There's no smoke without fire: Does the context of earnings management contain information about future stock returns?

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Abstract: This paper constructs a signal-based index, namely ESCORE, which captures the context of earnings management. ESCORE is a composite index that aggregates 15 individual signals which have been shown in the extant literature to be related to earnings management behaviour. Empirical test using UK data shows that firms do manage earnings with larger magnitude and are more likely to be most aggressive, both in accruals and real earnings management, when ESCORE is higher. It is also shown that firms with low ESCORE outperform those with high ESCORE by 1.37% per month after controlling for risk loadings on the size, book-to-market and momentum factors in up to one year after portfolio formation.

Key words: Earnings management, market anomaly, stock returns predictability, earnings management detection models.

1 Introduction

Extant literature on earnings management shows that the market overprices total and/or discretionary accrual component of earnings(see, for example Sloan, 1996; Xie, 2001). Since discretionary accruals, often estimated using the Jones' (1991) model or one of its variants (hereafter referred to as 'accruals models' for brevity), is widely used in the literature to proxy for earnings management, the evidence seems consistent with the premisethatthe market fails to fully appreciate managers' discretion to influence reported earnings. Evidence in support of the negative association of discretionary accruals and future stock returns is reported in various studies employing different methodologies, across different time periods and in different markets (Teoh et al., 1998a; Teoh et al., 1998b; Desai et al., 2004; Iqbal et al., 2009; Iqbal and Strong, 2010).

While it is well established that discretionary accruals arenot fully priced, one aspect of the existing literature is still subject to considerable criticism which is rooted mainly from the weaknesses of the accrual models to capture earnings management. For example,Dechow et al. (2010) observe that "the majority of the studies... are about the determinants and consequences of *abnormal accruals* derived from accrual models, with the idea that abnormal accruals, whether they represent errors or bias, erode decision usefulness". In other words, the literature has over-relied on models, such as the accruals models, to disentangle the component of earnings subject to managers' discretion from the 'normal' level of performance without fully appreciating that discretionary accrual is a 'noisy' measure of earnings management. A number of studies share the same concern (for example, Holthausen et al., 1995; Fields et al., 2001; Ball, 2013; Owens et al., 2013). With the lack of a comprehensive theory on the accrual generating process (i.e. what accrual would be if there is no manipulation), as a profession we are using (allegedly) mis-specified model trying to measure the 'immeasurable' (McNichols, 2000; Dechow et al., 2010; Owens et al., 2013). In addition, many other researchersraise a concern about the implausibly large magnitude and high frequency of earnings management documented in the extant literature using accruals models(e.g. Ball, 2013; Gerakos and Kovrijnykh, 2013). Ball (2013) "worries" that the current practice that considers a positive (negative) discretionary accrual seems to create "the incorrectly belief" that earnings management is "rife" because technically "no observation sits exactly on the regression line".

This paper is an attempt to mitigatethe above-mentioned weakness of the literature.Given the well-acknowledged difficulties to reliably measure earnings management using accruals models, we are motivated to develop an approach to get round the problem by assessing the likelihood of earnings management without having to directly measure discretionary accruals. Metonymically, if 'there's no smoke without fire', we are interested in developing a measure to capture the 'smoke' (which is more difficult to conceal and easier for the outsiders to observe) rather than the 'fire' (which the current literature suggests we are still, at best, struggling to have a well-specified model to detect). Hence, instead of directly measuring discretionary accruals, which is arguably not reliably measurable without a theory about the determinants of accruals in the absence of earnings management, we develop an empirical proxy that can capture the context in which earnings management is more likely to occur. The advantage of this approach is that our model does not affirmativelyindicate the existence of earnings management nor does it have a lot to say about the magnitude of such manipulation if it does happen, the area which currently attracts great criticism in the earnings management literature. Our model only ‘flags up’ firms which are suspicious based on the context surrounding it.

Discretionary accrual is typically calculated as the difference of reported accruals from a measure of ‘non-discretionary’ accruals estimated using some firm characteristics. As such, it represents the component of earnings that is subject to manager’s discretion. This methodology, however, fails to reflect the *context* in which earnings is managed. Supposed earnings management indeed occurs, discretionary accruals could arguably capture the magnitude of it but it is silent about how and why the incident happens. Assuming a semi-strong efficient market, the mispricing of discretionary accruals could be attributable to investors failing to fully reflect on the ‘true’ earnings that a manager knows but does not truthfully releases to the market. One can arguably question the intuition of such story. Earnings management, of course, does not happen for no reason. There should be a ‘context’which leads to the manager cooking the books, be it a personal motivation, a benefit to the shareholder, a pressure or enough suitable room for managing earnings. While amanager can assumingly hide the ‘true’ earnings through earnings management, he or she cannot hide the surrounding context. Let us take a fictitious firm A, for example, which is growing and currently in financial distress. Struggling to finance its growthstrategy, mostly through acquisitions of companies which provides it the needed supplementary resources, itdecides to resort to raising more equity since it believes the current stock price is good for a seasoned equity offer. Firm A is audited by a local less reputable auditor (compared to the Big 4). What we can observe is a very susceptible context in which Firm A is more likely to manage earnings, without having to observe the (arguably unobservable) actual earnings management behaviour. If Firm A indeed manages earnings and the market is ‘fooled’, we can reasonably extrapolate that the market has mispriced both the distorted earnings *and* the context leading to Firm A manipulating earnings. To date, while there is mounting evidence confirming the former hypothesis, the latter is not yet investigated in the extant literature.

This paper, to the best of authors' knowledge, is one of the first to empirically test if the context of earnings management is mispriced. We first of all develop a model that captures the context in which earnings management is likely to occur, based on various signals extracted mainly from annual financial statements. Our model generates a composite score, namely the ESCORE, that accumulates fifteen individual binary scores, i.e. each individual score can have a value of either one or zero, where a value of one suggesting a context in which the firm is more likely to engage in earnings management and zero otherwise. The ESCORE is built on the rich extant literature on likelysignals of earnings management. The signals are grouped into four broad categories. The first category covers the incentives for earnings management, the second captures the pressures, the third considers balance sheet bloat and external auditor as constraints to earnings management and the category covers firm's other innate characteristics. The ESCORE can theoretically range from zero to fifteen, with higher values suggesting a more 'susceptible context' in which earnings management is more likely. The paper provides evidence to support the effectiveness of the ESCORE in capturing the context of earnings management by showing that high-ESCORE stocks indeed engage in earnings management in larger magnitude and are more likely to engage in aggressive earnings management practices.

Using a sample of UK listed firms during the period 1995 to 2011, the study tests if ESCORE could predict one-year-ahead stock returns. The resultsshow that a zero-investment hedge portfolio that takes long position in low ESCORE stocks and short position in high ESCORE stocks would earn an average abnormal return of 1.37% per month after adjusting for the risk loadings on the market, size, book-to-market and momentum factors in up to one year after portfolio formation. In multivariate regressions, ESCORE is found to be negatively and significantly related to one-year-ahead buy-and-hold returns after controlling for other existing market 'anomalies', including the mispricing of discretionary accruals. The result is robust across different ways to construct the ESCORE, portfolio weighting schemes and models to estimate abnormal returns. Overall, the paper concludes that the context of earnings management does help predict future stock returns.

We contribute significantly to the literature in at least two ways. First, the ESCORE model is a novel and innovative way to detect earnings management which could mitigate the weaknesses of the existing accruals models. Using the ESCORE, the research design does not suffer from the mis-specification of accruals models, which could be a major problem in the absence of a theory on the accruals generating process. Second, we contribute new evidence to the 'market anomalies' literature showing that not only the market misprices earnings management, it also does not fully appreciate the information contained in the context surrounding such manipulation.

The rest of the paper is organized as follows. Section 2 reviews the related literature and states the testable hypothesis. Section 3 explains the sample selection and presents the descriptive statistics of the sample. Section 4describes how the composite ESCORE is constructed and how well the ESCORE perform in capturing the context of earnings management. Section 5 presents and discusses the returns earned from various portfolios formed on the basis of ESCORE. Section 6 presents the results of multivariate regressions used to test the association of ESCORE with future returns after controlling for other known returns patterns. Some robustness checks with modifications to the methodologies are performed and presented in section 7. Section 8 provides some concluding remarks.

2 Existing models of earnings management detection and the market mispricing of discretionary accruals

There are several existing models thatdetect earnings management. The most popular method measures discretionary accruals, the deviation of actual accruals from an expected level of accruals derived using some firm-specific characteristics (Jones, 1991; Dechow et al., 1995; Peasnell et al., 2000). Although there are a few variants to the models to estimate discretionary accruals, typically in the first stage a measure of accruals is regressed on some firm characteristics, such as revenues and plant, property and equipment, which are assumingly outside the discretion of managers. In the second stage, the estimated coefficients from the first-stage regression are then used to calculate a ‘normal’ level of accruals, from which the deviation of actual accruals is termed ‘abnormal’ (or ‘discretionary’) and used as proxy for earnings management. The abnormal accruals model helps detect one type of earnings management, namely managers exercise their discretion over accounting methods to influence reported earnings.

One may argue that to change reported earnings, managers do not necessarily resort to playing around with accounting methods and estimations, rather they could change real operation decisions, such as sales policies, production level, discretionary expense spending (such as advertising, R&D...) (Roychowdhury, 2006; Athanasakou et al., 2009; Gunny, 2010; Athanasakou et al., 2011; Zang, 2012). Such real earnings management has been shown to be increasingly more popular given the changes and close monitoring of financial reporting regulations (Cohen et al., 2008). To detect such real operation management, the existing literature normally measures the deviation of the actual level of real activities with the expected level derived using some firm-specific information. Besides the aforementioned two methods, there are also other models to detect other types of earnings management, such as timing of asset sales, classificatory shift, earnings guidance etc.(Gunny, 2010; Athanasakou et al., 2011; Athanasakou et al., 2009).

In general, the above-mentioned models of earnings management detection, albeit being used widely by academics, are arguably of limited use in practice due to various reasons. Dechow et al. (1995) note that existing discretionary accruals models typically require hundreds of observation to have a reasonable chance of detecting subtle earnings management. Data constraints and the complexity of econometric method also mean existing models of earnings management detection is hard to be used in practice. The problem of data unavailability could be intensified in smaller markets which effectively prevents us from gaining more knowledge on earnings management behaviour in those interesting settings. Therefore, it would certainly be preferable if there is a more practical model that allows relatively easierand realistic application in practice without having to collect large data.

In response to the above-mentioned limitations, Beneish (1997) develops a model, based on twelve signals which may reveal managerial incentives, to identify GAAP violators from accruals aggressors. Beneish (1999a) provides an accounting-based index which could help assess the likelihood of earnings overstatement. Dechow et al. (2011)develop a new model, namely the FSCORE, which can help predict the likelihood of earnings restatement. They start with an analysis of the characteristics of restated firms and employ a logistic regression to estimate the relation between firm's characteristics and the likelihood of misstatement. FSCORE is used as a 'barometer' for financial statement users to quickly and timely assess the likelihood of earnings misstatements.

Beneish (1997), Beneish (1999a) and Dechow et al. (2011) pave an innovative and highly practical way to detect earnings management. Nevertheless, these models are not entirely free from limitations. One issue is that these firms are subject to SEC enforcements, which are typically large since SEC would aim to maximize public benefits given its constrained budget. Moreover, Dechow et al. (2010) also highlight that SEC is more likely to target egregious misstatements and avoid ambiguity cases of aggressive but within-GAAP earnings management. Thus, the predictive power of the models cannot be generalized to other earnings management firms not enforced by SEC.

Despite the above-notedadvancements, the search for a 'good' model to detect earnings management is still ongoing and any further contribution along this line would be fruitful. Once earnings management is (arguably) detected, the next sensible question would reasonably be: what can we do about it? In other words, could those earnings management detection models make a difference to the investment practices? Sloan (1996) initiated a whole strand of the accounting literature by showing that accrualsare negatively related to future returns. Xie (2001) goes even further showing that it is the discretionary accrual component which mainly drives Sloan's results. The evidence seems to suggest that the market misprices the information contained in accruals, and especially the component over which managers could exercise their discretion to manipulate.

While it is quite established about the market mispricing of discretionary accruals, which measure earnings management, one question remains unanswered for which this paper is seeking the answer. We argue that if the market is ‘fooled’ by earnings management, it should misprice *both* the magnitude of earnings management (often proxied for by discretionary accruals), *and* the context in which such manipulation occurs. As the old saying goes, “there’s no smoke without fire”. If earnings management (the ‘fire’) is engaged, there should be a ‘context’ surrounding it (the ‘smoke’). The context could be a personal motivation, a benefit to the shareholder, a pressure or enough suitable room for managing earnings etc. While the manager can assumingly hide the ‘true’ earnings through earnings management, he or she cannot hide the surrounding context. To empirically test this intuitive story, this paper develops a model that captures the context of earnings management and investigates if such model can be used to predict future stock returns.

3 Sample selection and descriptive statistics

The sample comprises all UK listed stocks on London Stock Exchange (LSE) during the period 1995 to 2011. LSE is an interesting setting to do this research asit isone of the largest financial markets in the world which would make the results of the research a significant contribution to both academic knowledge and practice. In addition, the literature on earnings management in the UK hasgrown considerably in recent years (Athanasakou et al., 2009; Athanasakou et al., 2011).

The sample starts from 1995 for a number of reasons. First, FRS3 – Reporting Financial Performance – an important accounting standard that arguably enhances transparency in the UK accounting environment (Athanasakou et al., 2009), becameeffective from 1993. Second, Datastream’s data unavailability, especially for cash-flows-related items, is quite a serious issue for the years before 1994. Therefore, the sample starts from 1995 to ensure the sample is free from years with too few data and to stay within the post-FRS3 period, including lagged values needed to calculate a range of variables in this study.

To avoid survivorship bias, both live and dead stocks are included. Financial and utilities firms are excluded due to their distinct financial reporting requirements. This study employs data collected mainly from Datastream. For a number of variables, including external auditor and merger and acquisition deals, Bloomberg is used to source the data. Data from Datastream and Bloomberg are combined using the International Securities Identification Number (ISIN). Therefore, any stocks which do not have an ISIN are excluded. Following Gore et al. (2007), for firms which have more than one type of common stocks, only one is includedin the sample. To ensure comparability, the sample is also restricted to include only firms which report in British Sterling and whose financial years havebetween 350 and 380 days. Firms with market value lessthan £1 million are also excluded to avoid very small firms which are typically very thinly traded in practice but can influence the returns on the equally-weighted portfolios. In addition, stocks with negative market-to-book ratio are also excluded. Furthermore, requiring data availability to calculate thevariables as described in the Appendix results in afinal sample of 11,920 firm-year observations, consisting of1,866 unique firms across 43 Datastreamlevel-six industries. All continuous variables are winsorized at the 1st and 99th percentiles to mitigate the influence of outliers.

Table 1 presents some descriptive statistics of the main variables used in this study. It is noted that the mean market value of equity, MVE, (£390 million) is significantly larger than the median (£44 million) which suggests the existence of some very large observations. Those large firms could significantlyinfluence the returns of value-weighted portfolios. The paper, therefore, uses equally-weighted scheme forthe main portfolio tests (while we also estimatevalue-weighted returns as a robustness check). The mean change in debt, DDEBT, is also very large compared to the median suggesting the presence of very large values. However, sinceDDEBT is translated into a binary variable in our analyses, it does not cause any big concern.

[Insert Table 1 about here]

4 The construction of ESCORE

One of the key innovations of this paper is the empirical measure of the context of earnings management. Within the scope of this paper, we define the 'context of earnings management' as the incentives to manage earnings, the pressures under which managers are more likely to resort to earnings management, the constraints to earnings management, and the innate factors of the firm which could indicate the existence of earnings management. Of course, this is not a 'comprehensive' definition in the sense that it could not capture the whole context, i.e. every signal which suggests earnings management. We deliberately focus mainly on the context which could be easily extracted from annual financial statements, hence the exclusion of areas such as performance-linked compensation, institutional holding and corporate governance. The reason is two folds. First, we would like to create a parsimonious model which covers a reasonable range of signals for which data can be easily obtained in practice. This feature of the model makes it more useful for practitioners who want to apply the model in their trading practices. Second, we want to avoid the constraint of data availability which could severely depress the sample size if compensation, institutional holding and corporate governance variables are included. Dechow et al. (2011) argue that theinclusion of suchvariables would introduce biases into the sample due to data unavailability. Nevertheless, we believe those omissions do not affect the main conclusions we obtained from this paper and invite future research to expand our model to cover these aspects of the context of earnings management.

In this study, the ESCORE is constructed as the compositeof 15 individual binary variables, each takingavalue of one if a firm has a suspicious signal and zero otherwise. The selection of these signals is mainly guided by the extant earnings management literature and is presented in the next sub-sections. In selecting the individual signals, we focus on all signals that suggest higher likelihood of earnings management without preference to either aggressive or conservative practices. As a result, the ESCORE is not a *signed* measure of earnings management. We hypothesize thatthe relation between the ESCORE and future returns comes from the power of the ESCORE to reveal the context in which earnings management is likely, not from the model being able to reveal the sign and magnitude of such manipulation. While the existing literature suggests aggressive (conservative) earnings management is related to negative (positive) future stock returns (e.g. Xie, 2001),in this paper we make a novel contribution to the literature by showing that the presence of earnings management, regardless of the direction, affects stock returns negatively because we argue that any deviation from the 'true' earnings could distort the usefulness of reported earnings.

To construct the ESCORE, a number of the individual signals need a 'benchmark' to construct. For example, we know small firms may be suspicious of earnings management. However, we first need a 'benchmark' to determine which firms should be classifiedas 'small'. Such 'benchmarks' should reflect the characteristics of the corresponding industry. The next section explains how those benchmarks are constructed.

4.1 Benchmark construction procedure

First, in each industry-year, firms are ranked based on γ (where $\gamma$is substituted by the relevant financial signals used in this study). Second, the 20th and 80th percentiles in each industry-year are used as the lower and upper benchmarks, denoted $\gamma_{k,t}^{20}$ and $\gamma_{k,t}^{80}$ respectively, where *k* = 1... 43 are the unique Datastream level-six industries remained in the sample, and *t* = 1995... 2011represent the 17 sample years. If a signal is lower (higher) than $\gamma_{k,t}^{20}$ ($\gamma_{k,t}^{80}$), it would be considered as too low (high). Thisprocedure is appliedto all individual signals that require an industry-specific benchmark to construct. Table 2 reports the average $\gamma_{k,t}^{20}$ and $\gamma_{k,t}^{80}$ across the years.

[Insert Table 2 about here]

4.2 Incentives: Equity issue, debt issue, share-for-share merger and acquisition, and stock overvaluation

The first category of signals which constitute the ESCORE covers various incentives to engage in earnings management. Prior evidence suggests that firms inflate earnings prior to equity issues (Teoh et al., 1998b; Cohen and Zarowin, 2010; DuCharme et al., 2004; Siew Hong and Wong, 2002; Rangan, 1998; Shivakumar, 2000; Iqbal et al., 2009; Iqbal and Strong, 2010). This study defines ESEO as a dummy that takes a value of one if (i) a firm's outstanding shares increase by at least 5% compared to last year and (ii) there are positive proceeds from issuing common/preferred stocks, zero otherwise[1].

[1]In this study, IPOs are not considered since many of the signals need up to two years of lagged data, hence data availability constraint would technically eliminate those IPOs, which is expected to be just a small number of observations in the sample.

Managers may also like to 'decorate' financial statements prior to a major debt issue to negotiate the cost of debt down. Athanasakou and Olsson (2012) find a positive relation between an indicator of debt issue and earnings management. To capture debt-issue-related incentives to inflate earnings, EDDEBT is defined as a dummy that takes a value of one if DDEBT is 5% or higher, where DDEBT is calculated as the percentage change of total of short- and long-term debt[2] compared to last year's total debt, zero otherwise. The 5% benchmark is employed to ensure that the issue is large enough for managers to consider managing earnings.

Firms also have strong incentives to inflate earnings prior to share-for-share mergers and acquisitions (M&A) in an attempt to temporarily push stock price up to minimize the number of shares paid(Erickson and Wang, 1999; Botsari and Meeks, 2008; Louis, 2004). We define EMA as a dummy that takes a value of one if a firm announces an M&A deal within the financial year for which sharesare proposed as (part of) the payment method. The data for share-financed M&A transactions is collected from Bloomberg.

Recent literature also considers the effect of stock market overvaluation on earnings management. Jensen (2005) conjectures that overvaluation creates a pressure on firms to inflate earnings to maintain their high market valuation. Thispropositionhas attracted a lot of attention as it can potentially explain a series of accounting scandals in the 2000s involvinga number ofhigh profile firms. Empirical evidence also support the premisethat overvaluation induces income-increasing earnings management (Badertscher, 2008; Chi and Gupta, 2009; Houmes and Skantz, 2010). To capture this signal, the next variable, EOV, is defined as a dummy that takes a value of one if a firm's beginning market-to-book ratio (MTB hereafter), calculated as

[2] A value of zero is assigned to observations with missing Datastream's data for short- and long-term debt.

market value of equity at the end of fiscal year divided by common shareholders' equity, is higher than the corresponding $MTB_{k,t}^{80}$, zero otherwise.

4.3 Pressures: Meeting or just beating earnings benchmarks, financial distress, debt level, firm size and business life cycle

For listed companies, there are several earnings benchmarks which need to be met if the companies do not want to see a stock price drop. For example, Burgstahler and Dichev (1997) document a discontinuity of earnings around two important benchmarks, namely zero earnings and last year's earnings. Similar pattern has also been documented in the UK (Gore et al., 2007). To capture the pressure to meet or beat zero earnings benchmark, EROA is defined as a dummy that takes a value of one if a firm's returns-on-assets ratio (ROA hereafter), calculated as earnings before extraordinary items scaled by beginning total assets, is equal to or larger than zero but smaller than 0.01, zero otherwise. EDROA, employed to capture the pressure to avoid reporting earnings decreases, is defined as a dummy that takes a value of one if a firm's DROA, calculated as the change inearnings before extraordinary items compared to last year's figures scaled by beginning total assets, is equal to or larger than zero but smaller than 0.005, zero otherwise.

Furthermore, evidence shows that firms would engage in earnings management if the unmanaged earnings fall short of the expected dividends by small amount (Daniel et al., 2008; Atieh and Hussain, 2012). To capture this pressure, EDIV is defined as a dummy that takes a value of one if a firm's dividend deficit, denoted as DIVDEF, calculated as the difference between net income and total cash dividends scaled by beginning total assets, is equal to or larger than zero but smaller than 0.01, zero otherwise.[3]

Firms which are in financial distress are understandably under pressure to inflate earnings. Lara et al. (2009) provide evidence that financially distressed firms manage earnings upwards. Beneish (1997) reports that financial distress is a factor that leads to GAAP violation. To capture the presence of these pressures, the UK-based ZSCORE is calculated following (Taffler, 1983)[4]. Taffler (1983) and Agarwal and Taffler (2007) show that UK firms with negative ZSCORE are more likely to get bankrupt. Following this evidence, EDISTRESS is defined as a dummy that takes a value of one if a firm's ZSCORE is negative, zero otherwise.

The use of debt also has implications forearnings management. Watts and Zimmerman (1986) suggest that debt contracts have a vital influence on firms' accounting policy. On one hand, higher debts induce pressureson firms to inflate earnings. Indeed, debts usually come with some covenants which firms need to comply with. Breaking debt covenants leads to firms being penalized by lenders by means of higher cost of debt (Dichev and Skinner, 2002). Therefore, firms with more debt have a greater pressure to manage earnings to avoid violation of debt covenant. DeFond and Jiambalvo (1994) find that abnormal accruals are significantly higher in the years preceding debt covenant violations. Ghosh and Moon (2010) find that firms with high debt would have strong incentive to manage earnings. On the other hand, however, the literature also suggests that firms with low level of debt are also likely to engage in earnings management (Astami and Tower, 2006). In addition, the evidence that financial leverage is positively related to accounting conservatism

[3]Beside zero earnings, last year's earnings and dividends, consensus analysts' forecast is also an important earnings threshold. However, consensus analysts' forecast benchmark is not considered in this study since the data for this signal is not always easy to collect in practice.

[4] Please see the Appendix for details of the calculation of the ZSCORE.

(for example, Watts, 2003a; Watts, 2003b; Pae, 2007) implies that firms with little debt are less bound contractually and their reported earnings are less subject to scrutiny from lenders, hence there could bemore scope for earnings management. In brief, the literature suggests that firms which have either too high or too low debts are suspicious of earnings management. The ZSCORE, as explained earlier, has already captured firms with high debts (the x_3 is in fact a measure of leverage, the larger of which would reduce ZSCORE). To capture firms with too little debts, EDEBT is defined as a dummy that takes a value of one if a firms' beginning DEBT, measured as the total of short- and long-term debt scaled by total assets, is lower than the corresponding $DEBT_{k,t}^{20}$, zero otherwise. EDEBT captures the context in which firms are subject to less scrutiny from lenders, hence have more room for earnings management, in both directions.

It is also more difficult for large firms to manage earnings due to their high public visibility (Lang and Lundholm, 1993; Dechow and Dichev, 2002). Smaller firms, on the contrary, usually face less public attention and struggle to perform under various financial constraints. Hence small firmsare often more likely to engage in earnings management, especially if the managers believe the struggles are just transitory. Indeed, various studies in the earnings management literature use firm size as a control variable and the evidence is quite strong that firm size is related to discretionary accruals. To capture this signal, ESIZE is defined as a dummy that takes a value of one if a firm's beginning market value of equity (MVE hereafter) is lower than the corresponding $MVE_{k,t}^{20}$, zero otherwise. ESIZE captures the context in which firms are subject to less scrutiny from the public, hence could have more rooms to manage earnings, in both directions.

The last variable in this group, ECYCLE, is constructed to capture firms which are in the introduction and growth stage in their business life cycle. Young listed firms, most of which use funds from the capital market for the first time, are usually under pressure to perform and grow. Accounting manipulating could be a way for those young listed firms to respond to such pressures(Beneish, 1997; Dopuch et al., 1987). Growth firms usually face strong investment opportunities and are expected to deliver strong growth and financial performance. Fama and French (1995) show that growth firms typically report higher earnings. Lakonishok et al. (1994) suggest that the market generally places too much expectation on growth stocks which results in market overreaction. Under such pressure, firms might have to resort to earnings management should their underlying economic performance fall short of the expectation to avoid market penalty. Such prediction has been substantiated by empirical evidence (Skinner and Sloan, 2002). Following Dickinson (2011), ECYCLE is defined as a dummy that takes a value of one if a firm's operating cash flows are negative, financing cash flows are positive and investing cash flows are negative (introduction stage), or its operating and financing cash flows are positive while its investing cash flows are negative (growth stage), and zero otherwise.

4.4 Constraints: External auditor and balance sheet bloat

External audit quality also plays a major role in constraining accruals management (Becker et al., 1998; Francis et al., 1999). Krishnan (2003) find that firms whose external auditors have more industry experience on average have less discretionary accruals. Following thisevidence, several studies have used an indicator of firms being audited by the Big 5 as a control variable in regression where the dependent variable is discretionary accruals and in general a significant negative relationship is found (Zang, 2012; Athanasakou and Olsson, 2012). Nevertheless, the existing evidence about the constraining role of external auditors is mixed regarding the sign of the manipulation.For example, Becker et al. (1998) predict that the presence of the Big 5 auditors is negatively related to the signed discretionary accruals, while Francis et al. (1999) only present evidence about the relationship between Big 5 external auditors and the absolute value of discretionary accruals. It could be interpreted that the absence of Big 5 auditors could give room for firms to manage earnings more easily, in both directions. We, therefore, use external auditor as a signal of earnings management, but do not predict the sign of the manipulation. In this study, EAUDIT is defined as a dummy that takes a value of one if a firm is not audited by the Big 5 accountancy firms[5]. Data for this signal is sourced from Bloomberg.

Due to the reversal nature of accruals, past use of accruals management will act as a constraint to further engagement (Barton and Simko, 2002). In the extant literature, net operating asset (NOA hereafter) is usually used to measure the 'balance sheet bloat' which captures the constraint induced by past engagement in accruals management (Houmes and Skantz, 2010). Firms with high NOA have been shown to engage extensively in income-increasing accruals management in the past, which in turn constrains the firm's ability to further manage accruals. Following the literature, NOA is calculated as the sum of net book value of equity, total debts and cash and cash equivalents, all scaled by total assets. EBLOAT is defined as a dummy that takes a value of one if a firm's beginning NOA is lower than the corresponding $NOA_{k,t}^{20}$, zero otherwise. EBLOAT would identify firms which havevery low NOA, a

[5] The Big 5 is defined as the following firms and their affiliates: Arthur Andersen, Deloitte Touche Tohmatsu, Ernst and Young, KPMG, PriceWaterhouseCoopers. Audit firms which are later merged with one of the Big 5 are also considered as part of the Big 5 (e.g. Coopers and Lybrand is deemed as PriceWaterhouseCoopers). If data on the auditor is missing from Bloomberg for a firm in a year, it is assumed that the firm is not audited by a Big 5 auditor.

sign that there is still a lot of space for further engagement in earnings management, in both directions.

4.5 Innate characteristics: tangible assets intensity and book-tax difference

Earnings management is engaged not only because of managerial motives, but also due to some innate factors (Dechow and Dichev, 2002; Francis et al., 2005; Francis et al., 2004; Athanasakou and Olsson, 2012). Dechow and Dichev (2002) suggest some important innate factors which could imply earnings management, such asthe variability of some fundamentals such as sales or cash flows, firm size, operating cycle and incident of losses. It has also been shown that the intensity of intangible and tangible assets is inversely related to earnings quality (Francis et al., 2004; Athanasakou and Olsson, 2012). Several of these innate factors, including firm size, operating cycle and incident of losses, have been covered earlier. In this study, the variability of sales and cash flows, which requires long history of data to calculate, is not considered because requiring long history of data would eliminate young firms from the sample, a practice that may introduce bias in the main analysis in this study since some earnings management signals (e.g. ECYCLE) are designed to capture young firms. The intensity of intangible assets is also not considered due to insufficient data to establish plausible industry benchmarks[6]. To capture the intensity of tangible assets, CAP is calculated as the ratio of property, plant and equipment divided by total assets. The literature has shown that smaller CAP is associated with poor earnings quality, hence suchfirms are suspicious of earnings management (Athanasakou and Olsson, 2012; Francis et al., 2004). ECAP is defined as a dummy that takes a value of one if a firm's beginning CAP is smaller than the corresponding

[6] Many UK listed companies during the sample period do not report R&D expenses. A common approach in the literature is to replace those missing value by zero. Nevertheless, having too many zero values makes the lower benchmarks in many industry zero, which is quite problematic to use.

$CAP_{k,t}^{20}$, zero otherwise. For firms which have the signal ECAP of one, we do not predict the sign of the manipulation.

Lastly, some studies document the effect of book-tax conformity on earnings management (Hanlon and Heitzman, 2010; Athanasakou and Olsson, 2012). If one agrees that taxable profits are basically difficult and costly to manipulate, the more accounting earnings are diverged from taxable profits, the more likely that such accounting earnings have been manipulated. Generally, the evidence supports such intuition (Desai, 2005). Following the literature, BOOKTAX is calculated as the absolute value of the difference between reported pre-tax income and an estimate of total taxable profits, denoted by TTP, all scaled by sales. TTP is estimated using the lower and upper limit for marginal tax relief (denoted LL and UL, respectively), small profit tax rate (SR) and main tax rate (MR) applicable at the time in conjunction with the reported income tax expenses (TXT). LL, UL, SR and MR in each sample year are sourced from (HM Revenue & Customs, 2013). With only published information it is almost impossible to estimate TTP. Therefore, some assumptions need to be made to simplify the estimation. First, it is assumed that the reported tax expenses represent solely the amount of income tax levied in the considered period (i.e. no extraordinary penalty or retrospective payment or anything else of that nature). Second, for the profits that fall between the LL and UL, the tax rate is assumed to be the average of the SR and MR, denoted AR, to avoid complicated calculation. With those assumptions being made, TTP is worked back from the tax expenses as follows:

- If TXT ≤ 0, then $TTP = 0$
- If 0 < TXT ≤ LL x SR, then $TTP = \frac{TXT}{SR}$

- If LL x SR ≤ TXT ≤ (UL – LL) x AR, then $TTP = \frac{TXT-(LL\times SR)}{AR} + LL$
- If TXT ≥ (UL – LL) x AR, then $TTP = \frac{TXT-(LL\times SR)-[(UL-LL)\times AR]}{MR} + UL$ (1)

EBT is defined as a dummy that takes the value of one if a firm's BOOKTAX is higher than the corresponding $BOOKTAX_{k,t}^{20}$, zero otherwise. EBT, therefore, captures firms which have reported accounting earnings that aredifferentfrom taxable profits, an indication that accounting earnings may have been managed, in both directions.

4.6 The ESCORE

The composite ESCORE is finally calculated as the sum of all 15 individual binary signals as presented earlier:

ESCORE = ESEO + EDDEBT + EMA + EOV + EROA + EDROA + EDIV + EDISTRESS + EDEBT + ESIZE + ECYCLE + EAUDIT + EBLOAT + ECAP + EBT (2)

As designed, ESCORE is an integer which can range from 0 to 15. The smaller (larger) the ESCORE, the less (more) suspicious the context surrounding a firm is. Being aggregated from 15 individual signals, an immediate question is whether those signals are inter-correlated and thus could be reduced to a more parsimonious model through, for example, principal component analyses. To respond to this possibility, Table 3 reports the correlations between the individual signals. It could be observed that the correlations between the individual signals are quite low(the largest coefficient, which is between EDISTRESS and EBT, is only 38.1%) and insignificant in many cases. It suggests that the individual signals capture different uncorrelated dimensions of the context of earnings management.

[Insert Table 3 about here]

Panel A of Table 4 reports the Eigen values from principal components analysis. The first principal component, which has the largest variance of any linear combination of the individual scores, could explain only 12.83% of the total variance. Subsequent principal components contribute about the same proportion, ranging from 9.37% to 4.45%. Looking at the Eigen vectors in Panel B, there seems to be no too high loading on any particular variables, which suggests that none of the individual scores playsa dominant role in the variance of the composite ESCORE. Overall, it is unlikely that a variable reduction through principal component analysis would significantly enhance the ESCORE compared to the simple sum-of-binary-variable approach. We therefore proceed with the ESCORE as designed in equation (2) above.

[Insert Table 4 about here]

4.7 How well does ESCORE capture the context of earnings management?

This section shows the effectiveness of the ESCORE by looking at how other traditional measures of earnings management (e.g. discretionary accruals and real earnings management proxies) vary as the context (captured by ESCORE) changes. For this, we look at six proxies of earnings management.

To begin, we employ the modified-Jones model(Jones, 1991; Dechow et al., 1995) to estimate discretionary accruals[7] as follows. First, total accruals are calculated as the difference between income before extraordinary items and net operating cash flows. The calculation of total accruals follows the cash flows approach to avoid the potential measurement errors identified by Hribar and Collins (2002)[8]. In particular,

[7] In unreported results, we also employ the cross-sectional version of the original Jones model. The main conclusions remained unchanged.

[8]Hribar, P. and Collins, D. W. 2002. Errors in estimating accruals: Implications for empirical research. *Journal of Accounting Research,* 40**,** 105-134.argue that accruals estimated using the cash flows approach can overcome the potential error induced by 'non-articulation' transactions in the balance sheet approach. However, other authors, such as Gore, P., Pope, P. F. and Singh, A. K. 2007. Earnings management and the distribution of

the balance sheet approach, as used in Dechow et al. (1995), may induce errors into the measurement of total accruals in the presence of non-articulation transactions, such as mergers and acquisitions or divestitures. Second, the cross-sectional version of the modified-Jones model (Dechow et al., 1995) is estimated for each (Datastream level-six) industry-year with at least 15 observations to obtain discretionary accruals (DAC).

Althoughthere are other competing models to estimate discretionary accruals (Dechow et al., 1995; Guay et al., 1996; Bernard and Skinner, 1996; Young, 1999; Thomas and Zhang, 2000; Peasnell et al., 2000; Fields et al., 2001), the existing literature generally suggests that there is no other model that outperforms the modified-Jones model (Peasnell et al., 2000; Botsari and Meeks, 2008). Nevertheless, an issue that attracts considerable attention, especially in the UK context, is the treatment of depreciation in calculating accruals. Many UK studies focus only on working capital accruals arguing that depreciation is not a suitable means to manage earnings since it is highly visible and if earnings are managed through depreciation, the effects could be unwound quite easily by financial statement users (Young, 1999; Peasnell et al., 2000; Gore et al., 2007). To account for this argument, the second measure of earnings management, discretionary working capital accruals (DWAC), is estimatedusing the 'margin model' as describedin Peasnell et al. (2000), which has been shown to work well in the UK

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earnings relative to targets: Uk evidence. *Accounting and Business Research,* 37**,** 123-149., have argued that the cash flows approach is also problematic because 'non-articulation' transaction may also affect the cash flow approach and the accruals resulted from the cash flows approach may include items which cannot be classified as either discretionary or non-discretionary. Therefore, all accruals models are replicated using the balance sheet approach to account for the on-going contention surrounding this issue. Following Dechow, P. M., Sloan, R. G. and Sweeney, A. P. 1995. Detecting earnings management. *Accounting Review,* 70**,** 193-225., AC (total accruals) is estimated under the balance sheet approach as follows: $ACbs = (\Delta CA - \Delta CHE) - (\Delta CL - \Delta STD) - DP$, where ACbs is total accruals; ΔCA is change in current assets; ΔCHE is change in cash and cash equivalents; ΔCL is change in current liabilities; ΔSTD is change in short-term debts; DP is depreciation and amortization expenses. The results are not reported for brevity, but none of the main conclusions are changed qualitatively.

context. DWAC is estimated using a separate sample which requires data availability only for the variables needed to estimate Peasnell et al.'s (2000) 'margin model'. We require at least 15 observations in each industry-year to estimate the model.

We next consider real earnings management by followingRoychowdhury (2006) to estimate three measures of real earnings management, namely the abnormal cash flow (DCF), abnormal production cost (DPROD) and abnormal discretionary expense (DDISEXP). While DPROD is exactly as described in Roychowdhury (2006), we multiply Roychowdhury's (2006) measures of abnormal cash flow and abnormal discretionary expenses by -1 to arrive at DCF and DDISEXP. This makes a positive value of DCF and DDISEXP suggest income-increasing earnings management and vice versa, which is consistent with other measures of earnings management used in this paper. DCF, DPROD and DDISEXP are estimated using separate samples which require data availability only for the variables needed for each case. For regressions within each industry-year, we require at least 15 observations.

DCF, DPROD and DDISEXP capture three dimensions of real earnings management, namely the manipulation of sales activities, production activities and discretionary expenses. Those three ways of managing earnings could be usedas substitutes, i.e. a manager would manipulate earnings through changing real operation decisions in one or two areas of the three, not necessarily all of them. As a result, for example, when the context suggests a firm is inflating earnings and the firm decides to do it throughsales manipulation, DPROD and DDISEXP are not necessarily high. It is, hence, important to look at the overall real earnings management strategy rather than just the individual ones. To facilitate this, we also construct a composite measure that pools together the three measures of real earnings management:

$$\boldsymbol{TOTALRM_{i,t}} = \left[\frac{DCF_{i,t}-\overline{DCF_{t,k}}}{\sigma(DCF)_{t,k}} + \frac{DPROD_{i,t}-\overline{DPROD_{t,k}}}{\sigma(DPROD)_{t,k}} + \frac{DDISEXP_{i,t}-\overline{DDISEXP_{t,k}}}{\sigma(DISEXP)_{t,k}}\right]/\boldsymbol{3}\ (\boldsymbol{i} \in \boldsymbol{k}) \quad (3)$$

Where: $TOTALRM_{i,t}$ is the composite measure of real earnings management of firm *i* in year *t*; $\overline{DCF_{t,k}}$, $\overline{DPROD_{t,k}}$, $\overline{DDISEXP_{t,k}}$[$\sigma(DCF)_{t,k}$, $\sigma(DPROD)_{t,k}$, $\sigma(DISEXP)_{t,k}$]is, respectively, the mean [standard deviation]of DCF, DPROD, DDISEXP of all firms in industry *k* in year *t*; k=1…43 are 43 unique Datastreamlevel-six industries remained in the sample.

The above procedure converts DCF, DPROD and DDISEXP into standardized variables with similar distributions (i.e. within each industry-year, the standardized DCF, DPROD and DDISEXP are all distributed with an expected mean of zero and standard deviation of one) before averaging them. $TOTALRM_{i,t}$, therefore, captures the combined effects of the three Roychowdhury's (2006) real earnings management strategies.

We next examine how the above six measures of earnings management would vary as the context of earnings management (i.e. the ESCORE) changes. The ESCORE is primarily designed to capture the context in which earnings management is more likely to occur, not the *sign* of such manipulation. Many components of the ESCORE, includingESEO, EDDEBT, EMA, EOV, EROA, EDROA, EDIV, EDISTRESS, ECYCLE, do predict inflationary (i.e. aggressive) earnings management, while others, including EAUDIT, EBLOAT, EBT, ECAP, EDEBT, ESIZE, only suggest the possible presence of earnings management behaviour regardless of the sign. We, therefore, test the effectiveness of ESCORE in two ways. First, we examine if ESCORE is able to indicate the presence of earnings management, in both directions, by looking at how the absolute value of DAC, DWAC, DCF, DPROD, DDISEXPand TOTALRM (denoted ADAC, ADWAC, ADCF, ADPROD, ADDISEXP and ATOTALRM, respectively) vary across ESCORE groups. Second, becausea number of components of the ESCORE do suggest an inflation of earnings as explained above, we also expect that ESCORE could identify the context in which the most aggressive earnings management occurs. For investors, aggressive earnings management is arguably more harmful, hence it is important to see if the ESCORE can indicate those circumstances. For this purpose, we also examine the association of ESCORE with the indicators of aggressive earnings management, denoted by HDAC, HDWAC, HDCF, HDPROD, HDDISEXP and HTOTALRM and defined as the dummy variables that take the value of one if the stock is in the top quintile ranked in each industry-year by DAC, DWAC, DCF, DPROD, DDISEXP and TOTALRM,respectively.

Table 5 presents the mean of ADAC, ADWAC, ADCF, ADPROD, ADDISEXP, ATOTALRM (the absolute values) and HDAC, HDWAC, HDCF, HDPROD, HDDISEXP, HTOTALRM (the indicators of aggressive earnings management) across ESCORE groups, together with the t-test comparing the means of the High ESCORE group (ESCORE of six and above) with those of the Low ESCORE group (ESCORE of zero)[9]. As explained earlier, aswe estimate DAC, DWAC, DCF, DPROD, DDISEXP and TOTALRM using different samples (requiring data availability only for the variables needed to estimate each earnings management measure), Table 5 also reports the number of firms distributed across the ESCORE for each measure of earnings management. The results show that as ESCORE increases, all of the 12 measures of earnings management also increase monotonically and consistently. The differences acrossall measures between the High ESCORE and Low ESCORE group are positive, economically large, and

[9] Please refer to next section where we provide more explanations on the cut-off points to determine the High and Low ESCORE groups.

statistically significant. The results, therefore, strongly suggest that ESCORE is highly effective in capturing the context of earnings management as when the context is more susceptible (higher ESCORE), firms indeed manage earnings in larger magnitudes and are more likely to be an aggressor.

[Insert Table 5 about here]

5 Portfolio analyses

Each year, stocks are sorted by ESCORE. The ESCORE for year *t* (*t*= 1995… 2011) is calculated for all stocks with fiscal year ended in any month of the calendar year *t*. Based on the ESCORE of year *t*, portfolios are formed at the end of May year *t+1* and held until the end of May year *t+2*. For each month, buy-and-hold raw returns, assuming dividend reinvestment, for each stock, denotedby$BHRR_{i,j}^{m}$, are calculated as the percentage change of Datastream's Return Index. If a stock delists during the holding period, the delisting returns are treated as follows. If a stock does not have a monthly return for June (the first month after portfolio formation), the firm-year observation is excluded from the sample (equivalent to assuming that investors cannot consider the stock for trading due to non-existence). If a stock has a return for June, but then delisted before the end of the holding period due to non-performance-related reasons, it is assumed that the investors earn the returns from portfolio forming date to delisting date, and then reinvestthe proceeds in the size-matched portfolio which assumingly bears similar risk compared to the delisted firm. This approach has been used by other authors (for example, Soares and Stark, 2009; Desai et al., 2004)to reflect the reality that the returns in most M&A-related delisting cases are positive. Returns on the size-matched portfolio are estimated using similar procedure to calculate size-adjusted returns described below. If the delisting is performance-related, it is assumed that the whole initial investment is lost, hence a delisting return of –100% is used.

To test the profitability of the ESCORE-based trading strategies, the paper usesvarious measures of buy-and-hold abnormal returns. First of all firm-specific monthly buy-and-hold size-adjusted returns are calculated as follows. Each year all stocks with available data are sorted into deciles based on market capitalization at the end of thepreviousfiscal year. The returns on the size decileportfolio *d* (*d* = 1… 10), $SDR_{d,j}^{m}$, is calculated as the average $BHRR_{i,j}^{m}$ of all stocks which belong to decile*d*. For each stock, its corresponding size decile and size decile return are identified. The buy-and-hold size-adjusted return of stock *i* in month *j,* denotedby $BHSAR_{i,j}^{m}$,is then calculated as the difference between the raw returns and the returns on the corresponding size decile portfolio.

From the above firm-specific returns, the raw andsize-adjusted returns of portfolio*p*, denoted by$BHRR_{p,j}^{m}$and$BHSAR_{p,j}^{m}$,arerespectively the equally-weighted$BHRR_{p,j}^{m}$ and$BHSAR_{i,j}^{m}$ of all stocksin portfolio*p*.Following Desai et al. (2004), to avoid the potential inflation of the t-statistics when assessing the abnormal portfolio returns over time, we calculate $BHSAR_{p,j}^{m}$ for each month and treat it as one observation. The t-statistics used to test if $BHSAR_{p}^{m}$ and $BHMAR_{p}^{m}$ are significantly different from zero is calculated from 204 time-series monthly observations (across 17 sample years).

The $BHSAR_{p,j}^{m}$are calculated using reference portfolios, an approach which could bias the test statistics (Barber and Lyon, 1997; Kothari and Warner, 1997). Moreover, size-adjustedreturns are not capable of capturing some other known dimensions of risk, such asthe market-to-book and momentum factors. To strengthen the results, therefore, we also estimate an additional measure of abnormal portfolio returns byusing the Fama-French model augmented by the momentum factor. In particular, the following time-series regression is run:

$$BHRR_{p,j}^{m} - Rf_j = \alpha + \beta_1(Rm_j - Rf_j) + \beta_2 SMB_j + \beta_3 HML_j + \beta_4 UMD_j + \varepsilon \quad (4)$$

Where: $BHRR_{p,j}^{m}$ is the equally-weighted portfolio raw returns of portfolio *p* of month *j*; Rf_j, Rm_j, SMB_j, HML_j, UMD_j are, respectively, the monthly risk-free rate, returns on the market portfolio, size, market-to-book and momentum factors, all as described and downloaded from the database which is made publicly available byGregory et al. (2013).

We then calculate the monthly buy-and-hold portfolio abnormal returns using the estimated coefficients obtained from regression(4), denotedby$BHAR4F_{p,j}^{m}$.Similar to the t-test employed for size-adjusted returns, the t-statistic used to test if $BHAR4F_{p,j}^{m}$is significantly different from zero is calculated from 204 time-series monthly observations.

Of course, the above regression-based approach is also not flawless, especially in the UK context (for example, Lee et al., 2007; Bauer et al., 2010). Nevertheless, since we use both the reference and regression-based approaches, it would reasonably guard the results against any possible significant biases due to the way abnormal returns are calculated[10].

Table 6 shows the distribution of the firm-year observations across ESCORE portfolios. In the portfolio analyses, we pay particular attention to the profitability of the portfolios of Low and High ESCORE stocks, as well as the hedge portfolio that takes long position in low ESCORE stocks and short position in high ESCORE

[10] We also use market-adjusted returns, the CAPM and the Fama-French three-factor model. None of the main results change qualitatively using those abnormal returns metrics.

stocks. For this purpose, we arbitrarily group stocks with ESCORE of zero into the low-ESCORE portfolio, those with ESCORE of six and above into the High-ESCORE portfolio and the rest to the medium-ESCORE portfolio. Since there are fewer number of stocks having larger ESCORE, we group all stocks with ESCORE of 6 and above into the High ESCORE portfolio (865 observations). The idea is just to make sure the High ESCORE portfolio has comparable number of observations to contrast against the Low ESCORE counterpart (which comprises 862 stocks with ESCORE of zero). Intuitively, our grouping scheme is equivalent to considering that the context surrounding a stock which has accumulated six signals or above is highlysusceptible to earnings management[11].

[Insert Table 6 about here]

Table 7 reports the result of portfolio analyses. The table reports the buy-and-hold returns on each ESCORE portfolio (0-9), the low, medium and high ESCORE portfolios, and the hedge portfolio that takes long position in low ESCORE and short position in high ESCORE stocks, together with the t-statistics under the null hypothesis that the corresponding return is zero. The result is strikingly easy to summarize. First, as ESCORE increases, all measures of stock returns decrease monotonically. Secondly, low ESCORE stocks earn abnormally high and high ESCORE stocks earn abnormally low returns. Third, the hedge portfolio earns positive abnormal returns. Since the results are quite consistent across different return metrics, the followings illustrate using only the size-adjusted returns. The

[11] Of course the choice of the cut-off at six is quite arbitrage since we cannot say a stock with ESCORE of five is qualitatively less 'susceptible' than another one with ESCORE of six. While we cannot proceed without a arbitrarily-determined cut-off point, unreported results show that the main conclusions of this paper do not change qualitatively if we group stocks with ESCORE of zero and one into the Low ESCORE portfolio (3,080 observations) and those with ESCORE of four and above into the High ESCORE portfolio (3,534 observations). The BHSARm of the Low (High) ESCORE portfolio in that case is 0.37% (-0.50%, respectively) and that of the hedge portfolio is 0.87%, all are statistically significant at 1% level.

portfolio of stocks with ESCORE of zero outperforms the size-matched portfolio by 0.48% per month (significant at 1% level). As ESCORE increases, size-adjusted returns decrease monotonically to –0.83% for the portfolio of stocks with ESCORE of 9. The High ESCORE portfolio underperforms the size-matched portfolio by 0.69% (significant at 1% level). The hedge portfolio that takes long position in Low ESCORE stocks and short position in High ESCORE stocks earns 1.17% size-adjusted returns per month. Overall, the result strongly suggests that the market misprices the information contained in the ESCORE, which is designed to capture the context of earnings management.

[Insert Table 7 about here]

6 Is it other ‘market anomalies’ in disguise?

The results from the portfolio analyses strongly suggest that ESCORE is correlated to future returns. However, because of the way the ESCORE is constructed, there are some other known ‘market anomalies’ that are associated with ESCORE, and hence could partly explain the returns predictive power of the ESCORE. This section addresses such concern.

To see if the ESCORE is indeed related to other known patterns in realized returns, Table 8 presents fundamentalcharacteristics of stocks across ESCORE groups. Firm size, measured by either total asset or market capitalization, is negatively related with the ESCORE. Firms with higher ESCORE are also more likely to issue seasoned equity and debt and have lower NOA. High-ESCORE firms are also highly valued by the market evidenced by the monotonic increase of the market-to-book ratio across the ESCORE groups. The decrease of ROA and DROA as ESCORE increases also suggests that high ESCORE stocks are typically less profitable. High ESCORE stocks are also more financially distressed as measured by the ZSCORE.

[Insert Table 8 about here]

The above observed patterns impose a concern whether ESCORE could predict future returns beyond the known return effects embedded in it. To start with, it is clear that we construct the ESCORE based on the literature of earnings management, and not from the literature of market anomalies. Therefore, the signals embedded in the ESCORE do not necessarily include only those factors which are known as stock returns predictors. We argue that the predictive power of the ESCORE comes from the context of earnings management which is revealed *collectively* by the composite ESCORE, not by the predictive power of the individual signals separately. In fact, some signals, including ESIZE and EBLOAT, even predict future returns, based on the established literature, in the opposite direction because stocks with ESIZE and EBLOAT of one (smaller stocks and those which have smaller NOA) are expected to earn higher (not lower) future returns based on the established evidence of the size effect (e.g. Banz, 1981)and the irrational market reaction to balance sheet bloat (e.g. Hirshleifer et al., 2004). Meanwhile, the literature is silent about whether other signals, including EROA, EDROA, EDIV, EDEBT, EDDEBT, EMA, ECYCLE, EAUDIT and EBT, could predict future returns. The concern lies, therefore, mainly with the high market-to-book ratio, high likelihood of issuing seasoned equity, more financial distress and low profitability of high ESCORE stocks. It has been widely documented that abnormally low returns are associated with high market-to-book firms(e.g. Fama and French, 1992; Lakonishok et al., 1994), seasoned equity offers (e.g. Loughran and Ritter, 1995; Spiess and Affleck-Graves, 1995), firms with negative ZSCORE(e.g. Agarwal and Taffler, 2008), and firms with lower profitability(e.g. Ou and Penman, 1989a; Ou and Penman, 1989b; Piotroski, 2000; Fama and French, 2006a). Those known patterns of returns are embedded in the ESCORE through EOV, ESEOand EDISTRESS. In addition, because ESCORE is designed to capture the context of earnings management, it is also important to control for the documented market mispricing of discretionary accruals (Xie, 2001).

To demonstrate that ESCORE is still significantly associated with future returns after controlling for the above five anomalies, we regress future returns on all variables which are expected to be related to future returns beside the ESCORE. For the multivariate regressions, monthly returns are converted into annual buy-and-hold returns, denoted by an 'a' superscript in place of the 'm' after each measure of returns, to match with the annual update of the explanatory variables. In particular, we calculate for each firm in each portfolio holding year the annual buy-and-hold raw returns, denoted $BHRR_{i,t}^{a}$, by compounding twelve monthly returns. The firm-specific annual buy-and-hold size-adjusted returns are calculated as the difference between $BHRR_{i,t}^{a}$ and the corresponding annual buy-and-hold returns on the size-matched portfolio.

For the four-factor abnormal returns, we first estimate the following equation for each stock to obtain the estimated coefficients:

$$BHRR_{i,j}^{m} - Rf_j = \alpha + \beta_1(Rm_j - Rf_j) + \beta_2 SMB_j + \beta_3 HML_j + \beta_4 UMD_j + \varepsilon \qquad (5)$$

For regression(5),we require at least 12 observations. Therefore, any stocks with less than 12 monthly stock returns are dropped from the main sample. Using the estimated coefficientsfrom equation (5),the monthly expected returnsfor each stock are calculated.These monthly expected returns are then compounded to estimate annual expected returns and are subtracted from $BHRR^{a}_{i,t}$ to arrive at the measures of four-factor annual buy-and-hold abnormal returns, denotedby$BHAR4F^{a}_{i,t}$.

Using the annual buy-and-hold raw and abnormal returns as explainedabove, the following multivariate regression is estimated:

$$RET^{a}_{i,t+1} = \alpha + \beta_1 Log(MVE_{i,t}) + \beta_2 MTB_{i,t} + \beta_3 ROA_{i,t} + \beta_4 ESEO_{i,t} + \beta_5 EDISTRESS_{i,t} + \beta_6 NOA_{i,t} + \beta_7 DAC_{i,t} + \gamma ESCORE_{i,t} + \varepsilon \quad (6)$$

Where: $RET^{a}_{i,t+1}$ is annual buy-and-hold return measured from June of year *t+1* to May of year *t+2* and is replaced by $BHRR^{a}_{i,t+1}$, $BHSAR^{a}_{i,t+1}$ and $BHAR4F^{a}_{i,t+1}$.

Table 9 presents the results of estimating equation (6) along with four other specifications where ESCORE and DAC are dropped one by one and together as well as the last specification where only ESCORE and DAC are kept as explanatory variables. Each panel reports the results of a return metric and contains both a pooled regression and a regression using Fama-MacBeth methodology with the t-statistics calculated using the Newey-West corrected standard errors.

[Insert Table 9 about here]

In Table 9, all control variables have the predicted signs. DAC is always negative and significant, which is in line with the existing literature (e.g. Xie, 2001). It is the coefficient on ESCORE which is the focus of the paper. It is easy to observe that ESCORE is always negative and significant in all specifications and that adding ESCORE generally increases the R^2. It could be therefore concluded that ESCORE can predict stock returns beyond the existing anomalies. From the pooled regression of specification (4) in Panel B of Table 9, one unit increase in ESCORE pulls annual size-adjusted returns down by 1.72%. As a comparison with the portfolio analysis where we did not control for other market ‘anomalies’, the annualized buy-and-hold size-adjusted returns of the hedge portfolio reported in Table 6 is 15% (1.0117^12 – 1). The average ESCORE of the low ESCORE portfolio is 0 and that of the high ESCORE portfolio is 6.56 (519x6 + 232x7 + 88x8 + 26x9 / 879), yielding a difference of –6.56. Therefore, after adjusted for other risk factors, size-adjusted returns on the hedge portfolio shrinks from 15% to 11.29% per year (1.72 x 6.56), which is still highly significant in economic terms.

One issue with the above multivariate regression is the correlation between the control variables and ESCORE, as highlighted in Table 8. We respond to this issue in two ways. First we drop the control variables in equation (6) one at a time, one pair of a time, and all together. For brevity, we only report the result when all control variables are dropped (specification(5) in Table 9). In all of those specifications, the main conclusions of the paper remain unchanged.

Another way to deal with the issue is to exclude ESEO, EDISTRESS and EOV from the construction of the ESCORE. We calculate four compressed versions of the ESCORE in which ESEO, EDISTRESS and EOV are dropped one by one from the construction of ESCORE, and all together. We then redo the portfolio analyses and multivariate regressions. Unreported results confirm that none of the main results change qualitatively. The hedge portfolio, using ESCORE without ESEO, EDISTRESS and EOV, yields an average$BHSAR^m$ ($BHAR4F^m$) of 0.92% (1.01%, respectively) per month, all statistically significant at conventional levels. Using the compressed ESCORE without ESEO, EDISTRESS and EOV to estimate equation (6)andNewey-West-adjusted Fama-MacBethregressions, the coefficient on ESCORE is –0.0172 (–0.0138) when $BHSAR^a$ ($BHAR4F^a$, respectively) is the dependent variable, all beingstatistically significant at conventional levels. We therefore conclude that the power of the ESCORE to predict future returns go beyond the known patterns of returns related to other known market anomalies.

7 Other robustness checks

7.1 Value-weighted scheme

In the main tests, we report returns using the equally-weighted scheme. The advantage of that approach is that it could avoid the influential returns on very large stocks, which exists in the sample as evidenced in the descriptive statistics. Nevertheless, the pitfall of the equally-weighted scheme is that the portfolio returns could be largely influenced by returns on small stocks. Although we have excluded all very small stocks with market value of equity below £1 million, it is still necessary to check if investors could earn abnormal returns from applying the ESCORE if they form portfolios on a value-weighted basis. We redo the portfolio analyses using value-weighted scheme and the main results donot changed qualitatively. In particular, the hedge portfolio yields an average $BHSAR^{m}$ ($BHAR4F^{m}$) of 0.79% (0.78%, respectively), all beingstatistically significant at conventional levels. It is therefore unlikely that the main result of the paper is affected by portfolio weighting schemes.

7.2 Cumulative abnormal returns

The multivariate regressions in the main tests use buy-and-hold returns. This approach replicates more closely the real investment practice where returns are compounded. Nevertheless, we also employ the cumulative returns as a robustness check. Using the cumulative returns, we re-estimate equation (6). The results are untabulated for brevity.In brief, all of the main results remainqualitatively unchanged. In the Newey-West-adjusted Fama-MacBethregressions, for example, the coefficient on ESCORE is –0.0178 (–0.0142) when $CSAR^{a}$ ($CAR4F^{a}$, respectively) is the dependent variable, again all are statistically significant at conventional levels.

8 Conclusions

This study demonstrates that a model, namely the ESCORE which accumulates 15 individual financial-statement-based signals, can capture the context of earnings management and reliably predict future stock returns. The paper contributes to the literature in two ways. First, the ESCORE could be used as an alternateempirical proxy for earnings management. The appeal of the ESCORE is that it allows financial statement users to quickly assessthe reliability of reported earnings by looking at the surrounding context rather than at the magnitude of the actual earnings and its components. This aspect of the ESCORE is important, especially in settings such as in emerging markets where the collection of industry-wide data imposes a severe issue of data unavailability in order for traditional measures of earnings management (e.g. the Jones discretionary accruals) to be estimated. The second and more important contribution of the paper is that we have shown that the ESCORE can be applied by investors to screen out the information about the context of earnings management which is mispriced by the market, and hence earn economically large abnormal returns.

The ESCORE has undeniably not been designed to capture *all* signals of suspicious earnings management. As explained across the paper, a number of signals have been ignored (such as meeting or just beating consensus analysts' earnings forecast, sales and cash flows variability etc.). Besides, ESCORE does not cover many other areas, such as performance-linked compensation, managerial and institutional holdings, corporate governance... With those limitations being fully acknowledged, however, ESCORE has covered a wide range of financial-statement-based signals across different dimensions. We nevertheless leave it for future research to develop other models which capture the factors omitted by the ESCORE.

Appendix: Variable definitions

$\boldsymbol{\gamma}_{\mathbf{k,t}}^{\mathbf{20}}$ and $\boldsymbol{\gamma}_{\mathbf{k,t}}^{\mathbf{80}}$ are, respectively, the lower and upper benchmarks of industry *k* in year *t*, determined as the 20^{th} and 80^{th} percentiles of γ in each industry-year where: γ is substituted by DEBT, MTB, MVE, NOA, CAP, BOOKTAX (definitions of these variables are below); *k* = 1... 43 are 43 unique Datastream level 6 industries; *t* = 1995... 2012 represent the sample years.

EDDEBT is defined as a dummy that takes the value of one if DDEBT is 5% or higher, zero otherwise. DDEBT is the percentage change of total of short- and long-term debt compared to last year, and zero otherwise.

ESEO is one if CSHO increases by 5% compared to last year and PROISSUE is positive, zero otherwise. CSHO is number of outstanding shares. PROISSUE is the proceeds from issuing common/preferred stocks.

EMA is one if a firm announces a share-financed M&A deal in the financial year, zero otherwise.

EOV is one if beginning MTB is higher than the corresponding$\mathrm{MTB}_{\mathrm{k,t}}^{80}$, zero otherwise. MTB is calculated as market value of equity at the end of fiscal year divided by common shareholders' equity.

EROA is one if ROA is equal to or larger than zero but smaller than 0.01, zero otherwise. ROA is calculated as earnings before extraordinary items scaled by beginning total assets.

EDROA is one if DROA is equal to or larger than zero but smaller than 0.005, zero otherwise. DROA is calculated as the change of earnings before extraordinary items compared to last year scaled by beginning total assets.

EDIV is one if DIVDEF is equal to or larger than zero but smaller than 0.01, zero otherwise. DIVDEF is calculated as the difference between net income and total cash dividends scaled by beginning total assets.

EDISTRESS is one if ZSCORE is negative, zero otherwise. $\mathrm{ZSCORE} = 3.2 + 12.8\mathrm{x}_1 + 2.5\mathrm{x}_2 - 10.68\mathrm{x}_3 + 0.029\mathrm{x}_4$, where : x_1 is pre-tax income divided by current liabilities; x_2 is current assets divided by total liabilities; x_3 is current liabilities divided by total assets; x_4 is quick assets minus current liabilities divided by daily operating expense, where daily operating expense is sales minus pre-tax income minus depreciation expense divided by 365.

EDEBT is one if beginning DEBT is lower than the corresponding $\mathrm{DEBT}_{\mathrm{k,t}}^{20}$, zero otherwise. DEBT is the total of short- and long-term debts scaled by total assets.

ESIZE is one if beginning MVE is smaller than the corresponding $\mathrm{MVE}_{\mathrm{k,t}}^{20}$, zero otherwise. MVE is market value of equity at fiscal year-end.

ECYCLE is one if (i) CFO is negative, CFF is positive, CFI is negative, or (ii) CFO is positive, CFF is positive, CFI is negative, zero otherwise, whereCFO is operating cash flows,CFF is financing cash flows,CFI is investing cash flows.

EAUDIT is one if the financial statements are audited by one of the Big 5 audit firms, zero otherwise.

EBLOAT is one if beginning NOA is smaller than the corresponding $\mathrm{NOA}_{k,t}^{20}$, zero otherwise. NOA = (BVE + DEBT + CHE) / TA, where CHE is cash and cash equivalents, TA is total assets.

ECAP is one if beginning CAP is smaller than the corresponding $\mathrm{CAP}_{k,t}^{20}$, zero otherwise. CAP is plants, properties and equipment divided by total assets.

EBT is one if BOOKTAX is higher than the corresponding $\mathrm{BOOKTAX}_{k,t}^{80}$, zero otherwise. BOOKTAX is the absolute value of the difference between pre-tax income and TTP scaled by sales. The total taxable profit, TTP, is estimated as follows:

- If TXT ≤ 0, then TTP = 0
- If 0 < TXT ≤ LL x SR, then $\mathrm{TTP} = \frac{\mathrm{TXT}}{\mathrm{SR}}$
- If LL x SR ≤ TXT ≤ (UL – LL) x AR, then $\mathrm{TTP} = \frac{\mathrm{TXT}-(\mathrm{LL}\times\mathrm{SR})}{\mathrm{AR}} + \mathrm{LL}$
- If TXT ≥ (UL – LL) x AR, then $\mathrm{TTP} = \frac{\mathrm{TXT}-(\mathrm{LL}\times\mathrm{SR})-[(\mathrm{UL}-\mathrm{LL})\times\mathrm{AR}]}{\mathrm{MR}} + \mathrm{UL}$

where TXT is the reported income tax expense, LL is the lower limit for marginal tax relief, UL is the upper limit for marginal tax relief, SR is the small profit tax rate, MR is the main tax rate, AR = (SR + MR) / 2.

ESCORE = ESEO + EDDEBT + EMA + EOV + EROA + EDROA + EDIV + EDISTRESS + EDEBT + ESIZE + ECYCLE + EAUDIT + EBLOAT + ECAP + EBT

$\mathbf{BHRR_{i,j}^{m}}$is monthly buy-and-hold raw returns of stock *i* in month *j*, calculated as the percentage change in the Returns Index downloaded from Datastream at the end of each month.

$\mathbf{BHRR_{p,j}^{m}}$is monthly buy-and-hold raw returns of portfolio *p* in month *j*, calculated as the equally-weighted $\mathrm{BHRR}_{i,j}^{m}$ of all stocks belong to portfolio p.

$\mathbf{BHRR_{i,t}^{a}}$is annual buy-and-hold raw returns of stock *i* in year *t*, calculated as $\mathrm{BHRR}_{i,t}^{a} = \prod_{j=1}^{12}(1+\mathrm{BHRR}_{i,j}^{m}) - 1(\mathrm{j} = \text{ June of year t} \ldots \text{ May of year t} + 1)$.

$\mathbf{CRR_{i,t}^{a}}$is annual cumulative raw returns of stock *i* in year *t*, calculated as $\mathrm{CRR}_{i,t}^{a} = \sum_{j=1}^{12}\mathrm{BHRR}_{i,j}^{m}\ (\mathrm{j} = \text{ June of year t} \ldots \text{ May of year t} + 1)$.

$\mathbf{SDR_{d,j}^{m}}$ is the average monthly $\mathrm{BHRR}_{i,j}^{m}$of all stocks in size decile*d* in month *j* $(j = \text{ June of year t} \ldots \text{ May of year t} + 1)$, where the deciles are determined by sorting stocks by market value of equity at the end of year *t-1*.

$\mathbf{BHSAR_{i,j}^{m}}$is monthly buy-and-hold size-adjusted returns of stock *i* in month *j*, calculated as the difference between $\mathrm{BHRR}_{i,j}^{m}$ and the $\mathrm{SDR}_{d,j}^{m}$ of the corresponding size decile to which stock *i* belongs.

$\mathbf{BHSAR_{p,j}^{m}}$is monthly buy-and-hold size-adjusted returns of portfolio *p* in month *j*, calculated as the equally-weighted $\mathrm{BHSAR}_{i,j}^{m}$ of all stocks belong to portfolio *p*.

$\mathbf{BHSAR^a_{i,t}}$is annual buy-and-hold size-adjusted returns of stock *i* in year *t*, calculated as$\mathrm{BHSAR}^a_{i,t} = \prod_{j=1}^{12}(1 + \mathrm{BHRR}^m_{i,j}) - \prod_{j=1}^{12}\left(1 + \mathrm{SDR}^m_{d,j}\right)$ $(\mathrm{i} \in \mathrm{d}, \mathrm{j} = \text{ June of year t} \ldots \text{ May of year t} + 1)$

$\mathbf{CSAR^a_{i,t}}$is annual cumulative size-adjusted returns of stock *i* in year *t*, calculated as $\mathrm{CSAR}^a_{i,t} = \sum_{j=1}^{12}(\mathrm{BHRR}^m_{i,j} - \mathrm{SDR}^m_{d,j})$ $(\mathrm{i} \in \mathrm{d}, \mathrm{j} = \text{ June of year t} \ldots \text{ May of year t} + 1)$.

$\mathbf{BHAR4F^m_{p,j}} = \mathrm{BHRR}^m_{p,j} - [\mathrm{Rf_j} + \hat{\beta}^{4F}_{1,p}(\mathrm{Rm_j} - \mathrm{Rf_j}) + \hat{\beta}^{4F}_{2,p}\mathrm{SMB_j} + \hat{\beta}^{4F}_{3,p}\mathrm{HML_j} + \hat{\beta}^{4F}_{4,p}\mathrm{UMD_j}]$ is monthly buy-and-hold abnormal returns of portfolio *p* in month *j* adjusted for the market, size, book-to-market and momentum factors; where: $\hat{\beta}^{4F}_{1,p}$, $\hat{\beta}^{4F}_{2,p}$, $\hat{\beta}^{4F}_{3,p}$, $\hat{\beta}^{4F}_{4,p}$ is the estimated intercept from the regression $\mathrm{BHRR}^m_{p,j} - \mathrm{Rf_j} = \alpha + \beta_1(\mathrm{Rm_j} - \mathrm{Rf_j}) + \beta_2\mathrm{SMB_j} + \beta_3\mathrm{HML_j} + \beta_4\mathrm{UMD_j} + \varepsilon$; $\mathrm{Rf_j}$, $\mathrm{Rm_j}$, $\mathrm{SMB_j}$, $\mathrm{HML_j}$,$\mathrm{UMD_j}$ are, respectively, the risk-free rate, returns on the market portfolio, size factor, book-to-market factor, momentum factor in month *j*, all taken from Gregory et al. (2013).

$\mathbf{E(R4F^m_{i,j})} = \mathrm{Rf_j} + \hat{\beta}^{4F}_{1,i}(\mathrm{Rm_j} - \mathrm{Rf_j}) + \hat{\beta}^{4F}_{2,i}\mathrm{SMB_j} + \hat{\beta}^{4F}_{3,i}\mathrm{HML_j} + \hat{\beta}^{4F}_{4,i}\mathrm{UMD_j}$ is monthly buy-and-hold expected returns of stock *i* in month *j*adjusted for the market, size, book-to-market and momentum factors; where: $\hat{\beta}^{4F}_{1,i}$, $\hat{\beta}^{4F}_{2,i}$, $\hat{\beta}^{4F}_{3,i}$, $\hat{\beta}^{4F}_{4,i}$ is the estimated coefficient from the regression $\mathrm{BHRR}^m_{i,j} - \mathrm{Rf_j} = \alpha + \beta_1(\mathrm{Rm_j} - \mathrm{Rf_j}) + \beta_2\mathrm{SMB_j} + \beta_3\mathrm{HML_j} + \beta_4\mathrm{UMD_j} + \varepsilon$; $\mathrm{Rf_j}$, $\mathrm{Rm_j}$, $\mathrm{SMB_j}$, $\mathrm{HML_j}$,$\mathrm{UMD_j}$ are, respectively, the risk-free rate, returns on the market portfolio, size factor, book-to-market factor, momentum factor in month *j*, all taken from Gregory et al. (2013).

$\mathbf{BHAR4F^a_{i,t}}$is annual buy-and-hold abnormal returns of stock *i*in year *t* adjusted for the market, size, book-to-market and momentum factors, calculated as $\mathrm{BHAR4F}^a_{i,t} = \prod_{j=1}^{12}(1 + \mathrm{BHRR}^m_{i,j}) - \prod_{j=1}^{12}\left[1 + \mathrm{E}(\mathrm{R4F}^m_{i,j})\right]$ $(\mathrm{j} = \text{ June of year t} \ldots \text{ May of year t} + 1)$

$\mathbf{CAR4F^a_{i,t}}$is annual cumulative abnormal returns of stock *i* in year *t* adjusted for the market, size, book-to-market and momentum factors, calculated as $\mathrm{CAR4F}^a_{i,t} = \sum_{j=1}^{12}\left[\mathrm{BHRR}^m_{i,j} - \mathrm{E}(\mathrm{R4F}^m_{i,j})\right]$ $(\mathrm{j} = \text{ June of year t} \ldots \text{ May of year t} + 1)$.

$\mathbf{DAC_{i,t}} = \frac{\mathrm{AC_{i,t}}}{\mathrm{TA_{i,t-1}}} - \left[\hat{\alpha} + \hat{\beta}_1\left(\frac{1}{\mathrm{TA_{i,t-1}}}\right) + \hat{\beta}_2\left(\frac{\Delta\mathrm{REV_{i,t}} - \Delta\mathrm{REC_{i,t}}}{\mathrm{TA_{i,t-1}}}\right) + \hat{\beta}_3\left(\frac{\mathrm{PPE_{i,t}}}{\mathrm{TA_{i,t-1}}}\right)\right]$, is discretionary accruals of stock *i* in year *t*. $\hat{\alpha}$, $\hat{\beta}_1$, $\hat{\beta}_2$, $\hat{\beta}_3$ are the estimated coefficients from the following regression, which is run in each industry-year with at least 15 observations: $\frac{\mathrm{AC_{i,t}}}{\mathrm{TA_{i,t-1}}} = \alpha + \beta_1\left(\frac{1}{\mathrm{TA_{i,t-1}}}\right) + \beta_2\left(\frac{\Delta\mathrm{REV_{i,t}}}{\mathrm{TA_{i,t-1}}}\right) + \beta_3\left(\frac{\mathrm{PPE_{i,t}}}{\mathrm{TA_{i,t-1}}}\right) + \varepsilon_{i,t}$, where $\mathrm{AC_{i,t}}$ is total accruals of firm *i* in year *t*, which is calculated as the difference between income before extraordinary items and net operating cash flows; $\mathrm{TA_{i,t-1}}$ is total assets of firm *i* at the end of year *t – 1*; $\Delta\mathrm{REV_{i,t}}$ and $\Delta\mathrm{REC_{i,t}}$ are the changes in sales and receivables from year *t – 1* to year *t* of firm *i*, respectively; and $\mathrm{PPE_{i,t}}$ is gross plant, property and equipment of firm *i* at the end of year *t*.

ADAC is the absolute value of DAC.

HDAC is one if DAC is equal to or higher than the 80^{th} percentile of the corresponding industry-year ranked by DAC, zero otherwise.

$\mathbf{DWAC_{i,t}} = \frac{\mathrm{WAC_{i,t}}}{\mathrm{TA_{i,t-1}}} - \left[\hat{\alpha} + \hat{\beta}_1\left(\frac{\mathrm{REV_{i,t}}}{\mathrm{TA_{i,t-1}}}\right) + \hat{\beta}_2\left(\frac{\mathrm{REV_{i,t}} - \Delta\mathrm{REC}}{\mathrm{TA_{i,t-1}}}\right)\right]$, is discretionary working capital accruals of stock *i* in year *t*. $\hat{\alpha}$, $\hat{\beta}_1$, $\hat{\beta}_2$ are the estimated coefficients from the following regression, which is run in each industry-year with at least 15 observations: $\frac{\mathrm{WAC_{i,t}}}{\mathrm{TA_{i,t-1}}} = \alpha +$

$\beta_1\left(\frac{\mathrm{REV_{i,t}}}{\mathrm{TA_{i,t-1}}}\right)+\beta_2\left(\frac{\mathrm{REV_{i,t}-\Delta REC}}{\mathrm{TA_{i,t-1}}}\right)+\varepsilon_{i,t}$, where $\mathrm{WAC_{i,t}}$ is working capital accruals of stock *i* in year *t*, which is calculated as $\mathrm{WAC}=(\Delta\mathrm{CA}-\Delta\mathrm{CHE})-(\Delta\mathrm{CL}-\Delta\mathrm{STD})$ [ΔCA is change in current assets; ΔCHE is change in cash and cash equivalents; ΔCL is change in current liabilities; ΔSTD is change in short-term debts].

ADWAC is the absolute value of DWAC.

HDWAC is one if DWAC is equal to or higher than the 80th percentile of the corresponding industry-year ranked by DWAC, zero otherwise.

$\mathbf{DCF_{i,t}}=-1\times\left\{\frac{CFO_{i,t}}{TA_{i,t-1}}-\left[\hat{\alpha}+\hat{\beta}_1\left(\frac{1}{TA_{i,t-1}}\right)+\hat{\beta}_2\left(\frac{REV_{i,t}}{TA_{i,t-1}}\right)+\hat{\beta}_3\left(\frac{\Delta REV_{i,t}}{TA_{i,t-1}}\right)\right]\right\}$, is abnormal cash flowsof stock *i* in year *t*. $\hat{\alpha}$, $\hat{\beta}_1$, $\hat{\beta}_2$, $\hat{\beta}_3$ are the estimated coefficients from the following regression, which is run in each industry-year with at least 15 observations:$\frac{\mathrm{CFO_{i,t}}}{\mathrm{TA_{i,t-1}}}=\alpha+\beta_1\left(\frac{1}{\mathrm{TA_{i,t-1}}}\right)+\beta_2\left(\frac{\mathrm{REV_{i,t}}}{\mathrm{TA_{i,t-1}}}\right)+\beta_3\left(\frac{\Delta\mathrm{REV_{i,t}}}{\mathrm{TA_{i,t-1}}}\right)+\varepsilon_{i,t}$, where:$\mathrm{CFO_{i,t}}$ is net cash flows from operation of firm *i* in year *t.*

ADCF is the absolute value of DCF.

HDCF is one if DCF is equal to or higher than the 80th percentile of the corresponding industry-year ranked by DCF, zero otherwise.

$\mathbf{DPROD_{i,t}}=\frac{\mathrm{PROD_{i,t}}}{\mathrm{TA_{i,t-1}}}-\left[\hat{\alpha}+\hat{\beta}_1\left(\frac{1}{\mathrm{TA_{i,t-1}}}\right)+\hat{\beta}_2\left(\frac{\mathrm{REV_{i,t}}}{\mathrm{TA_{i,t-1}}}\right)+\hat{\beta}_3\left(\frac{\Delta\mathrm{REV_{i,t}}}{\mathrm{TA_{i,t-1}}}\right)+\hat{\beta}_4\left(\frac{\Delta\mathrm{REV_{i,t-1}}}{\mathrm{TA_{i,t-1}}}\right)\right]$, is abnormal production costs of stock *i* in year *t*. $\hat{\alpha}$, $\hat{\beta}_1$, $\hat{\beta}_2$, $\hat{\beta}_3$, $\hat{\beta}_4$ are the estimated coefficients from the following regression, which is run in each industry-year with at least 15 observations: $\frac{\mathrm{PROD_{i,t}}}{\mathrm{TA_{i,t-1}}}=\alpha+\beta_1\left(\frac{1}{\mathrm{TA_{i,t-1}}}\right)+\beta_2\left(\frac{\mathrm{REV_{i,t}}}{\mathrm{TA_{i,t-1}}}\right)+\beta_3\left(\frac{\Delta\mathrm{REV_{i,t}}}{\mathrm{TA_{i,t-1}}}\right)+\beta_4\left(\frac{\Delta\mathrm{REV_{i,t-1}}}{\mathrm{TA_{i,t-1}}}\right)+\varepsilon_{i,t}$, where:$\mathrm{PROD_{i,t}}$ is production cost, calculated as the sum of cost of goods sold and change in inventory, of firm *i* in year *t.*

ADPROD is the absolute value of DPROD.

HDPROD is one if DPROD is equal to or higher than the 80th percentile of the corresponding industry-year ranked by DPROD, zero otherwise.

$\mathbf{DDISEXP_{i,t}}=-1\times\left\{\frac{\mathrm{DISEXP_{i,t}}}{\mathrm{TA_{i,t-1}}}-\left[\hat{\alpha}+\hat{\beta}_1\left(\frac{1}{\mathrm{TA_{i,t-1}}}\right)+\hat{\beta}_2\left(\frac{\mathrm{REV_{i,t-1}}}{\mathrm{TA_{i,t-1}}}\right)\right]\right\}$, is abnormal discretionary expenses of stock *i* in year *t*. $\hat{\alpha}$, $\hat{\beta}_1$, $\hat{\beta}_2$ are the estimated coefficients from the following regression, which is run in each industry-year with at least 15 observations: $\frac{\mathrm{DISEXP_{i,t}}}{\mathrm{TA_{i,t-1}}}=\alpha+\beta_1\left(\frac{1}{\mathrm{TA_{i,t-1}}}\right)+\beta_2\left(\frac{\mathrm{REV_{i,t-1}}}{\mathrm{TA_{i,t-1}}}\right)+\varepsilon_{i,t}$, where:$\mathrm{DISEXP_{i,t}}$ is discretionary expenses, calculated as selling and general administrative expenses plus research and development expenses,of firm *i* in year *t.*

ADDISEXP is the absolute value of DDISEXP.

HDDISEXP is one if DDISEXP is equal to or higher than the 80th percentile of the corresponding industry-year ranked by DDISEXP, zero otherwise.

$\mathbf{TOTALRM_{i,t}} = \left[\frac{\mathrm{DCF_{i,t}} - \overline{\mathrm{DCF_{t,k}}}}{\sigma(\mathrm{DCF})_{t,k}} + \frac{\mathrm{DPROD_{i,t}} - \overline{\mathrm{DPROD_{t,k}}}}{\sigma(\mathrm{DPROD})_{t,k}} + \frac{\mathrm{DDISEXP_{i,t}} - \overline{\mathrm{DDISEXP_{t,k}}}}{\sigma(\mathrm{DISEXP})_{t,k}}\right] / 3\ (\mathrm{i} \in \mathrm{k})$ is total real earnings management, where: $\overline{\mathrm{DCF_{t,k}}}$, $\overline{\mathrm{DPROD_{t,k}}}$, $\overline{\mathrm{DDISEXP_{t,k}}}$ [$\sigma(\mathrm{DCF})_{t,k}$, $\sigma(\mathrm{DPROD})_{t,k}$, $\sigma(\mathrm{DISEXP})_{t,k}$] is, respectively, the mean [standard deviation] of DCF, DPROD, DDISEXP of all firms in industry *k* in year *t*; k=1…43 are 43 unique Datastream level 6 industries.

Table 1. Descriptive statistics (n = 11,920)

	Mean	25th percentile	Median	75th percentile	STD. DEV.
AT (£mil)	402	16	54	200	1,204
SALE (£mil)	409	14	55	232	1,149
NI (£mil)	19	-1	2	10	73
DIV (£mil)	10	0	1	4	33
MVE (£mil)	390	12	44	188	1,246
DSHARE	0.1130	0.0000	0.0033	0.0390	0.3619
DDEBT	1.3388	-0.2759	-0.0023	0.4303	7.0904
MTB	3.3217	1.0471	1.8317	3.3463	5.0650
ROA	-0.0072	-0.0288	0.0451	0.0965	0.2201
DROA	0.0135	-0.0309	0.0095	0.0449	0.1850
DIVDEF	-0.0311	-0.0417	0.0236	0.0626	0.2091
ZSCORE	12.7507	3.0669	9.1751	18.3813	27.0573
DEBT	0.1565	0.0190	0.1292	0.2521	0.1467
NOA	0.5004	0.3636	0.5398	0.6690	0.2363
CAP	0.4524	0.1507	0.3817	0.6906	0.3463
BOOKTAX	0.8242	0.0082	0.0252	0.0997	4.1755
DAC	0.0066	-0.0447	0.0096	0.0621	0.1251
ESEO	0.2107	0	0	0	0.4078
EDDEBT	0.3790	0	0	1	0.4852
EMA	0.0498	0	0	0	0.2176
EOV	0.2161	0	0	0	0.4116
EROA	0.0344	0	0	0	0.1823
EDROA	0.0496	0	0	0	0.2171
EDIV	0.0553	0	0	0	0.2285
EDISTRESS	0.1573	0	0	0	0.3641
EDEBT	0.2436	0	0	0	0.4293
ESIZE	0.2163	0	0	0	0.4117
ECYCLE	0.0273	0	0	0	0.1631
EAUDIT	0.4453	0	0	1	0.4970
EBLOAT	0.2159	0	0	0	0.4115
ECAP	0.2157	0	0	0	0.4113
EBT	0.2149	0	0	0	0.4108
ESCORE	2.7313	1	2	4	1.7346
BHRR[a]	0.0704	-0.2843	0.0114	0.3245	0.5467
BHSAR[a]	0.0079	-0.3003	-0.0420	0.2297	0.5047
BHAR4F[a]	-0.0096	-0.2968	-0.0568	0.2020	0.4976

Notes:The table reports the mean, 25^{th}, 50^{th} (the median), 75^{th} percentiles and standard deviation of selected variables. Definitions of variables are in the Appendix.

Table 2.Average industry benchmarks

Industry	N	$\overline{MVE_j^{20}}$(£mil)	$\overline{MTB_j^{80}}$	$\overline{BOOKTAX_j^{80}}$	$\overline{NOA_j^{20}}$	$\overline{CAP_j^{20}}$	$\overline{DEBT_j^{20}}$
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Building Mat.& Fix.	410	11	2.5853	0.0763	0.4294	0.4395	0.0344
Industrial Suppliers	276	19	3.3094	0.0362	0.4441	0.2082	0.0305
Specialty Chemicals	318	20	4.0362	0.3146	0.4549	0.3670	0.0421
Home Construction	258	36	1.5436	0.0188	0.5473	0.0238	0.0740
Electrical Equipment	371	6	3.4570	0.3935	0.3941	0.2042	0.0201
Heavy Construction	290	15	2.9180	0.0350	0.1079	0.1291	0.0232
Media Agencies	383	9	8.0574	0.1898	0.1249	0.1097	0.0290
Industrial Machinery	779	8	2.9728	0.0492	0.3813	0.3436	0.0315
Healthcare Providers	23	4	4.3513	0.0664	0.6398	0.0398	0.1294
Financial Admin.	13	22	7.0500	0.0218	0.2797	0.2131	0.0552
Exploration & Prod.	395	27	3.2060	3.1903	0.4571	0.2040	0.0074
Oil Equip. & Services	73	24	4.2967	0.1684	0.1369	0.1302	0.0317
Recreational Services	320	9	3.1160	0.2569	0.3706	0.4810	0.0592
Electronic Equipment	299	8	4.4093	0.2077	0.4070	0.2317	0.0236
Software	957	7	7.0822	0.4854	0.0854	0.1056	0.0003
Dur. Household Prod.	36	4	2.5772	0.0969	0.4870	0.5158	0.0000
Furnishings	87	8	2.9622	0.0432	0.4151	0.4919	0.0326
Transport Services	197	18	2.5858	0.1246	0.3755	0.3212	0.0735
Apparel Retailers	259	28	4.2323	0.0341	0.3796	0.3621	0.0116
Clothing & Accessory	318	5	2.7832	0.0914	0.4411	0.2317	0.0265
Food Products	384	27	3.5921	0.0494	0.4398	0.3716	0.1082
Restaurants & Bars	470	22	3.1987	0.0894	0.5689	0.6894	0.0677
Consumer Electronics	28	27	3.4635	0.0373	0.4746	0.4823	0.0204
Publishing	405	21	5.6911	0.1624	0.3103	0.0745	0.0288
Business Support Svs.	1,398	10	4.3210	0.0610	0.2607	0.1707	0.0361
Broadline Retailers	88	35	3.1222	0.0564	0.3830	0.5066	0.0093
Food Retail,Wholesale	63	61	3.0112	0.0198	0.4670	0.7491	0.0703
Specialty Retailers	458	17	3.4254	0.0323	0.3241	0.2590	0.0450
Pharmaceuticals	282	15	8.6519	4.2351	0.1321	0.0556	0.0007
Gambling	99	13	7.9496	0.2054	0.1682	0.0670	0.0274
Medical Supplies	20	13	6.2058	0.5928	0.1704	0.0756	0.0092
Broadcast & Entertain	340	7	6.7370	0.5503	0.2331	0.1221	0.0201
Gold Mining	71	24	3.5633	1.4136	0.4817	0.4019	0.0124
General Mining	159	21	3.5954	4.7763	0.3582	0.1448	0.0041
Telecom. Equipment	84	12	3.4032	0.5757	0.2526	0.1235	0.0038
Semiconductors	27	16	6.6568	1.7243	0.0556	0.0549	0.0000
Medical Equipment	266	7	5.4608	0.8935	0.3200	0.1701	0.0059
Bus.Train&Employmnt	344	8	6.6713	0.0857	0.2240	0.0813	0.0103
Fixed Line Telecom.	36	35	7.0520	0.5431	0.0882	0.3036	0.0752
Mobile Telecom.	20	12	5.8036	0.3703	0.1900	0.0231	0.0000
Computer Services	531	14	7.5568	0.1861	0.1505	0.1381	0.0054
Internet	12	4	4.4347	0.3279	0.0792	0.3561	0.0001
Biotechnology	273	21	7.0276	17.6279	-0.0033	0.0751	0.0002

Notes:Column (2) reports the distribution of observations across Datastream level-six industries. Columns (3), (6), (7) and (8) report the average of across the years of the 20th percentile of MVE, NOA, CAP and DEBT in each industry. Columns (4) and (5) report the average of across the years of the 80th percentile of MTB and BOOKTAX in each industry. Definitions of variables are in the Appendix.

Table 3.Correlations

	ESEO	EDDEBT	EMA	EOV	EROA	EDROA	EDIV	EDISTRESS	EDEBT	ESIZE	ECYCLE	EAUDIT	EBLOAT	ECAP	EBT	ESCORE
BHRR[a]	-0.123	-0.043	-0.069	-0.021	*0.016*	0.024	0.026	-0.055	*-0.016*	*-0.014*	-0.033	-0.056	*-0.010*	-0.031	-0.077	-0.112
BHSAR[a]	-0.097	-0.043	-0.052	-0.025	*0.008*	0.019	0.021	-0.062	*-0.004*	*-0.006*	-0.030	-0.022	*-0.010*	-0.028	-0.074	-0.092
BHAR4F[a]	-0.098	-0.028	-0.046	*-0.011*	*0.000*	0.023	*0.013*	-0.060	*-0.011*	*-0.012*	-0.029	-0.036	*-0.009*	-0.025	-0.076	-0.092
ESEO	1.000															
EDDEBT	0.078	1.000														
EMA	0.218	0.103	1.000													
EOV	0.053	*0.013*	0.034	1.000												
EROA	-0.025	*-0.008*	*-0.014*	-0.043	1.000											
EDROA	-0.049	0.022	*-0.017*	-0.026	0.021	1.000										
EDIV	-0.048	*-0.011*	*-0.010*	-0.056	0.333	0.024	1.000									
EDISTRESS	0.134	-0.042	*-0.007*	0.035	-0.049	-0.055	-0.058	1.000								
EDEBT	*-0.003*	-0.205	*0.008*	0.067	-0.043	-0.019	-0.044	0.041	1.000							
ESIZE	0.101	-0.056	*0.001*	-0.117	0.024	-0.026	*0.000*	0.153	0.058	1.000						
ECYCLE	0.101	0.029	*0.009*	*-0.003*	*-0.012*	-0.019	-0.023	0.117	*-0.003*	0.072	1.000					
EAUDIT	0.108	-0.030	0.021	*-0.003*	*-0.017*	*-0.015*	-0.037	0.061	0.089	0.223	0.029	1.000				
EBLOAT	0.025	-0.071	0.026	0.224	*-0.015*	-0.035	-0.035	0.119	0.233	0.023	*0.010*	0.020	1.000			
ECAP	0.089	-0.025	0.031	0.053	*-0.003*	-0.027	*-0.005*	0.096	0.118	0.047	0.023	0.064	0.173	1.000		
EBT	0.148	-0.056	*0.011*	*0.007*	-0.071	-0.069	-0.103	0.381	0.082	0.149	0.108	0.100	0.063	0.126	1.000	
ESCORE	0.435	0.200	0.232	0.304	0.089	0.057	0.071	0.434	0.344	0.386	0.202	0.431	0.420	0.415	0.448	1.000

Notes:The table reports Pearson correlation coefficients between selected variables. Definitions of variables are in the Appendix. Values reported in *italic* indicate the corresponding coefficients are *not significant at 5% level.*

Table 4.Principal components analysis

Panel A: Eigen values of the correlation matrix

Principal components	Eigenvalue	Difference	Proportion	Cumulative
1	1.9246	0.5198	0.1283	0.1283
2	1.4048	0.0552	0.0937	0.2220
3	1.3496	0.0909	0.0900	0.3119
4	1.2587	0.1562	0.0839	0.3959
5	1.1025	0.1143	0.0735	0.4694
6	0.9882	0.0511	0.0659	0.5352
7	0.9371	0.0084	0.0625	0.5977
8	0.9286	0.0288	0.0619	0.6596
9	0.8999	0.0930	0.0600	0.7196
10	0.8068	0.0561	0.0538	0.7734
11	0.7507	0.0328	0.0500	0.8234
12	0.7179	0.0493	0.0479	0.8713
13	0.6686	0.0012	0.0446	0.9159
14	0.6673	0.0726	0.0445	0.9604
15	0.5947	0.0396	1.0000	

Panel B: Eigen vectors

	Prin1	Prin2	Prin3	Prin4	Prin5	Prin6	Prin7	Prin8	Prin9	Prin10	Prin11	Prin12	Prin13	Prin14	Prin15
ESEO	0.2906	0.3144	-0.1603	0.3480	0.1554	-0.0540	-0.0399	-0.1708	0.1037	-0.3294	-0.3382	0.5928	-0.1539	0.0519	-0.0249
EDDEBT	-0.1154	0.3318	-0.3374	0.2857	-0.0613	0.1666	0.0492	0.4290	-0.1839	0.4405	0.3512	0.2924	0.1514	0.0562	0.0218
EMA	0.0966	0.1836	-0.2373	0.4637	0.3249	-0.1199	-0.2119	-0.4092	0.1207	0.1918	0.1445	-0.5245	0.0409	-0.0555	0.0353
EOV	0.1282	-0.3619	-0.2578	0.3311	-0.1377	0.0668	0.3126	0.2919	0.3823	-0.2704	-0.1217	-0.1652	0.4454	0.0935	0.0410
EROA	-0.1648	0.0835	0.5299	0.3882	-0.1477	-0.0148	0.0308	0.0349	0.1097	-0.0249	0.0550	0.0944	0.1175	-0.6768	0.1174
EDROA	-0.1317	-0.0058	0.0296	-0.0258	0.1346	0.9340	-0.1825	-0.1428	0.1766	-0.0523	-0.0470	-0.0005	-0.0004	-0.0038	-0.0271
EDIV	-0.2021	0.0679	0.5192	0.3767	-0.1471	-0.0278	-0.0117	-0.0153	0.0636	-0.0326	0.1106	-0.0397	-0.0771	0.6850	-0.1617
EDISTRESS	0.4301	0.1431	0.0655	-0.0800	-0.4248	0.0692	-0.1968	0.0535	0.2535	0.1131	0.0684	-0.0772	-0.1914	0.1142	0.6478
EDEBT	0.2622	-0.4336	0.1731	-0.0240	0.2657	-0.0134	0.0384	-0.3443	-0.0302	0.1647	0.4151	0.4126	0.3275	0.0999	0.1845
ESIZE	0.2793	0.2704	0.3306	-0.1542	0.2875	0.0211	0.1135	0.1528	0.0387	0.4213	-0.4988	-0.0869	0.3906	0.0853	-0.0355
ECYCLE	0.1841	0.2291	-0.0082	0.0195	-0.2786	0.2080	0.7077	-0.3993	-0.3295	-0.0399	0.0580	-0.1341	-0.0096	-0.0138	-0.0132
EAUDIT	0.2537	0.1465	0.1809	-0.0659	0.5259	0.0532	0.2711	0.4003	0.0947	-0.2957	0.3891	-0.1474	-0.3037	-0.0325	0.0332
EBLOAT	0.2844	-0.4571	0.0181	0.2652	-0.0448	0.0934	0.1107	0.0994	0.0101	0.4489	-0.1688	0.0183	-0.5383	-0.1084	-0.2732
ECAP	0.2760	-0.1559	0.0888	0.2342	0.0037	0.1289	-0.3284	0.1950	-0.7356	-0.2611	-0.1063	-0.1614	0.1280	0.0086	0.1057
EBT	0.4517	0.1607	0.0440	-0.1370	-0.3098	0.0150	-0.2673	-0.0011	0.1484	-0.0833	0.2982	-0.0188	0.1965	-0.1078	-0.6429

Notes:Panel A (B) reports the Eigen values (vectors) of the correlation matrix resulted from principal component analyses on 15 individual components of the ESCORE. Definitions of variables are in the Appendix.

Table 5. Measures of accruals management and real earnings management across ESCORE groups

Panel A: Accruals management

ESCORE	DAC			DWAC		
	N	ADAC	HDAC	N	ADWAC	HDWAC
0	862	0.0528	0.1334	861	0.0389	0.1092
1	2,218	0.0580	0.1479	2,212	0.0466	0.1695
2	2,925	0.0692	0.2051	2,911	0.0549	0.1996
3	2,381	0.0859	0.2373	2,363	0.0658	0.2294
4	1,675	0.0995	0.2591	1,662	0.0738	0.2575
5	994	0.1198	0.2807	983	0.0870	0.2981
6	519	0.1506	0.2832	513	0.0971	0.2807
7	232	0.1657	0.3017	231	0.1116	0.3030
8	88	0.1639	0.3636	86	0.1153	0.3256
9	26	0.1935	0.3846	25	0.1105	0.2800
Low (0)	862	0.0528	0.1334	861	0.0389	0.1092
High (6-9)	865	0.1573	0.2994	855	0.1032	0.2912
High - Low		0.1045	0.1660		0.0643	0.1821
t-stat		20.007***	8.549***		17.779***	9.665***

Panel B: Real earnings management

ESCORE	DCF			DPROD			DDISEXP			TOTALRM		
	N	ADCF	HDCF	N	ADPROD	HDPROD	N	ADDISEXP	HDDISEXP	N	ATOTALRM	HTOTALRM
0	773	0.0951	0.0841	766	0.1427	0.1606	627	0.1537	0.1722	623	0.3672	0.1252
1	1,981	0.0967	0.1075	1,943	0.1608	0.1765	1,587	0.1672	0.1916	1,552	0.4426	0.1727
2	2,601	0.1033	0.1646	2,532	0.1769	0.1971	2,135	0.1800	0.2117	2,076	0.4663	0.1956
3	2,116	0.1215	0.2202	2,008	0.1876	0.2321	1,800	0.2031	0.2117	1,711	0.4863	0.2238
4	1,482	0.1464	0.2753	1,382	0.1988	0.2381	1,297	0.2338	0.2290	1,206	0.4825	0.2313
5	878	0.1872	0.3702	789	0.2084	0.2763	769	0.2702	0.2848	689	0.5400	0.3309
6	456	0.2328	0.4386	375	0.2255	0.2933	405	0.3088	0.2444	333	0.5527	0.3423
7	211	0.2790	0.4787	175	0.2285	0.3086	200	0.3694	0.2450	167	0.6438	0.3473
8	80	0.2930	0.5750	71	0.2388	0.2958	70	0.3280	0.3286	61	0.6461	0.3279
9	22	0.3745	0.6364	19	0.2853	0.3684	20	0.4112	0.1500	18	0.8847	0.3889
Low (0)	773	0.0951	0.0841	766	0.1427	0.1606	627	0.1537	0.1722	623	0.3672	0.1252
High (6-9)	769	0.2558	0.4694	640	0.2296	0.3000	695	0.3311	0.2504	579	0.5991	0.3437
High - Low		0.1607	0.3854		0.0869	0.1394		0.1774	0.0781		0.2319	0.2185
t-stat		14.495***	18.713***		7.823***	6.205***		11.425***	3.5***		8.283***	9.181***

Notes:Panel A (B) reports the number of observations together with the mean of ADAC, HDAC, ADWAC, HDWAC (ADCF, HDCF, ADPROD, HDPROD, ADDISEXP, HDDISEXP, ATOTALRM, HTOTALRM) in each group sorted by ESCORE. Definitions of variables are in the Appendix. *, **, *** indicate significance at 10%, 5%, 1% levels, respectively.

Table 6. Distribution across ESCORE groups

ESCORE	N	ESCORE GROUP	N
0	862	Low (0)	862
1	2,218		
2	2,925		
3	2,381		
4	1,675		
5	994	Medium (1-5)	10,193
6	519		
7	232		
8	88		
9	26	High (6-9)	865

Notes:The table reports the distribution of observations across groups sorted by ESCORE. Definitions of variables are in the Appendix.

Table 7.Stock returns across ESCORE groups

ESCORE	BHRR^{m} (%)		BHSAR^{m} (%)		BHAR4F^{m} (%)	
	Returns	*t-statistic*	Returns	*t-statistic*	Returns	*t-statistic*
0	1.10	n/a	0.48	3.694***	0.33	2.086**
1	0.91	n/a	0.32	4.041***	0.18	1.553
2	0.80	n/a	0.23	3.678***	0.08	0.636
3	0.55	n/a	0.01	0.134	-0.16	-1.243
4	0.20	n/a	-0.27	-2.709***	-0.46	-2.752***
5	-0.19	n/a	-0.61	-4.178***	-0.80	-3.483***
6	-0.35	n/a	-0.72	-3.146***	-1.09	-3.586***
7	-0.11	n/a	-0.52	-1.512	-0.80	-2.075**
8	-2.02	n/a	-2.31	-3.562***	-2.49	-3.565***
9	-0.84	n/a	-0.83	-0.883	-1.56	-1.534
Low (0)	1.10	n/a	0.48	3.694***	0.33	2.086**
Medium (1-5)	0.55	n/a	0.02	1.121	-0.14	-1.239
High (6-9)	-0.31	n/a	-0.69	-3.662***	-1.04	-3.923***
Low - High	1.41	5.156***	1.17	4.584***	1.37	5.102***

Notes:The table reports the returns on different portfolios formed on the basis of ESCORE. Definitions of variables are in the Appendix. *, **, *** indicate significance at 10%, 5%, 1% levels, respectively.

Table 8. Fundamental characteristics across ESCORE groups

	ESCORE									
	0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
AT (£mil)	733	615	458	348	264	130	92	41	33	11
SALE (£mil)	703	611	472	362	274	140	97	65	67	9
NI (£mil)	41	32	23	16	10	2	-1	-1	-3	-1
DIV (£mil)	18	15	12	9	6	2	1	1	1	0
MVE (£mil)	689	576	443	349	270	134	94	61	25	17
DSHARE	0.0054	0.0224	0.0445	0.0904	0.1763	0.2677	0.3677	0.4911	0.6565	0.9111
DDEBT	-0.2765	0.1760	0.5336	1.6761	2.3236	3.6770	4.2057	5.4630	7.7978	8.8561
MTB	2.2047	2.3857	2.8669	3.2708	4.1842	4.3591	5.2342	6.4006	6.0342	5.9664
ROA	0.0589	0.0552	0.0476	0.0169	-0.0360	-0.1153	-0.2325	-0.3791	-0.4571	-0.5874
DROA	0.0335	0.0219	0.0185	0.0151	0.0074	-0.0018	-0.0071	-0.0346	-0.0026	-0.1953
DIVDEF	0.0343	0.0286	0.0208	-0.0086	-0.0598	-0.1320	-0.2451	-0.3863	-0.4589	-0.5908
ZSCORE	17.9433	16.6083	15.9328	13.6591	9.5750	7.0799	-1.1646	-4.3763	-8.2776	-12.5474
DEBT	0.1668	0.1755	0.1676	0.1572	0.1439	0.1289	0.1225	0.1038	0.1010	0.0760
NOA	0.5701	0.5603	0.5314	0.4906	0.4458	0.4340	0.3992	0.3501	0.3683	0.3702
CAP	0.5874	0.5562	0.5030	0.4316	0.3667	0.3127	0.2840	0.2453	0.2187	0.1969
BOOKTAX	0.0587	0.0831	0.1952	0.4172	1.0355	2.8103	3.8965	4.3297	4.0088	4.5332
DAC	0.0070	0.0054	0.0127	0.0085	0.0037	0.0079	-0.0101	-0.0239	-0.0059	0.0125
ESEO	0.0000	0.0437	0.1084	0.2230	0.3290	0.4608	0.5934	0.6810	0.7614	0.9615
EDDEBT	0.0000	0.2674	0.4017	0.4746	0.4412	0.4718	0.4721	0.4526	0.5568	0.5000
EMA	0.0000	0.0063	0.0191	0.0470	0.0818	0.1207	0.1503	0.1681	0.2841	0.5000
ECYCLE	0.0000	0.0032	0.0062	0.0189	0.0400	0.0915	0.0886	0.1293	0.1591	0.3077
EAUDIT	0.0000	0.2029	0.3921	0.5254	0.6209	0.6982	0.8054	0.8491	0.9773	0.9615

Notes: The table reports the mean of selected variables across groups sorted by ESCORE. Definitions of variables are in the Appendix.

Table 9.Stock returns regressed on DAC, ESCORE and control variables

	Predicted sign	Specification (1)		Specification(2)		Specification(3)		Specification(4)		Specification(5)	
		Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Panel A: BHRR[a]											
Pool regression											
INTERCEPT		0.1961	5.979***	0.3079	8.275***	0.2101	6.385***	0.3137	8.431***	0.1685	18.133***
Ln(MVE)	(-)	-0.0017	-0.629	-0.0064	-2.245**	-0.0032	-1.157	-0.0075	-2.6***		
MTB	(-)	-0.0054	-4.973***	-0.0046	-4.221***	-0.0051	-4.776***	-0.0044	-4.091***		
ROA	(+)	0.1666	5.651***	0.1547	5.244***	0.2034	6.677***	0.1881	6.16***		
ESEO	(-)	-0.1311	-10.224***	-0.0951	-6.794***	-0.1251	-9.722***	-0.0920	-6.563***		
EDISTRESS	(-)	-0.0107	-0.61	0.0154	0.857	-0.0165	-0.938	0.0088	0.485		
EBLOAT	(-)	-0.1165	-5.102***	-0.1387	-6.012***	-0.1112	-4.865***	-0.1326	-5.741***		
DAC	(-)					-0.1996	-4.727***	-0.1774	-4.189***	-0.1030	-2.59***
ESCORE	(-)			-0.0234	-6.328***			-0.0220	-5.936***	-0.0356	-12.425***
R2 (%)		2.26		2.58		2.44		2.73		1.32	
Fama-MacBeth regression with Newey-West adjusted t-statistics											
INTERCEPT		0.1810	2.21**	0.2756	3.98***	0.1947	2.44**	0.2794	4.14***	0.1587	4.23***
Ln(MVE)	(-)	-0.0007	-0.11	-0.0049	-0.86	-0.0021	-0.33	-0.0059	-1.05		
MTB	(-)	-0.0032	-1.8*	-0.0027	-1.4	-0.0030	-1.69	-0.0025	-1.34		
ROA	(+)	0.1383	3.81***	0.1255	3.09***	0.1806	4.26***	0.1645	3.54***		
ESEO	(-)	-0.0884	-3.65***	-0.0605	-3.41***	-0.0831	-3.67***	-0.0584	-3.56***		
EDISTRESS	(-)	-0.0428	-1.54	-0.0211	-1.03	-0.0484	-1.71	-0.0282	-1.35		
EBLOAT	(-)	-0.1162	-3.71***	-0.1359	-4.94***	-0.1107	-3.55***	-0.1291	-4.77***		
DAC	(-)					-0.2013	-3.47***	-0.1802	-3.47***	-0.0869	-2.21**
ESCORE	(-)			-0.0184	-2.24**			-0.0166	-2.1*	-0.0294	-2.84**
Panel B: BHSAR[a]											
Pool regression											
INTERCEPT		0.1911	6.295***	0.2796	8.117***	0.2044	6.713***	0.2853	8.283***	0.0822	9.559***
Ln(MVE)	(-)	-0.0084	-3.266***	-0.0121	-4.558***	-0.0098	-3.796***	-0.0131	-4.926***		
MTB	(-)	-0.0032	-3.191***	-0.0026	-2.552**	-0.0030	-2.989***	-0.0024	-2.414**		
ROA	(+)	0.1597	5.853***	0.1502	5.501***	0.1948	6.91***	0.1828	6.468***		
ESEO	(-)	-0.0888	-7.482***	-0.0603	-4.651***	-0.0831	-6.977***	-0.0572	-4.41***		
EDISTRESS	(-)	-0.0369	-2.271**	-0.0162	-0.971	-0.0424	-2.606***	-0.0227	-1.357		
EBLOAT	(-)	-0.1112	-5.258***	-0.1287	-6.026***	-0.1060	-5.014***	-0.1228	-5.741***		

DAC	(-)					-0.1905	-4.874***	-0.1731	-4.416***	-0.0804	-2.185**
ESCORE	(-)			-0.0186	-5.415***			-0.0172	-5.006***	-0.0270	-10.168***
R2 (%)		1.80		2.04		1.99		2.20		0.89	
Fama-MacBeth regression with Newey-West adjusted t-statistics											
INTERCEPT		0.1938	5.24***	0.2918	4.39***	0.2069	5.81***	0.2955	4.66***	0.0786	3.33***
Ln(MVE)	(-)	-0.0084	-2.69**	-0.0127	-2.84**	-0.0097	-3.14***	-0.0135	-3.12***		
MTB	(-)	-0.0031	-1.8*	-0.0025	-1.36	-0.0028	-1.69	-0.0023	-1.3		
ROA	(+)	0.1436	3.84***	0.1315	3.13***	0.1824	4.26***	0.1669	3.55***		
ESEO	(-)	-0.0838	-3.43***	-0.0548	-3.08***	-0.0788	-3.45***	-0.0529	-3.22***		
EDISTRESS	(-)	-0.0442	-1.57	-0.0215	-1.01	-0.0493	-1.72	-0.0281	-1.29		
EBLOAT	(-)	-0.1153	-3.54***	-0.1358	-4.58***	-0.1106	-3.4***	-0.1300	-4.43***		
DAC	(-)					-0.1846	-3.15***	-0.1627	-3.08***	-0.0709	-1.83*
ESCORE	(-)			-0.0192	-2.5**			-0.0175	-2.38**	-0.0251	-3.15***
Panel C: BHAR4F[a]											
Pool regression											
INTERCEPT		0.0791	2.639***	0.1586	4.662***	0.0932	3.1***	0.1647	4.843***	0.0642	7.575***
Ln(MVE)	(-)	0.0000	-0.016	-0.0034	-1.289	-0.0015	-0.602	-0.0045	-1.7*		
MTB	(-)	-0.0019	-1.904*	-0.0013	-1.327	-0.0017	-1.687*	-0.0012	-1.178		
ROA	(+)	0.1115	4.141***	0.1030	3.822***	0.1486	5.341***	0.1380	4.946***		
ESEO	(-)	-0.0941	-8.038***	-0.0686	-5.357***	-0.0882	-7.5***	-0.0653	-5.096***		
EDISTRESS	(-)	-0.0406	-2.531**	-0.0220	-1.336	-0.0464	-2.89***	-0.0290	-1.755*		
EBLOAT	(-)	-0.1097	-5.257***	-0.1255	-5.949***	-0.1043	-4.997***	-0.1191	-5.641***		
DAC	(-)					-0.2011	-5.213***	-0.1857	-4.799***	-0.1144	-3.155***
ESCORE	(-)			-0.0167	-4.925***			-0.0152	-4.485***	-0.0267	-10.216***
R2 (%)		1.56		1.76		1.79		1.95		0.94	
Fama-MacBeth regression with Newey-West adjusted t-statistics											
INTERCEPT		0.1012	1.42	0.1827	3.03***	0.1143	1.64	0.1858	3.17***	0.0559	2.27**
Ln(MVE)	(-)	-0.0024	-0.37	-0.0060	-1.07	-0.0038	-0.6	-0.0069	-1.23		
MTB	(-)	-0.0015	-1.13	-0.0010	-0.7	-0.0012	-0.96	-0.0009	-0.6		
ROA	(+)	0.1178	3.87***	0.1059	3.18***	0.1635	4.48***	0.1486	3.84***		
ESEO	(-)	-0.0781	-3.17***	-0.0544	-3.31***	-0.0724	-3.13***	-0.0519	-3.38***		
EDISTRESS	(-)	-0.0538	-2.93***	-0.0350	-3.37***	-0.0590	-3.11***	-0.0419	-3.78***		
EBLOAT	(-)	-0.1144	-4.15***	-0.1312	-5.56***	-0.1085	-3.98***	-0.1240	-5.43***		
DAC	(-)					-0.2119	-3.83***	-0.1917	-3.9***	-0.1030	-2.9**
ESCORE	(-)			-0.0158	-2.11*			-0.0140	-1.97*	-0.0237	-2.36**

Notes:Specification (4) reports the results of estimating the following equation: $RET^{a}_{i,t+1} = \alpha + \beta_1 Log\left(MVE_{i,t}\right) + \beta_2 MTB_{i,t} + \beta_3 ROA_{i,t} + \beta_4 ESEO_{i,t} + \beta_5 EDISTRESS_{i,t} + \beta_6 NOA_{i,t} + \beta_7 DAC_{i,t} + \gamma ESCORE_{i,t} + \varepsilon$. From (4) as the full specification, in specification (1) DAC and ESCORE are dropped, in specification (2) DAC is dropped, in specification (3) ESCORE is dropped, in specification (5) Ln(MVE), MTB, ROA, ESEO, EDISTRESS, EBLOAT are dropped from the explanatory variables. Panel A (B and C) reports the result when raw return (size-adjusted and four-factor abnormal return, respectively) is the dependent variable. Each panel reports the results from a pooled regression and a Fama-Macbeth regression in which the standard errors are adjusted for serial correlation using Newey-West procedure.Definitions of variables are in the Appendix. *, **, *** indicate significance at 10%, 5%, 1% levels, respectively.

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