

Research Article

Does Real Earnings Management Influence Stock Price Crash Risk? Evidence from Borsa İstanbul

*Reel Kâr Yönetimi Gelecekteki Hisse Senedi Fiyat Çöküşü Riskiyle İlişkili midir?
Borsa İstanbul'dan Bulgular*

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Abstract

In this study, I examine whether real earnings management affects future stock price crash risk using 2,839 firm-year observations from Borsa İstanbul, with predictor variables measured from 2005 to 2024 and crash-risk outcomes measured from 2006 to 2025. Real earnings management (REM) is measured from abnormal production costs, abnormal discretionary expenditures, and abnormal operating cash flows, while crash risk is gauged by negative conditional skewness and down-to-up volatility. Higher REM is associated with higher values of both crash risk measures. The result persists when alternative proxies, first-difference models, firm fixed effects, and entropy-balanced observations are used. This study contributes to the REM literature by providing evidence from an emerging market with distinct market conditions and reporting practices. Consistent with the hypotheses concerning firm overvaluation and information asymmetry, the cross-sectional results show that the positive REM–crash risk association is stronger among overvalued firms and firms with greater information asymmetry. This finding supports the view that valuation pressure may strengthen incentives to delay bad news recognition, while opaque information environments make underlying problems more difficult for market participants to detect.

Keywords: Real earnings management, Stock price crash risk, Information asymmetry, Firm overvaluation, Emerging markets

Öz

Bu çalışmada, Borsa İstanbul'da işlem gören şirketlere ait 2.839 firma-yıl gözleminden yararlanılarak reel kâr yönetiminin gelecekteki hisse senedi fiyat çöküşü riski üzerindeki etkisi incelenmektedir. Açıklayıcı değişkenler 2005–2024 döneminde, hisse senedi fiyat çöküşü riski ölçütleri ise 2006–2025 döneminde ölçülmüştür. Reel kâr yönetimi (REM), anormal üretim maliyetleri, anormal ihtiyari giderler ve anormal faaliyetlerden sağlanan nakit akışları kullanılarak ölçülürken, çöküş riski negatif koşullu çarpıklık ve aşağı-yukarı volatilité ölçütleriyle değerlendirilmektedir. Bulgular, daha yüksek REM düzeylerinin her iki çöküş riski ölçütünün de daha yüksek değerleriyle ilişkili olduğunu göstermektedir. Bu sonuç, alternatif ölçütler, birinci fark modelleri, firma sabit etkileri ve entropi dengelemesi uygulanmış gözlemler kullanıldığında da geçerliliğini korumaktadır. Çalışma, kendine özgü piyasa koşullarına ve raporlama uygulamalarına sahip gelişmekte olan bir piyasadan bulgular sunarak REM literatürüne katkıda bulunmaktadır. Firma aşırı değerlemesi ve bilgi asimetrisine ilişkin hipotezlerle tutarlı olarak, yatay kesit analizleri REM ile gelecekteki hisse senedi fiyat çöküşü riski arasındaki pozitif ilişkinin aşırı değerlendirilmiş firmalarda ve bilgi asimetrisinin daha yüksek olduğu firmalarda daha güçlü olduğunu

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göstermektedir. Bu bulgu, değerlendirme baskısının olumsuz haberlerin kamuya yansıtılmasını geciktirme yönündeki teşvikleri güçlendirebileceği, opak bilgi ortamlarının ise piyasa katılımcılarının şirketlerin temel sorunlarını tespit etmesini zorlaştırdığı görüşünü desteklemektedir.

Anahtar Kelimeler: *Reel kâr yönetimi, hisse senedi fiyat çöküşü riski, bilgi asimetrisi, firma aşırı değerlemesi, gelişmekte olan piyasalar*

1. Introduction

The risk of a sudden and severe decline in a firm's stock price has attracted considerable attention in the accounting and finance literature due to its consequences for investors, capital markets, and the efficient allocation of economic resources. Stock price crash risk refers to the probability of an unusually large negative movement in firm-specific stock returns over a relatively short period. Existing studies suggest that the delayed disclosure of adverse information accumulated within the firm plays a role in future stock price crashes.

The bad-news-hoarding argument developed by Jin and Myers (2006) provides the theoretical foundation for this literature. Managers may delay the disclosure of unfavorable information to protect compensation, reputation, employment, or contractual outcomes. If investors receive bad news gradually, prices can adjust in stages. However, withholding negative information may cause the market price to remain above the value supported by firm fundamentals. A crash becomes more likely when the accumulated news can no longer be concealed and reaches the market over a short interval (Hutton, Marcus, & Tehranian, 2009; Jin & Myers, 2006).

A number of earlier studies line up with this view. Crash risk tends to be higher when financial reports are more opaque (Hutton et al., 2009), when tax avoidance is aggressive (Kim, Li, & Zhang, 2011b), when accounting is less conservative (J. B. Kim & Zhang, 2016; Toksoz, 2024), or when managers hold stronger equity incentives (Kim, Li, & Zhang, 2011a). Governance quality, the auditor-client relationship, internal controls, and mandatory reporting rules have also been linked to crash risk (Andreou, Antoniou, Horton, & Louca, 2016; Callen & Fang, 2013, 2017; DeFond, Hung, Li, & Li, 2015). Collectively, these findings point to the firm's information environment as a key factor in whether bad news can build up before it is reflected in the share price.

Within this literature, considerably less attention has been devoted to the implications of REM for firms' future crash risk exposure. Existing evidence on this issue is concentrated in the context of U.S. capital markets. Francis, Hasan, and Li (2016) and Khurana, Pereira, and Zhang (2018) investigate whether distortions in firms' operating activities, derived from real earnings management models, and real earnings smoothing are associated with subsequent stock price crash risk among publicly traded U.S. firms. Extending the existing evidence, this study examines the relationship between REM and crash risk within the setting of a major emerging capital market. Specifically, it analyzes a sample of 2,839 firm-year observations drawn from companies listed on Borsa Istanbul over the 2005–2024 period to provide updated, international evidence on whether REM contributes to firms' future crash risk.

The sample consists of 2,839 firm-year observations spanning 2005–2024. I measure REM with the residual models introduced by Roychowdhury (2006) and used widely in subsequent work (Abad, Cutillas-Gomariz, Sánchez-Ballesta, & Yagüe, 2018; Badertscher, 2011; D. A. Cohen, Dey, & Lys, 2008; D. A. Cohen & Zarowin, 2010; Ge & Kim, 2014; Kim, Wang, & Zhang, 2021; Y. Kim, Park, & Wier, 2012; Lin & Zheng, 2026; Zang, 2012). Crash risk is captured by negative conditional skewness (NCSKEW) and down-to-up volatility (DUVOL). In both specifications the results indicate that more aggressive real earnings management is associated with higher future crash risk. The result holds under alternative measures, entropy balancing, first differences, and firm fixed effects.

The analysis also examines where the association is strongest. Managers of overvalued firms may feel greater pressure to avoid disclosing weak fundamentals, since such news could threaten the firm's market valuation. To check the idea that concealing more bad news in order to support high valuations raises future crash risk for overvalued firms, I split the sample using two common measures of overvaluation. Consistent with the prediction, the REM coefficient is positive and significant in the high overvaluation group, but not in the low overvaluation group.

A second partition concerns the degree of information asymmetry surrounding the firm. Prior literature argues that firms operating in more opaque informational environments tend to experience more severe agency conflicts because external stakeholders face greater difficulty in monitoring managers' operating decisions and assessing firms' underlying economic conditions. To investigate this issue, the sample is partitioned into subsamples using two alternative proxies for information asymmetry. With both measures, the positive relationship between REM and future crash risk appears in the high information asymmetry group but not in the low information asymmetry group. This result is consistent with information asymmetry making this relation stronger by enabling managers to conceal negative information through real operating activities for longer periods.

This paper makes three contributions. First, to the best of my knowledge, this is the first empirical study to connect REM with stock price crash risk using Borsa Istanbul data (2005–2024). Turkey's capital market differs significantly from the U.S. capital market in terms of depth, reporting standards, and liquidity. While REM research expanded after the Sarbanes–Oxley Act in the U.S., we still know very little about how it plays out in Turkish markets. Second, this paper adds valuable evidence to the literature on the consequences of REM, an area that has not received nearly as much attention as the causes of REM (Habib, Ranasinghe, Wu, Biswas, & Ahmad, 2022). Finally, this study extends prior research on the relationship between REM and stock price crash risk by factoring in firm overvaluation and information asymmetry, two critical dimensions that previous REM-crash risk studies have mostly overlooked.

The remainder of the paper is organized as follows. Section 2 reviews the existing research, and Section 3 develops the hypotheses. Section 4 describes the research design and methodology. Sections 5, 6, and 7 present the main results, robustness tests, and cross-sectional analyses, respectively. Section 8 discusses the findings and concludes.

2. Literature Review

The study draws on two related areas of research. The first examines the causes of stock price crashes. The second considers how REM is measured and what consequences it may have.

2.1. Stock Price Crash Risk

Research on crash risk generally starts with the idea that managers can delay the disclosure of firm-specific bad news. The main issue is therefore not only whether a firm performs poorly but also whether the firm's reporting and governance arrangements allow unfavorable information to accumulate before investors learn about it (Jin & Myers, 2006).

Hutton et al. (2009) find that opaque financial reporting is associated with higher future crash risk. Other studies link crash risk to CEO option incentives, tax avoidance, and CEO overconfidence, since these factors may affect a manager's incentive or ability to withhold bad news (Kim et al., 2011a, 2011b; Kim, Wang, & Zhang, 2016). In contrast, prior literature documents that mandatory IFRS adoption, accounting conservatism, dividend policy, audit quality, and board monitoring can restrict opacity or managerial discretion (Andreou et al., 2016; DeFond et al., 2015; Gul, Kim, & Qiu, 2010; Kim, Luo, & Xie, 2024; J. B. Kim & Zhang, 2016).

Crash risk is affected by a firm's financial reporting and earnings management practices. When accounting is aggressive or reporting quality is low, information asymmetry rises. This gives managers room to hide weakening performance for a while and increases the probability of sharp declines (Cohen, Cornett, Marcus, & Tehranian, 2014; Zhu, 2016). Subsequent studies show that abnormal operating decisions and real earnings smoothing can also mask poor results, push bad news further into the future, and leave the firm more exposed to crash events (Francis et al., 2016; Khurana et al., 2018). Overall, crash risk is expected to rise when information is opaque and monitoring is weak, and to decline when governance and reporting are stronger.

2.2. Real Earnings Management (REM)

Accrual-based earnings management changes accounting methods or estimates without directly altering operations. In contrast, REM changes actual business operations to meet reported earnings targets (Graham, Harvey, & Rajgopal, 2005; Roychowdhury, 2006). It involves offering substantial temporary

discounts or providing overly generous credit terms to boost sales, reducing necessary discretionary spending, or overproducing inventory to lower the cost of goods sold. These actions directly affect real cash flows and daily operations, and outsiders may find it difficult to distinguish them from ordinary business decisions.

Prior research examines the determinants and consequences of REM. Many firms started to rely more heavily on REM after the Sarbanes-Oxley Act made accounting rules much stricter (Cohen et al., 2008). In addition, REM is preferred before seasoned equity offerings (SEOs), even though this kind of short-term manipulation often damages a company's performance in the long run (Cohen & Zarowin, 2010). Managers choose between accrual and real manipulation depending on the cost and risk of the method (Zang, 2012). Even though Gunny (2010) argues that managers might occasionally use REM to meet benchmarks to signal favorable private information, many studies point to negative long-term consequences. For instance, aggressive REM usually leads to sharp performance drops (Vorst, 2016). It also increases information risk, which increases the firm's cost of equity (Kim & Sohn, 2013). The negative consequences of REM also extend to debt markets in the form of lower credit ratings and a higher cost of debt (Kim, Lee, & Yoo, 2020), alongside higher interest spreads, shorter maturities, and more restrictive covenants (Pappas, Walsh, & Xu, 2019). REM has also been associated with lower firm valuation (Mellado-Cid, Jory, & Ngo, 2018).

REM becomes more prevalent when firms face intense external monitoring. When high audit quality or long auditor tenure makes it too difficult to manage earnings using accruals, managers switch to real operating manipulation (Chi, Lisic, & Pevzner, 2011). At the same time, auditors view REM as a significant audit risk, which results in more audit adjustments (Commerford, Hatfield, & Houston, 2018) and higher audit fees (Choi, Choi, & Sohn, 2018; Choi, Lee, Park, & Sohn, 2022).

Finally, existing literature confirms that REM widens the information gap between insiders and outsiders (Abad et al., 2018) and significantly increases the risk of a future stock price crash (Francis et al., 2016; Khurana et al., 2018). Prior research also suggests that certain forms of institutional ownership can discourage myopic reductions in R&D, while stronger internal governance can constrain REM (Bushee, 1998; Cheng, Lee, & Shevlin, 2016).

Taken together, REM carries important consequences for firms' future performance, financing costs, audit outcomes, and market perceptions since it is an important tool managers use to influence reported earnings. The literature shows that REM is affected by regulatory, financing, audit, and governance factors.

3. Hypothesis Development

3.1. REM and Future Stock Price Crash Risk

There are several forms of income-increasing REM. First, a firm can offer discounts or grant easier credit terms to increase current sales, although this may lower cash flow relative to sales. Second, reducing R&D or SG&A to lower current expenses increases current-period income, although these expenditures may provide benefits in later periods. Third, another form involves overproducing. Producing more units spreads fixed overhead over a larger quantity and reduces reported cost per unit, but it also increases inventory. Although these decisions work in different ways, each can create a gap between current reported earnings and sustainable operating performance (Gunny, 2010; Roychowdhury, 2006).

It is difficult for investors to identify the motivation behind these decisions because each action can also have a valid business explanation. A sales promotion, a production increase, or a reduction in spending is part of normal operations and may attract less attention than a visible accounting adjustment (Cohen & Zarowin, 2010; Kothari, Mizik, & Roychowdhury, 2016; Zang, 2012). As a result, REM may make current earnings less useful for assessing future cash flows and may increase information asymmetry (Abad et al., 2018).

The bad-news-hoarding argument connects this problem to crash risk. Managers who benefit from delaying bad news may be able to keep it private for longer when the firm's operating and reporting environment is less transparent (Bao, Kim, Mian, & Su, 2019; Jin & Myers, 2006; Kothari, Shu, & Wysocki, 2009). REM may support reported earnings for a period even when the firm's economic

condition is becoming weaker. This process cannot continue indefinitely. If bad news builds up faster than it is disclosed, its eventual release may cause a sudden downward adjustment in the share price. I therefore test the following hypothesis:

H1: Real earnings management is positively associated with future stock price crash risk.

3.2. The Moderating Role of Firm Overvaluation

Firm overvaluation may strengthen the association between REM and future stock price crash risk by increasing managers' incentives to preserve prevailing market expectations. When a firm's market value exceeds the level supported by its underlying fundamentals, the disclosure of unfavorable information may lead to a substantial valuation correction. Managers of overvalued firms may therefore face greater pressure to maintain reported performance and postpone the recognition of deteriorating economic conditions (Jensen, 2005).

Prior research shows that overvalued firms engage in more income-increasing earnings management and may rely on real operating activities to sustain reported earnings when existing fundamentals do not support the firm's market valuation (Badertscher, 2011; Chi & Gupta, 2009). Because REM is embedded in production, sales, and expenditure decisions, it may make weak operating performance more difficult for outside investors to identify. If unfavorable information continues to accumulate while managers attempt to maintain an inflated valuation, its eventual disclosure may produce a more abrupt downward price adjustment. Accordingly, I propose the following hypothesis:

H2: The positive association between real earnings management and future stock price crash risk is stronger among firms with higher levels of overvaluation.

3.3. The Moderating Role of Information Asymmetry

Information asymmetry may strengthen the REM–crash-risk association by making abnormal operating activities more difficult for outside investors to evaluate. When firm-specific information is limited, investors and other external stakeholders have greater difficulty distinguishing opportunistic operating decisions from legitimate commercial responses. This weaker information environment reduces the effectiveness of external monitoring and provides managers with greater scope to postpone the disclosure of unfavorable information (Hutton et al., 2009; Jin & Myers, 2006).

REM may be particularly difficult to identify in such settings because price discounts, changes in production, and reductions in discretionary expenditures occur within the firm's ordinary operations. Prior research also shows that REM increases the information gap between corporate insiders and outside investors (Abad et al., 2018). Consequently, when information asymmetry is high, REM may enable adverse firm-specific information to remain concealed for longer. The eventual disclosure of the accumulated information may then result in a more severe price adjustment. Accordingly, I propose the following hypothesis:

H3: The positive association between real earnings management and future stock price crash risk is stronger among firms with greater information asymmetry.

4. Research Design

4.1. Sample

I construct a sample of 2,839 firm-year observations for companies listed on Borsa Istanbul from 2005 to 2024. Accounting and stock-return data are obtained from Compustat Global, while market-index returns are taken from Equity RT. I exclude financial firms and regulated utilities because their leverage, investment, and reporting structures differ from those of other firms. I also require at least 26 weekly return observations for each firm-year, as is common in the crash-risk literature (Chen, Ma, Wu, & Zhang, 2024; Hutton et al., 2009; Kim, Wang, & Zhang, 2019; Mamun, Balachandran, & Duong, 2020). Panel A of Table 1 summarizes the sample development.

Table 1. Sample Development and Descriptive Statistics**Panel A. Sample Development**

Sample-selection criterion	Firm-year observations
All Compustat Global firm-year observations, 2005–2024	5,652
Excluding firm-year observations:	
Financial firms and regulated utilities	193
Missing values required to calculate REM	2,536
Missing values required to calculate control variables	69
Incomplete one-year-ahead stock price crash-risk data (fewer than 26 weekly return observations)	15
Final sample	2,839

Panel B. Descriptive Statistics of the Variables Used in the Study

Variable	N	Mean	Std. Dev.	Q1	Median	Q3
$NCSKEW_{i,t+1}$	2,839	-0.43879	0.901686	-0.89859	-0.4383	0.019308
$DUVOL_{i,t+1}$	2,839	-0.27974	0.38916	-0.53175	-0.29676	-0.04072
$REM_{i,t}$	2,839	-0.0016	0.285483	-0.11426	0.007349	0.117289
$ABSDACC_{i,t}$	2,839	0.108574	0.134417	0.031276	0.072948	0.137679
$DTURN_{i,t}$	2,839	-0.00999	0.891534	-0.09979	-0.00397	0.067216
$RET_{i,t}$	2,839	-0.2398	0.81873	-0.24518	-0.1263	-0.06865
$SIGMA_{i,t}$	2,839	0.058395	0.037	0.037315	0.05054	0.070029
$MB_{i,t}$	2,839	2.365834	24.31107	0.223261	0.756471	1.91419
$SIZE_{i,t}$	2,839	5.40832	2.64552	3.551598	5.446963	7.253343
$ROA_{i,t}$	2,839	0.075331	0.257745	-0.00785	0.049851	0.125158
$LEV_{i,t}$	2,839	0.525878	0.4245	0.303842	0.502554	0.690379
$NCSKEW_{i,t}$	2,839	-0.42254	0.924729	-0.88609	-0.42738	0.045249

Notes: Panel A summarizes the sample development, and Panel B reports descriptive statistics for all variables used in the study.

4.2. Variable Measurement**4.2.1. Measuring Crash Risk**

I use two continuous measures of crash risk, both based on the asymmetry of firm-specific weekly returns: negative conditional skewness (NCSKEW) and down-to-up volatility (DUVOL). Following Chen, Hong, and Stein (2001), Hutton et al. (2009), and Kim et al. (2011a, 2011b), I first estimate an expanded market model.

Throughout the manuscript, i indexes firms, j indexes Fama-French 48 industries, t indexes fiscal years, τ indexes weeks within fiscal year t , and k indexes control variables.

$$r_{i,\tau} = \beta_{0i} + \beta_{1i}r_{m,\tau-2} + \beta_{2i}r_{m,\tau-1} + \beta_{3i}r_{m,\tau} + \beta_{4i}r_{m,\tau+1} + \beta_{5i}r_{m,\tau+2} + \varepsilon_{i,\tau} \quad (1)$$

where $r_{i,\tau}$ is the weekly return on the shares of firm i in week τ , and $r_{m,\tau}$ is the weekly return on the BIST All Shares Index (XUTUM), obtained from Equity RT. Stock returns are calculated from adjusted closing prices that account for stock splits and cash dividends. The index is market-capitalization weighted. The inclusion of two leads and two lags of the market return accounts for nonsynchronous trading. Firm-years are retained when at least 26 usable weekly observations remain after matching firm returns with the contemporaneous, lead, and lagged market returns. Firm-specific weekly returns are then calculated as:

$$W_{i,\tau} = \ln(1 + \varepsilon_{i,\tau})$$

where $\varepsilon_{i,\tau}$ is the residual obtained from Equation (1).

The first measure is negative conditional skewness (NCSKEW). It is based on the negative third moment of firm-specific weekly returns, scaled by the cubed standard deviation and adjusted for sample size.

$$NCSKEW_{i,t} = - [n(n-1)^{3/2} \sum W_{i,\tau}^3] / [(n-1)(n-2)(\sum W_{i,\tau}^2)^{3/2}] \quad (2)$$

where n is the number of available weekly firm-specific returns for firm i in year t . The negative sign is used so that a higher value of NCSKEW indicates greater negative skewness and therefore greater crash risk.

The second measure is down-to-up volatility (DUVOL). It compares the variation in firm-specific returns during weeks below the annual mean with the variation during weeks above the mean (Chen et al., 2001; Jin & Myers, 2006).

To calculate DUVOL, I divide the weekly firm-specific returns into down and up weeks. A week is classified as a down week when $W_{i,\tau}$ is below the annual mean firm-specific return and as an up week when it is equal to or above the annual mean. DUVOL is calculated as:

$$DUVOL_{i,t} = \ln \{ [(nu-1) \sum_{down} W_{i,\tau}^2] / [(nd-1) \sum_{up} W_{i,\tau}^2] \} \quad (3)$$

where nu and nd are the number of up and down weeks in year t , respectively. A higher DUVOL value indicates that the variation in firm-specific returns is greater during down weeks than during up weeks and therefore represents greater downside asymmetry.

4.2.2. Measuring Real Earnings Management

I estimate REM from the three residual models proposed by Roychowdhury (2006). These models produce measures of abnormal cash flow from operations, abnormal discretionary expenditures, and abnormal production costs.

Each measure captures a different pattern in operating activity. The first type of REM is sales manipulation. Managers may attempt to boost current-period sales by offering temporary discounts or extending more favorable credit terms to customers. While such actions can increase reported revenue, they often lead to lower operating cash flows during the same period. A second approach involves reducing discretionary expenditures. Companies can cut spending on research and development (R&D), advertising, or selling, general, and administrative (SG&A) activities to improve reported earnings in the short run. The third type relates to production decisions. Firms may produce more goods than needed to spread fixed overhead costs across a larger number of units and reduce the reported cost of goods sold, thereby temporarily increasing reported earnings.

First, I estimate normal cash flow from operations (CFO) as a function of current sales and the change in sales. All flow variables are scaled by total assets at the beginning of the year:

$$\frac{CFO_{i,t}}{A_{i,t-1}} = \beta_0 + \beta_1 \frac{1}{A_{i,t-1}} + \beta_2 \frac{S_{i,t}}{A_{i,t-1}} + \beta_3 \frac{\Delta S_{i,t}}{A_{i,t-1}} + \varepsilon_{i,t} \quad (4)$$

In Equation (4), A is total assets at the end of the previous fiscal year, S is sales, and the change in S is the annual change in sales. ABCFO is the difference between actual CFO and the value predicted by the industry-year model.

The second REM proxy is based on discretionary expenditures (DISEXP), defined as the combined value of R&D expenditures and SG&A expenses¹. I estimate their normal level using sales in the previous year:

$$\frac{DISEXP_{i,t}}{A_{i,t-1}} = \beta_0 + \beta_1 \frac{1}{A_{i,t-1}} + \beta_2 \frac{S_{i,t-1}}{A_{i,t-1}} + \varepsilon_{i,t} \quad (5)$$

The residual from Equation (5), ABDISEXP, is the difference between reported discretionary expenditures and the amount predicted by the model.

Production costs (PROD) are defined as cost of goods sold plus the change in inventory. I estimate normal production costs using current sales, the current change in sales, and the lagged change in sales:

$$\frac{PROD_{i,t}}{A_{i,t-1}} = \beta_0 + \beta_1 \frac{1}{A_{i,t-1}} + \beta_2 \frac{S_{i,t}}{A_{i,t-1}} + \beta_3 \frac{\Delta S_{i,t}}{A_{i,t-1}} + \beta_4 \frac{\Delta S_{i,t-1}}{A_{i,t-1}} + \varepsilon_{i,t} \quad (6)$$

ABPROD is the residual from Equation (6). A positive value means that production costs are higher than the level predicted from the firm's sales activity.

Firms are assigned to the Fama–French 48 industries using their primary four-digit SIC codes reported in Compustat Global and the standard Fama–French SIC-code mapping. Consistent with the cross-sectional approach adopted in prior REM studies (Cheng et al., 2016; Francis et al., 2016; Kim et al., 2021; Roychowdhury, 2006; Wang, Fang, Hu, & Huang, 2025; Zang, 2012), I estimate Equations (4)–(6) separately for each fiscal-year–industry cell. Each equation is estimated only for cells containing at least eight observations with complete data for the respective model. Appendix Table A1 reports the number and size distribution of the eligible industry-year cells.

The overall measure is calculated as $REM = ABPROD - ABDISEXP - ABCFO$. I multiply ABCFO and ABDISEXP by minus one so that all three components have the same direction. A larger REM value therefore represents a higher level of income-increasing abnormal real activity since higher abnormal production costs combined with lower abnormal discretionary expenditures and lower abnormal operating cash flows are indicative of income-increasing REM (Abad et al., 2018; Badertscher, 2011; Cohen et al., 2008; Cohen & Zarowin, 2010; Ge & Kim, 2014; Kim et al., 2021; Lin & Zheng, 2026; Zang, 2012).

4.3. Research Design

For the baseline analysis, I regress each crash-risk measure in year $t+1$ on REM and the control variables measured in year t . Industry fixed effects control for persistent differences across industries, while year fixed effects capture shocks that affect Borsa Istanbul firms in the same year. I use heteroskedasticity-robust standard errors clustered by firm. The baseline model and the definitions of the control variables are specified below:

$$CRASH_{i,t+1} = \beta_0 + \beta_1 REM_{i,t} + \sum_{k=1}^K \gamma_k CONTROL_{k,i,t} + \delta_j + \lambda_t + \varepsilon_{i,t+1} \quad (7)$$

In Equation (7), CRASH denotes either NCSKEW or DUVOL, δ_j and λ_t represent industry and year fixed effects, respectively, and k indexes the control variables.

$ABSDACC_{it}$	Absolute discretionary accruals estimated with the modified Jones model.
$DTURN_{it}$	Change in average monthly share turnover from year $t-1$ to year t ; monthly turnover equals trading volume divided by month-end shares outstanding.
RET_{it}	Mean firm-specific weekly return during year t , multiplied by 100.
$SIGMA_{it}$	Standard deviation of firm-specific weekly returns during year t .
MB_{it}	Market value of equity divided by book value of equity.
$SIZE_{it}$	Natural logarithm of the market value of equity.
ROA_{it}	Net income before extraordinary items divided by beginning total assets.
LEV_{it}	Total liabilities divided by total assets.

5. Results

5.1. Descriptive Statistics

Panel B of Table 1 presents the descriptive statistics. The mean and median values of NCSKEW are -0.439 and -0.438 , respectively, while the corresponding values for DUVOL are -0.280 and -0.297 . These values are broadly comparable with those reported in earlier Borsa Istanbul studies (Canbaloglu, Alp, & Gurgun, 2022; Toksoz, 2024) but are lower than the averages reported in some U.S. samples.

The difference should be interpreted cautiously. One potentially relevant institutional feature is Borsa Istanbul's use of daily price limits and stock-specific and market-wide circuit breakers, which may affect the timing with which large price adjustments are incorporated into observed returns. However, evidence from Borsa Istanbul suggests that price limits may increase and prolong volatility and delay price discovery following both upper- and lower-limit events (Danışoğlu & Güner, 2018).

Differences in sample composition, sample periods, liquidity, and model implementation may also contribute to the observed cross-country differences.

REM has a mean of -0.002 and a median of 0.007. A mean close to zero is expected because the three components of REM are estimated from cross-sectional residual models.

5.2. Baseline Results: The Association Between Real Earnings Management and Crash Risk

Table 2 reports the baseline results. The coefficient on REM is 0.24 in the NCSKEW regression ($t = 3.18$) and 0.10 in the DUVOL regression ($t = 3.42$). The significantly positive coefficients on REM in both columns indicate that aggressive real earnings management is associated with greater future crash risk.

Table 2. Association between Real Earnings Management and Future Stock Price Crash Risk

	NCSKEW _{i,t+1}	DUVOL _{i,t+1}
REM _{i,t}	0.24 3.18***	0.10 3.42***
ABSDACC _{i,t}	0.0702 0.63	0.0141 0.29
DTURN _{i,t}	0.00865 0.8	0.00637 1.45
RET _{i,t}	0.000704 0.03	-0.0101 -0.76
SIGMA _{i,t}	1.258 1.35	0.115 0.29
MB _{i,t}	-0.00066 -0.9	-0.000343 -1.06
SIZE _{i,t}	0.0426 4.58***	0.0201 4.87***
ROA _{i,t}	0.356 2.40**	0.108 2.69***
LEV _{i,t}	0.0306 0.83	0.0169 0.89
NCSKEW _{i,t}	0.0723 3.00***	0.0324 3.50***
Constant	-0.493 -2.40**	-0.327 -3.44***
Year FE	Yes	Yes
Industry FE	Yes	Yes
Observations	2,839	2,839
Adj. R ²	0.043	0.056

Notes: t-statistics are reported below the coefficients. Robust standard errors are clustered by firm. *, **, and *** indicate two-tailed statistical significance at the 10%, 5%, and 1% levels, respectively.

To evaluate the economic magnitude of these associations, I calculate the change in each crash-risk measure, expressed in standard-deviation units, associated with a one-standard-deviation increase in REM. Specifically, the standardized effect is calculated as $\beta_{\text{REM}} \times \text{SD}(\text{REM})/\text{SD}(Y)$, where Y denotes the relevant crash-risk measure. All economic magnitudes and confidence intervals are calculated using the unrounded regression estimates.

A one-standard-deviation increase in REM is associated with an approximate 0.075 standard-deviation increase in NCSKEW (95% confidence interval: (0.0287237, 0.1218926)) and an approximate 0.074 standard-deviation increase in DUVOL (95% confidence interval: (0.03122, 0.1158742))ⁱⁱ.

Among the controls, SIZE, ROA, and lagged NCSKEW are positive and significant in both regressions, consistent with the established crash-risk literature. The remaining controls are not statistically significant in the baseline specifications. Collectively, the findings document a significant positive relation between REM and subsequent stock price crash risk after controlling for a comprehensive set of firm-level characteristics as well as industry and year fixed effects. The sign is consistent with the proposed view that unusually aggressive operating choices may make current performance less transparent and allow adverse information to accumulate.

6. Robustness Tests

6.1. Alternative Measures of Crash Risk and Real Earnings Management

In Table 3, I replace NCSKEW and DUVOL with COUNT and EXTRASIGMA. COUNT is widely utilized in the literature (An & Zhang, 2013; Bao et al., 2019; Callen & Fang, 2013, 2015; Chen, Kim, & Yao, 2017; Hong, Kim, & Welker, 2017; Jin & Myers, 2006; Khurana et al., 2018).

COUNT is defined as the difference between the count of stock price crash weeks and the count of stock price jump weeks for firm i in year t . A crash week (jump week) is identified as a week during which the firm-specific weekly return falls more than 3.09 standard deviations below (rises more than 3.09 standard deviations above) the firm's mean weekly return in year t .

EXTRASIGMA measures how far the firm's most negative weekly return is from its annual mean, relative to its annual standard deviation. I multiply the measure by minus one so that higher values represent greater downside tail risk (Andreou, Louca, & Petrou, 2017; Bradshaw, Hutton, Marcus, & Tehranian, 2010; Hasan, Taylor, & Richardson, 2022; Hong et al., 2017). Specifically, it is measured as follows:

$$EXTRASIGMA_{i,t} = -\min_{\tau \in t} \left[\frac{W_{i,\tau} - \bar{W}_{i,t}}{\sigma_{W,i,t}} \right] \quad (8)$$

where $W_{i,\tau} = \ln(1 + \hat{\varepsilon}_{i,\tau})$ is the firm-specific weekly return for firm i in week τ ; $\bar{W}_{i,t}$ is the mean of the firm-specific weekly returns for firm i during fiscal year t ; and $\sigma_{W,i,t}$ is the corresponding annual standard deviation. The negative sign is applied so that larger EXTRASIGMA values indicate greater downside tail risk.

The REM coefficient remains positive in both columns of Table 3. It is significant at the 5% level for COUNT and at the 10% level for EXTRASIGMA. These findings show that the main results are robust to alternative definitions of future crash risk.

Table 3. Alternative Dependent Variables

	COUNT _{i,t+1}	EXTRASIGMA _{i,t+1}
<i>REM_{i,t}</i>	0.11 2.11**	0.11 1.96*
<i>ABSDACC_{i,t}</i>	0.0475 0.48	0.0392 0.37
<i>DTURN_{i,t}</i>	0.0238 2.89***	0.00888 1.19
<i>RET_{i,t}</i>	-0.0147 -0.68	0.0563 2.65***
<i>SIGMA_{i,t}</i>	-0.0352 -0.05	2.442 3.46***
<i>MB_{i,t}</i>	0.000722 2.05**	-0.000147 -0.26
<i>SIZE_{i,t}</i>	0.0331 4.25***	0.00595 0.89
<i>ROA_{i,t}</i>	0.167 3.92***	0.184 1.5
<i>LEV_{i,t}</i>	-0.00403 -0.15	0.0162 0.53
<i>NCSKEW_{i,t}</i>	0.0405 2.43**	0.013 0.75
Constant	-0.332 -2.21**	2.268 11.46***
Year FE	Yes	Yes
Industry FE	Yes	Yes
Observations	2,839	2,839
Adj. R ²	0.021	0.031

Notes: t-statistics are reported below the coefficients. Robust standard errors are clustered by firm. *, **, and *** indicate two-tailed statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 4 uses an alternative rank-based measure of REM, following Kim and Sohn (2013), to reduce the effect of measurement error. Firms are first assigned to REM deciles each year, and these ranks are then rescaled between zero and one. RANK_REM is positive and significant in both the NCSKEW and DUVOL regressions. This suggests that the baseline result is not driven solely by extreme values or by the scale of the composite REM measure.

Table 4. Alternative REM Measure

	NCSKEW _{i,t+1}	DUVOL _{i,t+1}
<i>RANK_REM_{i,t}</i>	0.157 2.49**	0.0756 2.87***
<i>ABSDACC_{i,t}</i>	0.0945 0.81	0.0242 0.49
<i>DTURN_{i,t}</i>	0.00924 0.84	0.00661 1.48
<i>RET_{i,t}</i>	0.00111 0.04	-0.00999 -0.76
<i>SIGMA_{i,t}</i>	1.306 1.41	0.133 0.33
<i>MB_{i,t}</i>	-0.000593 -0.78	-0.000312 -0.96
<i>SIZE_{i,t}</i>	0.0424 4.53***	0.0201 4.85***
<i>ROA_{i,t}</i>	0.296 1.81*	0.0838 1.76*
<i>LEV_{i,t}</i>	0.00966 0.25	0.00857 0.42
<i>NCSKEW_{i,t}</i>	0.0728 3.02***	0.0325 3.52***
Constant	-0.564 -2.64***	-0.362 -3.68***
Year FE	Yes	Yes
Industry FE	Yes	Yes
Observations	2,839	2,839
Adj. R ²	0.041	0.054

Notes: t-statistics are reported below the coefficients. Robust standard errors are clustered by firm. *, **, and *** indicate two-tailed statistical significance at the 10%, 5%, and 1% levels, respectively.

6.2. Entropy-Balanced Sample

I employ entropy balancing as an additional robustness analysis to reduce observable differences between firm-year observations with relatively high and low REM. This method applies nonnegative weights to observations in the low-REM group so that the first two moments of the control variables match those of the high-REM group (Hainmueller, 2012). This procedure optimizes covariate balance while retaining the full treatment sample in the analysis. Because the entropy-balancing procedure implemented in Stata requires a binary treatment indicator, I construct HIGH_REM separately within each industry-year group. HIGH_REM equals one if a firm-year observation has an REM value at or above the corresponding industry-year median and zero otherwise. The binary indicator is used solely to construct the entropy-balancing weights. High-REM observations form the target group, whereas low-REM observations are reweighted so that the prespecified moments of the balancing covariates match those of the high-REM group.

After constructing the weights, I re-estimate the baseline regressions using REM in its original continuous form. Retaining continuous REM preserves variation in the magnitude of REM within the high- and low-REM groups and facilitates comparison with the baseline estimates. Therefore, the coefficient on REM represents the weighted partial association between continuous REM and subsequent stock price crash risk in the entropy-balanced pseudo-sample.

Panel A of Table 5 shows that the weighting procedure produces very similar means and variances for the two groups. In Panel B, REM remains positive and significant for both crash-risk measures. This finding reinforces the baseline results, making it less likely that the main relationship is driven by reverse causality or omitted variable bias.

As an additional specification, I replace continuous REM with HIGH_REM in the weighted regressions. The positive and statistically significant coefficient on HIGH_REM in the untabulated results indicates that high-REM firm-year observations exhibit greater subsequent crash risk than observationally comparable low-REM observations.

Table 5. Entropy-Balancing Analysis

Panel A. Covariate Balance Before and After Entropy Balancing

Variable	High REM			Low REM		
	N	Mean	Variance	N	Mean	Variance
Before balancing						
<i>ABSDACC_{i,t}</i>	1,468	0.1087	0.01779	1,371	0.1085	0.01838
<i>DTURN_{i,t}</i>	1,468	-0.01355	0.5652	1,371	-0.00617	1.041
<i>RET_{i,t}</i>	1,468	-0.2469	0.6321	1,371	-0.2321	0.7117
<i>SIGMA_{i,t}</i>	1,468	0.05931	0.001469	1,371	0.05742	0.001261
<i>MB_{i,t}</i>	1,468	1.683	264	1,371	3.097	940.6
<i>SIZE_{i,t}</i>	1,468	5.197	6.503	1,371	5.635	7.436
<i>ROA_{i,t}</i>	1,468	0.05169	0.07349	1,371	0.1006	0.05769
<i>LEV_{i,t}</i>	1,468	0.5203	0.1117	1,371	0.5319	0.2536
<i>NCSKEW_{i,t}</i>	1,468	-0.4128	0.832	1,371	-0.433	0.8803
After balancing						
<i>ABSDACC_{i,t}</i>	1,468	0.1087	0.01779	1,371	0.1088	0.01785
<i>DTURN_{i,t}</i>	1,468	-0.01355	0.5652	1,371	-0.01356	0.5652
<i>RET_{i,t}</i>	1,468	-0.2469	0.6321	1,371	-0.247	0.632
<i>SIGMA_{i,t}</i>	1,468	0.05931	0.001469	1,371	0.05931	0.001469
<i>MB_{i,t}</i>	1,468	1.683	264	1,371	1.683	264
<i>SIZE_{i,t}</i>	1,468	5.197	6.503	1,371	5.197	6.504
<i>ROA_{i,t}</i>	1,468	0.05169	0.07349	1,371	0.05159	0.07363
<i>LEV_{i,t}</i>	1,468	0.5203	0.1117	1,371	0.5207	0.113
<i>NCSKEW_{i,t}</i>	1,468	-0.4128	0.832	1,371	-0.4128	0.8319

Notes: High-REM observations form the target group. Low-REM observations are reweighted so that the first two moments of the balancing covariates match those of the high-REM group.

Panel B. Entropy-Balanced Regression Results

	NCSKEW _{i,t+1}	DUVOL _{i,t+1}
REM _{i,t}	0.226 3.01***	0.104 3.47***
ABSDACC _{i,t}	0.108 0.91	0.00556 0.1
DTURN _{i,t}	0.00438 0.28	0.00555 0.81
RET _{i,t}	-0.0371 -0.91	-0.023 -1.45
SIGMA _{i,t}	1.728 1.63	0.313 0.69
MB _{i,t}	0.0000102 0.01	-0.000141 -0.69
SIZE _{i,t}	0.0465 4.80***	0.0214 5.05***
ROA _{i,t}	0.309 2.29**	0.102 2.89***
LEV _{i,t}	-0.00293 -0.06	0.00572 0.26
NCSKEW _{i,t}	0.063 2.46**	0.0287 2.90***
Constant	-0.409 -1.57	-0.281 -2.37**
Year FE	Yes	Yes
Industry FE	Yes	Yes
Observations	2,839	2,839
Adj. R ²	0.053	0.064

Notes: t-statistics are reported below the coefficients. Robust standard errors are clustered by firm. *, **, and *** indicate two-tailed statistical significance at the 10%, 5%, and 1% levels, respectively.

6.3. First-Difference Specification

I use a first-difference specification to examine whether within-firm changes in REM are associated with subsequent changes in stock price crash risk. For each crash-risk measure, the dependent variable is calculated as:

$$\text{CHANGE_CRASH}_{i,t+1} = \text{CRASH}_{i,t+1} - \text{CRASH}_{i,t}$$

where CRASH represents either NCSKEW or DUVOL.

REM and each control variable are differenced between years t-1 and t:

$$\text{CHANGE_X}_{i,t} = X_{i,t} - X_{i,t-1}$$

where X represents REM, ABSDACC, DTURN, RET, SIGMA, MB, SIZE, ROA, LEV, or NCSKEW. Accordingly, CHANGE_REM_{i,t} captures the change in REM from t-1 to t, while the dependent variable captures the subsequent change in crash risk from t to t+1. Because DTURN is itself defined as the annual change in average monthly share turnover, CHANGE_DTURN_{i,t} represents the year-over-year change in DTURN.

First-differencing removes time-invariant firm-specific characteristics. Industry fixed effects are retained to allow average year-over-year changes in crash risk to differ systematically across industries, while year fixed effects control for common annual shocks affecting all firms. Thus, the industry fixed effects in the differenced specification capture differences in industry-specific changes rather than time-invariant differences in the levels of crash risk.

For these tests, I begin with the original pooled sample of 2,839 firm-year observations. The first-difference specification requires consecutive firm-year observations to calculate year-over-year changes. Consequently, 272 observations without the required immediately preceding firm-year information are excluded, resulting in a first-difference sample of 2,567 observations. Table 6 shows that $\Delta \text{CHANGE_REM}$ is positive and statistically significant for both ΔNCSKEW and ΔDUVOL , indicating that increases in REM are associated with subsequent increases in stock price crash risk.

Table 6. First-Difference Specification

	$\Delta \text{NCSKEW}_{i,t+1}$	$\Delta \text{DUVOL}_{i,t+1}$
$\text{CHANGE_REM}_{i,t}$	0.23 2.54**	0.09 2.62***
$\text{CHANGE_ABSDACC}_{i,t}$	0.118 0.9	0.0221 0.36
$\text{CHANGE_DTURN}_{i,t}$	-0.00623 -0.56	0.000423 0.08
$\text{CHANGE_RET}_{i,t}$	0.0499 1.49	0.026 1.48
$\text{CHANGE_SIGMA}_{i,t}$	2.938 2.76***	1.558 3.20***
$\text{CHANGE_MB}_{i,t}$	-0.0000683 -0.22	-0.0000212 -0.15
$\text{CHANGE_SIZE}_{i,t}$	0.00000027 0.41	0.000000169 0.66
$\text{CHANGE_ROA}_{i,t}$	0.343 2.45**	0.0973 3.10***
$\text{CHANGE_LEV}_{i,t}$	-0.039 -0.74	-0.0154 -0.55
$\text{CHANGE_NCSKEW}_{i,t}$	-0.458 -26.15***	-0.184 -22.30***
Constant	-0.141 -0.41	-0.206 -1.2
Year FE	Yes	Yes
Industry FE	Yes	Yes
Observations	2,567	2,567
Adj. R ²	0.255	0.236

Notes: t-statistics are reported below the coefficients. Robust standard errors are clustered by firm. *, **, and *** indicate two-tailed statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix Table A2 reports the between-firm and within-firm standard deviations of all variables used in the analysis. REM exhibits variation both across firms and within firms over time, with between-firm and within-firm standard deviations of 0.248 and 0.216, respectively. The corresponding standard deviations are 0.508 and 0.831 for NCSKEW and 0.226 and 0.356 for DUVOL.

6.4. Firm Fixed Effects

In Table 7, I estimate the baseline model with firm and year fixed effects. The model uses variation within the same firm and controls for all observed and unobserved firm characteristics that remain constant over time and may simultaneously influence both REM practices and future stock price crash risk. REM remains positive and significant at the 5% level in both the NCSKEW and DUVOL regressions. The baseline relation is therefore not limited to permanent differences across firms and is unlikely to be explained by omitted firm characteristics correlated with both REM and future crash risk.

Table 7. Firm Fixed-Effects Specification

	NCSKEW _{i,t+1}	DUVOL _{i,t+1}
<i>REM_{i,t}</i>	0.20 2.16**	0.08 2.15**
<i>ABSDACC_{i,t}</i>	0.109 0.93	0.0256 0.48
<i>DTURN_{i,t}</i>	0.00181 0.15	0.00318 0.7
<i>RET_{i,t}</i>	-0.00673 -0.2	-0.00794 -0.5
<i>SIGMA_{i,t}</i>	1.194 1.04	0.278 0.57
<i>MB_{i,t}</i>	-0.000374 -0.57	-0.0000931 -0.43
<i>SIZE_{i,t}</i>	0.137 5.14***	0.0623 6.01***
<i>ROA_{i,t}</i>	0.341 2.03**	0.0941 2.06**
<i>LEV_{i,t}</i>	0.0381 0.59	0.0201 0.62
<i>NCSKEW_{i,t}</i>	-0.0369 -1.54	-0.0142 -1.52
Constant	-0.682 -2.89***	-0.437 -4.20***
Year FE	Yes	Yes
Firm FE	Yes	Yes
Observations	2,839	2,839
Adj. R ²	0.048	0.061

Notes: t-statistics are reported below the coefficients. Robust standard errors are clustered by firm. *, **, and *** indicate two-tailed statistical significance at the 10%, 5%, and 1% levels, respectively.

7. Results for the Moderating Role of Firm Overvaluation (H2) and the Moderating Role of Information Environment (H3)

This section tests whether the baseline REM–crash-risk association varies with firm overvaluation and information asymmetry. H2 predicts that the positive association is stronger among overvalued firms because managers face greater pressure to preserve elevated market valuations. H3 predicts that the association is stronger when information asymmetry is greater because outsiders have more difficulty evaluating abnormal operating decisions. Table 8 tests H2 using Tobin's Q and residual valuation, while Table 9 tests H3 using the Amihud and Florackis illiquidity measures.

7.1. The Moderating Role of Firm Overvaluation

To test H2, I use two measures of firm valuation: Tobin's Q and the residual valuation component developed by Rhodes-Kropf, Robinson, and Viswanathan (2005). For each measure, firms at or above the industry-year median are assigned to the high valuation group, while those below the median form the low valuation group (Adebambo & Yan, 2018; J. D. Chi & Gupta, 2009; Dumitrescu & Zakriya, 2021).

Tobin's Q is calculated as the market value of assets divided by the book value of assets. The market value of assets equals book assets plus market equity, minus book equity and deferred taxes. This measure captures both market valuation and growth opportunities and is widely used in earlier research (Bebchuk, Cohen, & Ferrell, 2009; Dumitrescu & Zakriya, 2021; Wu & Suardi, 2025). Panel A of Table 8 presents the results for the high and low Tobin's Q groups formed at the industry-year median. In the high Tobin's Q group, REM is positive and significant for NCSKEW and DUVOL. The coefficients are not significant in the low Tobin's Q group. Tests based on seemingly unrelated regressions show that the REM coefficients differ significantly across the two groups for both crash-risk measures.

The second measure, RRV, comes from the valuation model of Rhodes-Kropf et al. (2005). The model relates market value to book value, net income, and leverageⁱⁱⁱ. RRV is the component of market value that is not explained by the industry valuation relation and is used as a measure of firm-specific misvaluation.

To construct RRV, I estimate the following valuation model separately for each fiscal year and Fama-French 48 industry:

$$M_{i,t} = \beta_0 + \beta_1 B_{i,t} + \beta_2 N_{i,t} + \beta_3 DNEG N_{i,t} * N_{i,t} + \beta_4 LEV_{i,t} + \varepsilon_{it} \quad (9)$$

where M is the natural logarithm of market value, B is the natural logarithm of book value, N is the natural logarithm of the absolute value of net income, $DNEG$ is an indicator function for negative net income observations, and LEV is the leverage ratio. Consistent with the REM estimation procedure, each industry-year regression requires at least eight valid observations. RRV is the firm-year residual from this equation.

RRV measures the component of a firm's market valuation that is not explained by its book value, net income, and leverage relative to other firms in the same industry and year. A positive RRV indicates that observed market value exceeds the value implied by the industry-year valuation model, whereas a negative value indicates the opposite. Firm-year observations with RRV at or above the corresponding industry-year median are assigned to the high-RRV group, while those below the median form the low-RRV group.

Constructing RRV requires valid information for all variables included in Equation (9) and an estimable industry-year valuation model. Of the 2,839 observations in the baseline sample, 208 observations are excluded because of missing data for variables in Equation (9) or an insufficient number of valid observations in the relevant industry-year cell. These exclusions reduce the RRV sample to 2,631 observations, consisting of 1,363 high-RRV and 1,268 low-RRV firm-years.

Panel B of Table 8 presents the results. In the high-RRV group, the REM coefficient is positive and significant for NCSKEW and DUVOL. Neither coefficient is significant in the low-RRV group. The difference between the group coefficients is significant at the 5% level for NCSKEW and at the 1% level for DUVOL.

The two valuation measures therefore give the same general picture. The significantly positive REM coefficient is concentrated among overvalued firms. This pattern is consistent with the idea that the pressure to maintain inflated market valuations and preserve the perception of strong corporate performance gives managers a stronger reason to delay bad news.

Table 8. Overvaluation and the Association between REM and Future Crash Risk**Panel A. Tobin's Q**

	NCSKEW _{i,t+1}		DUVOL _{i,t+1}	
	High Tobin's Q	Low Tobin's Q	High Tobin's Q	Low Tobin's Q
<i>REM_{i,t}</i>	0.38 3.83***	0.01 0.12	0.16 4.12***	0.02 0.49
<i>ABSDACC_{i,t}</i>	0.0598 0.38	0.219 1.25	0.0236 0.34	0.0572 0.72
<i>DTURN_{i,t}</i>	-0.0202 -0.33	0.0122 1.51	-0.00964 -0.42	0.00756 2.05**
<i>RET_{i,t}</i>	0.527 1.66*	0.00531 0.12	0.253 1.93*	-0.00462 -0.23
<i>SIGMA_{i,t}</i>	5.924 1.85*	1.586 1.09	2.475 1.86*	0.35 0.58
<i>MB_{i,t}</i>	-0.00074 -1.06	0.000224 0.22	-0.000347 -1.15	-0.000111 -0.28
<i>SIZE_{i,t}</i>	0.0604 4.01***	0.0308 2.34**	0.031 4.69***	0.0151 2.72***
<i>ROA_{i,t}</i>	0.436 2.57**	0.234 1.75*	0.132 2.77***	0.104 1.67*
<i>LEV_{i,t}</i>	0.0488 1.25	0.0552 0.45	0.0234 1.21	0.0731 1.35
<i>NCSKEW_{i,t}</i>	0.107 2.99***	0.0256 0.95	0.0406 3.09***	0.0196 1.69*
<i>Constant</i>	-0.954 -3.62***	-0.262 -0.85	-0.61 -4.76***	-0.192 -1.46
<i>Year FE</i>	Yes	Yes	Yes	Yes
<i>Industry FE</i>	Yes	Yes	Yes	Yes
<i>Observations</i>	1,468	1,371	1,468	1,371
<i>Adj. R²</i>	0.061	0.030	0.069	0.050
<i>Difference in REM (χ^2)</i>	7.67***		6.39**	

Panel B. Residual Valuation (RRV)

	NCSKEW _{i,t+1}		DUVOL _{i,t+1}	
	High RRV	Low RRV	High RRV	Low RRV
<i>REM_{i,t}</i>	0.41 3.69***	0.04 0.39	0.19 4.08***	0.01 0.23
<i>ABSDACC_{i,t}</i>	0.0731 0.43	0.139 0.72	0.0311 0.42	-0.006 -0.07
<i>DTURN_{i,t}</i>	0.0092 0.61	0.0138 0.36	0.00626 1	0.00941 0.58
<i>RET_{i,t}</i>	0.465 1.59	-0.0101 -0.22	0.198 1.70*	-0.0151 -0.7
<i>SIGMA_{i,t}</i>	5.117 1.68*	0.982 0.65	2.013 1.68*	0.139 0.21
<i>MB_{i,t}</i>	-0.000803 -1.06	0.00061 0.46	-0.000324 -1	-0.000607 -0.73
<i>SIZE_{i,t}</i>	0.0653 4.21***	0.0426 3.16***	0.0295 4.37***	0.0244 4.20***
<i>ROA_{i,t}</i>	0.268 2.58**	0.403 2.55**	0.113 2.26**	0.102 2.22**
<i>LEV_{i,t}</i>	0.0795 1.56	0.0166 0.35	0.0463 1.81*	0.00393 0.21
<i>NCSKEW_{i,t}</i>	0.0501 1.25	0.0857 2.43**	0.0246 1.56	0.0348 2.61***
<i>Constant</i>	-1.342 -4.05***	-0.388 -1.3	-0.687 -4.14***	-0.214 -1.55
<i>Year FE</i>	Yes	Yes	Yes	Yes
<i>Industry FE</i>	Yes	Yes	Yes	Yes
<i>Observations</i>	1,363	1,268	1,363	1,268
<i>Adj. R²</i>	0.042	0.045	0.061	0.054
<i>Difference in REM (χ^2)</i>	6.59**		9.32***	

Notes: t-statistics are reported below the coefficients. Robust standard errors are clustered by firm. *, **, and *** indicate two-tailed statistical significance at the 10%, 5%, and 1% levels, respectively. The χ^2 statistics test whether the REM coefficients differ between the high- and low-valuation subsamples.

7.2. The Moderating Role of Information Environment

To test H3, I use stock-market illiquidity as an observable proxy for information asymmetry. The first proxy is the Amihud (2002) measure, and the second is the price-impact measure developed by Florackis, Gregoriou, and Kostakis (2011).

The Amihud (2002) illiquidity measure is calculated as the annual average of the absolute daily stock return divided by daily trading value. A higher value means that a given amount of trading is associated with a larger price change and therefore indicates lower liquidity.

The price-impact measure of Florackis et al. (2011) replaces daily trading value with the daily turnover ratio and is also averaged over the year. As with the Amihud measure, a higher value indicates lower liquidity (Ellington, 2018; Florackis, Kontonikas, & Kostakis, 2014; Le & Gregoriou, 2022; Meles, Pellegrino, Salerno, & Verdoliva, 2026; Nasraoui, Ajina, & Kahloul, 2024; Piñeiro-Chousa, Šević, & González-López, 2023; Zhang & Gregoriou, 2019).

Panel A of Table 9 divides the sample at the industry-year median of Amihud illiquidity. In the high illiquidity group, REM is positive and significant for NCSKEW and DUVOL. The coefficients are not significant in the low illiquidity group. The differences between the two groups are significant at the 1% level for both outcomes. Panel B presents the results based on the Florackis measure. Again, REM is

positive and significant in the high illiquidity group for NCSKEW and DUVOL, but not in the low illiquidity group. The differences between the group coefficients are significant at the 5% level.

The results are therefore similar under both information asymmetry measures. The positive relation between REM and crash risk is concentrated among firms characterized by greater information asymmetry. This finding is consistent with the proposed role of information asymmetry, suggesting that opaque informational environments provide managers with greater opportunities to conceal unfavorable information and engage in bad-news-hoarding behavior through REM.

Table 9. Information Environment and the Association between REM and Future Crash Risk
Panel A. Amihud Illiquidity

	NCSKEW _{i,t+1}		DUVOL _{i,t+1}	
	Low	High	Low	High
<i>REM_{i,t}</i>	0.01 0.1	0.38 3.88***	0.01 0.15	0.16 4.41***
<i>ABSDACC_{i,t}</i>	0.293 1.25	-0.018 -0.12	0.0805 0.83	-0.0128 -0.19
<i>DTURN_{i,t}</i>	-0.0117 -0.31	0.0122 1.26	-0.00054 -0.03	0.00678 1.77*
<i>RET_{i,t}</i>	0.618 1.09	0.0237 0.7	0.288 1.24	-0.000102 -0.01
<i>SIGMA_{i,t}</i>	5.523 1.23	2.096 1.88*	2.348 1.25	0.51 1.1
<i>MB_{i,t}</i>	-0.00573 -1.95*	0.0000794 0.16	-0.00233 -2.28**	-0.0000288 -0.21
<i>SIZE_{i,t}</i>	0.0453 3.18***	0.0314 2.31**	0.02 3.18***	0.0128 2.34**
<i>ROA_{i,t}</i>	0.135 0.81	0.397 2.70***	0.0375 0.5	0.115 3.17***
<i>LEV_{i,t}</i>	-0.0181 -0.16	0.0529 1.49	-0.0173 -0.33	0.0262 1.37
<i>NCSKEW_{i,t}</i>	0.0346 1.16	0.1 2.85***	0.0208 1.6	0.0393 2.97***
<i>Constant</i>	-0.47 -1.98**	-0.637 -2.01**	-0.308 -3.11***	-0.403 -2.60***
<i>Year FE</i>	Yes	Yes	Yes	Yes
<i>Industry FE</i>	Yes	Yes	Yes	Yes
<i>Observations</i>	1,371	1,468	1,371	1,468
<i>Adj. R²</i>	0.030	0.062	0.042	0.074
<i>Difference in REM (χ^2)</i>	8.27***		8.93***	

Panel B. Florackis et al. (2011) Illiquidity Measure

	NCSKEW _{i,t+1}		DUVOL _{i,t+1}	
	Low	High	Low	High
<i>REM_{i,t}</i>	0.05 0.53	0.36 3.98***	0.02 0.45	0.15 4.31***
<i>ABSDACC_{i,t}</i>	0.262 1.12	0.0398 0.31	0.0745 0.74	0.00377 0.06
<i>DTURN_{i,t}</i>	-0.0183 -0.46	0.012 2.10**	-0.00837 -0.48	0.00769 3.20***
<i>RET_{i,t}</i>	0.502 0.93	-0.0187 -0.52	0.237 1.04	-0.0213 -1.31
<i>SIGMA_{i,t}</i>	6.381 1.45	0.585 0.47	2.846 1.52	-0.292 -0.57
<i>MB_{i,t}</i>	-0.000752 -1.17	-0.000575 -0.65	-0.0000565 -0.27	-0.000332 -0.89
<i>SIZE_{i,t}</i>	0.0499 3.99***	0.0438 3.08***	0.024 4.49***	0.0202 3.24***
<i>ROA_{i,t}</i>	0.0394 0.23	0.452 3.24***	0.0312 0.39	0.138 3.94***
<i>LEV_{i,t}</i>	0.077 0.81	0.0443 1.2	0.0501 1.11	0.0222 1.11
<i>NCSKEW_{i,t}</i>	0.0537 1.88*	0.0817 2.40**	0.0234 2.14**	0.0369 2.70***
<i>Constant</i>	-0.878 -3.17***	-0.333 -1.01	-0.546 -4.12***	-0.227 -1.55
<i>Year FE</i>	Yes	Yes	Yes	Yes
<i>Industry FE</i>	Yes	Yes	Yes	Yes
<i>Observations</i>	1,371	1,468	1,371	1,468
<i>Adj. R²</i>	0.021	0.080	0.035	0.095
<i>Difference in REM (χ^2)</i>	5.66**		5.73**	

Notes: t-statistics are reported below the coefficients. Robust standard errors are clustered by firm. *, **, and *** indicate two-tailed statistical significance at the 10%, 5%, and 1% levels, respectively. The χ^2 statistics test whether the REM coefficients differ between the low- and high-illiquidity subsamples.

8. Discussion and Conclusion

Using 2,839 firm-year observations for firms listed on Borsa Istanbul after excluding financial firms and regulated utilities, with explanatory variables measured from 2005 to 2024 and stock price crash-risk outcomes measured from 2006 to 2025, this study examines whether real earnings management (REM) is associated with subsequent stock price crash risk. The results show that higher REM is positively associated with both NCSKEW and DUVOL. This finding remains robust when alternative crash-risk proxies, a rank-based REM measure, entropy-balanced regressions, first-difference models, and firm fixed-effects specifications are used.

The positive association is consistent with U.S.-based studies linking abnormal real operating activities and real earnings smoothing to subsequent stock price crash risk. The present findings extend this evidence to Borsa Istanbul and suggest that the association is not confined to the U.S. market.

The cross-sectional analyses provide additional context for the baseline findings. The positive REM coefficient is concentrated among firms with high Tobin's Q or high residual valuation and among firms with greater stock-market illiquidity. These patterns are consistent with the view that valuation pressure may strengthen incentives to postpone the recognition of unfavorable information and that weaker information environments may make abnormal operating activities more difficult for outside investors to evaluate. However, the subsample analyses do not directly observe managerial incentives, private information, or disclosure decisions.

The findings also complement the growing Borsa Istanbul literature on stock price crash risk. Previous domestic studies have examined the relevance of financing structure and accounting conservatism, including Canbaloglu et al. (2022) and Toksoz (2024). The present study adds abnormal real operating activity to this literature and shifts attention from conventional accounting and financing characteristics to operating decisions involving production, discretionary expenditures, sales policies, and operating cash flows. The average NCSKEW and DUVOL values in the present sample are broadly comparable with those reported in earlier Borsa Istanbul studies, although differences in sample periods and measurement choices limit direct comparisons.

The statistical significance of the REM coefficients and their persistence across several specifications indicate that the positive conditional association is not confined to a single model, variable definition, or estimation method. Statistical significance, however, does not by itself establish practical importance. The practical relevance of the findings lies in the possibility that unusual combinations of production costs, discretionary expenditures, and operating cash flows may provide supplementary information about future downside risk, particularly when a firm also has a relatively high valuation or illiquid shares. REM should therefore be viewed as an additional screening indicator rather than as a deterministic predictor of a future crash or as stand-alone evidence of managerial misconduct.

The results have implications for several groups of capital-market participants. Regulators, including the Capital Markets Board of Türkiye, may consider whether existing disclosure requirements provide investors with sufficient information about economically significant changes in production, inventory accumulation, sales incentives, credit terms, and discretionary expenditures. Additional disclosure may be especially useful for highly valued or illiquid firms, for which unusual operating patterns may be more difficult for outsiders to interpret.

Auditors may also consider large and unexplained changes in production, discretionary expenditures, and operating cash flow when assessing engagement and financial-reporting risk. Such patterns do not establish that manipulation has occurred, but they may warrant additional inquiry into whether reported earnings are supported by sustainable operating performance. Boards and audit committees may similarly request clear economic explanations for unusual operating decisions and monitor whether short-term earnings objectives create incentives that conflict with long-term firm value. Institutional investors and financial analysts may benefit from considering firms' deviations from industry operating norms as an additional input when evaluating downside risk.

This study is subject to several limitations. First, REM is estimated using residual-based models. Although these models are widely used, the residuals may reflect both potentially opportunistic behavior and legitimate operating responses to demand conditions, business strategy, or other economic developments. They therefore cannot distinguish perfectly between deliberate earnings manipulation and economically justified operating decisions. Measurement error in ABCFO, ABDISEXP, or ABPROD may also carry through to the composite REM measure. Second, although the study employs several robustness tests, including entropy balancing, first-difference models, and firm fixed-effects specifications, these procedures cannot eliminate all concerns regarding endogeneity, omitted variables, reverse causality, or measurement error. Unobserved firm, industry, or market conditions that change over time may affect both operating decisions and subsequent crash risk.

Third, Tobin's Q and RRV are widely used measures of firm valuation, while the Amihud and Florackis measures are commonly employed in the accounting and finance literature as proxies for firms' information environments. Nevertheless, these measures do not directly capture valuation pressure, managerial incentives, or the private information available to managers. Fourth, the sample is limited to publicly listed firms in Türkiye. Institutional characteristics specific to Borsa Istanbul may therefore limit the generalizability of the results to markets with different ownership structures, disclosure regimes, enforcement mechanisms, and liquidity conditions.

These limitations provide several opportunities for future research. Studies could use regulatory, disclosure, auditing, or governance changes that create more exogenous variation in managers' ability or incentives to engage in REM. Further research could also examine whether board characteristics, audit quality, ownership structure, executive compensation, or environmental, social, and governance performance moderate the REM–crash-risk association. Qualitative interviews or surveys of executives,

auditors, and audit committee members could provide more direct evidence about the operating and reporting considerations underlying changes in production, sales policies, and discretionary expenditures. Cross-country analyses could determine whether the stronger association observed among highly valued and informationally opaque firms is specific to Borsa Istanbul or extends to other emerging and developed markets.

Overall, this study contributes to the literature by showing that the positive association between abnormal real operating activity and subsequent stock price crash risk, documented primarily in U.S. research, is also present among firms listed on Borsa Istanbul. It further shows that this association is not uniform across firms but is concentrated among firms with high valuations and weaker information environments. Although the study is subject to limitations common to empirical research, the findings identify abnormal real operating activity as a relevant consideration in assessing future downside risk and emphasize the importance of evaluating the sustainability of reported earnings by examining the underlying operating decisions.

References

- Abad, D., Cutillas-Gomariz, M. F., Sánchez-Ballesta, J. P., & Yagüe, J. (2018). Real earnings management and information asymmetry in the equity market. *European Accounting Review*, 27(2), 209–235. <https://doi.org/10.1080/09638180.2016.1261720>
- Adebambo, B. N., & Yan, X. (2018). Investor overconfidence, firm valuation, and corporate decisions. *Management Science*, 64(11), 5349–5369. <https://doi.org/10.1287/mnsc.2017.2806>
- Amihud, Y. (2002). Illiquidity and stock returns: Cross-section and time-series effects. *Journal of Financial Markets*, 5(1), 31–56. [https://doi.org/10.1016/S1386-4181\(01\)00024-6](https://doi.org/10.1016/S1386-4181(01)00024-6)
- An, H., & Zhang, T. (2013). Stock price synchronicity, crash risk, and institutional investors. *Journal of Corporate Finance*, 21, 1–15. <https://doi.org/10.1016/j.jcorpfin.2013.01.001>
- Andreou, P. C., Antoniou, C., Horton, J., & Louca, C. (2016). Corporate governance and firm-specific stock price crashes. *European Financial Management*, 22(5), 916–956. <https://doi.org/10.1111/eufm.12084>
- Andreou, P. C., Louca, C., & Petrou, A. P. (2017). CEO age and stock price crash risk. *Review of Finance*, 21(3), 1287–1325. <https://doi.org/10.1093/rof/rfw056>
- Badertscher, B. A. (2011). Overvaluation and the choice of alternative earnings management mechanisms. *The Accounting Review*, 86(5), 1491–1518. <https://doi.org/10.2308/accr-10092>
- Bao, D., Kim, Y., Mian, G. M., & Su, L. (2019). Do managers disclose or withhold bad news? Evidence from short interest. *The Accounting Review*, 94(3), 1–26. <https://doi.org/10.2308/accr-52205>
- Bebchuk, L., Cohen, A., & Ferrell, A. (2009). What matters in corporate governance? *The Review of Financial Studies*, 22(2), 783–827. <https://doi.org/10.1093/rfs/hhn099>
- Bradshaw, M. T., Hutton, A. P., Marcus, A. J., & Tehranian, H. (2010). Opacity, crash risk, and the option smirk curve. *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.1640733>
- Bushee, B. J. (1998). The influence of institutional investors on myopic R&D investment behavior. *The Accounting Review*, 73(3), 305–333. <https://doi.org/10.2308/TAR-902584>
- Callen, J. L., & Fang, X. (2013). Institutional investor stability and crash risk: Monitoring versus short-termism? *Journal of Banking & Finance*, 37(8), 3047–3063. <https://doi.org/10.1016/j.jbankfin.2013.02.018>
- Callen, J. L., & Fang, X. (2015). Short interest and stock price crash risk. *Journal of Banking & Finance*, 60, 181–194. <https://doi.org/10.1016/j.jbankfin.2015.08.009>
- Callen, J. L., & Fang, X. (2017). Crash risk and the auditor–client relationship. *Contemporary Accounting Research*, 34(3), 1715–1750. <https://doi.org/10.1111/1911-3846.12311>

- Canbaloglu, B., Alp, O. S., & Gurgun, G. (2022). Debt maturity structure and stock price crash risk: The case of Türkiye. *Borsa Istanbul Review*, 22(5), 985–991. <https://doi.org/10.1016/j.bir.2022.07.005>
- Chen, C., Kim, J. B., & Yao, L. (2017). Earnings smoothing: Does it exacerbate or constrain stock price crash risk? *Journal of Corporate Finance*, 42, 36–54. <https://doi.org/10.1016/j.jcorpfin.2016.11.004>
- Chen, J., Hong, H., & Stein, J. C. (2001). Forecasting crashes: Trading volume, past returns, and conditional skewness in stock prices. *Journal of Financial Economics*, 61(3), 345–381. [https://doi.org/10.1016/S0304-405X\(01\)00066-6](https://doi.org/10.1016/S0304-405X(01)00066-6)
- Chen, S., Ma, H., Wu, Q., & Zhang, H. (2024). Common institutional ownership and stock price crash risk. *Contemporary Accounting Research*, 41(1), 679–711. <https://doi.org/10.1111/1911-3846.12915>
- Cheng, Q., Lee, J., & Shevlin, T. (2016). Internal governance and real earnings management. *The Accounting Review*, 91(4), 1051–1085. <https://doi.org/10.2308/accr-51275>
- Chi, J. D., & Gupta, M. (2009). Overvaluation and earnings management. *Journal of Banking & Finance*, 33(9), 1652–1663. <https://doi.org/10.1016/j.jbankfin.2009.03.014>
- Chi, W., Lisic, L. L., & Pevzner, M. (2011). Is enhanced audit quality associated with greater real earnings management? *Accounting Horizons*, 25(2), 315–335. <https://doi.org/10.2308/acch-10025>
- Choi, A., Choi, J. H., & Sohn, B. C. (2018). The joint effect of audit quality and legal regimes on the use of real earnings management: International evidence. *Contemporary Accounting Research*, 35(4), 2225–2257. <https://doi.org/10.1111/1911-3846.12370>
- Choi, A., Lee, E. Y., Park, S., & Sohn, B. C. (2022). The differential effect of accrual-based and real earnings management on audit fees: International evidence. *Accounting and Business Research*, 52(3), 254–290. <https://doi.org/10.1080/00014788.2021.1911779>
- Cohen, D. A., Dey, A., & Lys, T. Z. (2008). Real and accrual-based earnings management in the pre- and post-Sarbanes-Oxley periods. *The Accounting Review*, 83(3), 757–787. <https://doi.org/10.2308/accr.2008.83.3.757>
- Cohen, D. A., & Zarowin, P. (2010). Accrual-based and real earnings management activities around seasoned equity offerings. *Journal of Accounting and Economics*, 50(1), 2–19. <https://doi.org/10.1016/j.jacceco.2010.01.002>
- Cohen, L. J., Cornett, M. M., Marcus, A. J., & Tehranian, H. (2014). Bank earnings management and tail risk during the financial crisis. *Journal of Money, Credit and Banking*, 46(1), 171–197. <https://doi.org/10.1111/jmcb.12101>
- Commerford, B. P., Hatfield, R. C., & Houston, R. W. (2018). The effect of real earnings management on auditors' scrutiny of managements' other financial reporting decisions. *The Accounting Review*, 93(5), 145–163. <https://doi.org/10.2308/accr-52032>
- Danışoğlu, S., & Güner, Z. N. (2018). Do price limits help control stock price volatility? *Annals of Operations Research*, 260(1), 129–157. <https://doi.org/10.1007/s10479-016-2317-y>
- DeFond, M. L., Hung, M., Li, S., & Li, Y. (2015). Does mandatory IFRS adoption affect crash risk? *The Accounting Review*, 90(1), 265–299. <https://doi.org/10.2308/accr-50859>
- Dumitrescu, A., & Zakriya, M. (2021). Stakeholders and the stock price crash risk: What matters in corporate social performance? *Journal of Corporate Finance*, 67, 101871. <https://doi.org/10.1016/j.jcorpfin.2020.101871>
- Ellington, M. (2018). Financial market illiquidity shocks and macroeconomic dynamics: Evidence from the UK. *Journal of Banking & Finance*, 89, 225–236. <https://doi.org/10.1016/j.jbankfin.2018.02.013>

- Florackis, C., Gregoriou, A., & Kostakis, A. (2011). Trading frequency and asset pricing on the London Stock Exchange: Evidence from a new price impact ratio. *Journal of Banking & Finance*, 35(12), 3335–3350. <https://doi.org/10.1016/j.jbankfin.2011.05.014>
- Florackis, C., Kontonikas, A., & Kostakis, A. (2014). Stock market liquidity and macro-liquidity shocks: Evidence from the 2007–2009 financial crisis. *Journal of International Money and Finance*, 44, 97–117. <https://doi.org/10.1016/j.jimonfin.2014.02.002>
- Francis, B., Hasan, I., & Li, L. (2016). Abnormal real operations, real earnings management, and subsequent crashes in stock prices. *Review of Quantitative Finance and Accounting*, 46(2), 217–260. <https://doi.org/10.1007/s11156-014-0468-y>
- Ge, W., & Kim, J. B. (2014). Real earnings management and the cost of new corporate bonds. *Journal of Business Research*, 67(4), 641–647. <https://doi.org/10.1016/j.jbusres.2013.01.021>
- Graham, J. R., Harvey, C. R., & Rajgopal, S. (2005). The economic implications of corporate financial reporting. *Journal of Accounting and Economics*, 40(1–3), 3–73. <https://doi.org/10.1016/j.jacceco.2005.01.002>
- Gul, F. A., Kim, J. B., & Qiu, A. A. (2010). Ownership concentration, foreign shareholding, audit quality, and stock price synchronicity: Evidence from China. *Journal of Financial Economics*, 95(3), 425–442. <https://doi.org/10.1016/j.jfineco.2009.11.005>
- Gunny, K. A. (2010). The relation between earnings management using real activities manipulation and future performance: Evidence from meeting earnings benchmarks. *Contemporary Accounting Research*, 27(3), 855–888. <https://doi.org/10.1111/j.1911-3846.2010.01029.x>
- Habib, A., Ranasinghe, D., Wu, J. Y., Biswas, P. K., & Ahmad, F. (2022). Real earnings management: A review of the international literature. *Accounting & Finance*, 62(4), 4279–4344. <https://doi.org/10.1111/acfi.12968>
- Hainmueller, J. (2012). Entropy balancing for causal effects: A multivariate reweighting method to produce balanced samples in observational studies. *Political Analysis*, 20(1), 25–46. <https://doi.org/10.1093/pan/mpr025>
- Hasan, M. M., Taylor, G., & Richardson, G. (2022). Brand capital and stock price crash risk. *Management Science*, 68(10), 7221–7247. <https://doi.org/10.1287/mnsc.2021.4197>
- Hong, H. A., Kim, J. B., & Welker, M. (2017). Divergence of cash flow and voting rights, opacity, and stock price crash risk: International evidence. *Journal of Accounting Research*, 55(5), 1167–1212. <https://doi.org/10.1111/1475-679X.12185>
- Hutton, A. P., Marcus, A. J., & Tehranian, H. (2009). Opaque financial reports, R^2 , and crash risk. *Journal of Financial Economics*, 94(1), 67–86. <https://doi.org/10.1016/j.jfineco.2008.10.003>
- Jensen, M. C. (2005). Agency costs of overvalued equity. *Financial Management*, 34(1), 5–19. <https://doi.org/10.1111/j.1755-053X.2005.tb00090.x>
- Jin, L., & Myers, S. C. (2006). R^2 around the world: New theory and new tests. *Journal of Financial Economics*, 79(2), 257–292. <https://doi.org/10.1016/j.jfineco.2004.11.003>
- Khurana, I. K., Pereira, R., & Zhang, E. (2018). Is real earnings smoothing harmful? Evidence from firm-specific stock price crash risk. *Contemporary Accounting Research*, 35(1), 558–587. <https://doi.org/10.1111/1911-3846.12353>
- Kim, J. B., Li, Y., & Zhang, L. (2011a). CFOs versus CEOs: Equity incentives and crashes. *Journal of Financial Economics*, 101(3), 713–730. <https://doi.org/10.1016/j.jfineco.2011.03.013>
- Kim, J. B., Li, Y., & Zhang, L. (2011b). Corporate tax avoidance and stock price crash risk: Firm-level analysis. *Journal of Financial Economics*, 100(3), 639–662. <https://doi.org/10.1016/j.jfineco.2010.07.007>

- Kim, J. B., Luo, L., & Xie, H. (2024). Do dividends mitigate bad news hoarding, overinvestments, and stock price crash risk? *Accounting & Finance*, 64(4), 3999–4038. <https://doi.org/10.1111/acfi.13297>
- Kim, J. B., & Sohn, B. C. (2013). Real earnings management and cost of capital. *Journal of Accounting and Public Policy*, 32(6), 518–543. <https://doi.org/10.1016/j.jaccpubpol.2013.08.002>
- Kim, J. B., Wang, J. J., & Zhang, E. X. (2021). Does real earnings smoothing reduce investors' perceived risk? *Journal of Business Finance & Accounting*, 48(9–10), 1560–1595. <https://doi.org/10.1111/jbfa.12529>
- Kim, J. B., Wang, Z., & Zhang, L. (2016). CEO overconfidence and stock price crash risk. *Contemporary Accounting Research*, 33(4), 1720–1749. <https://doi.org/10.1111/1911-3846.12217>
- Kim, J. B., Wang, Z., & Zhang, L. (2019). Readability of 10-K reports and stock price crash risk. *Contemporary Accounting Research*, 36(2), 1184–1216. <https://doi.org/10.1111/1911-3846.12452>
- Kim, J. B., & Zhang, L. (2016). Accounting conservatism and stock price crash risk: Firm-level evidence. *Contemporary Accounting Research*, 33(1), 412–441. <https://doi.org/10.1111/1911-3846.12112>
- Kim, J. H., Lee, S. H., & Yoo, Y. K. (2020). Real earnings management and the cost of debt capital: International evidence. *Asia-Pacific Journal of Accounting & Economics*, 27(2), 151–172. <https://doi.org/10.1080/16081625.2018.1518148>
- Kim, Y., Park, M. S., & Wier, B. (2012). Is earnings quality associated with corporate social responsibility? *The Accounting Review*, 87(3), 761–796. <https://doi.org/10.2308/accr-10209>
- Kothari, S. P., Mizik, N., & Roychowdhury, S. (2016). Managing for the moment: The role of earnings management via real activities versus accruals in SEO valuation. *The Accounting Review*, 91(2), 559–586. <https://doi.org/10.2308/accr-51153>
- Kothari, S. P., Shu, S., & Wysocki, P. D. (2009). Do managers withhold bad news? *Journal of Accounting Research*, 47(1), 241–276. <https://doi.org/10.1111/j.1475-679X.2008.00318.x>
- Le, H., & Gregoriou, A. (2022). Liquidity and asset pricing: Evidence from a new free-float-adjusted price impact ratio. *Journal of Economic Studies*, 49(4), 751–771. <https://doi.org/10.1108/JES-04-2021-0182>
- Lin, Y., & Zheng, R. (2026). Biodiversity risk and corporate real earnings management: Empirical evidence from China. *Borsa Istanbul Review*, 26(2), 100778. <https://doi.org/10.1016/j.bir.2025.100778>
- Mamun, M. A. A., Balachandran, B., & Duong, H. N. (2020). Powerful CEOs and stock price crash risk. *Journal of Corporate Finance*, 62, 101582. <https://doi.org/10.1016/j.jcorpfin.2020.101582>
- Meles, A., Pellegrino, L. R., Salerno, D., & Verdoliva, V. (2026). The hidden costs of hedge fund activism: Insights into market liquidity dynamics. *The European Journal of Finance*, 32(9), 1037–1071. <https://doi.org/10.1080/1351847X.2026.2655250>
- Mellado-Cid, C., Jory, S. R., & Ngo, T. N. (2018). Real activities manipulation and firm valuation. *Review of Quantitative Finance and Accounting*, 50(4), 1201–1226. <https://doi.org/10.1007/s11156-017-0659-4>
- Nasraoui, M., Ajina, A., & Kahloul, A. (2024). The influence of economic policy uncertainty on stock market liquidity? The mediating role of investor sentiment. *The Journal of Risk Finance*, 25(4), 664–683. <https://doi.org/10.1108/JRF-06-2023-0129>
- Pappas, K., Walsh, E., & Xu, A. L. (2019). Real earnings management and loan contract terms. *The British Accounting Review*, 51(4), 373–401. <https://doi.org/10.1016/j.bar.2019.03.002>

- Piñeiro-Chousa, J., Šević, A., & González-López, I. (2023). Impact of social metrics in decentralized finance. *Journal of Business Research*, 158, 113673. <https://doi.org/10.1016/j.jbusres.2023.113673>
- Rhodes-Kropf, M., Robinson, D. T., & Viswanathan, S. (2005). Valuation waves and merger activity: The empirical evidence. *Journal of Financial Economics*, 77(3), 561–603. <https://doi.org/10.1016/j.jfineco.2004.06.015>
- Roychowdhury, S. (2006). Earnings management through real activities manipulation. *Journal of Accounting and Economics*, 42(3), 335–370. <https://doi.org/10.1016/j.jacceco.2006.01.002>
- Toksoz, T. (2024). Crash risk and conservatism: Evidence from Borsa Istanbul. *Borsa Istanbul Review*, 24(4), 787–796. <https://doi.org/10.1016/j.bir.2024.04.010>
- Vorst, P. (2016). Real earnings management and long-term operating performance: The role of reversals in discretionary investment cuts. *The Accounting Review*, 91(4), 1219–1256. <https://doi.org/10.2308/accr-51281>
- Wang, Y., Fang, R., Hu, N., & Huang, R. (2025). Credit default swaps and borrowers' real earnings management: Evidence from credit default swap initiation. *Journal of Accounting, Auditing & Finance*, 40(1), 3–36. <https://doi.org/10.1177/0148558X221140723>
- Wu, W. S., & Suardi, S. (2025). Heterogeneity in the effects of banklines of credit on capital investment efficiency. *Financial Review*, 60(2), 601–621. <https://doi.org/10.1111/fire.12424>
- Zang, A. Y. (2012). Evidence on the trade-off between real activities manipulation and accrual-based earnings management. *The Accounting Review*, 87(2), 675–703. <https://doi.org/10.2308/accr-10196>
- Zhang, S., & Gregoriou, A. (2019). Initial bank loans, zero-leverage firms and stock market liquidity: New empirical evidence from the UK. *Journal of Economic Studies*, 46(5), 1028–1051. <https://doi.org/10.1108/JES-05-2018-0190>
- Zhu, W. (2016). Accruals and price crashes. *Review of Accounting Studies*, 21(2), 349–399. <https://doi.org/10.1007/s11142-016-9355-1>

Endnotes

ⁱ While Roychowdhury (2006) defines discretionary expenses as the sum of R&D, advertising, and SG&A expenses, the advertising component is excluded here because it is not reported in Compustat Global. Furthermore, following standard conventions, missing R&D expenditures are set to zero as long as the firm reports non-missing SG&A expenses.

ⁱⁱ The confidence interval is obtained by multiplying the lower and upper confidence limits of the REM coefficient by $SD(REM)/SD(Y)$, where Y denotes the relevant crash-risk measure.

ⁱⁱⁱ A detailed explanation can be found in Adebambo and Yan (2018).

Appendix Table A1. Industry-Year Cells Used to Estimate REM

REM variable	Eligible industry-year cells	Mean	Std. Dev.	Q1	Median	Q3
ABCFO	229	14.18	4.97	10	14	16
ABDISEXP	255	14.13	4.90	10	14	16
ABPROD	236	13.74	4.58	10	13	16

Notes: Each REM component is estimated only in Fama–French 48 industry-year cells containing at least eight valid observations.

Appendix Table A2. Between-Firm and Within-Firm Variation

Variable	Between-firm SD	Within-firm SD
$NCSKEW_{i,t+1}$	0.5083	0.8313
$DUVOL_{i,t+1}$	0.2256	0.3564
$REM_{i,t}$	0.2475	0.2164
$ABSDACC_{i,t}$	0.0847	0.1198
$DTURN_{i,t}$	0.1219	0.8879
$RET_{i,t}$	0.3143	0.7300
$SIGMA_{i,t}$	0.0192	0.0320
$MB_{i,t}$	6.2007	23.2259
$SIZE_{i,t}$	2.1690	1.7602
$ROA_{i,t}$	0.1327	0.2334
$LEV_{i,t}$	0.3034	0.2973
$NCSKEW_{i,t}$	0.4512	0.8571

Notes: Between-firm SD reflects variation in firm-specific means, whereas within-firm SD reflects variation over time around each firm's mean. The statistics are based on 2,839 firm-year observations from 312 firms, with an average of 9.10 observations per firm.

Araştırma Makalesi

Does Real Earnings Management Influence Stock Price Crash Risk? Evidence from Borsa İstanbul

*Reel Kâr Yönetimi Gelecekteki Hisse Senedi Fiyat Çöküşü Riskiyle İlişkili
midir? Borsa İstanbul'dan Bulgular*

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Genişletilmiş Özet

Bu araştırma, Borsa İstanbul'da (BIST) işlem gören finansal olmayan şirketlere ait 2.839 firma-yıl gözleminden yararlanarak reel kâr yönetimi (REM) ile gelecekteki hisse senedi fiyat çöküşü riski arasındaki ilişkiyi incelemektedir. REM ve diğer açıklayıcı değişkenler 2005–2024 döneminde (t), bir sonraki yıla ait çöküş riski ölçütleri ise 2006–2025 döneminde (t+1) ölçülmüştür. Hisse senedi fiyat çöküşü riski, firmaya özgü getirilerde kısa bir süre içinde ortaya çıkan olağandışı ve şiddetli düşüşleri ifade etmektedir. Çalışmanın kuramsal dayanağını oluşturan kötü haber biriktirme yaklaşımına göre yöneticiler, tazminatlarını, itibarlarını veya iş güvencelerini korumak amacıyla olumsuz bilgilerin açıklanmasını erteleyebilir, biriken bilgiler daha fazla gizlenemediğinde ise fiyatlarda ani bir aşağı yönlü düzeltme meydana gelebilir. REM ile sonraki dönem çöküş riski arasındaki doğrudan kanıtların büyük ölçüde ABD piyasasına dayanması nedeniyle bu çalışma, söz konusu ilişkinin gelişmekte olan bir piyasa olan Borsa İstanbul'da da gözlenip gözlenmediğini araştırmaktadır.

Tahakkuk esaslı kâr yönetiminden farklı olarak REM, raporlanan kârı etkilemek amacıyla gerçek işletme faaliyetlerinde değişiklik yapılmasını ifade etmektedir. Satışları hızlandırmak için geçici fiyat indirimleri veya daha esnek kredi koşulları sunulması, Ar-Ge ile satış, genel ve yönetim giderleri gibi ihtiyari harcamaların azaltılması ve sabit genel üretim giderlerini daha fazla birime yaymak amacıyla aşırı üretim yapılması başlıca REM kanallarıdır. Ancak bu faaliyetler meşru ticari gerekçelerle de ortaya çıkabileceğinden, kalıntı temelli REM ölçütleri yönetsel niyeti doğrudan gözlemleyemez. Bu kuramsal çerçevede üç hipotez geliştirilmiştir. H1, REM'in gelecekteki çöküş riskiyle pozitif ilişkili olduğunu; H2, bu pozitif ilişkinin aşırı değerlenmiş firmalarda daha güçlü olduğunu; H3 ise ilişkinin bilgi asimetrisinin daha yüksek olduğu firmalarda güçlendiğini öngörmektedir. Aşırı değerlendirme, yöneticilerin yüksek piyasa değerini koruma yönündeki teşviklerini artıran bir kanal, bilgi asimetrisi ise dış paydaşların olağandışı operasyonel kararları değerlendirmesini güçleştiren bir fırsat kanalı olarak ele alınmaktadır.

Muhasebe ve hisse senedi getirisi verileri Compustat Global ve Equity RT veri tabanlarından elde edilmiştir. Finansal kuruluşlar ile düzenlemeye tabi altyapı ve hizmet şirketleri örneklem dışında bırakılmış, REM, kontrol değişkenleri ve bir sonraki yıla ait çöküş riski için gerekli verilerin mevcut olması ve her firma-yıl için en az 26 haftalık getiri bulunması koşulları aranmıştır. Çöküş riski, BIST

Tüm Endeksi'ne göre tahmin edilen firmaya özgü haftalık getirilerden hesaplanan negatif koşullu çarpıklık (NCSKEW) ve aşağı-yukarı volatilité (DUVOL) ölçütleriyle değerlendirilmiştir. REM ise Fama–French 48 endüstri sınıflandırmasına göre, mali yıl bazında tahmin edilen anormal üretim maliyetleri (ABPROD), anormal ihtiyari giderler (ABDISEXP) ve anormal faaliyetlerden sağlanan nakit akışları (ABCFO) kalıntılarının $REM = ABPROD - ABDISEXP - ABCFO$ biçiminde birleştirilmesiyle oluşturulmuştur. Her endüstri-yıl modeli en az sekiz geçerli gözlem içeren hücrelerde tahmin edilmiştir. Temel regresyonlarda firma düzeyinde kümelenmiş dayanıklı standart hatalar ile endüstri ve yıl sabit etkileri kullanılmıştır.

Tanımlayıcı istatistiklerde NCSKEW ve DUVOL ortalamaları sırasıyla $-0,439$ ve $-0,280$ 'dir. Bu değerler önceki Borsa İstanbul çalışmalarındaki bulgularla genel olarak uyumlu olmakla birlikte bazı ABD örneklemelerinde bildirilen ortalamalardan daha düşüktür. Söz konusu farklılık dikkatle yorumlanmalıdır. Borsa İstanbul'daki günlük fiyat limitleri ile hisse bazlı ve piyasa genelindeki devre kesiciler, büyük fiyat ayarlamalarının zamanlamasını etkileyebilir; ancak Danışoğlu ve Güner (2018), hem üst hem de alt fiyat limiti olaylarının ardından volatilitenin arttığını ve yüksek volatilitenin daha uzun sürdüğünü, fiyat keşfinin ise geciktiğini göstermektedir. Örneklem dönemleri, haftalık getiri kapsamı, likidite ve piyasa modeli uygulamalarındaki farklılıklar da ülkeler arası karşılaştırmaları etkileyebilir.

Temel regresyonlarda REM katsayıları NCSKEW ve DUVOL için sırasıyla $0,24$ ($t = 3,18$) ve $0,10$ ($t = 3,42$) olup her ikisi de %1 düzeyinde anlamlıdır. Yuvarlanmamış katsayılar kullanılarak hesaplanan ekonomik büyüklüklere göre REM'deki bir standart sapmalık artış, NCSKEW'de yaklaşık $0,075$ standart sapmalık (%95 güven aralığı: $0,029-0,122$), DUVOL'de ise yaklaşık $0,074$ standart sapmalık (%95 güven aralığı: $0,031-0,116$) bir artışla ilişkilidir. Firma büyüklüğü, aktif kârlılığı ve cari dönem NCSKEW de temel modellerde pozitif ve anlamlı katsayılarla sahiptir. Bu sonuçlar, REM ile sonraki yıl çöküş riski arasında istatistiksel olarak güvenilir bir ilişki bulunduğunu göstermekte, ancak araştırmanın gözlemsel yapısı nedeniyle nedensel bir etki olarak yorumlanmamaktadır.

Sonuçların farklı ölçüm ve tahmin tercihlerine duyarlı olup olmadığını değerlendirmek amacıyla beş sağlamlık analizi uygulanmıştır. Çöküş ve sıçrama haftalarının sayıları arasındaki farkı ölçen COUNT ile en olumsuz haftalık getirinin yıllık ortalamadan standart sapma cinsinden uzaklığını ölçen EXTRASIGMA kullanıldığında REM katsayısı pozitifliğini korumuştur. REM'in yıllık ondalık dilimlere ayrılıp sıfır ile bir arasında yeniden ölçeklendirildiği RANK_REM ölçütüyle de benzer sonuçlar elde edilmiştir. Entropi dengelemesinde, endüstri-yıl medyanına göre oluşturulan ikili HIGH_REM göstergesi yalnızca ağırlıkların hesaplanmasında kullanılmış, bilgi kaybını önlemek ve temel modellerle karşılaştırılabilirliği korumak amacıyla ağırlıklı sonuç regresyonlarında sürekli REM değişkeni tutulmuştur. Sürekli REM ve HIGH_REM ile yapılan alternatif tahminlerin her ikisinde de sonuçlar anlamlıdır. Ardışık firma-yıl gözlemleri gerektiren birinci fark modellerinde örneklem 2.567 gözleme düşmesine rağmen CHANGE_REM pozitif ve anlamlıdır. Firma ve yıl sabit etkilerinin kullanıldığı modellerde de REM katsayısı %5 düzeyinde anlamlılığını korumuştur.

Yatay kesit sonuçları H2 ve H3 ile uyumludur. Firma aşırı değerlemesini ölçmek amacıyla Tobin'in Q oranı ve Rhodes-Kropf vd. (2005) tarafından geliştirilen artık değerleme bileşeni (RRV) kullanılmıştır. Her iki ölçütte de REM katsayısı yalnızca yüksek değerleme grubunda pozitif ve anlamlıyken düşük değerleme grubunda anlamsızdır, gruplar arasındaki katsayı farkları da istatistiksel olarak anlamlıdır. Bilgi asimetrisi Amihud ve Florackis likidite düşüklüğü ölçütleriyle değerlendirildiğinde benzer bir örüntü ortaya çıkmıştır: REM ile çöküş riski arasındaki pozitif ilişki yalnızca likiditesi düşük, dolayısıyla bilgi asimetrisi daha yüksek firmalarda gözlenmiştir. Bu bulgular, yüksek değerlemenin kötü haberlerin açıklanmasını erteleme teşvikini, bilgi asimetrisinin ise bunu yapma olanağını güçlendirdiği açıklamasıyla uyumludur. Bununla birlikte, alt örneklem testleri yönetsel niyeti, özel bilgiyi veya açıklama kararlarını doğrudan gözlemlemediğinden kötü haber biriktirme mekanizmasını kanıtlamamaktadır.

Bulguların pratik önemi, REM'in tek başına bir çöküş tahmini veya manipülasyon kanıtı olması değil, üretim maliyetleri, ihtiyari giderler ve faaliyetlerden sağlanan nakit akışlarındaki olağandışı birleşimlerin özellikle yüksek değerlemeli ya da düşük likiditeli firmalarda ek bir risk tarama sinyali sunabilmesidir. Düzenleyiciler, üretim, stok birikimi, satış teşvikleri, kredi koşulları ve ihtiyari harcamalardaki ekonomik açıdan önemli değişikliklere ilişkin açıklamaların yeterliliğini değerlendirebilir. Denetçiler ile yönetim ve denetim kurulları, açıklanamayan operasyonel değişikliklerin sürdürülebilir performansla uyumlu olup olmadığını daha ayrıntılı inceleyebilir. Kurumsal yatırımcılar ve finansal analistler ise firmaların endüstri normlarından sapmalarını aşağı yönlü risk değerlendirmesinde ek bir girdi olarak kullanabilir. Bununla birlikte, tahmin edilen REM kalıntıları tek başına yönetsel suistimalin kesin kanıtı olarak değerlendirilmemelidir.

Çalışmanın bazı sınırlılıkları bulunmaktadır. Kalıntı temelli REM ölçütleri fırsatçı davranışların yanı sıra talep koşullarına, işletme stratejisine veya diğer ekonomik gelişmelere verilen meşru tepkileri de içerebilir. Entropi dengeleme, birinci fark ve firma sabit etkileri analizleri, çeşitli alternatif açıklamalara ilişkin kaygıları azaltmakla birlikte endojenlik, zaman içinde değişen gözlenemeyen etkenler, tersine nedensellik ve ölçüm hatası sorunlarını tamamen ortadan kaldıramaz. Tobin'in Q oranı, RRV ve likidite ölçütleri de yönetsel teşvikleri ve özel bilgiyi dolaylı olarak temsil etmektedir. Ayrıca tek bir ülkenin halka açık firmalarına dayanan bulguların farklı kurumsal yapılara genellenebilirliği sınırlı olabilir. Gelecekteki çalışmalar düzenleyici, açıklama, denetim veya yönetim değişikliklerinden yararlanarak dışsallığı daha güçlü araştırma tasarımları geliştirebilir; yönetim kurulu yapısının, denetim kalitesinin, mülkiyet yapısının, yönetici ücretlerinin ve çevresel, sosyal ve yönetim performansının düzenleyici rollerini inceleyebilir; yöneticiler, denetçiler ve denetim komitesi üyeleriyle yapılacak nitel görüşmeler veya anketlerle yönetsel karar süreçlerine doğrudan yaklaşabilir ve ülkeler arası karşılaştırmalar yapabilir. Bu sınırlılıklar çerçevesinde çalışma, ABD ağırlıklı literatürde belgelenen REM-çöküş riski ilişkisinin Borsa İstanbul'da da gözlemlendiğini ve bu ilişkinin yüksek değerlemeye ve zayıf bilgi ortamına sahip firmalarda yoğunlaştığını ortaya koymaktadır.