DOI: 10.1111/jbfa.12264

JBFA

Earnings quality and short selling: Evidence from real earnings management in the United States

KoEun Park

College of Management, University of Massachusetts Boston

Correspondence
KoEun Park, Department of Accounting and Finance, College of Management, University of Massachusetts Boston, 100 Morrissey Blvd., Boston, MA 02125, United States.
Email: KoEun.Park@umb.edu

Abstract

Prior research provides evidence consistent with managers using real earnings management (REM) to increase earnings. This study examines whether short sellers exploit the overvaluation of firms employing REM. I find that firms with more REM have higher subsequent short interest. The positive relation between REM and short interest is more pronounced in settings where the costs associated with accrual-based earnings management are high, such as when a firm has low accounting flexibility or faces greater scrutiny from a high quality auditor. I also find some evidence that short sellers respond to REM more than to other fundamental signals of firm overvaluation. My inferences are robust to the use of propensity score matching. Collectively, my evidence suggests that short sellers not only trade on REM information, but they also trade as if they understand the substitutive nature of alternative earnings management methods. This study provides additional insight into the important role that short sellers play in monitoring managerial operating decisions and overall earnings quality.

KEYWORDS

corporate governance, earnings quality, real earnings management, short selling

1 | INTRODUCTION

Short sellers have been viewed in the academic literature as well-informed and sophisticated investors (e.g., Diamond & Verrecchia, 1987).[1] In particular, several studies provide evidence that short sellers identify overvalued firms that have engaged in accruals management.[2] Yet managers also engage in real earnings management (REM), a practice that has become prevalent and that brings more severe consequences than accrual-based earnings management (e.g., Cohen & Zarowin, 2010; Cohen, Dey, & Lys, 2008). Since REM's negative implications for future performance tend to be incorporated into stock prices with a delay,[3] short sellers likely have incentives to target firms engaging in REM. Despite

[1] Although the media and some regulators claim that short selling causes an unwarranted downward spiral in stock price (e.g., Karpoff & Lou, 2010; Drake, Myers, Myers, & Stuart, 2015), these claims are largely based on anecdotal evidence.

[2] See, for example, Desai et al. (2006), Karpoff and Lou (2010), and Hirshleifer et al. (2011).

[3] See, for example, Li (2012).

the substitutive relation between accrual-based earnings management and REM (e.g., Zang, 2012), we know very little about whether short sellers also monitor REM or ignore it, thereby potentially encouraging managers to switch to REM. My goal is to provide evidence of the level of sophistication in short sellers' response to managers' abnormal operating decisions. More specifically, I examine whether and how short interest is related to a firm's REM as compared to other fundamental signals identified by prior studies. Doing so provides a more complete picture of short sellers' monitoring of the overall quality of corporate earnings.

Short selling refers to the sale of a stock by an investor who does not own it but borrows it from other investors in anticipation of profiting from a price decline. Given the high costs associated with short positions, short sellers have strong incentives to identify overpriced firms, thereby facilitating the incorporation of unfavorable information into market prices. A number of studies suggest that short sellers are sophisticated investors by providing evidence that their positions predict future returns (e.g., Asquith, Pathak, & Ritter, 2005; Desai, Ramesh, Thiagarajan, & Balachandran, 2002) and that short-selling constraints result in prices that do not fully reflect negative information (e.g., Boehme, Danielsen, & Sorescu, 2006; Jones & Lamont, 2002). Short sellers tend to target firms that are overpriced relative to fundamentals (e.g., Curtis & Fargher, 2014; Dechow, Hutton, Meulbroek, & Sloan, 2001). In particular, several studies examine whether short sellers consider overpricing associated with poor earnings quality in their decision process by focusing on accruals. For example, Hirshleifer, Teoh, and Yu (2011) provide evidence that short interest is positively associated with accruals, suggesting that short sellers exploit the accrual anomaly.

Earnings quality has been identified as a critical element in capital markets. Prior research suggests that managers manipulate reported earnings by changing accounting methods or estimates used to represent their operating activities.[4] However, short-term-focused financial reporting behavior is not limited to manipulating accounting practices. To artificially boost short-term reported earnings, managers can change the timing or structuring of real operations. This practice, also known as REM, has received considerable attention (e.g., Cohen & Zarowin, 2010; Cohen et al., 2008; Roychowdhury, 2006; Zang, 2012). For example, managers may cut prices or extend more lenient credit terms to accelerate sales into the current period. They may overproduce to decrease cost of goods sold (COGS) to meet their earnings targets in the current period. Given the different nature between accrual-based earnings management and REM, prior evidence of short sellers' trading on accruals information does not necessarily provide an answer about whether short sellers also monitor and respond to managers' abnormal operating decisions.

The focus of this study is to explore whether short sellers' trading is related to a firm's REM. I argue that direct investigation into the relation between REM and short interest warrants further research for three major reasons. First, unlike accrual-based earnings management, REM has negative implications for future cash flows and firm value because these practices alter real operations (e.g., Cohen & Zarowin, 2010; Cohen et al., 2008; Ewert & Wagenhofer, 2005; Leggett, Parsons, & Reitenga, 2009; Mizik, 2010; Mizik & Jacobson, 2008). Second, while investors can be aided by audit reports to discover accrual-based earnings management, it is more difficult for the average investor to detect REM (e.g., Kim & Sohn, 2013). If investors fixate on firms' reported earnings while failing to fully respond to the negative impact of REM activities, firms with high levels of REM will be overvalued (e.g., Li, 2012). The overpricing can motivate short sellers to profit from subsequent stock price declines of high REM firms. Third, Zang (2012) finds that managers trade off between accrual-based earnings management and REM. Managers facing short sellers' scrutiny on accruals management might switch to REM if short sellers do not respond to REM. Investigating the relation between REM and subsequent short interest conditioning on a firm's ability to engage in accrual-based earnings management is an approach that better reflects short sellers' sophistication and monitoring role with regard to overall corporate earnings quality.

Following prior studies, I use monthly short interest (e.g., Chi, Pincus, & Teoh, 2014; Curtis & Fargher, 2014; Hirshleifer et al., 2011) and examine real activities management that increases earnings by offering price discounts, overproducing, and cutting discretionary expenses (e.g., Roychowdhury, 2006; Zang, 2012).[5] My baseline tests

[4] This practice is known as accrual-based earnings management. Dechow, Ge, and Schrand (2010), Fields, Lys, and Vincent (2001), Healy and Wahlen (1999) and Kothari (2001), among others, provide a survey of the literature on accrual-based earnings management.

[5] I define REM as deviations in real activities from normal business practices for the primary purpose of inflating short-term earnings (Roychowdhury, 2006).

indicate that, on average, firms with higher levels of REM through sales manipulation and overproduction have greater subsequent short interest, consistent with short sellers trading on REM information. Specifically, short interest is negatively (positively) related to abnormal cash flows from operations (abnormal production costs). My baseline model includes an extensive set of control variables that prior research finds to be associated with short interest and uses a firm fixed effects approach. My results are robust to the use of propensity score matching.

To gain a clearer understanding of short sellers' sophistication, I then examine whether short sellers' response to REM is conditioned on the costs associated with accrual-based earnings management. Given the high costs associated with short positions, short sellers are likely to focus on firms with greater perceived risk of REM. In particular, if accrual-based earnings management is constrained by accounting flexibility or scrutiny from outsiders, managers tend to switch to REM (e.g., Zang, 2012). Indeed, I find that the positive relation between REM and subsequent short interest is more pronounced when the firm has low accounting flexibility and faces greater scrutiny from a high quality auditor. These results are consistent with the notion that short sellers are highly informed about how managers trade off alternative earnings management methods, suggesting short sellers' monitoring of overall earnings quality. I also find some evidence that REM is relatively high up in short sellers' trading pecking order, compared to accruals, book-to-market, earnings-to-price, value-to-market ratios and negative earnings surprises. Lastly, long-short trading strategies based on REM produce positive abnormal returns with hedge returns being concentrated in the period around three to six months after portfolio formation.

The main contribution of this study to the literature is that, to my knowledge, it is the first to examine whether short sellers target firms that engage in REM. Although prior research links short sellers' activities to accounting misrepresentation (e.g., Desai, Krishnamurthy, & Venkataraman, 2006; Hirshleifer et al., 2011; Karpoff & Lou, 2010; Massa, Zhang, & Zhang, 2015), few studies have examined whether short sellers are able to detect managers' abnormal and aggressive operating behavior. Short sellers' monitoring of such practices is beneficial to capital markets and directly contributes to the real economy. My study also advances our understanding of short sellers' sophistication. Prior research on short arbitrage of the accrual anomaly does not provide an answer about how short sellers use accruals information. In contrast, this study provides evidence that short sellers not only trade on REM information but also refine their trading strategies through the sophisticated use of the substitutive nature between alternative earnings management methods. My results have important implications for academics, investors, and regulators; greater ease of short selling is likely to help improve managerial operating decisions and overall financial reporting.

In addition, prior research on short sellers' investment decision processes has focused on low fundamental-to-price ratios (e.g., Dechow et al., 2001; Drake, Rees, & Swanson, 2011), accruals (e.g., Hirshleifer et al., 2011), and bad news (e.g., Christophe, Ferri, & Angel, 2004). This study contributes to the literature by exploring short sellers' use of REM information as compared to other known firm fundamentals that predict low future returns, and I provide complementary evidence that REM is relatively high in short sellers' trading pecking order. My study also broadly contributes to the earnings management literature. Prior research investigates the determinants and consequences of REM, including institutional ownership (Bushee, 1998), auditors' client-retention decisions (Kim & Park, 2014), and analyst pressures (Irani & Oesch, 2016). My evidence of the relation between REM and short interest suggests an additional external governance mechanism for monitoring corporate REM.

2 | PRIOR RESEARCH AND HYPOTHESIS DEVELOPMENT

Rule 3b-3 of the Securities Exchange Act of 1934 defines a short sale as 'any sale of a security which the seller does not own or any sale which is consummated by delivery of a security borrowed by, or for the account of, the seller'. A short seller establishes a position by selling a borrowed share and closes the position by buying the share back at a later time. Short selling is profitable if the price of the share declines following the short sale. Although the media and some regulators claim that short sellers may follow manipulative and predatory trading strategies, short selling is, in principle, a legitimate trading strategy. A large literature in economics, finance, and accounting suggests that short sellers are sophisticated investors.[6] Several studies provide evidence that short positions predict future returns. For instance, Boehmer, Jones, and Zhang (2008) find that heavily-shorted stocks tend to underperform lightly-shorted stocks. Furthermore, Miller (1977) shows that binding short sale constraints causes pessimists to be under-represented in price formation,[7] leading to overvaluation when a strong divergence of opinion about a stock exists. Boehme et al. (2006) provide evidence of significant overvaluation for stocks that are subject to short-sale constraints and dispersion of investor opinion.[8]

Prior research has also examined how short sellers identify their targets. Dechow et al. (2001) find that short interest is concentrated in firms with low fundamental-to-price ratios. Drake et al. (2011) provide evidence that short sellers trade on information in accounting, valuation, growth and momentum variables. Curtis and Fargher (2014) find that short interest following a price decline is concentrated in firms identified as overpriced based on financial statement analysis. In particular, several studies examine whether short sellers identify overpriced firms with low earnings quality by focusing on the magnitude of accruals or SEC enforcement actions. For example, Desai et al. (2006) find that short sellers accumulate their positions in restating firms several months in advance of restatement announcements and that such an increase in short selling is more pronounced for high accruals firms. Karpoff and Lou (2010) find that short sellers can properly identify firms that are disciplined by the SEC for financial misrepresentation before the public revelation. Hirshleifer et al. (2011) find a positive relation between accruals and short interest, with the concentration in the highest accruals decile. More recently, Massa et al. (2015) suggest short selling as an external governance mechanism to discipline managers' accrual-based earnings management.

Empirical and anecdotal evidence suggests that managers exercise substantial discretion over reported earnings (e.g., Bergstresser & Philippon, 2006; Cheng & Warfield, 2005). In particular, managers engage in REM by changing the timing or structuring of real operations. Roychowdhury (2006) finds evidence suggesting that managers manipulate real activities when they are close to a zero-earnings benchmark. Cohen and Zarowin (2010) find that firms use REM as well as accrual-based earnings management around seasoned equity offerings (SEOs). Several studies suggest that REM has more severe performance consequences than accrual-based earnings management, as it entails changes in real operations (e.g., Cohen & Zarowin, 2010; Cohen et al., 2008; Duellman, Ahmed, & Abdel-Meguid, 2013; Ewert & Wagenhofer, 2005; Kim & Sohn, 2013; Leggett et al., 2009; Mizik, 2010; Mizik & Jacobson, 2008). For example, Ewert and Wagenhofer (2005) show that firm value directly depends on the level of expected REM. Leggett et al. (2009) find that REM is negatively related to operating performance. Cohen and Zarowin (2010) provide evidence that a decline in post-SEO performance attributable to REM is more severe than the performance decline attributable to accrual-based earnings management.

This paper extends prior research by examining how short sellers monitor and respond to a firm's abnormal and aggressive operating decisions, which is still an under-explored topic in the literature. If investors naïvely fixate on reported earnings by failing to understand the implications of earnings management for future performance, earnings management causes overvaluation, and subsequent low abnormal returns when this overvaluation is corrected. Sloan (1996) finds that firms with high accruals experience negative future abnormal stock returns. Xie (2001) suggests that the overpricing of accruals is due largely to abnormal accruals. Some argue that REM is more difficult for the average investor to detect (e.g., Kim & Sohn, 2013). Li (2012) indeed finds evidence that stocks of firms with high levels of REM underperform in subsequent years, suggesting that investors, on average, tend to be overoptimistic about the future prospects of firms with abnormal and aggressive operating decisions. If REM is a negative predictor of future stock returns, short sellers have incentives to identify firms with high levels of REM to profit from subsequent price declines, potentially contributing significantly to monitoring of operating decisions. I thus expect to find a positive relation between REM and short interest, unless the expected costs of shorting stocks of firms with high levels of REM

[6] Diamond and Verrecchia (1987) argue that short sellers will not trade unless they expect the price to fall enough to cover the additional costs of short selling.

[7] Jain, Jain, McInish, and McKenzie (2013) examine short selling in a worldwide, multimarket framework and find that home country short selling restrictions curtail short selling in the home market, as well as in the US market where the securities are cross-listed as American Depository Receipts.

[8] Chang, Cheng, and Yu (2007) examine the effect of short-sale restrictions on price discovery in the Hong Kong market and reach a similar conclusion. Saffi and Sigurdsson (2011) find that stock price efficiency is affected by short-sale constraints in internal markets.

exceed the expected benefits and/or if short sellers take their positions primarily for liquidity or hedging purposes. This discussion leads to the first hypothesis:

H1a: A firm's real earnings management is positively related to subsequent short interest.

In addition to considering short sellers' use of REM, I also consider how the costs of an alternative form of earnings management influence this relation. Zang (2012) argues that firms are likely to face different levels of constraints for each earnings management strategy, which leads to varying abilities to use them. She provides evidence that managers switch between two earnings management strategies based on their relative costs. For example, accrual-based earnings management is constrained by the flexibility of a firm's accounting system (e.g., Barton & Simko, 2002). A firm lacking this flexibility due to aggressive accounting assumptions in previous periods has high risk of being detected by its auditor or violating GAAP when it engages in accrual-based earnings management. Accrual-based earnings management is also more likely to be detected when the firm faces heightened scrutiny from a high quality auditor (e.g., Cohen et al., 2008). Managers of these firms tend to switch from accrual-based earnings management to REM. Because short selling is a costly activity (e.g., Diamond & Verrecchia, 1987), short sellers refine their trading strategies to maximize their investment returns (e.g., Dechow et al., 2001). If short sellers are sophisticated enough to understand the substitutive relation between accrual-based earnings management and REM, they will be likely to trade on REM information more heavily when a firm faces the high costs associated with accrual-based earnings management. This discussion leads to my second hypothesis:

H1b: The positive relation between a firm's real earnings management and subsequent short interest is more pronounced when the firm has low accounting flexibility or faces greater scrutiny from a high quality auditor.

3 | RESEARCH DESIGN

3.1 | Data and sample

My initial sample consists of common stocks (share codes 10 and 11) listed on NYSE/AMEX stock exchanges (exchange codes 1 and 2) over the 1989–2014 period to ensure that cash flow statement data are available. Firms listed on different stock exchanges are likely to differ in earnings quality, the degree of the mispricing associated with REM, and costs of short selling (Hirshleifer et al., 2011). I thus focus on NYSE/AMEX firms. Following prior studies (e.g., Chi et al., 2014; Curtis & Fargher, 2014; Hirshleifer et al., 2011), I use monthly short interest obtained from the Compustat Security Short Interest database.[9] Short interest reflects open short positions of stocks with settlements on the 15th of each month or the preceding business day if the 15th is not a business day.[10]

I obtain financial data from the Compustat, stock return data from the Center for Research in Security Prices (CRSP),[11] institutional ownership data from the Thompson's CDA/Spectrum (form 13f), analyst data from the Institutional Brokers' Estimate System (I/B/E/S), and Fama and French three factors and the momentum factor from the Ken French website.[12] Following the earnings management literature, I exclude firms in utilities and financial industries (SIC 4400–5000 and SIC 6000–6999, respectively) and firms with missing values for REM and other control variables employed in the regressions. These restrictions result in a final sample that consists of 24,979 stock-year observations.

[9] Several recent studies use daily short selling volume (e.g., Diether, Lee, & Werner, 2009). As explained by Karpoff and Lou (2010), daily data cover a short period of time. These daily data do not contain information about short positions that are covered, making it impossible to calculate the net change in short interest. Therefore, monthly short interest data are more appropriate for this study.

[10] In addition, they are also required to report their positions as of settlement on the last business day of the month from 2007. To maintain consistency, I use only short interest that is reported as of settlement on the 15th of each month or on the preceding business day if the 15th is not a business day throughout the entire sample period.

[11] I merge Compustat and CRSP following Beaver, McNichols, and Price (2007).

[12] See http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. Further details on these factors are available at this website.

3.2 | Measurement of real earnings management

Following Roychowdhury (2006), I estimate and examine three types of REM (see Appendix A for details): (1) abnormal cash flows from operations (*ABCFO*), (2) abnormal production costs (*ABPROD*), and (3) abnormal discretionary expenses (*ABDEXP*). Subsequent studies provide evidence of the construct validity of these proxies (e.g., Cohen & Zarowin, 2010; Cohen et al., 2008; Zang, 2012). Managers may provide temporary incentives for customers to buy more products in an attempt to increase sales during the year. They can overproduce to lower COGS and inflate current earnings. They can also reduce discretionary expenditures, such as R&D, advertising, maintenance, or employee training expenses, which are immediately expensed without generating immediate revenues, to boost current reported earnings. Certain manipulating activities are possibly optimal actions in certain economic circumstances (Roychowdhury, 2006). However, if managers engage in these types of activities more extensively than is normal (given their economic circumstances), I assume they engage in REM.

3.3 | Measurement of short interest

I use short interest reported in the fifth month after the firm's fiscal year-end (e.g., Chi et al., 2014; Hirshleifer et al., 2011). The four-month gap between the fiscal year-end and the short interest date ensures that short sellers have financial information available to them prior to taking short positions.[13] I divide the raw short interest number by the CRSP number of shares outstanding on the same date and multiply the ratio by 100 (e.g., Asquith et al., 2005; Curtis & Fargher, 2014).[14] I then calculate abnormal short interest (*ABSI*), which is measured as raw short interest minus the expected level of short interest. The expected level of short interest is calculated based on the firm's market capitalization, book-to-market ratio, past stock performance, and industry (Karpoff & Lou, 2010).[15] Specifically, I calculate expected short interest as the fitted value from the following regression:

$$SI_{it} = \alpha + \sum_{g=low}^{medium} s_{gt} Size_{igt} + \sum_{g=low}^{medium} b_{gt} BTM_{igt} + \sum_{g=low}^{medium} m_{gt} Mom_{igt} + \beta industry_{it} + u_{it} \tag{1}$$

where SI_{it} is the short interest ratio in the fifth month after the fiscal year-end.

The first three sets of explanatory variables are indicator variables that jointly define the 27 size-, book-to-market-, and momentum-based portfolios. Each stock is assigned to one of 27 portfolios constructed by independently sorting stocks by size, book-to-market, and momentum. For example, if firm *i* is assigned to the portfolio with the lowest market capitalization in month *t*, then $Size_{i,low,t} = 1$, $Size_{i,medium,t} = 0$, and $Size_{i,high,t} = 0$. The base portfolio in this regression is the portfolio with the highest market capitalization, book-to-market ratio, and momentum for each industry. Thus, the coefficients are interpreted as the difference between short interest of the given portfolio and that of the base portfolio. Equation (1) is estimated for each month. The untabulated results of the estimation indicate that stocks with lower book-to-market ratios are more heavily shorted (Dechow et al., 2001). Momentum has the U-shaped relation with short interest, consistent with Duarte's et al. (2006) evidence.

3.4 | Control variables

Following the short interest literature, I control for a number of firm-specific characteristics that could determine short interest (e.g., Curtis & Fargher, 2014; Dechow et al., 2001; Desai et al., 2006; Hirshleifer et al., 2011; Karpoff & Lou, 2010). In the baseline analysis, my control variables include total accruals (*ACC*), firm size (*SIZE*), growth

[13] Following prior research (e.g., Chi et al., 2014; Dechow et al., 2001; Hirshleifer et al., 2011), I retain only one observation for each stock-year to mitigate potential concerns of overlap-induced autocorrelations in short interest ratios within the same stock-year.

[14] If a firm does not have available short interest in the database, its short interest variable is assumed to be zero.

[15] These controls reflect evidence from Dechow et al. (2001), Asquith et al. (2005) and Duarte, Lou, and Sadka (2006) that short interest is related to market capitalization, the book-to-market ratio, and momentum. I also use expected short interest calculated based on another benchmark that additionally controls for share turnover and institutional ownership (Karpoff & Lou, 2010) and find similar results.

TABLE 1 Descriptive statistics of variables

Variable	N	Mean	Standard Deviation	25%	Median	75%
Short Interest Variables						
SI (%)	24,979	2.685	4.217	0.178	1.133	3.309
ABSI (%)	24,979	0.026	3.256	−1.360	−0.279	0.443
Real Earnings Management Variables						
ABCFO	24,979	−0.000	0.169	−0.045	0.003	0.049
ABPROD	24,979	−0.001	0.201	−0.091	0.005	0.095
ABDEXP	24,979	0.003	0.243	−0.100	−0.018	0.077
Control Variables						
ACC	24,979	−0.069	0.352	−0.093	−0.051	−0.016
SIZE	24,979	6.401	2.185	4.836	6.524	7.931
GROWTH	24,979	0.497	0.500	0.000	0.000	1.000
MOM	24,979	0.147	0.642	−0.170	0.076	0.341
SUE	24,979	−0.002	7.813	−0.025	0.006	0.026
IOR	24,979	0.520	0.289	0.284	0.564	0.757
DIVY	24,979	0.014	0.075	0.000	0.003	0.020
AILLIQ	24,979	−4.237	3.351	−6.829	−4.654	−1.817
STDRES	24,979	0.027	0.021	0.016	0.022	0.032
LEV	24,979	0.267	0.308	0.114	0.239	0.365
AF	24,979	2.005	1.169	1.099	2.197	2.890
STO	24,979	5.653	6.179	1.925	3.736	7.242
EISSUE	24,979	0.430	0.495	0.000	0.000	1.000

Notes: Table 1 presents descriptive statistics for the main variables used in this study. The sample contains common stocks of firms that are listed on NYSE/AMEX stock exchanges. Firms in utilities and financial industries (SIC 4400–5000 and 6000–6999, respectively) and those with missing values for REM and other control variables are excluded. The sample period is from 1989 to 2014. The variables are raw short interest (*SI*), abnormal short interest (*ABSI*), abnormal cash flows from operations (*ABCFO*), abnormal production costs (*ABPROD*), abnormal discretionary expenses (*ABDEXP*), total accruals (*ACC*), firm size (*SIZE*), growth opportunities (*GROWTH*), past stock performance (*MOM*), unexpected earnings (*SUE*), institutional ownership (*IOR*), the dividend yield (*DIVY*), Amihud illiquidity (*AILLIQ*), the standard deviation of market model residuals (*STDRES*), leverage (*LEV*), analyst following (*AF*), stock price turnover (*STO*), and stock issuance (*EISSUE*). Definitions of the variables are in Appendix B.

opportunities (*GROWTH*), past stock performance (*MOM*), unexpected earnings (*SUE*), institutional ownership (*IOR*),[16] the dividend yield (*DIVY*),[17] the Amihud (2002) illiquidity measure (*AILLIQ*), the standard deviation of market model residuals (*STDRES*), leverage (*LEV*), the number of analysts following the firm (*AF*), stock price turnover (*STO*), and stock issuance (*EISSUE*). I provide detailed variable definitions in Appendix B.

4 | MAIN RESULTS

4.1 | Descriptive statistics

Table 1 presents descriptive statistics for the main variables used in this study. The mean (median) raw short interest ratio (*SI*) in the full sample is 2.685% (1.133%) of the number of shares outstanding, and the mean (median) abnormal

[16] Shares that have high institutional ownership are easier to borrow for short selling (e.g., Asquith et al., 2005; D'Avolio, 2002).

[17] Dividends must be paid by short sellers out of their own capital, thereby increasing short selling costs (e.g., D'Avolio, 2002).

short interest ratio (*ABSI*) is 0.026% (–0.279%) of the number of shares outstanding. Consistent with prior studies, short interest is skewed. The mean (median) values of *ABCFO*, *ABPROD* and *ABDEPX* are –0.000 (0.003), –0.001 (0.005), and 0.003 (–0.018), respectively. Regarding control variables, the mean (median) values for accruals and size in the final sample are –0.069 (–0.051) and 6.401 (6.524), respectively.

4.2 | The baseline model

To assess the relation between REM and subsequent short interest, I estimate the following firm fixed effects ordinary least squares (OLS) regression:

$$ABSI_{it} = \alpha + \beta REM_{it} + \gamma Z_{it} + \delta firmfixed_i + \theta yearfixed_t + \varepsilon_{it} \tag{2}$$

where $ABSI_{it}$ is the abnormal short interest ratio, calculated as described in Section 3.3;[18] REM_{it} refers to a firm's REM, measured as abnormal cash flows from operations (*ABCFO*), abnormal production costs (*ABPROD*), or abnormal discretionary expenses (*ABDEXP*), as described in Section 3.2; Z_{it} represents the set of control variables, as defined in Section 3.4.

I include a wide range of firm-level determinants that can vary over time and control for firm fixed effects to account for unobserved, time-invariant heterogeneity in short selling activities across firms (e.g., Karpoff & Lou, 2010).[19] I also include year fixed effects to control for cross-sectional dependence due to general market conditions influencing the overall level of short interest.

Columns (1)–(3) of Table 2 report the results of my baseline fixed effects regressions in Equation (2) using *ABCFO*, *ABPROD* and *ABDEXP* as main explanatory variables. The estimated coefficient on *ABCFO* (*ABPROD*) is significantly negative (positive). Since a lower (higher) level of *ABCFO* (*ABPROD*) indicates more aggressive REM, these results are consistent with my hypothesis that higher levels of REM are associated with greater subsequent short interest. On the other hand, the estimated coefficient on *ABDEXP* is significantly positive, inconsistent with my prediction. I will further explore and discuss this result of REM through cutting discretionary expenses in the later subsection.

If there are fixed costs associated with short selling, I expect short interest to be concentrated in firms that appear to be the most overvalued (e.g., Hirshleifer et al., 2011). I thus investigate whether firms engaging in extremely high levels of REM exhibit greater subsequent short interest. I regress subsequent short interest on an indicator variable coded one if the firm is in the bottom decile of *ABCFO* (*LABCFO*), top decile of *ABPROD* (*HABPROD*), or bottom decile of *ABDEXP* (*LABDEXP*). Columns (4)–(6) of Table 2 report the results. The estimated coefficient on *LABCFO* or *HABPROD* is significantly positive, consistent with the explanation that short sellers increase their positions in firms that heavily engage in REM through sales manipulation and overproduction. Holding constant all other control variables, the average effect of a firm being within the lowest (highest) *ABCFO* (*ABPROD*) decile is an increase in *ABSI* of 0.497% (0.161%). Since the sample mean of *ABSI* is 0.026%, the effect of REM on short interest is economically significant.

However, the coefficient on *LABDEXP* is not statistically significant. Li (2012) finds that the predictive power of abnormal discretionary expenses for future returns disappears after adjusting for control variables. A potential explanation of this result is that REM conducted through cutting discretionary expenses takes more time to realize its negative impact on future operating performance and stock prices than other REM methods. Since short sellers desire to keep their short positions open for a relatively short period of time to minimize associated costs, short sellers might not trade on the information conveyed by abnormal discretionary expenses. Another potential explanation for the result is that the market immediately impounds negative implications of REM through cutting discretionary expenses in the stock price.

In summary, the results in Table 2 are consistent with my hypothesis that short sellers, on average, trade on REM through sales manipulation and overproduction. More generally, these results indicate that short sellers exploit

[18] I also use raw short interest for all the tests as robustness tests and find similar results.

[19] The Hausman test results reject the null hypothesis that the random effects regression is the preferred method.

TABLE 2 Real earnings management and short interest

Dependent Variable:	ABSI					
REM Variable:	*ABCFO*	*ABPROD*	*ABDEXP*	*LABCFO*	*HABPROD*	*LABDEXP*
	(1)	(2)	(3)	(4)	(5)	(6)
ABCFO	−0.354***			0.497***		
	(−2.88)			(6.95)		
ABPROD		0.637***			0.161**	
		(4.53)			(2.14)	
ABDEXP			0.207*			−0.116
			(1.76)			(−1.46)
ACC	0.221***	0.258***	0.281***	−0.048	0.057	0.064
	(3.27)	(3.90)	(4.16)	(−0.73)	(0.89)	(1.01)
SIZE	−0.918***	−0.920***	−0.917***	−0.917***	−0.926***	−0.922***
	(−16.82)	(−16.86)	(−16.80)	(−16.82)	(−16.96)	(−16.88)
GROWTH	0.060	0.071	0.058	0.055	0.058	0.059
	(1.25)	(1.46)	(1.19)	(1.13)	(1.19)	(1.21)
MOM	0.090***	0.091***	0.086***	0.094***	0.086***	0.084***
	(2.93)	(2.95)	(2.79)	(3.05)	(2.80)	(2.74)
SUE	−0.004	−0.004*	−0.005*	0.002	0.002	0.002
	(−1.34)	(−1.66)	(−1.86)	(0.81)	(0.78)	(0.77)
IOR	2.331***	2.324***	2.335***	2.324***	2.330***	2.329***
	(14.83)	(14.79)	(14.86)	(14.80)	(14.82)	(14.81)
DIVY	−0.254	−0.249	−0.255	−0.240	−0.260	−0.263
	(−1.03)	(−1.01)	(−1.04)	(−0.97)	(−1.05)	(−1.07)
AILLIQ	−0.341***	−0.342***	−0.337***	−0.346***	−0.344***	−0.341***
	(−9.53)	(−9.54)	(−9.41)	(−9.66)	(−9.60)	(−9.52)
STDRES	−1.400	−1.532	−1.286	−1.813	−1.592	−1.544
	(−0.90)	(−0.99)	(−0.83)	(−1.17)	(−1.03)	(−1.00)
LEV	−0.019	−0.031	−0.003	−0.035	−0.027	−0.022
	(−0.25)	(−0.42)	(−0.03)	(−0.47)	(−0.36)	(−0.29)
AF	−0.014	−0.013	−0.014	−0.012	−0.012	−0.012
	(−0.37)	(−0.35)	(−0.39)	(−0.34)	(−0.33)	(−0.34)
STO	0.193***	0.193***	0.193***	0.192***	0.192***	0.192***
	(37.35)	(37.37)	(37.36)	(37.17)	(37.22)	(37.27)
EISSUE	0.040	0.041	0.042	0.041	0.042	0.042
	(0.96)	(1.01)	(1.01)	(1.01)	(1.01)	(1.03)
N	24,979	24,979	24,979	24,979	24,979	24,979
Adjusted R^2	0.374	0.375	0.374	0.375	0.374	0.374

Notes: Table 2 presents fixed effects ordinary least squares (OLS) regressions of subsequent short interest on REM. The dependent variable is the abnormal short interest ratio (*ABSI*). The REM variables are *ABCFO* (*LABCFO*), *ABPROD* (*HABPROD*), and *ABDEXP* (*LABDEXP*) in columns 1 (4), 2 (5), and 3 (6), respectively. *LABCFO*, *HABPROD*, and *LABDEXP* are an indicator variable for the high level of REM coded one if the firm belongs to the lowest *ABCFO*, highest *ABPROD*, and lowest *ABDEXP* decile, respectively. The regression model is

$$ABSI_{it} = \alpha + \beta REM_{it} + \gamma Z_{it} + \delta firmfixed_i + \theta yearfixed_t + \varepsilon_{it},$$

(Continues)

TABLE 2 (Continued)

where Z_{it} includes total accruals (*ACC*), firm size (*SIZE*), growth opportunities (*GROWTH*), past stock performance (*MOM*), unexpected earnings (*SUE*), institutional ownership (*IOR*), the dividend yield (*DIVY*), Amihud illiquidity (*AILLIQ*), the standard deviation of market model residuals (*STDRES*), leverage (*LEV*), analyst following (*AF*), stock price turnover (*STO*), and stock issuance (*EISSUE*). The accrual variable (*ACC*) is continuous total accruals in columns (1)–(3), while an indicator variable for the highest *ACC* decile in columns (4)–(6). Definitions of variables are in Appendix B. Each regression includes firm fixed effects and year indicators. *t*-statistics are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

investors' failure to understand the implications of REM through sales manipulation and overproduction on future performance.

4.3 | Propensity score matched sample analysis

While the baseline results are consistent with my hypothesis that REM positively relates to short interest, it is a challenging empirical task to establish a causal statement about the impact of REM on short interest. Specifically, the short interest literature suggests that short sellers load up on firms with particular observable characteristics. These same observable characteristics might motivate managers to engage in REM. To correct for any endogenous selection on observable characteristics, I perform propensity score matching analysis. This approach reduces the potential for overt bias that can result from either omission of observable variables or the specification of an improper functional form for the relation between observable variables and the outcome variable of interest (e.g., Armstrong, Jagolinzer, & Larcker, 2010). In the matched design, each treatment observation is paired with a control observation that did not receive that treatment but is similar along all other relevant dimensions. Thus, any difference in the outcome between treatment and control samples can be attributed to the treatment effect (e.g., Armstrong et al., 2010; Chung, Kim, Kim, & Zhang, 2015; Shipman, Swanquist, & Whited, 2017; Yuan & Zhang, 2015).

Since my treatment of interest is whether a firm engages in REM, I require a propensity score model of the conditional probability of being a REM firm given observable covariates. Prior research suggests a number of characteristics that determine a firm's earnings management. For example, capital market incentives are the most significant ones in affecting earnings management activities (e.g., Fields et al., 2001; Healy & Wahlen, 1999). Institutional investors are sophisticated investors who serve a monitoring role in reducing managerial abnormal operating decisions (e.g., Bushee, 1998). I also control for the firm's size, capital structure, and growth opportunities. Specifically, I estimate the following probit model:

$$PROB(REMFIRMS_{it}) = \alpha + \beta_1 EISSUE_{it+1} + \beta_2 AF_{it} + \beta_3 IOR_{it} + \beta_4 SIZE_{it} + \beta_5 LEV_{it} + \beta_6 GROWTH_{it} + \gamma industryfixed_{it} + \delta yearfixed_t + \varepsilon_{it} \quad (3)$$

where $REMFIRMS_{it}$ is an indicator variable coded one if the firm's *ABCFO* or *ABDEXP* (*ABPROD*) is in the bottom (top) decile, and zero otherwise; $EISSUE_{it+1}$ is an indicator variable coded one if the firm's net proceeds from equity financing are positive in year t+1, and zero otherwise; AF_{it} is the natural logarithm of one plus the number of analysts following the firm; IOR_{it} is institutional ownership; $SIZE_{it}$ is the natural logarithm of market capitalization; LEV_{it} is the leverage ratio; $GROWTH_{it}$ is the low book-to-market ratio.

To control for firm fixed effects, the regression is estimated by the conditional probit regression with firm being the group level. I include year fixed effects to control for cross-sectional dependence. I also include industry fixed effects in the first stage prediction model because REM varies across industries (e.g., Roychowdhury, 2006).

Panel A of Table 3 presents the first stage model used for estimating propensity scores (column (1)). The pseudo-R^2 is 0.127 and the area under the receiver operating characteristic (ROC) curve is 0.745, suggesting good fit. Based on this model, I compute a propensity score, that is, the predicted probability that a firm engages in REM. I then form matched pairs, without replacement, by selecting a REM firm (treatment firm) and a non-REM firm (control firm) with the closest propensity score. I conduct several diagnostic tests to evaluate the successfulness of my matching procedure (e.g., Dhaliwal, Judd, Serfling, & Shaikh, 2016). First, I repeat the probit model restricted to the matched sample

TABLE 3 Propensity score matching

Panel A. Pre-match Propensity Score Regression and Post-match Diagnostic Regression		
Dependent Variable:	***REMFIRMS***	
	Pre-match	**Post-match**
	(1)	**(2)**
EISSUE	0.101***	0.003
	(5.34)	(0.11)
AF	−0.019	−0.011
	(−1.41)	(−0.60)
IOR	−0.349***	0.099
	(−7.76)	(1.61)
SIZE	−0.110***	−0.006
	(−14.46)	(−0.55)
LEV	0.419***	0.066
	(10.70)	(1.15)
GROWTH	−0.106***	−0.000
	(−5.45)	(−0.01)
N	24,979	7,440
Pseudo R^2	0.127	0.003
Area under the ROC curve	0.745	

Panel B. Covariate Balance Test						
	Treatment Mean	**Control Mean**	**Treatment Median**	**Control Median**	***t*-test Difference *p*-value**	**KS-test Difference *p*-value**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
EISSUE	0.451	0.447	0.000	0.000	0.71	1.00
AF	1.799	1.816	1.946	1.946	0.53	0.88
IOR	0.475	0.471	0.486	0.478	0.47	0.23
SIZE	5.941	5.962	5.973	6.012	0.67	0.58
LEV	0.268	0.264	0.242	0.238	0.38	0.64
GROWTH	0.461	0.465	0.000	0.000	0.74	1.00

Notes: Panel A of Table 3 presents the first stage probit regression used for estimating propensity scores for the matching procedure (column (1)) and the diagnostic probit regression restricted to the matched sample (column (2)). The dependent variable is an indicator variable (*REMFIRMS*) coded one if the firm's *ABCFO* or *ABDEXP* is in the lowest decile, or its *ABPROD* is in the highest decile, and zero otherwise. The first stage model is:

$$PROB\ (REMFIRMS_{it}) = \alpha + \beta_1 EISSUE_{it+1} + \beta_2 AF_{it} + \beta_3 IOR_{it} + \beta_4 SIZE_{it} + \beta_5 LEV_{it} + \beta_6 GROWTH_{it} + \gamma industryfixed_{it} + \delta yearfixed_t + \varepsilon_{it},$$

where *EISSUE* is stock issuance, *AF* is analyst following, *IOR* is institutional ownership, *SIZE* is firm size, *LEV* is leverage, and *GROWTH* is growth opportunities. The regressions are estimated by conditional probit regressions with firm being the group level and include industry indicators and year indicators. *z*-statistics are in parentheses. Panel B of Table 3 presents the means (medians) of covariates for treatment and matched control samples in columns 1/2 (3/4), *p*-values of the *t*-test of the difference in means in column (5), and *p*-values for the Kolmogorov-Smirnov test of the difference in distributions in column (6).

and report the results in column (2) of Panel A. All of the explanatory variables are insignificant, and the pseudo-R^2 drops to 0.003, indicating that the explanatory variables do not explain any variation in whether a firm engages in REM following the matching.[20] Second, I examine the difference between the propensity scores of REM and non-REM

[20] If the matching procedure is successful, I should find that the control variables in the matched sample do not explain any variation in whether the firm is a REM firm (e.g., Dhaliwal et al., 2016).

firms. The mean difference is less than 0.001 and insignificantly different from zero (untabulated). Lastly, I evaluate covariate balance that determines the similarity in the distributions of treatment and matched control firms. Panel B of Table 3 reports the results of covariate balance analyses. The *p*-values for the *t*-test and Kolmogorov-Smirnov (KS)-test indicate that the matching was successful in achieving balance for all covariates. Specifically, all of the *t*-tests and KS-tests are not statistically significant. Taken together, these diagnostic tests suggest that the matching procedure is successful.

I then examine whether the results from my baseline tests are robust to the use of propensity score matching. The univariate result in column (1) of Table 4 indicates that REM firms have 0.421% higher short interest than non-REM firms. I also conduct multivariate analysis using the matched sample. I regress subsequent short interest on an indicator variable (*Treatment*) coded one for REM firms, and zero for propensity score matched non-REM firms. Column (2) of Table 4 reports the results. The estimated coefficient on *Treatment* is significantly positive, consistent with prior results. Taken together, the results provide evidence that it is REM, not another factor, that attracts short sellers to the stock.

However, there are several limitations of using the matched sample design (e.g., Lennox, 2016; Shipman et al., 2017). For example, because matching significantly reduces the size of the control group, the power of tests reduces. Inferences can be sensitive to matching design choices. In addition, this research design does not address endogeneity concerns relating to selection on unobservable factors. Thus, I report the results using the propensity score matched sample, as well as the full sample in the following sections.

4.4 | Real earnings management and extremely high short interest

Dechow et al. (2001) suggest that a high level of short interest is more likely to represent a consensus among short sellers that a stock is overpriced, while a low level of short interest may reflect short selling attributable to other activities, such as convertible bond arbitrage or takeover arbitrage. I thus examine whether firms with more aggressive REM are more likely to be heavily shorted by employing the logit regression. I use the 95th percentile short interest cutoff for heavily-shorted firms (Asquith et al., 2005).[21] Table 5 reports the results of logit regressions.[22] The dependent variable of *HABSI* is an indicator variable coded one if the firm's *ABSI* is in the top 5% of the sample. Columns (1)–(3) report the results of full sample tests and column (4) reports the result of the propensity score matched sample test. These models have good discriminatory power since the areas under ROC curves for these models are in the range of 0.827 to 0.838. The coefficient on *ABCFO* (*ABPROD*) is significantly negative (positive), indicating that the stocks of firms that increase earnings by offering price discounts or overproducing are more likely to be heavily shorted. The coefficient on *Treatment* is also significantly positive.

5 | ADDITIONAL TESTS

5.1 | Real earnings management, accounting flexibility, and short interest

Managers use REM and accrual-based earnings management as substitutes to achieve the desired earnings targets, and managers' trade-off decisions depend on the relative costliness of the two earnings management methods (e.g., Zang, 2012). For example, accrual-based earnings management is constrained by the extent to which net assets are already overstated on the balance sheet (e.g., Barton & Simko, 2002). Managers of firms lacking this accounting flexibility tend to switch to REM. If short sellers expect such trade-offs, they will likely refine their REM trading strategies. I thus examine whether the positive relation between REM and subsequent short interest is more pronounced when the firm's accounting flexibility is low.

[21] I also use the 99th percentile short interest cutoff and find similar results.

[22] To control for firm fixed effects, the regressions are estimated by conditional logistic regressions with firm being the group level.

TABLE 4 Real earnings management firms and short interest: Propensity score matched sample

	Difference in Means	Multivariate Estimates
Dependent Variable:	*ABSI*	
REM Variable:	*Treatment*	
	(1)	**(2)**
Treatment	0.421***	0.316***
	(5.32)	(3.32)
ACC		0.602***
		(2.99)
SIZE		−0.764***
		(−6.63)
GROWTH		0.180*
		(1.71)
MOM		0.036
		(0.61)
SUE		−0.019
		(−0.65)
IOR		2.440***
		(7.41)
DIVY		0.005
		(0.01)
AILLIQ		−0.320***
		(−4.30)
STDRES		3.227
		(0.85)
LEV		1.229***
		(4.12)
AF		−0.087
		(−1.17)
STO		0.193***
		(17.33)
EISSUE		−0.022
		(−0.25)
N	7,440	7,440
Adjusted R^2		0.382

Notes: Table 4 presents the difference in the means of short interest for treatment and control samples (column (1)) and the firm fixed effects OLS regression of subsequent short interest on REM using the propensity score matched sample (column (2)). In column (2), the dependent variable is the abnormal short interest ratio (*ABSI*). *Treatment* is an indicator variable coded one if the firm's *ABCFO* or *ABDEXP* is in the lowest decile, or if its *ABPROD* is in the highest decile, and zero otherwise. The regression model is:

$$ABSI_{it} = \alpha + \beta Treatment_{it} + \gamma Z_{it} + \delta firmfixed_i + \theta yearfixed_t + \varepsilon_{it},$$

where Z_{it} includes total accruals (*ACC*), firm size (*SIZE*), growth opportunities (*GROWTH*), past stock performance (*MOM*), unexpected earnings (*SUE*), institutional ownership (*IOR*), the dividend yield (*DIVY*), Amihud illiquidity (*AILLIQ*), the standard deviation of market model residuals (*STDRES*), leverage (*LEV*), analyst following (*AF*), stock price turnover (*STO*), and stock issuance (*EISSUE*). Definitions of variables are in Appendix B. The regression includes firm fixed effects and year indicators. *t*-statistics are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

TABLE 5 Real earnings management and extremely high short interest

	Full Sample			Propensity Score Matched Sample
Dependent Variable:		*HABSI*		
REM Variable:	*ABCFO*	*ABPROD*	*ABDEXP*	*Treatment*
	(1)	(2)	(3)	(4)
ABCFO	−0.729***			
	(−2.81)			
ABPROD		0.674***		
		(4.03)		
ABDEXP			0.304**	
			(2.08)	
Treatment				0.371***
				(3.40)
ACC	0.597*	0.732**	0.819**	0.009
	(1.86)	(2.30)	(2.36)	(0.02)
SIZE	−1.541***	−1.547***	−1.519***	−1.516***
	(−16.15)	(−16.19)	(−16.04)	(−10.67)
GROWTH	0.297***	0.325***	0.275***	0.339***
	(4.39)	(4.78)	(4.02)	(3.03)
MOM	0.151***	0.146***	0.139**	0.160**
	(2.83)	(2.73)	(2.57)	(2.45)
SUE	−0.024*	−0.029*	−0.032**	−0.005
	(−1.75)	(−1.96)	(−1.99)	(−0.25)
IOR	1.778***	1.761***	1.762***	1.861***
	(8.87)	(8.76)	(8.75)	(6.01)
DIVY	−2.537	−2.650	−2.447	−4.948
	(−1.11)	(−1.12)	(−1.10)	(−0.95)
AILLIQ	−1.063***	−1.063***	−1.043***	−1.154***
	(−14.25)	(−14.28)	(−14.04)	(−10.62)
STDRES	7.543**	7.636**	8.177**	16.971***
	(2.51)	(2.54)	(2.44)	(4.88)
LEV	0.255	0.244	0.300	0.825**
	(1.09)	(1.05)	(1.06)	(3.59)
AF	−0.165***	−0.159***	−0.168***	−0.270***
	(−3.11)	(−3.00)	(−3.14)	(−3.56)
STO	0.077***	0.077***	0.078***	0.060***
	(8.72)	(8.70)	(8.79)	(4.50)
EISSUE	0.252***	0.256***	0.266***	0.179
	(3.76)	(3.84)	(3.98)	(1.63)
N	24,979	24,979	24,979	7,440
Pseudo R^2	0.186	0.185	0.184	0.210
Area under the ROC curve	0.828	0.827	0.828	0.838

(Continues)

TABLE 5 (Continued)

Notes: Table 5 presents logit regressions of the high level of short interest on REM using the full sample (columns (1)–(3)) and the propensity score matched sample (column (4)). The dependent variable is an indicator variable (*HABSI*) coded one if the firm's abnormal short interest is in the top 5% of the sample. The REM variables are *ABCFO*, *ABPROD*, *ABDEXP*, and *Treatment* in columns (1), (2), (3) and (4), respectively. The regression model is

$$HABSI_{it} = \alpha + \beta REM_{it} + \gamma Z_{it} + \delta firmfixed_i + \theta yearfixed_t + \varepsilon_{it},$$

where Z_{it} includes total accruals (*ACC*), firm size (*SIZE*), growth opportunities (*GROWTH*), past stock performance (*MOM*), unexpected earnings (*SUE*), institutional ownership (*IOR*), the dividend yield (*DIVY*), Amihud illiquidity (*AILLIQ*), the standard deviation of market model residuals (*STDRES*), leverage (*LEV*), analyst following (*AF*), stock price turnover (*STO*), and stock issuance (*EISSUE*). Regressions are estimated by conditional logistic regressions with firm being the group level. Definitions of variables are in Appendix B. Each regression includes year indicators. *t*-statistics are in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

To test this notion, I generate an indicator variable (*ABNOA*) coded one if the firm's net operating assets (*NOA*) at the beginning of the year divided by lagged sales are above the sample median and then interact the indicator variable with REM measures. Table 6 reports the results of cross-sectional analyses. Columns (1)–(3) report the results using the full sample, and column (4) reports the result using the propensity score matched sample. For the sake of conciseness, I suppress the coefficients of all the control variables. The coefficient on the interaction term between *ABPROD* or *Treatment* (*ABCFO*) and *ABNOA* is significantly positive (negative). The coefficient on the interaction term between *ABDEXP* and *ABNOA* is not significant. These results are consistent with stronger effects of REM on short sellers' trading when available accounting flexibility is low.

5.2 | Real earnings management, accounting scrutiny, and short interest

Accrual-based earnings management is also constrained by the presence of high quality auditors (e.g., Cohen et al., 2008; Zang, 2012). Ewert and Wagenhofer (2005) show that REM increases when heightened accounting scrutiny makes accrual-based earnings management more costly. Managers of firms under scrutiny by high quality auditors tend to switch to REM. If short sellers expect such trade-offs, they will be likely to refine their REM trading strategies. I thus examine whether the positive relation between REM and subsequent short interest is more pronounced when the firm is audited by a Big 5 accounting firm.[23]

To test this notion, I generate an indicator variable (*BIG5*) coded one if the firm is audited by a Big 5 auditor and then interact the indicator variable with REM measures. Table 7 reports the results of cross-sectional analyses. Columns (1)–(3) report the results using the full sample, and column (4) reports the result using the propensity score matched sample. For the sake of conciseness, I suppress the coefficients of all the control variables. The coefficient on the interaction term between *ABCFO* (*ABPROD*) and *BIG5* is significantly negative (positive). The results are consistent with stronger effects of REM on short sellers' trading when a firm faces greater scrutiny from a high quality auditor.

Taken together, the results in Tables 6 and 7 suggest that short sellers trade as if they understand the substitutive nature among different earnings management strategies and provide further insight into short sellers' sophistication as external monitors of overall earnings quality.

5.3 | Short sellers' trading on various fundamental signals

Prior research provides evidence that short sellers target firms with various attributes predicting negative future returns (e.g., Dechow et al., 2001; Drake et al., 2011; Hirshleifer et al., 2011). It is undoubtedly of empirical interest to find which of the fundamental signals short sellers tend to respond to the most. Although full resolution of this

[23] Big 5 accounting firms include Arthur Andersen, Deloitte & Touche, Ernst & Young, KPMG and PricewaterhouseCoopers (auditor codes 1, 4, 5, 6 and 7, respectively). I also repeat the cross-sectional analysis based on Big 6 firms by adding Coopers & Lybrand and find similar results.

TABLE 6 Real earnings management, accounting flexibility and short interest

	Full Sample			Propensity Score Matched Sample
Dependent Variable:	*ABSI*			
REM Variable:	*ABCFO*	*ABPROD*	*ABDEXP*	*Treatment*
	(1)	(2)	(3)	(4)
ABCFO	−0.212			
	(−1.62)			
ABCFO × *ABNOA*	−0.922***			
	(−3.05)			
ABPROD		0.485***		
		(3.14)		
ABPROD × *ABNOA*		0.503**		
		(2.10)		
ABDEXP			0.280**	
			(2.24)	
ABDEXP × *ABNOA*			−0.286	
			(−1.35)	
Treatment				0.140
				(1.19)
Treatment × *ABNOA*				0.461***
				(2.74)
ABNOA	0.164***	0.155***	0.168***	−0.009
	(3.39)	(3.21)	(3.46)	(−0.06)
Controls	Yes	Yes	Yes	Yes
N	24,979	24,979	24,979	7,440
Adjusted R^2	0.375	0.375	0.374	0.384

Notes: Table 6 presents cross-sectional analyses of short interest on REM based on accounting flexibility using the full sample (columns (1)–(3)) and the propensity score matched sample (column (4)). The dependent variable is the abnormal short interest ratio (*ABSI*). The REM variables are *ABCFO*, *ABPROD*, *ABDEXP*, and *Treatment* in columns (1), (2), (3) and (4), respectively. The regression model is:

$$ABSI_{it} = \alpha + \beta_1 REM_{it} + \beta_2 REM_{it} \times ABNOA_{it} + \beta_3 ABNOA_{it} + \gamma Z_{it} + \delta firmfixed_i + \theta yearfixed_t + \varepsilon_{it},$$

where Z_{it} includes total accruals (*ACC*), firm size (*SIZE*), growth opportunities (*GROWTH*), past stock performance (*MOM*), unexpected earnings (*SUE*), institutional ownership (*IOR*), the dividend yield (*DIVY*), Amihud illiquidity (*AILLIQ*), the standard deviation of market model residuals (*STDRES*), leverage (*LEV*), analyst following (*AF*), stock price turnover (*STO*), and stock issuance (*EISSUE*). *ABNOA* is an indicator variable coded one if the firm's beginning net operating assets are greater than the sample median, and zero otherwise. For the sake of conciseness, I suppress the coefficients of all the control variables. Definitions of variables are in Appendix B. Each regression includes firm fixed effects and year indicators. *t*-statistics are in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

question is beyond the scope of this study, this paper can shed some light on it by exploring short sellers' trading on REM information compared to other fundamental signals identified by prior studies.[24]

Dechow et al. (2001) find that short interest is concentrated in firms with low fundamental-to-price ratios. Hirshleifer et al. (2011) find a positive association between short interest and accruals. I thus investigate the relative magnitude of short sellers' response to REM compared to accruals (*ACC*), book-to-market (*BTM*), earnings-to-price

[24] Since I have thus far found that short sellers target firms engaging in REM through sales manipulation and overproduction, this section focuses on *ABCFO* and *ABPROD*.

TABLE 7 Real earnings management, accounting scrutiny and short interest

	Full Sample			Propensity Score Matched Sample
Dependent Variable:			*ABSI*	
REM Variable:	*ABCFO*	*ABPROD*	*ABDEXP*	*Treatment*
	(1)	(2)	(3)	(4)
ABCFO	−0.127			
	(−0.88)			
ABCFO × *BIG5*	−0.728***			
	(−2.87)			
ABPROD		0.044		
		(0.21)		
ABPROD × *BIG5*		0.951***		
		(3.67)		
ABDEXP			0.378**	
			(2.39)	
ABDEXP × *BIG5*			−0.344	
			(−1.61)	
Treatment				0.106
				(0.52)
Treatment × *BIG5*				0.256
				(1.15)
BIG5	−0.230***	−0.224***	−0.229***	−0.315
	(−2.76)	(−2.68)	(−2.74)	(−1.57)
Controls	Yes	Yes	Yes	Yes
N	24,979	24,979	24,979	7,440
Adjusted R^2	0.375	0.375	0.374	0.383

Notes: Table 7 presents cross-sectional analyses of short interest on REM based on auditor scrutiny using the full sample (columns (1)–(3)) and the propensity score matched sample (column (4)). The dependent variable is the abnormal short interest ratio (*ABSI*). The REM variables are *ABCFO*, *ABPROD*, *ABDEXP*, and *Treatment* in columns (1), (2), (3) and (4), respectively. The regression model is

$$ABSI_{it} = \alpha + \beta_1 REM_{it} + \beta_2 REM_{it} \times BIG5_{it} + \beta_3 BIG5_{it} + \gamma Z_{it} + \delta firmfixed_i + \theta yearfixed_t + \varepsilon_{it},$$

where Z_{it} includes total accruals (*ACC*), firm size (*SIZE*), growth opportunities (*GROWTH*), past stock performance (*MOM*), unexpected earnings (*SUE*), institutional ownership (*IOR*), the dividend yield (*DIVY*), Amihud illiquidity (*AILLIQ*), the standard deviation of market model residuals (*STDRES*), leverage (*LEV*), analyst following (*AF*), stock price turnover (*STO*), and stock issuance (*EISSUE*). *BIG5* is an indicator variable coded one if the firm is audited by Arthur Andersen, Deloitte & Touche, Ernst & Young, KPMG, or PricewaterhouseCoopers, and zero otherwise. For the sake of conciseness, I suppress the coefficients of all the control variables. Definitions of variables are in Appendix B. Each regression includes firm fixed effects and year indicators. *t*-statistics are in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

(*EP*) and value-to-market (*VP*) ratios. I start by comparing short positions across deciles sorted based on these fundamental signals (e.g., Dechow et al., 2001). Specifically, I rank firms each month based on each fundamental signal variable and sort them into deciles. I then pool observations for the highest and lowest decile portfolios across the sample period.[25] Panel A of Table 8 reports proportions of heavily-shorted firms in the lowest (column (1)) and highest (column (2)) decile portfolios, differences in proportions between the two extreme portfolios (column (3)), and their

[25] I focus on the highest and lowest extreme deciles because I expect short selling to be concentrated in the most overvalued firms (e.g., Hirshleifer et al., 2011). More specifically, the low *ABCFO* group contains the stocks of firms in the lowest decile of *ABCFO*, while the high *ABCFO* group contains the stocks of the firms in the highest decile of *ABCFO*.

TABLE 8 Short sellers' trading on various fundamental signals

Panel A. Univariate Analysis: Short Interest across Fundamental Signal Portfolios

	Lowest	Highest	Lowest-Highest	*p*-value
	(1)	(2)	(3)	
Sorting by abnormal cash flows from operations, *ABCFO*				
ABSI	0.090	0.046	0.044***	0.00
SI	0.087	0.044	0.043***	0.00
Sorting by abnormal production costs, *ABPROD*				
ABSI	0.041	0.058	−0.018***	0.01
SI	0.039	0.056	−0.017***	0.00
Sorting by accruals, *ACC*				
ABSI	0.074	0.059	0.015**	0.03
SI	0.069	0.060	0.009	0.21
Sorting by book-to-market, *BTM*				
ABSI	0.075	0.062	0.013*	0.08
SI	0.077	0.062	0.015**	0.05
Sorting by earnings-to-price, *EP*				
ABSI	0.069	0.077	−0.008	0.28
SI	0.065	0.082	−0.017**	0.03
Sorting by value-to-market, *VP*				
ABSI	0.078	0.064	0.014*	0.06
SI	0.079	0.063	0.017**	0.03

Panel B. Multivariate Analysis: Fundamental Signals of Overvaluation and Short Interest

	Full Sample				Propensity Score Matched Sample	
Dependent Variable:	*ABSI*		*SI*		*ABSI*	*SI*
REM Variable:	*ABCFO*	*ABPROD*	*ABCFO*	*ABPROD*	*Treatment*	
	(1)	(2)	(3)	(4)	(5)	(6)
ABCFO	−0.320**		−0.567***			
	(−2.59)		(−4.24)			
ABPROD		0.638***		0.617***		
		(4.53)		(4.05)		
Treatment					0.323***	0.331***
					(3.39)	(3.25)
ACC	0.323***	0.368***	0.258***	0.339***	0.648***	0.486**
	(4.09)	(4.78)	(3.03)	(4.07)	(3.20)	(2.25)
BTM	−0.011**	−0.013**	−0.008	−0.011*	−0.036**	−0.035**
	(−2.12)	(−2.41)	(−1.44)	(−1.91)	(−2.20)	(−2.03)
EP	0.045	0.057	0.032	0.041	−0.007	0.040
	(0.94)	(1.18)	(0.62)	(0.79)	(−0.08)	(0.45)
VP	−0.001	−0.001	−0.001	−0.001	−0.000	−0.001
	(−0.29)	(−0.26)	(−0.58)	(−0.53)	(−0.10)	(−0.19)
Controls	Yes	Yes	Yes	Yes	Yes	Yes

(Continues)

TABLE 8 (Continued)

Panel B. Multivariate Analysis: Fundamental Signals of Overvaluation and Short Interest						
	Full Sample				Propensity Score Matched Sample	
Dependent Variable:	*ABSI*		*SI*		*ABSI*	*SI*
REM Variable:	*ABCFO*	*ABPROD*	*ABCFO*	*ABPROD*	*Treatment*	
	(1)	(2)	(3)	(4)	(5)	(6)
N	24,979	24,979	24,979	24,979	7,440	7,440
Adjusted R^2	0.374	0.375	0.565	0.565	0.383	0.576

Panel C. Real Earnings Management versus Earnings Surprises

	Lowest *ABCFO* decile			Highest *ABCFO* decile			Difference: Lowest - Highest decile	
	Positive Surprise	Negative Surprise	Negative-Positive	Positive Surprise	Negative Surprise	Negative-Positive	Positive Surprise	Negative Surprise
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
N	795	966		986	991			
ABSI	0.705	0.888	0.183	0.075	0.171	0.096	0.630***	0.717***
			(0.37)			(0.55)	(0.00)	(0.00)
SI	3.539	3.644	0.105	2.783	2.913	0.130	0.756***	0.731***
			(0.68)			(0.53)	(0.00)	(0.00)

	Lowest *ABPROD* decile			Highest *ABPROD* decile			Difference: Lowest - Highest decile	
	Positive Surprise	Negative Surprise	Negative-Positive	Positive Surprise	Negative Surprise	Negative-Positive	Positive Surprise	Negative Surprise
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
N	1049	929		881	968			
ABSI	−0.086	0.008	0.094	0.226	0.264	0.039	−0.312**	−0.256
			(0.52)			(0.82)	(0.04)	(0.12)
SI	2.813	2.629	−0.184	2.964	2.905	−0.060	−0.152	−0.276
			(0.33)			(0.78)	(0.45)	(0.17)

Notes: Table 8 presents analyses relating to short sellers' trading on various fundamental signals. Panel A presents proportions of heavily-shorted firms in the lowest (column (1)) and highest (column (2)) decile portfolios of fundamental signals, differences in proportions between the extreme decile portfolios (column (3)), and their corresponding *p*-values. Heavily-shorted firms are defined as those for which *ABSI* (*SI*) is in the top 5% of the sample. Panel B presents firm fixed effects OLS regressions of subsequent short interest on REM, fundamental signals, and other control variables. The dependent variable is the abnormal short interest ratio (*ABSI*) in columns 1/2/5, and the raw short interest ratio (*SI*) in columns 3/4/6, respectively. The REM variables are *ABCFO*, *ABPROD*, *Treatment* in columns 1/3, 2/4, and 5/6, respectively. The regression model is

$$ABSI_{it}\,(SI_{it}) = \alpha + \beta_1 REM_{it} + \beta_2 ACC_{it} + \beta_3 BTM_{it} + \beta_4 EP_{it} + \beta_5 VP_{it} + \gamma Z_{it} + \delta firmfixed_i + \theta yearfixed_t + \varepsilon_{it},$$

where *ACC* is total accruals, *BTM* is the book-to-market ratio, *EP* is the earnings-to-price ratio, *VP* is the value-to-market ratio, and Z_{it} includes firm size (*SIZE*), growth opportunities (*GROWTH*), past stock performance (*MOM*), unexpected earnings (*SUE*), institutional ownership (*IOR*), the dividend yield (*DIVY*), Amihud illiquidity (*AILLIQ*), the standard deviation of market model residuals (*STDRES*), leverage (*LEV*), analyst following (*AF*), stock price turnover (*STO*), and stock issuance (*EISSUE*). Each regression includes firm fixed effects and year indicators. *t*-statistics are in parentheses. Panel C presents the means of short interest of extreme *ABCFO* and *ABPROD* decile portfolios grouped by the sign of the earnings surprise, their differences, and their corresponding *p*-values. Column 3 (6) presents the differences in short interest between firms with negative and positive earnings surprises within the lowest (highest) *ABCFO* or *ABPROD* decile. Column 7 (8) presents the differences in short interest between firms in the lowest and highest *ABCFO* or *ABPROD* deciles before positive (negative) earnings surprises. The earnings surprise is measured as the return on the stock from the closing prices of day −1 to +1, where day 0 is the earnings announcement date. *p*-values are in parentheses. Definitions of variables are in Appendix B. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

corresponding *p*-values.[26] To be directly comparable to prior studies, I report the results of using raw short interest (*SI*), as well as abnormal short interest (*ABSI*) in this section. Differences in proportions between extreme deciles of *ABCFO*, *ABPROD*, *BTM* and *VP* are statistically significant, consistent with the notion that variations in these signals have significant effects on short interest. For example, the proportion of heavily-shorted firms in terms of *ABSI* is 9.0% in the lowest *ABCFO* decile, whereas it is 4.6% in the highest *ABCFO* decile. The difference of 4.4% between the two extreme deciles is statistically significant. The sorts on REM measures (*ABCFO* and *ABPROD*) produce differences ranging from 1.7% to 4.4%, while the sorts on other fundamental signals produce differences ranging from 1.3% to 1.7%. However, the differences for *ACC* and *EP* are inconsistent with the prediction. These results could reflect positions based on other reasons for short selling in my sample.

I next use a multivariate regression framework to determine which signals have more marginal ability to predict short interest. Panel B of Table 8 reports the results of firm fixed effects regressions of short interest on REM, fundamental signals of overvaluation, and other controls. Columns (1)–(4) report the results using the full sample, and columns (5) and (6) report the results using the propensity score matched sample. For the sake of conciseness, I suppress the coefficients of all other control variables. REM, accruals, and book-to-market ratio variables have marginal explanatory power. In terms of economic significance, in general, short sellers' use of REM information is similar to *ACC* and superior to *BTM*. For example, a one standard deviation increase in *ABPROD* is associated with 3.9% standard deviation increase in *ABSI* in column (2). In the same regression, a one standard deviation increase in *ACC* is associated with 4.0% standard deviation increase in *ABSI*, and a one standard deviation decrease in *BTM* is associated with 2.5% standard deviation increase in *ABSI*. On the other hand, the coefficients on *EP* or *VP* are not statistically significant. Taken together, these results provide some evidence that short sellers respond to REM more than to other fundamental signals of overvaluation.

Several prior studies find that short sellers anticipate negative events. For example, Christophe et al. (2004) find that short selling increases in the days before negative earnings surprises. I thus examine whether high levels of short interest associated with high levels of REM are attributable to upcoming negative earnings announcements.[27] I measure the earnings surprise as the return on the stock from the closing prices of day −1 to +1, where day 0 is the earnings announcement date.[28] I focus on firms in the highest and lowest deciles of REM measures (Christophe et al., 2004). I divide each extreme REM decile into positive and negative earnings surprise groups. If short sellers make their short selling decisions based upon REM information, short interest should be a function of REM and independent of the eventual sign of the earnings surprise.

Panel C of Table 8 reports, for each extreme decile, the means and differences of *ABSI* and *SI* in these stocks grouped by the sign of the earnings surprise. With regard to within-REM decile differences (columns (3) and (6)), all of the differences are not significantly different from zero. For example, the difference of 0.183% in *ABSI* between firms with negative and positive earnings surprises within the lowest *ABCFO* decile (column (3)) is not significantly different from zero. The results of other deciles display similar patterns. In contrast, with regard to between-REM decile differences (columns (7) and (8)), the five differences are significantly different from zero. Short positions prior to negative (or positive) earnings surprises of high-REM firms are greater than those positions of low-REM firms, consistent with the explanation that levels and differences in short interest reflect REM. For example, the difference of 0.630% (0.717%) in *ABSI* between extreme *ABCFO* decile firms prior to positive (negative) earnings surprises in column (7) ((8)) is significantly different from zero. These results are consistent with short sellers responding to REM more than to the sign of the earnings surprise.[29]

[26] As in Table 5, I use the 95th percentile short interest cutoff for heavily-shorted firms. In other words, heavily-shorted firms are defined as those for which *ABSI* (*SI*) is in the top 5% of the sample.

[27] To minimize factors that could confound the relation between negative earnings surprises and short interest, I restrict upcoming earnings announcements to those made within the three months after the short interest report month (months t+1 to t+4).

[28] This earnings surprise is chosen because the market's reaction to the announcement reveals whether the announcement contains a surprise (Christophe et al., 2004).

[29] Using entire sample firms, I find that short positions on firms with negative earnings surprises are greater than short positions on firms with positive earnings surprises, consistent with prior evidence of short sellers' general ability to anticipate bad earnings news.

5.4 | Profitability of trading on real earnings management

Next, I investigate whether short sellers profit from trading in firms engaging in REM. Following the tradition of anomaly studies, I examine stock returns over 12 months following the formation of portfolios based on REM. I allow a four-month minimum lag between the fiscal year-end and the month of return to ensure that accounting information is publicly available. Specifically, the annual REM of the fiscal year-end (month *t*) is matched with monthly stock returns from month $t+5$ through $t+16$. I rank firms each month based on each REM measure and then sort them into deciles.[30] The monthly abnormal return for each decile portfolio is measured as the intercept from three- and four-factor models in columns 1/3/5 and 2/4/6, respectively (e.g., Cahart, 1997; Fama & French, 1993). I then form hedge portfolios by taking long positions in highest (lowest) *ABCFO* or *ABDEXP* (*ABPROD*) decile firms and short positions in lowest (highest) *ABCFO* or *ABDEXP* (*ABPROD*) decile firms.

Panel A of Table 9 reports hedge portfolio returns obtained from long-short positions in the extreme deciles. Although the association between REM and subsequent returns is not perfectly monotonic, the trend in abnormal returns, in general, is decreasing as *ABCFO* (*ABPROD*) decreases (increases). The monthly return spread between extreme deciles of *ABCFO* (*ABPROD*) in my sample is 110 (78) basis points per month using the three-factor model in column (1) ((3)) and 97 (71) basis points using the four-factor model in column (2) ((4)). In contrast, the hedge portfolio based on *ABDEXP* does not provide significant abnormal returns, consistent with my argument in the earlier section. I also examine the stability of these hedge returns over time. Panel B of Table 9 reports hedge returns by month following portfolio formation. The significant hedge portfolio returns, in general, are concentrated in the period around three to six months after portfolio formation. Taken together, these results are consistent with short sellers profiting from trading on REM through sales manipulation and overproduction.

6 | CONCLUSION

I examine whether short sellers take positions in overvalued firms that engage in REM to increase earnings. This question is particularly relevant given the recent prevalence of REM activities and the negative impact of such practices on future cash flows and firm value. REM is less subject to scrutiny by corporate boards, auditors and regulators, and it is difficult for the average investor to detect REM. Investors' failure to understand the negative implications of REM on future performance causes overvaluation and subsequent declines in stock prices. Prior studies find short arbitrage of the anomaly associated with accounting adjustments to earnings. However, despite managers' trade-offs between accrual-based earnings management and REM, we know little about whether short sellers detect and respond to managerial abnormal operating decisions as well.

My empirical results can be summarized as follows. First, I find that short sellers tend to target firms engaging in REM through sales manipulation and overproduction. More specifically, I find a negative (positive) relation between abnormal cash flows from operations (abnormal production costs) and subsequent short interest. Second, the relation is stronger for firms that have made aggressive accounting assumptions in prior years and are scrutinized by high quality auditors. This evidence is consistent with the notion that short sellers trade on REM more heavily when the costs associated with accrual-based earnings management are high. Third, I find some evidence that REM is relatively high up in short sellers' trading pecking order as compared to other fundamental signals of overvaluation. Fourth, my results are robust to the use of propensity score matching. Lastly, I find that long-short trading strategies based on REM through sales manipulation and overproduction produce positive abnormal returns with hedge returns being concentrated in the period around three to six months after portfolio formation.

Taken together, my evidence suggests that short sellers are able to see through REM. To the best of my knowledge, this paper is the first to investigate short arbitrage of the overpricing associated with managerial abnormal and aggressive operating decisions. Furthermore, my evidence that short sellers refine their REM trading strategies based on the

[30] Since firms have different fiscal year-ends, I rebalance the REM portfolios each month.

TABLE 9 Profitability of trading on real earnings management

Panel A. Real Earnings Management and Abnormal Returns						
REM Variable:	*ABCFO*		*ABPROD*		*ABDEXP*	
	3-factor	4-factor	3-factor	4-factor	3-factor	4-factor
REM Decile	(1)	(2)	(3)	(4)	(5)	(6)
Lowest	−0.907***	−0.636***	0.309**	0.433***	0.031	0.193*
	(−3.59)	(−3.17)	(2.01)	(3.30)	(0.24)	(1.68)
2	−0.328**	−0.025	0.174*	0.31***	0.045	0.211*
	(−2.10)	(−0.21)	(1.73)	(3.13)	(0.29)	(1.77)
3	−0.214	0.032	0.114	0.258**	−0.149	0.030
	(−1.45)	(0.29)	(0.84)	(2.20)	(−0.95)	(0.23)
4	0.01	0.217	−0.029	0.188	−0.036	0.17
	(−0.07)	(1.58)	(−0.20)	(1.61)	(−0.21)	(1.25)
5	−0.023	0.122	−0.009	0.168	−0.274	−0.061
	(−0.18)	(1.17)	(−0.06)	(1.30)	(−1.28)	(−0.31)
6	0.077	0.253*	−0.165	0.005	−0.183	0.015
	(0.51)	(1.93)	(−1.13)	(0.04)	(−0.84)	(0.09)
7	0.072	0.233**	−0.391**	−0.103	−0.199	−0.000
	(0.54)	(2.01)	(−2.38)	(−0.70)	(−1.04)	(−0.00)
8	0.173	0.312***	−0.15	0.057	−0.206*	0.029
	(1.46)	(3.15)	(−0.79)	(0.35)	(−1.92)	(0.28)
9	0.202*	0.310***	−0.122	0.115	0.029	0.169
	(1.73)	(2.85)	(−0.75)	(0.77)	(0.26)	(1.61)
Highest	0.19	0.332***	−0.471**	−0.276*	0.212	0.409***
	(1.42)	(2.73)	(−2.27)	(−1.70)	(1.21)	(2.68)
Hedge Return	1.096***	0.968***	0.780***	0.709***	0.181	0.216
	(5.25)	(5.01)	(4.45)	(4.18)	(1.41)	(1.54)

Panel B. Stability of Hedge Returns Based on Real Earnings Management						
REM Variable:	*ABCFO*		*ABPROD*		*ABDEXP*	
	3-factor	4-factor	3-factor	4-factor	3-factor	4-factor
Month	(1)	(2)	(3)	(4)	(5)	(6)
1–2	0.454	0.352	0.134	0.082	0.051	−0.097
	(0.84)	(0.65)	(0.24)	(0.14)	(0.12)	(−0.21)
3–4	1.394**	1.154*	0.769*	0.537	−0.702	−0.792
	(2.15)	(1.69)	(1.86)	(1.33)	(−1.41)	(−1.37)
5–6	1.949***	2.034***	1.087**	1.083	−0.199	−0.048
	(3.79)	(3.74)	(2.03)	(1.61)	(−0.41)	(−0.09)
7–8	1.283*	1.113	0.831	0.961	0.783*	0.953*
	(1.69)	(1.41)	(1.53)	(1.65)	(1.66)	(1.91)
9–10	0.925	0.607	0.680**	0.780***	0.055	0.294
	(1.56)	(1.08)	(2.38)	(2.67)	(0.12)	(0.64)
11–12	0.668	0.499	0.921	0.770	0.554	0.612
	(1.18)	(0.93)	(1.53)	(1.27)	(0.95)	(1.03)

(Continues)

TABLE 9 (Continued)

Notes: Table 9 presents average monthly abnormal returns for REM portfolios. Panel A presents the averages of monthly abnormal returns for REM portfolios over 12 months following portfolio formation. For each firm, its annual REM measures as of fiscal year-end (month *t*) are matched with CRSP monthly returns from month *t*+5 to *t*+16. Since firms have different fiscal year-ends, REM decile portfolios are rebalanced each month to take into consideration the new REM data available. The monthly abnormal return for each portfolio is measured as the intercept from three- and four-factor regression models in columns 1/3/5 and 2/4/6, respectively. The REM variables are *ABCFO*, *ABPROD* and *ABDEXP* in columns 1/2, 3/4 and 5/6, respectively. The hedge return represents the return from the hedge portfolio taking long positions in highest *ABCFO* or *ABDEXP* (lowest *ABPROD*) decile firms and short positions in lowest *ABCFO* or *ABDEXP* (highest *ABPROD*) decile firms. Panel B presents hedge returns by month following portfolio formation. For example, the first row (Month 1–2) reports hedge returns in the period around one to two months after portfolio formation (months *t*+5 and *t*+6). Definitions of variables are in Appendix B. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

costs associated with accrual-based earnings management suggests that short sellers trade as if they understand the substitutive nature between alternative earnings management methods. In conclusion, my study provides additional insight into short sellers' monitoring of overall earnings quality, which is beneficial to the real economy as well as capital markets. It has important implications for academics, investors and regulators. Regulations restricting short selling are likely to risk limiting a potentially important source of improvement for managerial operating actions and overall financial reporting.

ACKNOWLEDGEMENTS

The author would like to thank Theodore E. Christensen (the Editor), an anonymous referee, seminar participants at Purdue University, University of Massachusetts Boston, and 2013 AAA Annual Meeting for valuable comments and discussions. As the earlier version of this paper is based upon the author's dissertation at Purdue University, she would especially like to thank her committee – Mark Bagnoli (co-chair), Susan Watts (co-chair), Byung Ro and Lin Nan – for their guidance and support. (Paper received July 2015, revised revision accepted June 2017)

REFERENCES

Amihud, Y. (2002). 'Illiquidity and stock returns: Cross-section and time-series effects', *Journal of Financial Markets*, *5*(1), 31–56.

Armstrong, C. S., Jagolinzer, A. D., & Larcker, D. F. (2010). 'Chief executive officer equity incentives and accounting irregularities', *Journal of Accounting Research*, *48*(2), 225–271.

Asquith, P., Pathak, P. A., & Ritter, J. R. (2005). 'Short interest, institutional ownership, and stock returns', *Journal of Financial Economics*, *78*(2), 243–276.

Barton, J., & Simko, P. J. (2002). 'The balance sheet as an earnings management constraint', *The Accounting Review*, *77*(s-1), 1–27.

Beaver, W., McNichols, M., & Price, R. (2007). 'Delisting returns and their effect on accounting-based market anomalies', *Journal of Accounting and Economics*, *43*(2–3), 341–368.

Bergstresser, D., & Philippon, T. (2006). 'CEO incentives and earnings management', *Journal of Financial Economics*, *80*(3), 511–529.

Boehme, R. D., Danielsen, B. R., & Sorescu, S. M. (2006). 'Short-sale constraints, differences of opinion, and overvaluation', *Journal of Financial and Quantitative Analysis*, *41*(2), 455–487.

Boehmer, E., Jones, C. M., & Zhang, X. (2008). 'Which shorts are informed?' *Journal of Finance*, *63*(2), 491–527.

Bushee, B. J. (1998). 'The influence of institutional investors on myopic R&D investment behavior', *The Accounting Review*. *73*(3), 305–333.

Carhart, M. M. (1997). 'On persistence in mutual fund performance', *Journal of Finance*, *52*(1), 57–82.

Chang, E. C., Cheng, J. W., & Yu, Y. (2007). 'Short-sales constraints and price discovery: Evidence from the Hong Kong market', *Journal of Finance*, *62*(5), 2097–2121.

Cheng, Q., & Warfield, T. D. (2005). 'Equity incentives and earnings management', *The Accounting Review*, *80*(2), 441–476.

Chi, S. S., Pincus, M., & Teoh, S. H. (2014). 'Mispricing of book-tax differences and the trading behavior of short sellers and insiders', *The Accounting Review*, *89*(2), 511–543.

Christophe, S. E., Ferri, M. G., & Angel, J. J. (2004). 'Short-selling prior to earnings announcements', *Journal of Finance*, *59*(4), 1845–1876.

Chung, K. H., Kim, J.-C., Kim, Y. S., & Zhang, H. (2015). 'Information asymmetry and corporate cash holdings', *Journal of Business Finance & Accounting*, *42*(9–10), 1341–1377.

Cohen, D. A., & Zarowin, P. (2010). 'Accrual-based and real earnings management activities around seasoned equity offerings', *Journal of Accounting and Economics*, *50*(1), 2–19.

Cohen, D. A., Dey, A., & Lys, T. Z. (2008). 'Real and accrual-based earnings management in the pre- and post-Sarbanes-Oxley periods', *The Accounting Review*, *83*(3), 757–787.

Curtis, A., & Fargher, N. L. (2014). 'Does short selling amplify price declines or align stocks with their fundamental values?' *Management Science*, *60*(9), 2324–2340.

D'Avolio, G. (2002). 'The market for borrowing stock', *Journal of Financial Economics*, *66*(2–3), 271–306.

Dechow, P. M., Hutton, A. P., Meulbroek, L., & Sloan, R. G. (2001). 'Short-sellers, fundamental analysis, and stock returns', *Journal of Financial Economics*, *61*(1), 77–106.

Dechow, P., Ge, W., & Schrand, C. (2010). 'Understanding earnings quality: A review of the proxies, their determinants and their consequences', *Journal of Accounting and Economics*, *50*(2–3), 344–401.

Desai, H., Ramesh, K., Thiagarajan, S. R., & Balachandran, B. V. (2002). 'An investigation of the informational role of short interest in the Nasdaq market', *Journal of Finance*, *57*(5), 2263–2287.

Desai, H., Krishnamurthy, S., & Venkataraman, K. (2006). 'Do short sellers target firms with poor earnings quality? Evidence from earnings restatements', *Review of Accounting Studies*, *11*(1), 71–90.

Dhaliwal, D., Judd, J. S., Serfling, M., & Shaikh, S. (2016). 'Customer concentration risk and the cost of equity capital', *Journal of Accounting and Economics*, *61*(1), 23–48.

Diamond, D. W., & Verrecchia, R. E. (1987). 'Constraints on short-selling and asset price adjustment to private information', *Journal of Financial Economics*, *18*(2), 277–311.

Diether, K. B., Lee, K.-H., & Werner, I. M. (2009). 'Short-sale strategies and return predictability', *Review of Financial Studies*, *22*(2), 575–607.

Drake, M. S., Myers, J. N., Myers, L. A., & Stuart, M. D. (2015). 'Short sellers and the informativeness of stock prices with respect to future earnings', *Review of Accounting Studies*, *20*(2), 747–774.

Drake, M. S., Rees, L., & Swanson, E. P. (2011). 'Should investors follow the prophets or the bears? Evidence on the use of public information by analysts and short sellers', *The Accounting Review*, *86*(1), 101–130.

Duarte, J., Lou, X., & Sadka, R. (2006). 'Can liquidity events explain the low-short-interest puzzle? Implications from the options market', Working Paper (University of Washington).

Duellman, S., Ahmed, A. S., & Abdel-Meguid, A. M. (2013). 'An empirical analysis of the effects of monitoring intensity on the relation between equity incentives and earnings management', *Journal of Accounting and Public Policy*, *32*(6), 495–517.

Ewert, R., & Wagenhofer, A. (2005). 'Economic effects of tightening accounting standards to restrict earnings management', *The Accounting Review*, *80*(4), 1101–1124.

Fama, E. F., & French, K. R. (1993). 'Common risk factors in the returns on stocks and bonds', *Journal of Financial Economics*, *33*(1), 3–56.

Fields, T. D., Lys, T. Z., & Vincent, L. (2001). 'Empirical research on accounting choice', *Journal of Accounting and Economics*, *31*(1–3), 255–307.

Healy, P. M., & Wahlen, J. M. (1999). 'A review of the earnings management literature and its implications for standard setting', *Accounting Horizons*, *13*(4), 365–383.

Hirshleifer, D., Teoh, S. H., & Yu, J. J. (2011). 'Short arbitrage, return asymmetry, and the accrual anomaly', *Review of Financial Studies*, *24*(7), 2429–2461.

Irani, R. M., & Oesch, D. (2016). 'Analyst coverage and real earnings management: Quasi-experimental evidence', *Journal of Financial and Quantitative Analysis*, *51*(2), 589–627.

Jain, A., Jain, P. K., McInish, T. H., & McKenzie, M. (2013). 'Worldwide reach of short selling regulations', *Journal of Financial Economics*, *109*(1), 177–197.

Jones, C. M., & Lamont, O. A. (2002). 'Short-sale constraints and stock returns', *Journal of Financial Economics*, *66*(2–3), 207–239.

Karpoff, J. M., & Lou, X. (2010). 'Short sellers and financial misconduct', *Journal of Finance*, *65*(5), 1879–1913.

Kim, J.-B., & Sohn, B. C. (2013). 'Real earnings management and cost of capital', *Journal of Accounting and Public Policy*, *32*(6), 518–543.

Kim, Y., & Park, M. S. (2014). 'Real activities manipulation and auditors' client-retention decisions', *The Accounting Review*, *89*(1), 367–401.

Kothari, S. P. (2001). 'Capital markets research in accounting', *Journal of Accounting and Economics*, *31*(1–3), 105–231.

Leggett, D., Parsons, L. M., & Reitenga, A. L. (2009). 'Real earnings management subsequent operating performance', Working Paper (University of Alabama).

Lennox, C. S. (2016). 'Did the PCAOB's restrictions on auditors' tax services improve audit quality?' *The Accounting Review*, *91*(5), 1493–1512.

Li, X. (2012). 'Real earnings management and subsequent stock returns', Working Paper (Hong Kong University of Science & Technology).

Massa, M., Zhang, B., & Zhang, H. (2015). 'The invisible hand of short selling: Does short selling discipline earnings management?' *Review of Financial Studies*, *28*(6), 1701–1736.

Miller, E. M. (1977). 'Risk, uncertainty, and divergence of opinion', *Journal of Finance*, *32*(4), 1151–1168.

Mizik, N. (2010). 'The theory and practice of myopic management', *Journal of Marketing Research*, *47*(4), 594–611.

Mizik, N., & Jacobson, R. (2008). 'Earnings inflation through accruals and real activity manipulation: Its prevalence at the time of an SEO and the financial market consequences', Working Paper (University of Washington).

Roychowdhury, S. (2006). 'Earnings management through real activities manipulation', *Journal of Accounting and Economics*, *42*(3), 335–370.

Saffi, P. A. C., & Sigurdsson, K. (2011). 'Price efficiency and short selling', *Review of Financial Studies*, *24*(3), 821–852.

Shipman, J. E., Swanquist, Q. T., & Whited, R. L. (2017). 'Propensity score matching in accounting research', *The Accounting Review*, *92*(1), 213–244.

Sloan, R. G. (1996). 'Do stock prices fully reflect information in accruals and cash flows about future earnings?' *The Accounting Review*, *71*(3), 289–315.

Xie, H. (2001). 'The mispricing of abnormal accruals', *The Accounting Review*, *76*(3), 357–373.

Yuan, Q., & Zhang, Y. (2015). 'Do banks price litigation risk in debt contracting? Evidence from class action lawsuits', *Journal of Business Finance & Accounting*, *42*(9–10), 1310–1340.

Zang, A. Y. (2012). 'Evidence on the trade-off between real activities manipulation and accrual-based earnings management', *The Accounting Review*, *87*(2), 675–703.

How to cite this article: Park K. Earnings quality and short selling: Evidence from real earnings management in the United States. *J Bus Fin Acc*. 2017;00:1–27. https://doi.org/10.1111/jbfa.12264

APPENDIX A

Measurements of real earnings management

Following prior studies (e.g., Cohen & Zarowin, 2010; Cohen et al., 2008; Roychowdhury, 2006), I use three measures of REM: (1) abnormal cash flows from operations (*ABCFO*), (2) abnormal production costs (*ABPROD*), and (3) abnormal discretionary expenses (*ABDEXP*).

Specifically, I estimate the normal level of cash flows from operations as a linear function of contemporaneous sales and change in sales:

$$\frac{CFO_{it}}{TA_{it-1}} = \alpha_0 + \alpha_1 \frac{1}{TA_{it-1}} + \alpha_2 \frac{SALE_{it}}{TA_{it-1}} + \alpha_3 \frac{\Delta SALE_{it}}{TA_{it-1}} + \varepsilon_{it} \tag{A1}$$

where CFO_{it} is cash flows from operations; TA_{it-1} is beginning total assets;. $SALE_{it}$ is sales; $\Delta SALE_{it} = SALE_{it} - SALE_{it-1}$.

Equation (A1) is estimated for each two-digit SIC-year with at least 15 observations. The abnormal level of cash flows from operations (*ABCFO*) is the estimated residual from the regression.

Production costs (*PROD*) are defined as the sum of *COGS* and change in inventory during the year. I model *COGS* as a linear function of contemporaneous sales:

$$\frac{COGS_{it}}{TA_{it-1}} = \alpha_0 + \alpha_1 \frac{1}{TA_{it-1}} + \alpha_2 \frac{SALE_{it}}{TA_{it-1}} + \varepsilon_{it} \tag{A2}$$

where $COGS_{it}$ is cost of goods sold.

Next, I model inventory growth as a linear function of contemporaneous and lagged changes in sales:

$$\frac{\Delta INV_{it}}{TA_{it-1}} = \alpha_0 + \alpha_1 \frac{1}{TA_{it-1}} + \alpha_2 \frac{\Delta SALE_{it}}{TA_{it-1}} + \alpha_3 \frac{\Delta SALE_{it-1}}{TA_{it-1}} + \varepsilon_{it}, \tag{A3}$$

where INV_{it} is inventory; $\Delta INV_{it} = INV_{it} - INV_{it-1}$; $\Delta SALE_{it-1} = SALE_{it-1} - SALE_{it-2}$.

Using Equations (A2) and (A3), I estimate the normal level of production costs as follows:

$$\frac{PROD_{it}}{TA_{it-1}} = \alpha_0 + \alpha_1 \frac{1}{TA_{it-1}} + \alpha_2 \frac{SALE_{it}}{TA_{it-1}} + \alpha_3 \frac{\Delta SALE_{it}}{TA_{it-1}} + \alpha_4 \frac{\Delta SALE_{it-1}}{TA_{it-1}} + \varepsilon_{it} \tag{A4}$$

where $PROD_{it}$ is production costs.

Equation (A4) is estimated for each two-digit SIC-year with at least 15 observations. The abnormal level of production costs (*ABPROD*) is the estimated residual from the regression.

Discretionary expenses (*DEXP*) are defined as the sum of R&D, advertising, and selling, general and administrative (SG&A) expenses. I model discretionary expenses as a function of lagged sales because modeling discretionary expenses as a function of contemporaneous sales creates a mechanical problem (Roychowdhury, 2006). If a firm manages sales upward in the current year, it results in abnormally low residual in the model with current sales. I estimate the normal level of discretionary expenses using the following regression:

$$\frac{DEXP_{it}}{TA_{it-1}} = \alpha_0 + \alpha_1 \frac{1}{TA_{it-1}} + \alpha_2 \frac{SALE_{it-1}}{TA_{it-1}} + \varepsilon_{it} \tag{A5}$$

where $DEXP_{it}$ is discretionary expenses.

Equation (A5) is estimated for each two-digit SIC-year with at least 15 observations. The abnormal level of discretionary expenses (*ABDEXP*) is the estimated residual from the regression.

A lower (higher) level of *ABCFO* or *ABDEXP* (*ABPROD*) implies more aggressive earnings management.

APPENDIX B

Variable definitions

Variable Name	Definition
Short Interest Variables	
SI (%)	Raw short interest, calculated as the short position in the fifth month after the fiscal year-end divided by the number of shares outstanding on the same date, then multiplied by 100 to express as a percentage.
ABSI (%)	Abnormal short position, calculated as the estimated residual from Equation (1), as described in Section 3.3.
Real Earnings Management Variables	
ABCFO	Abnormal cash flows from operations, measured as the estimated residual from Equation (A1), as described in Appendix A.
ABPROD	Abnormal production costs, measured as the estimated residual from Equation (A4), as described in Appendix A.
ABDEXP	Abnormal discretionary expenses, measured as the estimated residual from Equation (A5), as described in Appendix A.

(Continues)

Variable Name	Definition
Control Variables	
ACC	Total accruals, measured as earnings before extraordinary items less cash flows from operations.
SIZE	Natural logarithm of market capitalization.
GROWTH	An indicator variable coded one if the firm's book-to-market ratio is below the sample median, and zero otherwise.
MOM	Compounded monthly return over a one-year window ending one month prior to the short interest report month.
SUE	Unexpected earnings, defined as the difference between current and lagged earnings per share divided by stock price.
IOR	Institutional holdings, calculated as the total number of shares held by institutions divided by the total number of shares outstanding.
DIVY	Annual dividend divided by stock price.
AILLIQ	Natural logarithm of the Amihud illiquidity measure, where Amihud illiquidity is defined as the average ratio of the daily absolute return to the dollar trading volume (trading volume in millions of shares times the closing stock price) on that day calculated over a one-year window ending one month prior to the short interest report month.
STDRES	Standard deviation of the market model residuals for daily returns over a one-year window ending one month prior to the short interest report month.
LEV	Long-term debt plus debt in current liabilities divided by total assets.
AF	Natural logarithm of one plus the number of analysts following the firm over a one-year window ending on the short interest report month.
STO	Stock turnover, defined as the average ratio of the daily trading volume to shares outstanding on the same date, calculated over a one-year window ending one month prior to the short interest report month.
EISSUE	An indicator variable coded one if the firm's net proceeds from equity financing are positive in year $t+1$, and zero otherwise.
ABNOA	An indicator variable coded one if the firm's beginning net operating assets (NOA) are greater than the sample median, and zero otherwise, where NOA is shareholder's equity less cash and marketable securities plus total debt.
BIG5	An indicator variable coded one if the firm is audited by Arthur Andersen, Deloitte & Touche, Ernst & Young, KPMG, or PricewaterhouseCoopers, and zero otherwise.
BTM	Book value of equity divided by market value of equity.
EP	Earnings-to-price ratio, calculated as operating income after depreciation divided by market capitalization.
VP	Value-to-market ratio, calculated as (book value of common equity + alpha × abnormal earnings)/market capitalization, as described by Dechow et al. (2001).