006)			
AEM#Entrenched				3.483		
				(0.407)		
Vulnerability	8.591*	9.080*	20.624*	23.800**	− 14.490	36.436**
	(0.068)	(0.074)	(0.063)	(0.042)	(0.310)	(0.046)
REM	− 0.224		− 0.459		5.010***	− 0.229
	(0.611)		(0.584)		(0.000)	(0.724)
AEM		2.714**		− 0.506		
		(0.024)		(0.893)		
Entrenched			0.593	0.671		
			(0.568)	(0.516)		
Abnormal returns	− 33.133	− 22.461	− 5.672	20.435	23.365	− 79.450
	(0.374)	(0.543)	(0.910)	(0.648)	(0.762)	(0.315)
Profitability	− 0.203*	− 0.201*	− 0.162	− 0.164	− 0.158	− 0.185
	(0.096)	(0.093)	(0.261)	(0.213)	(0.333)	(0.701)
Tobin's *q*	− 0.322***	− 0.331***	− 0.325*	− 0.263*	− 0.567**	− 0.261
	(0.004)	(0.003)	(0.063)	(0.063)	(0.049)	(0.312)
Sales growth	0.054	0.049	− 0.515	− 0.544*	− 1.588***	− 0.001
	(0.591)	(0.619)	(0.129)	(0.090)	(0.000)	(0.995)
Liquidity	0.688	0.790*	0.893*	1.023**	− 0.165	2.117**
	(0.139)	(0.093)	(0.063)	(0.042)	(0.852)	(0.039)
Leverage	0.216	0.195	0.669	0.405	0.924	1.771*
	(0.656)	(0.681)	(0.354)	(0.520)	(0.459)	(0.080)
Growth-resource	0.057	0.053	− 0.205	− 0.250	0.534	− 0.813*
	(0.798)	(0.816)	(0.505)	(0.403)	(0.240)	(0.070)
Disturbance	1.260	1.140	− 0.609	− 1.387	4.153**	− 2.990
	(0.332)	(0.394)	(0.659)	(0.268)	(0.036)	(0.248)
Firm size	− 0.029	− 0.026	0.020	0.039	− 0.100**	0.077
	(0.385)	(0.449)	(0.578)	(0.219)	(0.049)	(0.244)
Firm size#Firm size	2.261***	2.327***	2.486**	2.352**	9.065***	− 1.470
	(0.006)	(0.006)	(0.042)	(0.029)	(0.000)	(0.209)
Free cash flow	0.119	0.190	− 1.024	− 0.769	− 0.101	− 4.194***
	(0.729)	(0.585)	(0.101)	(0.214)	(0.905)	(0.000)
Tangible assets	− 0.027	− 0.039	− 0.095	− 0.104	− 0.519**	0.348**
	(0.799)	(0.713)	(0.540)	(0.497)	(0.038)	(0.032)
Firm age	− 0.025	− 0.052	0.095	0.055	− 1.658***	1.047
	(0.932)	(0.861)	(0.870)	(0.923)	(0.010)	(0.332)
Block holders	− 15.675	− 14.467	1.624	8.937	− 42.243**	23.780
	(0.202)	(0.251)	(0.904)	(0.457)	(0.028)	(0.329)
Constant	− 15.675	− 14.467	1.624	8.937	− 42.243**	23.780
	(0.202)	(0.251)	(0.904)	(0.457)	(0.028)	(0.329)

(*Continued*).

Table 9. Continued.

					Entrenchment	
	Full sample		Three-way interaction		High	Low
Observations	1552	1517	637	630	340	297
χ^2	48.10	52.19	37.58	72.15	50.59	37.12
Prob (χ^2)	(0.000)	(0.000)	(0.010)	(0.000)	(0.000)	(0.002)
Pseudo R^2	0.110	0.116	0.157	0.144	0.361	0.264

Note: This table presents the probit regression estimates from Equation (3) which explores the takeover deterrent effect of earnings management (EM) using a propensity score matched sample. Columns 1–2 presents coefficient estimates of Equation (3) based on our entire sample. Columns 3–4 present coefficient estimates of Equation (3) when interacted with the entrenchment indicator. Columns 5–6 presents coefficient estimates of Equation (3) from two sub-samples; high and low entrenchment firms. We define high (low) entrenchment as a sub-sample of firms in which the value of compensation made up of long term incentive plans (LTIP) as a proportion total compensation (averaged across all board members) is less (greater) than the 2-digit SIC code industry-year median value. The model controls for firm characteristics that influence takeover likelihood, as well as industry and year fixed effects. All variables are fully defined in Appendix A1. *P*-values are presented in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

possibly through takeovers (Danbolt et al., 2016). Further, in the UK, firms in highly concentrated industries might be shielded from takeovers by antitrust regulation as further consolidation within the industry might adversely impact customer welfare (Danbolt et al., 2016). Our second instrument – market sentiment – is drawn from prior research (Tunyi, 2019) which suggests that merger activity, and hence, the likelihood of selection, generally increases in periods of stock market growth (i.e., market sentiment). Our third instrument – merger intensity – is derived from the merger wave literature, which contends that acquisitions cluster by industry as takeovers within an industry incentivise other firms within the industry to engage in mergers in order to retain their competitive position (Gort, 1969; Palepu, 1986). These instruments are plausibly exogenous and theoretically unrelated to the level premiums offered for specific firms. In addition to our three instruments, the selection model controls for profitability, market to book (or valuation), firm size and the availability of free cash flow. All independent variables are lagged by one year.

The first stage regression results are presented in panel A of Table 10. Here, we find that the coefficients of our instruments are statistically significant in the expected direction. Specifically, the likelihood of being selected into the sample, for both our REM (column 1) and AEM (column 3) regressions, increases with market sentiment and merger intensity but declines with industry concentration. We further ascertain the validity of our instruments through the likelihood ratio test of excluded instruments. Our test results (LR χ^2 of about 55 with a *p*-value of 0.000) suggest that the three instruments together increase the model's explanatory power or goodness-of-fit. Conceptually, the non-selection hazard (i.e., Inverse Mills Ratio) computed from the first stage regression[21] is included as an additional control in the second stage regression (i.e., Equation (4)).

One thing we need to be mindful of, is multicollinearity in the second stage regression arising from the inclusion of the Inverse Mills Ratio and four variables (profitability, market to book, firm size and free cash flow) it derives from. To attenuate this concern, we compute VIF and, in panel B of Table 10, present the highest VIF (which incidentally equals the VIF of the Inverse

[21]The Inverse Mills Ratio is estimated as, $\frac{\psi Z}{\phi Z}$ where Z is the fitted value of the probit regression function; ψZ is the probability density function (PDF) for standard normal distribution; and ϕZ is the cumulative density function (CDF) for a standard normal distribution.

Table 10. Pre-emptive earnings management and premiums: Heckman's two-stage regressions.

Panel A: Heckman's first-stage selection model

	Target (REM equation)		Target (AEM equation)	
	Coeff.	*p*-value	Coeff.	*p*-value
Variables	(1)	(2)	(3)	(4)
Concentration	– 0.354***	(0.000)	– 0.369***	(0.000)
Sentiment	0.387***	(0.000)	0.380***	(0.000)
Merger intensity	0.010***	(0.005)	0.011***	(0.004)
Profitability	0.319***	(0.002)	0.272***	(0.006)
Market to book	– 0.043***	(0.000)	– 0.043***	(0.000)
Firm size	0.046***	(0.000)	0.048***	(0.000)
Free cash flow	0.392***	(0.005)	0.390***	(0.005)
Constant	– 2.593***	(0.000)	– 2.611***	(0.000)
Observations	24,917		24,921	
χ^2	202.7		191.4	
p	(0.000)		(0.000)	
Likelihood-ratio test of excluded instruments				
LR χ^2	53.42	(0.000)	55.48	(0.000)

Panel B: Heckman's second-stage regression model

	Premium (REM equation)		Premium (AEM equation)	
Variables	Coeff. (1)	*p*-value (2)	Coeff. (3)	*p*-value (4)
Inverse Mills Ratio	29.055	(0.174)	21.773	(0.291)
Vulnerability	11.076	(0.842)	10.742	(0.848)
Vulnerability#REM	163.298*	(0.068)		
Vulnerability#AEM			109.448	(0.632)
REM	– 8.345	(0.203)		
AEM			– 10.433	(0.579)
Profitability	9.118	(0.438)	5.644	(0.621)
Firm size	– 2.233*	(0.054)	– 2.458**	(0.034)
Market to book	– 3.640***	(0.004)	– 3.248***	(0.010)
Debt issue	0.147	(0.537)	0.081	(0.733)
Leverage	1.879	(0.813)	2.107	(0.794)
Free cash flow	– 5.981	(0.689)	– 3.590	(0.810)
Block holders	– 13.057*	(0.080)	– 11.152	(0.138)
Cash payment	5.239*	(0.076)	6.297**	(0.037)
Cross border	5.940**	(0.035)	6.521**	(0.022)
Bid attitude	5.708	(0.166)	5.168	(0.221)
Competing bids	24.716***	(0.000)	25.152***	(0.000)
Diversifying bids	0.789	(0.750)	1.971	(0.434)
Constant	15.076	(0.822)	33.301	(0.611)
Observations	24,917		24,921	
Industry FE	Yes		Yes	
Year FE	Yes		Yes	
Selected cases	897		901	
Wald χ^2	202.7	(0.000)	191.4	(0.000)
Highest VIF	2.420		2.290	
VIF of Inverse Mills Ratio	2.420		2.290	

Note: The table presents results from Heckman's two-stage regression analysis testing H3. The first stage results are presented in panel A while the second stage results are presented in panel B. The independent variables in panel B are lagged by 1 period. All predictor variables are fully defined in Appendix A1. *P*-values are presented in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Mills Ratio). Our results show that VIFs are below the generally accepted threshold, thus suggesting that multicollinearity is not a concern. Further, we find that the coefficient of the Inverse Mills Ratio is positive but not statistically significant across the two models, indicating that the selection problem is negligible. Importantly, our main results hold after controlling for selection bias. That is, pre-emptive REM is positively related to merger premiums. The coefficient of the interaction term which captures pre-emptive AEM is positive (coefficient of 109.448) but statistically insignificant at the 10% level.

5. Concluding Remarks

Prior research has documented firms' EM behavior across various contexts. This line of research suggests that managers engage in EM before major events such as IPOs, SEOs, acquisitions and management buyouts (Botsari & Meeks, 2008; Cohen & Zarowin, 2010; Erickson & Wang, 1999; Higgins, 2013; Mao & Renneboog, 2015). Additionally, this research has established that EM is costly, and any benefits from managing earnings are likely to be transitory (Graham et al., 2005; Gunny, 2010; Kothari et al., 2016). Therefore, the expectation is that managers will engage in EM, perhaps, only sparingly when the need arises. We extend this body of research by exploring EM behavior under conditions when the nature and timing of events are uncertain and the unconditional likelihood of the event occurring is low. Specifically, we focus on the extent to which firms that are vulnerable to takeovers engage in pre-emptive EM. After establishing the baseline results, we explore the possible motives and consequences of such pre-emptive EM.

Using a UK sample, we uncover evidence that vulnerable firms pre-emptively manage earnings mainly via REM strategies, specifically, overproduction and aggressive reduction of discretionary expenses. Our findings suggest that, while pre-emptive REM and AEM are deployed in a complementary manner, firms primarily exhaust REM opportunities and plausibly only turn to AEM when takeovers become more imminent. Specifically, we find that the positive relationship between vulnerability to takeovers and EM behavior is stronger in periods of high M&A intensity, in which, ceteris paribus, firms' acquisition likelihood broadly increases. The vulnerability–EM relationship is neither confined to underperforming firms nor firms typically expected to manage earnings. In uncovering this evidence, we contribute to the literature by showing that (1) firms manage earnings in anticipation of uncertain events, (2) prospective target firms engage in pre-emptive EM, specifically REM in the first instance, and also plausibly AEM when takeovers become imminent, and (3) vulnerability to takeovers partly explains firms' EM behavior.

Drawing from managerial entrenchment and opportunism perspectives, we examine the motives of pre-emptive EM by exploring the takeover deterrent effects of pre-emptive EM. Specifically, we test whether the likelihood of receiving future takeover bids reduces when firms pre-emptively manage earnings. Our evidence suggests that pre-emptive REM only deters takeovers in a subset of firms with relatively higher managerial entrenchment problems. Overall, our findings contribute to the literature exploring the takeover deterrent effects of managerial actions such as open market share repurchase and increased dividend payouts (Billett & Xue, 2007; Driver et al., 2020) by documenting the deterrent effect of pre-emptive EM in a sub-sample of entrenched firms. Nonetheless, the finding also highlights the possibility that several firms engage in EM for other reasons.

We also examine the consequences of pre-emptive EM on merger outcomes, focusing on merger premiums. Merger premiums are an important M&A outcome as they capture the impact of a deal on target shareholders, and at the same time, the acquirer's assessment of the target.

Incidentally, in this context, merger premiums can also give us an insight into the relative benefits of pre-emptive REM versus AEM. We find that, contingent on receiving bids, firms that pre-emptively manage earnings using REM extract comparatively higher bid premiums. Taken together, our findings that pre-emptive EM might play a takeover deterrent role but still allow firms to optimize merger outcomes is consistent with the view that takeover defences, when they are ineffective in deterring takeovers, serve the interest of shareholders by raising the bid premium (Holl & Kyriazis, 1997; Kadyrzhanova & Rhodes-Kropf, 2011).

The results contribute to the literature by showing that EM plays a signaling role within this context. Prior studies have drawn on the case of EM ahead of IPOs, SEOs and acquisitions to show that, while the stock market reacts positively to EM (evidence of signaling), this reaction is often short-term, with reversals documented in the medium to long term (Gunny, 2010). The finding on reversals obfuscates inferences on whether EM is driven by signaling or agency motives. Our focus on non-reversible merger premiums instead of stock prices provides a fresh perspective on the subject.

We have conducted several additional checks to ensure that are our findings are generally robust to typical biases and endogeneity issues, including reverse causality, self-selection and look-ahead biases. Nonetheless, as is typical in studies of this nature, we cannot completely rule out endogeneity problems. Additionally, our findings create opportunities for further research on the subject. For example, while our study focuses on targets, admittedly, it ignores the response of acquirers. Secondly, there are opportunities for more detailed analysis of the trade-offs between REM and AEM, as well as the different REM strategies used by vulnerable firms. Finally, there are opportunities to explore how acquirer pre-takeover EM (Botsari & Meeks, 2008; Erickson & Wang, 1999; Higgins, 2013) and target pre-emptive EM interact to shape M&A outcomes.

Overall, this study enhances our understanding of how firms react to takeover exposure (i.e., by managing earnings) and how their reaction shapes the dynamics of M&As. By way of implications, the study highlights, in practical terms, why it might be sub-optimal for shareholders (of vulnerable firms) to prohibit EM. As our findings suggest, EM benefits shareholders by allowing them to extract higher merger premiums from acquirers.

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References

Achleitner, A.-K., Günther, N., Kaserer, C., & Siciliano, G. (2014). Real earnings management and accrual-based earnings management in family firms. *European Accounting Review*, *23*(3), 431–461. https://doi.org/10.1080/09638180.2014.895620

Agyei-Boapeah, H., Osei, D., & Franco, M. (2019). Leverage deviations and acquisition probability in the UK: the moderating effect of firms' internal capabilities and deal diversification potential. *European Management Review*, *16*(4), 1059–1077. https://doi.org/10.1111/emre.12307

Anagnostopoulou, S. C., & Tsekrekos, A. E. (2013). Do firms that wish to be acquired manage their earnings? evidence from major european countries. *International Review of Financial Analysis*, *30*, 57–68. https://doi.org/10.1016/j.irfa.2013.06.002

Anagnostopoulou, S. C., & Tsekrekos, A. E. (2015). Earnings management in firms seeking to be acquired. *The British Accounting Review*, *47*(4), 351–375. https://doi.org/10.1016/j.bar.2014.07.001

Baber, W. R., Kang, S. -H., & Li, Y. (2011). Modeling discretionary accrual reversal and the balance sheet as an earnings management constraint. *The Accounting Review*, *86*(4), 1189–1212. https://doi.org/10.2308/accr-10037

Barton, J., & Simko, P. J. (2002). The balance sheet as an earnings management constraint. *The Accounting Review*, *77*(s-1), 1–27. https://doi.org/10.2308/accr.2002.77.s-1.1

Bartov, E., Givoly, D., & Hayn, C. (2002). The rewards to meeting or beating earnings expectations. *Journal of Accounting and Economics*, *33*(2), 173–204. https://doi.org/10.1016/S0165-4101(02)00045-9

Berger, P. G., Ofek, E., & Yermack, D. L. (1997). Managerial entrenchment and capital structure decisions. *The Journal of Finance*, *52*(4), 1411–1438. https://doi.org/10.1111/j.1540-6261.1997.tb01115.x

Billett, M. T., & Xue, H. (2007). The takeover deterrent effect of open market share repurchases. *The Journal of Finance*, *62*(4), 1827–1850. https://doi.org/10.1111/j.1540-6261.2007.01258.x

Boone, J. P., Khurana, I. K., & Raman, K. (2010). Do the Big 4 and the second-tier firms provide audits of similar quality? *Journal of Accounting and Public Policy*, *29*(4), 330–352. https://doi.org/10.1016/j.jaccpubpol.2010.06.007

Botsari, A., & Meeks, G. (2008). Do acquirers manage earnings prior to a share for share bid? *Journal of Business Finance & Accounting*, *35*(5-6), 633–670. https://doi.org/10.1111/j.1468-5957.2008.02091.x

Brar, G., Giamouridis, D., & Liodakis, M. (2009). Predicting european takeover targets. *European Financial Management*, *15*(2), 430–450. https://doi.org/10.1111/eufm.2009.15.issue-2

Brennan, N. (1999). Voluntary disclosure of profit forecasts by target companies in takeover bids. *Journal of Business Finance & Accounting*, *26*(7-8), 883–917. https://doi.org/10.1111/jbfa.1999.26.issue-7&8

Buchholtz, A. K., & Ribbens, B. A. (1994). Role of chief executive officers in takeover resistance: Effects of CEO incentives and individual characteristics. *Academy of Management Journal*, *37*(3), 554–579. https://doi.org/10.5465/256700

Cohen, D. A., Dey, A., & Lys, T. Z. (2008). Real and accrual-based earnings management in the pre-and post-sarbanes-oxley periods. *The Accounting Review*, *83*(3), 757–787. https://doi.org/10.2308/accr.2008.83.3.757

Cohen, D. A., & Zarowin, P. (2010). Accrual-based and real earnings management activities around seasoned equity offerings. *Journal of Accounting and Economics*, *50*(1), 2–19. https://doi.org/10.1016/j.jacceco.2010.01.002

Cremers, K. M., Nair, V. B., & John, K. (2009). Takeovers and the cross-section of returns. *The Review of Financial Studies*, *22*(4), 1409–1445. https://doi.org/10.1093/rfs/hhn032

Danbolt, J., Siganos, A., & Tunyi, A. (2016). Abnormal returns from takeover prediction modelling: challenges and suggested investment strategies. *Journal of Business Finance & Accounting*, *43*(1-2), 66–97. https://doi.org/10.1111/jbfa.12179

Dechow, P. M., & Shakespear, C. (2009). Do managers time securitization transactions to obtain accounting benefits? *The Accounting Review*, *84*(1), 99–132. https://doi.org/10.2308/accr.2009.84.1.99

Dechow, P. M., Sloan, R. G., & Sweeney, A. P. (1995). Detecting earnings management. *The Accounting Review*, *70*(2), 193–225. http://www.jstor.org/stable/248303

DeFond, M. L., & Park, C. W. (2001). The reversal of abnormal accruals and the market valuation of earnings surprises. *The Accounting Review*, *76*(3), 375–404. https://doi.org/10.2308/accr.2001.76.3.375

Driver, C., Grosman, A., & Scaramozzino, P. (2020). Dividend policy and investor pressure. *Economic Modelling*, Elsevier, *89*, 559–576. https://doi.org/10.1016/j.econmod.2019.11.016

Erickson, M., & Wang, S.-w. (1999). Earnings management by acquiring firms in stock for stock mergers. *Journal of Accounting and Economics*, *27*(2), 149–176. https://doi.org/10.1016/S0165-4101(99)00008-7

Feito-Ruiz, I., & Renneboog, L. (2017). Takeovers and (excess) CEO compensation. *Journal of International Financial Markets, Institutions and Money*, *50*, 156–181. https://doi.org/10.1016/j.intfin.2017.06.003

Ge, W., & Kim, J.-B. (2014). Boards, takeover protection, and real earnings management. *Review of Quantitative Finance and Accounting*, *43*(4), 651–682. https://doi.org/10.1007/s11156-013-0388-2

Goergen, M., & Renneboog, L. (2011). Managerial compensation. *Journal of Corporate Finance*, *17*(4), 1068–1077. https://doi.org/10.1016/j.jcorpfin.2011.06.002

Gort, M. (1969). An economic disturbance theory of mergers. *The Quarterly Journal of Economics*, *83*(4), 624–642. https://doi.org/10.2307/1885453
Graham, J. R., Harvey, C. R., & Rajgopal, S. (2005). The economic implications of corporate financial reporting. *Journal of Accounting and Economics*, *40*(1-3), 3–73. https://doi.org/10.1016/j.jacceco.2005.01.002
Graham, J. R., Harvey, C. R., & Rajgopal, S. (2006). Value destruction and financial reporting decisions. *Financial Analysts Journal*, *62*(6), 27–39. https://doi.org/10.2469/faj.v62.n6.4351
Gunny, K. A. (2010). The relation between earnings management using real activities manipulation and future performance: Evidence from meeting earnings benchmarks. *Contemporary Accounting Research*, *27*(3), 855–888. https://doi.org/10.1111/j.1911-3846.2010.01029.x
Herrmann, D., Inoue, T., & Thomas, W. B. (2003). The sale of assets to manage earnings in japan. *Journal of Accounting Research*, *41*(1), 89–108. https://doi.org/10.1111/joar.2003.41.issue-1
Higgins, H. N. (2013). Do stock-for-stock merger acquirers manage earnings? evidence from japan. *Journal of Accounting and Public Policy*, *32*(1), 44–70. https://doi.org/10.1016/j.jaccpubpol.2012.10.001
Holl, P., & Kyriazis, D. (1997). Agency, bid resistance and the market for corporate control. *Journal of Business Finance & Accounting*, *24*(7-8), 1037–1066. https://doi.org/10.1111/jbfa.1997.24.issue-7&8
Jensen, M. C. (1986). Agency costs of free cash flow, corporate finance, and takeovers. *The American Economic Review*, *76*(2), 323–329. https://www.jstor.org/stable/1818789
Jenson, M. C. (1984). Takeovers: Folklore and science'. *Harvard Business Review*, *62*, 109–114. http://dx.doi.org/10.2139/ssrn.350425
Jindra, J., & Walkling, R. A. (2004). Speculation spreads and the market pricing of proposed acquisitions. *Journal of Corporate Finance*, *10*(4), 495–526. https://doi.org/10.1016/S0929-1199(03)00030-0
Jones, J. J. (1991). Earnings management during import relief investigations. *Journal of Accounting Research*, *29*(2), 193–228. https://doi.org/10.2307/2491047
Kadyrzhanova, D., & Rhodes-Kropf, M. (2011). Concentrating on governance. *The Journal of Finance*, *66*(5), 1649–1685. https://doi.org/10.1111/j.1540-6261.2011.01684.x
Kasznik, R., & McNichols, M. F. (2002). Does meeting earnings expectations matter? evidence from analyst forecast revisions and share prices. *Journal of Accounting Research*, *40*(3), 727–759. https://doi.org/10.1111/1475-679X.00069
Kim, J.-B., Chung, R., & Firth, M. (2003). Auditor conservatism, asymmetric monitoring, and earnings management. *Contemporary Accounting Research*, *20*(2), 323–359. https://doi.org/10.1506/J29K-MRUA-0APP-YJ6V
Kim, J.-B., & Sohn, B. C. (2013). Real earnings management and cost of capital. *Journal of Accounting and Public Policy*, *32*(6), 518–543. https://doi.org/10.1016/j.jaccpubpol.2013.08.002
Kim, J. H., Lee, S. H., & Keun Yoo, Y. (2020). Real earnings management and the cost of debt capital: international evidence. *Asia-Pacific Journal of Accounting & Economics*, *27*(2), 151–172. https://doi.org/10.1080/16081625.2018.1518148
Kothari, S. P., Mizik, N., & Roychowdhury, S. (2016). Managing for the moment: The role of earnings management via real activities versus accruals in seo valuation. *The Accounting Review*, *91*(2), 559–586. https://doi.org/10.2308/accr-51153
Loderer, C., & Waelchli, U. (2015). Corporate aging and takeover risk. *Review of Finance*, *19*(6), 2277–2315. https://doi.org/10.1093/rof/rfu048
Mao, Y., & Renneboog, L. (2015). Do managers manipulate earnings prior to management buyouts? *Journal of Corporate Finance*, *35*, 43–61. https://doi.org/10.1016/j.jcorpfin.2015.08.005
Mikkelson, W. H., & Partch, M. M. (1997). The decline of takeovers and disciplinary managerial turnover. *Journal of Financial Economics*, *44*(2), 205–228. https://doi.org/10.1016/S0304-405X(97)00003-2
Palepu, K. G. (1986). Predicting takeover targets: A methodological and empirical analysis. *Journal of Accounting and Economics*, *8*(1), 3–35. https://doi.org/10.1016/0165-4101(86)90008-X
Pound, J., & Zeckhauser, R. (1990). Clearly heard on the street: The effect of takeover rumors on stock prices. *Journal of Business*, *63*(3), 291–308. https://doi.org/10.1086/jb.1990.63.issue-3
Powell, R. G. (2001). Takeover prediction and portfolio performance: A note. *Journal of Business Finance & Accounting*, *28*(7-8), 993–1011. https://doi.org/10.1111/jbfa.2001.28.issue-7&8
Roychowdhury, S. (2006). Earnings management through real activities manipulation. *Journal of Accounting and Economics*, *42*(3), 335–370. https://doi.org/10.1016/j.jacceco.2006.01.002
Rubin, D. B. (2001). Using propensity scores to help design observational studies: application to the tobacco litigation. *Health Services and Outcomes Research Methodology*, *2*(3-4), 169–188. https://doi.org/10.1023/A:1020363010465
Schoenberg, R., & Thornton, D. (2006). The impact of bid defences in hostile acquisitions. *European Management Journal*, *24*(2-3), 142–150. https://doi.org/10.1016/j.emj.2006.03.004
Staiger, D., Stock, J. H., & Watson, M. W. (1997). The nairu, unemployment and monetary policy. *Journal of Economic Perspectives*, *11*(1), 33–49. https://doi.org/10.1257/jep.11.1.33

Stock, J. H., Wright, J. H., & Yogo, M. (2002). A survey of weak instruments and weak identification in generalized method of moments. *Journal of Business & Economic Statistics*, *20*(4), 518–529. https://doi.org/10.1198/073500102288618658

Stock, J. H., & Yogo, M. (2002). *Testing for weak instruments in linear IV regression* (Tech. Rep.). National Bureau of Economic Research.

Subramanyam, K. (1996). The pricing of discretionary accruals. *Journal of Accounting and Economics*, *22*(1-3), 249–281. https://doi.org/10.1016/S0165-4101(96)00434-X

Sul, E. (2020, February 4). *Takeover threats, job security concerns, and earnings management* [Job Security Concerns, and Earnings Management].

Teoh, S. H., Welch, I., & Wong, T. J. (1998). Earnings management and the long-run market performance of initial public offerings. *The Journal of Finance*, *53*(6), 1935–1974. https://doi.org/10.1111/0022-1082.00079

Tunyi, A. (2019). Firm size, market conditions and takeover likelihood. *Review of Accounting and Finance*. *18*(3), 483–507. https://doi.org/10.1108/RAF-07-2018-0145

Tunyi, A. A. (2021). Revisiting acquirer returns: Evidence from unanticipated deals. *Journal of Corporate Finance*, *66*, Article 101789. https://doi.org/10.1016/j.jcorpfin.2020.101789

Tunyi, A. A., & Ntim, C. G. (2016). Location advantages, governance quality, stock market development and firm characteristics as antecedents of African M&As. *Journal of International Management*, *22*(2), 147–167. https://doi.org/10.1016/j.intman.2016.01.005

Tunyi, A. A., Ntim, C. G., & Danbolt, J. (2019). Decoupling management inefficiency: Myopia, hyperopia and takeover likelihood. *International Review of Financial Analysis*, *62*, 1–20. https://doi.org/10.1016/j.irfa.2019.01.004

Zang, A. Y. (2012). Evidence on the trade-off between real activities manipulation and accrual-based earnings management. *The Accounting Review*, *87*(2), 675–703. https://doi.org/10.2308/accr-10196

Zhao, Y., & Chen, K. H. (2008). The influence of takeover protection on earnings management. *Journal of Business Finance & Accounting*, *35*(3-4), 347–375. https://doi.org/10.1111/j.1468-5957.2008.02081.x

Zhao, Y., Chen, K. H., Zhang, Y., & Davis, M. (2012). Takeover protection and managerial myopia: Evidence from real earnings management. *Journal of Accounting and Public Policy*, *31*(1), 109–135. https://doi.org/10.1016/j.jaccpubpol.2011.08.004

Appendix. Variable Descriptions

Table A1. Variable descriptions.

Variables (Abbrev.)	Construction (Worldscope codes)
Panel A: Main variables	
Target = 1	Dummy variable which takes a value of one if a firm is the subject of a takeover bid and a value of zero otherwise.
Vulnerability	Takeover likelihood as at the start of the period. Derived from Equation (1).
High (Low) vulnerability	Indicator variable capturing whether a firm's level of vulnerability in each year is greater than (i.e., high) or less than (i.e., low) the median vulnerability (defined above).
Abnormal production (REMprod)	Following prior studies (Cohen et al., 2008; Roychowdhury, 2006; Zang, 2012), we model total production costs as a function of sales (WC01001), change in sales and the lagged change in sales and capture the abnormal portion of production costs (REMprod) as the residual from the (2-digit SIC code) industry-year cross-sectional regressions. $$\frac{PROD_{it}}{Assets_{it-1}} = \beta_0 + \beta_1 \frac{1}{Assets_{it-1}} + \beta_2 \frac{Sales_{it}}{Assets_{it-1}} + \beta_3 \frac{\Delta Sales_{it}}{Assets_{it-1}} + \beta_4 \frac{\Delta\ Sales_{it-1}}{Assets_{it-1}} + \epsilon_{it} \quad (A1)$$
Abnormal discretionary expenses (REMdisx)	Following prior studies (Cohen et al., 2008; Roychowdhury, 2006; Zang, 2012), we model total discretionary expenses (the sum of R&D expenditures (WC01201) and selling, general and administrative (SG&A) expenditures (WC01101)) costs) as a function of sales (WC01001). REMdisx is the residual from the (2-digit SIC code) industry-year cross-sectional regressions, multiplied by negative one. $$\frac{DISX_{it}}{Assets_{it-1}} = \beta_0 + \beta_1 \frac{1}{Assets_{it-1}} + \beta_2 \frac{Sales_{it-1}}{Assets_{it-1}} + \epsilon_{it} \quad (A2)$$

(*Continued*).

Table A1. Continued.

Variables (Abbrev.)	Construction (Worldscope codes)
Abnormal cash flow from operations (REMcfo)	Following Roychowdhury (2006), we model normal CFO (WC04860) as a function of sales (WC01001) and change in sales. REMcfo is the residual from the (2-digit SIC code) industry-year cross-sectional regressions, multiplied by negative one. $$\frac{CFO_{it}}{Assets_{it-1}} = \beta_0 + \beta_1 \frac{1}{Assets_{it-1}} + \beta_2 \frac{Sales_{it}}{Assets_{it-1}} + \beta_3 \frac{\Delta Sales_{it}}{Assets_{it-1}} + \epsilon_{it} \quad (A3)$$
Real earnings management (REM)	The sum of Abnormal production (REMprod) and Abnormal discretionary expenses (REMdisx).
Accrual earnings management (AEM)	We use the modified-Jones model (Dechow et al., 1995) to estimate discretionary accruals. Total accruals (Accruals) is modeled as a function of property, plant and equipment (PPE, WC02051) and the difference between change in sales (WC01001) and change in receivables (WC02051). AEM is the residual from the (2-digit SIC code) industry-year cross-sectional regressions. $$\frac{Accruals_{it}}{Assets_{it-1}} = \beta_0 + \beta_1 \frac{1}{Assets_{it-1}} + \beta_2 \frac{\Delta Sales_{it} - \Delta Receivables_{it}}{Assets_{it-1}} + \beta_3 \frac{PPE_{it}}{Assets_{it-1}} + \epsilon_{it} \quad (A4)$$
Premium	Difference between offer price and target stock price (4 weeks before the announcement) as a ratio of target stock price.
Panel B: Control variables – Firm financial characteristics	
Abnormal returns	Abnormal returns of the last year computed using the OLS market model. Alpha and beta estimates are first computed from the previous year by regressing stock returns on market returns. Estimates of alpha and beta are then used to compute abnormal return in the current year.
Profitability	Return on assets computed as ratio of earnings before interest and tax (WC18191) total assets (WC02999).
Tobin's Q	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	Market value of equity (MVE) divided by book value of equity (WC02999-WC03255).
Sales growth	Change in total revenues (WC01001) as a ratio of previous year's total revenues (WC01001).
Liquidity	Cash and short-term investments (WC02001) to total assets (WC02999).
Leverage	Total debt (WC03255) to total assets (WC02999).
Debt issue	Percentage change in total debt (WC03255).
Growth-resource dummy	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. (see, Danbolt et al., 2016; Palepu, 1986).
Industry disturbance dummy	Dummy is one if any merger is completed within a firm's two-digit SIC industry in the year before the bid, and a value of zero otherwise.
Firm size	Natural log of total assets (WC02999).
Free cash flow	Ratio of net cash flow from operating activities (WC04860) minus capital expenditures (WC04601) scaled by total assets (WC02999).
Tangible assets	Ratio of property, plant and equipment (WC02501) to total assets (WC02999).
Firm age	Number of years since date of incorporation (WC18273).
Block holder	Proportion of shares held by strategic shareholder (NOSHST) – i.e., shareholders with at least 5% shareholding.
Z–Score	Taffler Z–Score estimated using the following equation. $$Z_{it} = 3.20 + 12.18 * X_1 + 2.50 * X_2 - 10.68 * X_3 + 0.029 * X_4 \quad (A5)$$ where X_1 is the ratio of profit before tax (PBT) to current liabilities (CL), X_2 is the ratio of current assets to total liabilities, X_3 is the ratio of CL to total assets, X_4 is the ratio of quick assets minus CL to daily operating expenses (DOE). DOE is computed as sales minus PBT minus depreciation divided by 365.
Net operating assets	Shareholders' equity less cash and marketable securities plus total debt, deflated by total sales.

(*Continued*).

Table A1. Continued.

Variables (Abbrev.)	Construction (Worldscope codes)
Panel C: Control variables – Corporate Governance characteristics	
Audit quality	The ratio of audit fee to total assets.
Board size	The total number of directors on the board.
CEO duality	A dummy variable which takes a value of one if the chief executive officer (CEO) is also the board chairman, and a value of zero otherwise.
Gender diversity	The proportion of female board members within the board.
Board independence	The proportion of independent directors within the board.
Director experience	The average age of board members.
Board tenure	The average length of time each board member has been on the board.
Audit committee	An indicator variable for the presence or not of an audit committee.
Panel D: Control variables – M&A characteristics	
Cash payment	A dummy variable that takes a value of one, when a target receives an all-cash merger offer.
Crossborder	A dummy variable which takes a value of one if an acquirer is a foreign firm i.e., not listed on the London Stock Exchange, and a value of zero otherwise.
Bid attitude	A dummy variable which takes a value of one if the deal is characterized as a hostile deal, and a value of zero otherwise.
Competing bids	A dummy variable which takes a value of one if multiple firms were bidding for the same target within the same period, and a value of zero otherwise.
Diversifying bids	A dummy variable which takes a value of one if the acquirer and target are from different industries, and a value of zero otherwise.
Panel E: Other variables (including instruments)	
Concentration (industry)	Herfindahl-Hirschman Index (HHI); sum of squared market shares (computed from revenues) of firms in each 2-digit SIC code industry in each year.
Sentiment (market)	Change in the FTSE-All share index over the last 12-months.
Merger intensity	Natural log of number of M&A bids announced within a firm's 2-digit SIC code industry in the previous year.
Industry rumors	The number of merger rumors within a firm's 2-digit SIC code industry in the previous year scaled by 100.
Peer vulnerability	The mean vulnerability of peer firms (excluding the focal firms) within each 2-digit SIC code industry-year.
Entrenchment	An indicator variable identifying firms in which the ratio of the value of long term incentive plans (LTIP) to total managerial compensation for the period, averaged over all board members, is less than the 2-digit SIC code industry-year median value.