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Analyst Coverage and Real Earnings Management: Quasi-Experimental Evidence

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Abstract

We study how securities analysts influence managers' use of different types of earnings management. To isolate causality, we employ a quasi-experiment that exploits exogenous reductions in analyst following resulting from brokerage house mergers. We find that managers respond to the coverage loss by decreasing real earnings management while increasing accrual manipulation. These effects are significantly stronger among firms with less coverage and for firms close to the zero-earnings threshold. Our causal evidence suggests that managers use real earnings management to enhance short-term performance in response to analyst pressure, effects that are not uncovered when focusing solely on accrual-based methods.

I. Introduction

Do the recommendations and short-term earnings benchmarks emphasized by securities analysts pressure managers to manipulate reported earnings?[1] Firms failing to meet or beat quarterly expectations experience a loss of stock market valuation (Bartov, Givoly, and Hayn (2002)). Managers of these firms experience declines in compensation (Matsunaga and Park (2001)) and a greater likelihood of turnover (Hazarika, Karpoff, and Nahata (2012), Mergenthaler, Rajgopal, and Srinivasan (2012)). Given these expected private costs to managers, a large literature emphasizes analysts' role in pressuring managers and in decreasing overall

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[1]Earnings manipulation is suitably defined as follows: "Earnings management occurs when managers use judgment in financial reporting and in structuring transactions to alter financial reports to either mislead some stakeholders about the underlying economic performance of the company or to influence contractual outcomes that depend on reported accounting practices" (Healy and Wahlen (1999), p. 6).

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transparency (e.g., see Dechow, Richardson, and Tuna (2003), Fuller and Jensen (2002), and Grundfest and Malenko (2012)).

Conversely, do securities analysts serve as effective external monitors? As accounting and finance professionals with industry expertise, analysts process and disseminate information disclosed by firms in financial statements and other sources as well as scrutinizing management during conference calls. Dyck, Morse, and Zingales (2010) document the important role analysts play as whistle blowers, who are often the first to detect corporate fraud. In light of the adverse wealth, reputation, and career consequences management experience in the wake of such incidents (Karpoff, Lee, and Martin (2008a)), an alternative view is that analysts deter misreporting and discipline managerial misbehavior by serving as monitors alongside traditional mechanisms of corporate governance (e.g., Yu (2008)).

These issues are at the center of a divisive debate over how analysts affect managers' behavior and whether they have a positive effect on firm value, relations that have not yet been clearly established in the literature and warrant further research (Leuz (2003)). Moreover, understanding the causes of earnings manipulation is of particular importance, given the substantial direct adverse consequences of misreporting (Karpoff et al. (2008a), (2008b)), as well as potential macroeconomic distortions, excessive hiring and investment, that could accompany overstated performance (Kedia and Philippon (2009)).

In this article, we examine how securities analysts affect managers' incentives to engage in earnings management activities. We follow a recent earnings management literature that proposes "real activities manipulation," changing investments, advertising, or the timing and structure of operational activities, as a natural alternative to accrual-based methods (e.g., S.-S. Chen and Huang (2013), Cohen, Dey, and Lys (2008), Roychowdhury (2006), and Zang (2012)).[2,3] Our analysis expands the scope of previous studies on the impact of analysts on earnings management by incorporating real activities manipulation as an alternative earnings management mechanism. We argue that by focusing on one earnings management technique in isolation (e.g., accrual-based methods), it is not possible to provide a complete picture of how analysts influence earnings reporting.[4] Accordingly, the purpose of this article is to provide the first observational empirical study into how securities analysts affect both accrual-based and real earnings management.

Recent evidence documents the importance of real activities manipulation as a way for managers to meet analysts' expectations. In a survey of 401 U.S.

[2]The terms "real earnings management" and "real activities manipulation" have the same meaning and are used interchangeably throughout this article.

[3]These recent papers build off prior work emphasizing earnings manipulation via operational adjustments. For example, Bens, Nagar, and Wong (2002), Dechow and Sloan (1991), and Bushee (1998) emphasize cutting research and development (R&D) expenses as a means of managing earnings. In addition, Bartov (1993) and Burgstahler and Dichev (1997) provide evidence on the management of real activities other than through R&D.

[4]Recent research finds that greater analyst coverage results in fewer discretionary accruals used in corporate financial reporting (Irani and Oesch (2013), Lindsey and Mola (2013), and Yu (2008)), concluding that analysts constrain earnings management and serve as external monitors of managers (as in Jensen and Meckling (1976)). However, these studies do not consider real activities manipulation as an alternative earnings management tool at managers' disposal.

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financial executives, Graham, Harvey, and Rajgopal (2005) find that a majority of executives were willing to use real activities manipulation to meet an earnings target, despite cash-flow implications that may be value destroying from a shareholder perspective.[5,6] Thus, if analyst following pressures managers to meet earnings targets, this may induce managers to use real activities manipulations to boost short-term reported earnings. Conversely, if analysts monitor companies' R&D investment, cost structure, and operational decisions, they may prioritize deterring managers' use of real actions to manipulate short-run earnings, especially given the potentially great long-term loss of shareholder value.

This survey evidence also finds that managers may prefer to manage earnings using real activities, since accrual-based earnings management may be more likely to attract scrutiny from regulators, auditors, securities analysts or other market participants.

Along these lines, Cohen et al. (2008) argue that managers prefer real activities manipulation because it may be harder to detect than accrual-based methods and thus entails lower expected private costs. In support of this argument, recent research documents a shift in earnings management behavior among U.S. corporations toward real activities manipulation and away from accrual-based methods in the wake of the Sarbanes–Oxley Act (SOX), a stricter regulatory regime (see also S.-S. Chen and Huang (2013)).[7] Thus, if analysts monitor managers alongside regulators and other stakeholders, as previous research ascertains (e.g., T. Chen, Harford, and Lin (2015), Irani and Oesch (2013), and Yu (2008)), then it is imperative that real activities manipulation be incorporated when attempting to measure the effect of analyst following on earnings management.

Empirical identification of the firm-level impact of analyst following on the use of real or accrual-based earnings management tools is severely hampered by endogeneity. Should a regression uncover a relation between coverage and a measure of earnings management, it is difficult to rule out reverse causality, as

[5]"We find strong evidence that managers take real economic actions to maintain accounting appearances. In particular, 80% of survey participants report that they would decrease discretionary spending on R&D, advertising, and maintenance to meet an earnings target. More than half (55.3%) state that they would delay starting a new project to meet an earnings target, even if such a delay entailed a small sacrifice in value" (Graham et al. (2005), p. 32).

[6]Real activities manipulation can reduce firm value because actions taken to increase short-run earnings can have a detrimental impact on future cash flows. For example, the use of price discounts to boost sales and meet earnings benchmarks may lead customers to expect such discounts in the future, implying lower margin sales going forward (Roychowdhury (2006)). Kedia and Philippon (2009) show that firms incur significant costs associated with the suboptimal operating decisions (excessive hiring and investment) they make to meet financial reporting goals. In addition, Bushee (1998) presents evidence that such short-termism can lead managers to forgo potentially valuable long-term investment in innovative projects that are highly risky and slow in generating revenues (see also He and Tian (2013)). Conversely, accrual manipulation involves only changes to the accounting methods that are used to represent the underlying economic activities of the firm. If such changes are within the limits of generally accepted accounting principles (GAAP), this should not have a negative impact on firm value (e.g., Cohen and Zarowin (2010), Zang (2012)).

[7]Dechow, Sloan, and Sweeney (1996) present further evidence that real activities manipulation is more difficult to detect than accrual manipulation. They conduct a comprehensive investigation of enforcement actions undertaken by the U.S. Securities and Exchange Commission (SEC) for alleged violations of GAAP. None of the allegations they describe indicate that the enforcement action commenced because of some real economic decision.

corporate prospects and policies, including transparency (as in Healy, Hutton, and Palepu (1999), Lang and Lundholm (1993)), inevitably drive decisions to initiate and terminate coverage. A further identification problem arises if some omitted factor attracts coverage and influences earnings management (such as a seasoned equity offering, as in Cohen and Zarowin (2010)).

To address this serious endogeneity issue, we implement a quasi-experimental research design and examine the adjustment in managers' behavior to a plausibly exogenous reduction in analyst following caused by brokerage house mergers (originally proposed by Hong and Kacperczyk (2010)).[8] Following a brokerage house merger, the newly formed entity often has several redundant analysts (due to overlapping coverage universes) and, as a result, one or more analysts might be let go (Wu and Zang (2009)). For instance, both merging houses might have an airline stock analyst covering the same set of companies. After the merger, in the newly formed entity, it is likely that one of these stock analysts will be surplus to requirements. Thus, a loss of analyst coverage for the firms being covered by both houses arises because of these merger-related factors and not because of the prospects of these firms.

Our empirical approach uses 13 brokerage house merger events staggered over time from 1994 until 2005 and accommodates all publicly traded U.S. firms. Associated with these mergers are 1,266 unique firms that were covered in the year before the merger by both houses. These firms form our treatment sample. Using a difference-in-differences (DiD) approach, we compare the adjustment in earnings management behavior of the treatment sample relative to a control group of observationally similar firms that were unaffected by the merger. Thus, we identify the causal change in earnings management strategies resulting from the loss of coverage.

We provide causal evidence that securities analysts influence earnings management. Using both discretionary accrual-based (Dechow, Sloan, and Sweeney (1995), Jones (1991)) and real activities manipulation-based (Roychowdhury (2006), Zang (2012)) measures of earnings management, we document two adjustments in behavior following an exogenous loss of analyst coverage. First, our estimates imply that a reduction in analyst coverage leads managers to use less real activities manipulation in their financial reporting. We find that the adjustment in real activities manipulation comes primarily from a reduction in abnormal discretionary expenses, which includes R&D expenses. This suggests that analyst following pressures managers to meet outside expectations through real activities manipulation, for instance, by disincentivizing innovative activity.[9] Second, we find that the loss of coverage results in greater accrual manipulation.

[8]This quasi-experiment has been validated extensively in the literature studying security analyst coverage and analyst reporting bias (Fong, Hong, Kacperczyk, and Kubik (2013), Hong and Kacperczyk (2010)), firm valuation and the cost of capital (Derrien, Kecskes, and Mansi (2012), Kelly and Ljungqvist (2007), (2012)), real firm performance and corporate policies (Derrien and Kecskes (2013)), innovation (He and Tian (2013)), corporate governance (T. Chen et al. (2015), Irani and Oesch (2013)), and stock liquidity (Balakrishnan, Billings, Kelly, and Ljungqvist (2014)).

[9]This finding fits into a broader literature that examines how earnings management through real activities affects R&D (e.g., Baber, Fairfield, and Haggard (1991), Bushee (1998), and Dechow and Sloan (1991)).

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Together with the first result, this is consistent with managers preferring to use real activities manipulation in response to analyst pressure, perhaps because it is harder to detect and hence entails lower expected private costs to managers.

On further examination of the cross-section, we find that the treatment effect is nonlinear and more pronounced for treated firms with less analyst coverage prior to the merger, providing direct evidence that earnings management responds to large percentage drops in analyst coverage. We also observe a stronger treatment effect among "suspect" firms, those firms in close proximity to the zero earnings threshold (e.g., Degeorge, Patel, and Zeckhauser (1999)), and firms lacking experienced analysts. These three findings bolster our confidence in the plausibility of our quasi-experimental results, as we would expect the loss of coverage to matter most for these firms. In addition, following the coverage drop, we observe a stronger shift from real activities toward accrual-based earnings manipulation among treated firms with greater accounting flexibility or shorter auditor tenure; that is, those firms with lower costs of accrual manipulation. This suggests an important interaction effect between analyst following and other costs of accrual manipulation, which together impact managers' preferred mix of earnings management tools.

We conduct a battery of tests to check the validity and robustness of our results. We mitigate the concern that our findings could be driven by systematic differences in industries, mergers, or firms by showing that our estimates are robust to the inclusion of the respective fixed effects. Additionally, we demonstrate that our estimates are not merely capturing ex ante differences in the observable characteristics of treated and control firms by including control variables in our panel regression framework and by implementing DiD matching estimators. Consistent results emerge when we consider alternative measures of accrual-based and real earnings management, including several non-regression-based measures of accruals. We also examine the validity of our quasi-experiment, particularly, the parallel trends assumption, by constructing placebo mergers that shift the merger date 1 year backward or forward.

We wrap up our empirical analysis by running a series of ordinary least squares (OLS) regressions of real and accrual-based earnings management on analyst coverage without taking into account the endogeneity of coverage. These estimates imply that analyst following is largely uncorrelated with earnings management behavior.[10] This is in contrast to the robust directional effects we uncover using our identification strategy. Moreover, these OLS results are tricky to interpret because analyst coverage is likely to be endogenous. These mixed findings underscore the importance of our quasi-experimental research design.

This article makes two main contributions to the literature. First, it advances the empirical literature on the interaction between analyst coverage and earnings management. Of note, Yu (2008) examines earnings management and analyst following and finds evidence of a negative relation, consistent with an external monitoring role of analysts. We develop this line of thought in two ways. First, we employ a quasi-experimental design, allowing us to establish a direct causal

[10]In a similar OLS framework, Roychowdhury (2006) finds weak evidence on the use of real activities manipulation to meet annual analyst forecasts.

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relation and demonstrate that a reduction in analyst coverage causes an adjustment in earnings management.[11] Second, we consider firms' overall earnings management strategy (i.e., abnormal discretionary accruals, cash flows from operations, production costs, and discretionary expenses) rather than accrual manipulation in isolation (see also Irani and Oesch (2013)). As a consequence, and in contrast to studies that base inferences solely on accrual-based methods, we find that analysts may pressure managers to meet expectations via real activities manipulation, particularly through the reduction of discretionary expenses. Thus, our evidence offers a more complete picture of how analysts influence earnings management, in a well-identified empirical setting.

Our second contribution is to the earnings management literature. In light of the Graham et al. (2005) survey findings that managers prefer real activities manipulation, several notable studies have emerged examining this form of earnings management and whether there is any complementary or substitute interaction with accrual-based practices.[12]

Zang (2012) assesses the trade-offs between accrual manipulation and real earnings management and, by focusing on the timing and costs of each strategy, concludes that managers treat the two strategies as substitutes. Consistent with the idea that regulatory scrutiny affects the costs of accrual-based strategies, recent studies on the impact of the SOX on the use of accrual-based and real earnings management provide evidence that managers substitute toward real activities manipulation in the post-SOX era (S.-S. Chen and Huang (2013), Cohen et al. (2008)). Our contribution is to analyze how securities analysts influence managers' preferred mix of accrual and real activities manipulation. In our context, we find corroborative evidence that these two earnings management techniques are substitutes.

The remainder of this article is structured as follows: Section II describes the data and empirical design. Section III reports the results of the empirical analysis. Section IV concludes.

II. Empirical Strategy and Data

A. Identification

In this section, we lay out the details of our identification strategy and DiD estimator.

[11] This evidence is based on correlations between the level of analyst coverage and discretionary accruals, as well as on an instrumental variables strategy that uses S&P 500 index inclusion as an instrument for coverage. Unfortunately, this instrument is unlikely to satisfy the exclusion restriction, as index inclusion is likely to reflect news about fundamentals that both attracts coverage and affects the decision to manage earnings.

[12] It is a priori unclear that real and accrual-based earnings management methods are substitutes. For instance, in a theoretical model, Kedia and Philippon (2009) show that accrual-manipulating firms need to hire and invest suboptimally and excessively, in fact, to mimic highly productive firms, fool investors, and avoid detection. In a model of real and financial intertemporal smoothing, Acharya and Lambrecht (2015) show that managers may choose to lower outsiders' expectations by underreporting earnings and underinvesting. In these asymmetric information frameworks, under certain conditions, the two earnings management tools are complements.

The most straightforward way to examine the issue of how monitoring by securities analysts affects earnings management is to regress a measure of corporate financial reporting on analyst following. However, the estimates from such regressions are difficult to interpret because of endogeneity (omitted variables bias, reverse causality, etc.).[13] For example, if a positive relation between analyst following and the use of accruals were uncovered, this may reflect the fact that analysts are attracted to firms with higher quality financial reporting (as in Healy et al. (1999)), as opposed to (the reverse) causal impact of analyst coverage on reporting.

To address this endogeneity concern and identify a casual effect, we use brokerage house mergers as a source of exogenous variation in analyst coverage. For our quasi-experiment to be relevant, we require that the two merging brokerage houses, both covering the same stock before the merger, let one of these analysts go, leading to a loss of analyst coverage for a given firm. Most importantly, the coverage termination is unlikely to be a choice made by the analyst and, thus, is independent of firm prospects and other factors that have the potential to confound inference.

We follow Hong and Kacperczyk (2010) in selecting the set of relevant mergers. We begin by gathering mergers in the Securities Data Company (SDC) Mergers and Acquisitions database involving financial institutions (firms with Standard Industrial Classification (SIC) code 6211, "Investment Commodity Firms, Dealers, and Exchanges"). We keep mergers that have earnings estimates in Thomson Reuters Institutional Brokers' Estimate System (IBES) for both the bidder and target brokerage houses. We retain merging houses that have overlapping coverage universes; that is, each house covers at least one identical company. This ensures the relevance of our empirical approach. Finally, we consider post-1988 mergers to make the calculation of our earnings management measures feasible. These constraints yield 13 mergers, which are used in this article.

To isolate the effects of each of these mergers on analyst career outcomes as well as stock coverage, we proceed as follows. First, we identify the IBES identifiers of the merging brokerage houses and the newly formed (merged) entity.[14] With these identifiers, we obtain the unique analyst identifiers for all analysts of the merging houses that provide an earnings forecast (in the year before the merger date) and all analysts that provide a forecast at the newly formed entity (in the year after the merger). The intersection of these two sets is a collection of analysts that were retained by the merged entity. Next, we create two lists of stocks covered by these analysts, one list for the bidder analysts and one for the target analysts, by compiling a list of unique stocks (identified by PERMNO) for which an earnings forecast was provided in the year before the merger date. The intersection of these two lists is the set of stocks covered by both houses premerger.

[13] Given the inherent identification problem, empirical research on this relation has produced ambiguous results so far. Lang and Lundholm (1993) and Healy et al. (1999), for instance, conclude that companies with high disclosure quality (less earnings management) are followed by more analysts. Of note, Anantharaman and Zhang (2012) find that firms increase the volume of public financial guidance in reaction to a loss of analyst coverage.

[14] We show these identifiers in Table 1, and they can also be found in the Appendix in Hong and Kacperczyk (2010).

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There is overlapping coverage at the merging houses for this set of stocks. These are the ("treated") stocks that are the central focus of this article.

Table 1 displays key information on the 13 mergers. We give the names and IBES identification numbers of the merging brokerage houses, showing the bidding house in the top row of each partition. We provide a description of analyst employment at both houses both before and after the merger. We also detail stock coverage at each house, in particular, a count of the unique U.S. stocks followed by each house in the year before the merger, as well as the coverage overlap.

TABLE 1

Descriptive Statistics for Mergers

Table 1 reports details of the merger events considered in this article. The details were compiled from Institutional Brokers' Estimate System (IBES) following Hong and Kacperczyk (2010), as described in the text. The names and dates of the merging brokerage houses are included. For each merger, the brokerage house in the top row is the acquiring house and the brokerage house in the bottom row is the target. The table describes analyst career outcomes in the wake of the merger. The table also breaks out the number of stocks that were covered by both the merging brokerage houses and the overlap in coverage before the merger. These stocks make up our treatment sample and are the focus of this article. The number of overlapping stocks retained is also included. This refers to the number of overlapping stocks from before the merger that continue to be covered by analysts retained at the new entity (which were previously employed at the bidder and by the target, respectively) in the year following the merger.

			Analyst Employment			Stock Coverage		
Brokerage House	IBES Identifier	Merger Date	Before	After	Separation Postmerger (%)	No. of Stocks	Overlap	Overlap Retained
Paine Webber	189	12/31/1994	52	43	17.3	816	171	121
Kidder Peabody	150		57	10	82.6	722		40
Morgan Stanley	192	5/31/1997	89	78	12.4	1,081	180	160
Dean Witter Reynolds	232		39	6	84.6	553		11
Smith Barney (Travelers)	254	11/28/1997	108	81	25.0	1,367	256	164
Salomon Brothers	242		91	47	48.4	936		122
EVEREN Capital	829	1/9/1998	32	23	28.1	249	8	7
Principal Financial Securities	495		19	2	89.5	212		0
DA Davidson & Co	79	2/17/1998	7	5	29.6	108	12	4
Jensen Securities	932		5	5	0.0	73		11
Dain Rauscher	76	4/6/1998	50	31	38.0	459	39	11
Wessels Arnold & Henderson	280		17	11	35.3	201		24
First Union	282	10/1/1999	39	30	23.1	417	24	15
EVEREN Capital	829		37	13	64.9	277		1
Paine Webber	189	6/12/2000	62	49	21.0	758	17	11
JC Bradford	34		23	0	100.0	229		0
Credit Suisse First Boston	100	10/15/2000	141	113	19.9	1,359	299	178
Donaldson Lufkin and Jenrette	86		98	25	74.5	1,021		76
UBS Warburg Dillon Read	85	12/10/2000	121	91	24.8	936	165	107
Paine Webber	189		67	39	41.8	730		98
JPMorgan	873	12/31/2000	92	67	31.4	721	80	47
Chase Manhattan	125		50	35	30.0	598		34
Fahnestock	98	9/18/2001	19	12	36.8	161	7	7
Josephthal Lyon & Ross	933		14	0	100.0	121		0
Janney Montgomery Scott	142	3/22/2005	14	13	7.1	165	8	8
Parker/Hunter	860		5	3	40.0	64		1

To illustrate our identification strategy, consider the Morgan Stanley and Dean Witter Reynolds merger, which took place May 31, 1997. There was significant analyst turnover as a consequence of the merger. More precisely, Morgan Stanley had 89 analysts before the merger and Dean Witter Reynolds had 39. After the merger, the combined entity had a total of 84 analysts, retaining 78 from Morgan Stanley and only 6 from Dean Witter Reynolds. We also see that

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there were 180 (treated) stocks that were covered by both firms before the merger. However, as evidenced by the final column of Table 1, following the merger the new entity had fewer analysts with coverage overlap. In particular, the 6 Dean Witter Reynolds analysts retained in-house continued to cover only 11 of the 180 treated stocks.

We replicate this procedure for each of the remaining 12 mergers and identify a total of 1,266 unique treated stocks. A pattern similar to Morgan Stanley's merger with Dean Witter Reynolds emerges for the full set of mergers: On average, stocks with overlapping coverage lose coverage following the merger and coverage is retained by analysts at the acquiring house.[15] We verify this explicitly in Section III and use this variation to estimate a causal impact of analyst coverage on accrual-based and real earnings management.

To implement our identification strategy, we select an event window around the merger to isolate potential effects resulting from the merger. In contrast to short-term event studies that use daily stock market data, we use annual accounting data and require a longer event window. To this end, we follow other studies also using brokerage house mergers and financial statement data (e.g., Derrien and Kecskes (2013), Irani and Oesch (2013)) and use a 2-year window consisting of 1 year (365 days) before the merger and 1 year after the merger. To calculate the number of analysts covering a stock around the merger date, we use the same window. To calculate accounting ratios, we use financial statement data from the last fiscal year that ended before the merger as the premerger year and the first complete fiscal year following the merger as the postmerger year. For example, consider a treated firm with a Dec. fiscal year-end and a Nov. 28, 1997 merger date. In such a case, the premerger year ($t-1$) is set to the year ending Dec. 31, 1996, and the postmerger year ($t+1$) is set to the year ending Dec. 31, 1998. This yields two nonoverlapping observations for all firms included in our sample, one pre- and one postmerger.

The simplest way to test for differences in firms' earnings management behavior following a reduction in analyst coverage is to contrast the corporate financial reporting of treated firms before the merger shock with the reporting of treated firms after the merger. This approach disregards, however, potential trends that affect all stocks (regardless of whether they are included in the treatment sample). For example, new accounting regulations might limit the use of accrual-based accounting manipulation for all firms in a way that coincides with the pre- or postperiod of a particular merger (e.g., SOX in 2002 as in S.-S. Chen and Huang (2013), Cohen et al. (2008)). By considering only the time-series (i.e., post minus pre) difference for treated firms, this could lead us to falsely attribute an adjustment in treated firms' reporting behavior to the merger. We adopt a commonly used method to address potential time trends: incorporating a control group

[15] Wu and Zang (2009) confirm that analyst turnover is concentrated at the target brokerage house and tends to reflect the acquirer's elimination of duplicate research coverage. This indicates that coverage terminations follow a clear pattern that is unrelated to analyst skill or firm performance. Hong and Kacperczyk (2010) examine a similar set of treated stocks and find that the mergers led to a decline in analyst performance, measured by annual earnings per share forecast updates and accuracy (forecast error variance). These findings alleviate the concern that the loss of coverage for treated stocks coincides with an improvement in the quality of analyst coverage.

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and using DiD methodology. This method compares the difference in the variable of interest across the event window between the treated and control firms. In our setting, the control firms are all stocks that do not have overlapping coverage at the merging brokerage houses.

One residual concern with our identification strategy is that ex ante differences between treatment and control samples could affect the estimated impact of the coverage loss. In our context, this could be due to the fact that larger firms tend to be covered by more brokerage houses (and are thus more likely to be a treated firm), but that these larger firms are also less likely to manipulate earnings. Thus, it is important to control for such differences in the characteristics in our empirical specification to ensure we are correctly identifying the effect of the coverage shock. We mitigate this concern using two approaches. First, as detailed below, we incorporate control variables into our linear regression framework. Second, as detailed in Section III, we implement a DiD propensity score matching estimator.

To empirically test how firms react to the exogenous coverage loss, we implement our quasi-experiment using the following panel regression specification:

$$\begin{aligned} (1) \qquad \mathrm{EM}_i \;=\; & \alpha + \beta_1 \mathrm{POST}_i + \beta_2 \mathrm{TREATED}_i \\ & + \beta_3 \mathrm{POST}_i \times \mathrm{TREATED}_i + \gamma' \mathrm{X}_i + \epsilon_i, \end{aligned}$$

where EM_i denotes our measure of earnings management (i.e., accrual-based or real) for firm i; POST_i denotes an indicator variable that is equal to 1 in the postmerger period, and 0 otherwise; and $\mathrm{TREATED}_i$ is an indicator variable that identifies whether a firm is treated or not. The coefficient of interest is β_3, which corresponds to the DiD effect, namely, the impact of the merger on the earnings management behavior of treated firms relative to control firms.

We employ several versions of equation (1). Our preferred specification includes industry, merger, and firm fixed effects that account for time-invariant (potentially unobservable) factors particular to a merger, an industry, or a firm that may influence the earnings management behavior between units. This specification permits the inclusion of firm-specific control variables (to be defined below), which we incorporate as part of the vector X_i on the right-hand side of equation (1). This specification is estimated using heteroskedasticity-robust standard errors, which we cluster at the firm level.[16]

B. Sample Construction

In this section we detail how we construct our sample. First, we collect data on analyst coverage from IBES. For the 13 mergers that comprise our identification strategy, we consider a 365-day window around the brokerage house merger calendar date and keep all publicly traded U.S. companies that have an earnings forecast in this window. This yields 144,943 firm-year observations.

Next, we merge this sample with financial statement data from Standard & Poor's (S&P) Compustat. To this end, we assign fiscal years to the 365-day

[16]We experimented with various clusterings (e.g., by merger, industry, and merger and industry). Our results are robust to these clustering schemes. Clustering at the firm level tends to produce the largest, and thus most conservative, standard errors, so we report these throughout.

windows before and after the merger date. We assign the last completed fiscal year before the merger date to the 365-day window before the merger date and the first complete fiscal year after the merger date to the 365-day window after the merger date. We link 110,482 firm-year observations.

Next, we require that each firm-year observation has the variables necessary to calculate our primary measures of earnings management (AM and RM, as defined below). This requirement results in a final sample of 61,442 firm-year observations, which consists of 1,266 treated firms. This reduction in sample size results from missing accounting data or SIC code, or a firm belonging to an industry-year with fewer than 15 observations.

In further specifications, we include control variables (defined below) that use both balance sheet and securities price data from the merged Center for Research in Security Prices (CRSP)/Compustat database. Constructing these variables imposes data constraints that reduce the sample for these analyses to a maximum of 60,758 firm-year observations.

C. Measuring Earnings Management

In our empirical analysis, our main dependent variables are an accrual-based measure of earnings management (AM) and a measure of real activities manipulation (RM). We follow the extant earnings management literature when constructing these variables.

We construct AM in the following way. First, we estimate the "normal" level of accruals for a given firm, using coefficients obtained from an industry-level cross-sectional regression model of accruals.[17] To estimate the normal level of accruals, we use the Jones (1991) model in its modified version (Dechow et al. (1995)). To this end, we first run the following regression for each industry and year pair:

$$\frac{\mathrm{TA}_{it}}{\mathrm{A}_{i,t-1}} = a_1 \frac{1}{\mathrm{A}_{i,t-1}} + a_2 \frac{\Delta \mathrm{REV}_{it}}{\mathrm{A}_{i,t-1}} + a_3 \frac{\mathrm{PPE}_{it}}{\mathrm{A}_{i,t-1}} + \epsilon_{it}, \tag{2}$$

where TA_{it} denotes total accruals of firm i in year t, computed as the difference between net income (Compustat item *ni*) and cash flow from operations (item *oancf*); ΔREV is the difference in sales revenues (item *sale*); and PPE is gross property, plant, and equipment (item *ppegt*). These variables are all normalized by lagged total assets (item *at*).[18]

The estimated coefficients from equation (2) are then used to calculate normal accruals (NA) for each firm:

$$\frac{\mathrm{NA}_{it}}{\mathrm{A}_{i,t-1}} = \widehat{a}_1 \frac{1}{\mathrm{A}_{i,t-1}} + \widehat{a}_2 \frac{\Delta \mathrm{REV}_{it} - \Delta \mathrm{AR}_{it}}{\mathrm{A}_{i,t-1}} + \widehat{a}_3 \frac{\mathrm{PPE}_{it}}{\mathrm{A}_{i,t-1}}, \tag{3}$$

[17]The advantage of such a cross-sectional approach is that it helps us deal with the severe data restrictions and survivorship bias that arise in time-series models. Moreover, given our focus on year-to-year changes around the merger dates, a time-series estimate would not be appropriate.

[18]In our baseline results, we use the 48 Fama–French (1997) industries. In Section III, we show that our results are robust to using the 2-digit SIC code (SIC2).

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where ΔAR is the change in receivables (item *rect*) and the other variables are the same as above. Finally, we calculate our measure of accruals management, AM, as the absolute difference between total accruals and the predicted firm-level normal accruals ("abnormal accruals"). Large absolute abnormal accruals reflect high differences between the cash flows and the earnings of a firm, relative to an industry-year benchmark. We attenuate the distortions arising from extreme outliers by winsorizing our AM variable at the 1% and 99% levels.[19]

In robustness tests, we consider alternative measures of accrual-based earnings management. First, we use two non-regression-based measures of current accruals. Following Sloan (1996), we calculate the current accruals as:

$$\text{CA}_{it} = \frac{\Delta\text{CAT}_{it} - \Delta\text{CL}_{it} - \Delta\text{CASH}_{it} - \text{DEP}_{it}}{\text{A}_{i,t-1}}, \tag{4}$$

where ΔCAT is the change in current assets (item *act*), ΔCL is the change in current liabilities (item *lct*), ΔCASH is the change in cash holdings (item *che*), and DEP is the depreciation and amortization expense (item *dp*). We exclude short-term debt from current liabilities, as managers will lack discretion over this item in the short run (Richardson, Sloan, Soliman, and Tuna (2005)). We take the absolute value of these current accruals as an alternative measure of accruals manipulation.

We also consider a variant of this accruals measure, CA(Excl_Depr), calculated by removing depreciation from equation (4). We do so following Barton and Simko (2002), who argue that managers have limited discretion over depreciation schedules in the short run.

The third non-regression-based measure of accrual manipulation follows Hribar and Collins (2002) and is based on data from the income and cash flows statement, as opposed to the balance sheet. These authors show that using balance sheet information to calculate accruals relies on a well-defined mapping between the statement of cash flows and the balance sheet. However, nonoperating events such as mergers and acquisitions activity or foreign currency transactions can lead to a breakdown in basic relation among financial statements.[20] Specifically, changes in current assets and liabilities brought about by such events show up on the balance sheet but do not flow through the income statement as earnings are unaffected. As a consequence, Hribar and Collins show that using a balance sheet approach to estimate abnormal accruals can lead to the incorrect conclusion that earnings management exists when in fact it does not. A measure not subject to this problem can be computed as:

$$\text{CA(Cash_Flow)}_{it} = \frac{\text{EBXI}_{it} - \text{CFO}_{it}}{\text{A}_{i,t-1}}, \tag{5}$$

where EBXI denotes earnings before extraordinary items and discontinued operations (item *ibc*) and CFO is the operating cash flows from continuing operations

[19] A potential concern with this measure is that standard Jones (1991)-type models of discretionary accruals are not able to adequately control for firm growth. In robustness tests, we follow the procedure outlined in Collins, Pungaliya, and Vijh (2012) and adjust the discretionary accruals for sales growth. We find our results to be unaffected by this adjustment. The same is also true when we use performance-matched discretionary accruals, as advocated by Kothari, Leone, and Wasley (2005).

[20] This is commonly referred to as a "nonarticulation" problem (e.g., Wilkins and Loudder (2000)).

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taken from the statement of cash flows (item *oancf* minus item *xidoc*). This measure is conceptually similar to a balance-sheet accruals measure in that it aims to capture the difference between earnings and cash flows. The key difference is that it is calculated using data from the income statement and the statement of cash flows, rather than the balance sheet.

Construction of a valid RM proxy uses the model introduced by Dechow, Kothari, and Watts (1998), as implemented by Roychowdhury (2006) among others (e.g., S.-S. Chen and Huang (2013), Cohen et al. (2008), and Zang (2012)). We follow these earlier works and consider the abnormal levels of cash flow from operations (CFO), discretionary expenses (DISX), and production costs (PROD) that arise from the following three manipulation methods: i) sales manipulation achieved by acceleration of the timing of sales via more favorable credit terms or steeper price discounts; ii) reduction of discretionary expenditures, which include selling, general, and administrative expenses (SG&A), advertising, and R&D; and iii) reporting a lower cost of goods sold (COGS) by increasing production.[21]

As a first step we generate the normal levels of CFO, DISX, and PROD. We express normal CFO as a linear function of sales and change in sales. We estimate this model with the following cross-sectional regression for each industry and year combination:

$$\frac{\text{CFO}_{it}}{\text{A}_{i,t-1}} = b_1\frac{1}{\text{A}_{i,t-1}} + b_2\frac{\text{SALES}_{it}}{\text{A}_{i,t-1}} + b_3\frac{\Delta\text{SALES}_{it}}{\text{A}_{i,t-1}} + \epsilon_{it}. \tag{6}$$

Abnormal CFO (RM_{CFO}) is actual CFO minus the normal level of CFO calculated using the estimated coefficients from equation (6). CFO is cash flow from operations in period t (item *oancf* minus item *xidoc*).

Production costs are defined as the sum of cost of goods sold (COGS) and change in inventory during the year. We model COGS as a linear function of contemporaneous sales:

$$\frac{\text{COGS}_{it}}{\text{A}_{i,t-1}} = c_1\frac{1}{\text{A}_{i,t-1}} + c_2\frac{\text{SALES}_{it}}{\text{A}_{i,t-1}} + \epsilon_{it}. \tag{7}$$

Next, we model inventory growth as:

$$\frac{\Delta\text{INV}_{it}}{\text{A}_{i,t-1}} = d_1\frac{1}{\text{A}_{i,t-1}} + d_2\frac{\Delta\text{SALES}_{it}}{\text{A}_{i,t-1}} + d_3\frac{\Delta\text{SALES}_{i,t-1}}{\text{A}_{i,t-1}} + \epsilon_{it}. \tag{8}$$

Using equations (7) and (8), we estimate the normal level of production costs as:

$$\begin{aligned}\frac{\Delta\text{PROD}_{it}}{\text{A}_{i,t-1}} = {} & e_1\frac{1}{\text{A}_{i,t-1}} + e_2\frac{\text{SALES}_{it}}{\text{A}_{i,t-1}} \\ & + e_3\frac{\Delta\text{SALES}_{it}}{\text{A}_{i,t-1}} + e_4\frac{\Delta\text{SALES}_{i,t-1}}{\text{A}_{i,t-1}} + \epsilon_{it}.\end{aligned} \tag{9}$$

[21] Roychowdhury (2006) provides a detailed description of the mechanics of these real activities manipulation methods.

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PROD represents the production costs in period t, defined as the sum of COGS (item *cogs*) and the change in inventories (item *invt*). The abnormal production costs (RM_{PROD}) are computed as the difference between the actual values and the normal levels predicted from equation (9).

We model discretionary expenses as a function of lagged sales and estimate the following model to derive normal levels of discretionary expenses:

$$\frac{\Delta DISX_{it}}{A_{i,t-1}} = f_1 \frac{1}{A_{i,t-1}} + f_2 \frac{SALES_{i,t-1}}{A_{i,t-1}} + \epsilon_{it}, \tag{10}$$

where DISX represents the discretionary expenditures in period t, defined as the sum of advertising expenses (item *xad*), R&D expenses (item *xrd*), and SG&A (item *xsga*). Abnormal discretionary expenses (RM_{DISX}) are computed as the difference between the actual values and the normal levels predicted from equation (10).

Finally, throughout our analysis we consider two aggregate measures of real earnings management activities that incorporate the information in RM_{CFO}, RM_{PROD}, and RM_{DISX}. These measures are computed following Zang (2012) and Cohen and Zarowin (2010) as:

$$RM_1 = RM_{PROD} - RM_{DISX}, \tag{11}$$

$$RM_2 = -RM_{CFO} - RM_{DISX}. \tag{12}$$

Higher values of RM_1 and RM_2 imply that the firm is more likely to have used real activities manipulation.[22,23]

D. Control Variables

To mitigate concerns regarding observable differences among treated and control firms we incorporate control variables in empirical specification (1). In this section, we describe these control variables.

To select appropriate control variables, we follow prior research that also uses measures of accrual-based and real earnings management as dependent variables (e.g., Anantharaman and Zhang (2012), Armstrong, Balakrishnan, and Cohen (2012), Li (2008), Yu (2008), and Zang (2012)). These variables include the natural logarithm of a firm's market capitalization (ln(SIZE)), where a firm's market capitalization is calculated as the number of common shares outstanding times price. We include a company's return on assets (ROA) as a measure of profitability, computed by dividing a company's net income by its total assets. We include the natural logarithm of a company's book value divided by its market capitalization (MTB). We include a company's sales growth (SALES_GR) computed as the yearly growth in sales. All of these variables are based on information

[22] RM_{PROD} is not multiplied by -1, as higher production costs suggest excess production and lower COGS. Moreover, as discussed in Cohen and Zarowin (2010) and Roychowdhury (2006), we do not combine abnormal cash flow from operations and abnormal production costs, as it is likely that the same activities will give rise to abnormally low CFO and high PROD, and a double-counting problem as a consequence.

[23] We also experimented with performance-matched measures of real earnings management, in the spirit of Kothari et al. (2005) and Cohen, Pandit, Wasley, and Zach (2013). We found our results to be robust to these alternative measures.

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obtained from Compustat. Finally, from IBES, we include the number of unique analysts covering a particular firm in a given fiscal year (COVERAGE). All continuous nonlogarithmized variables are winsorized at the 1% and 99% levels.

The data constraints imposed by these additional variables reduce the sample from 61,442 to 60,758 firm-year observations. Summary statistics for these variables for both treatment and control samples are shown in Table 2. Panel A presents summary statistics for the earnings management variables. Panels B and C summarize the control and other variables used in cross-sectional analyses, respectively.

TABLE 2

Summary Statistics for the Treatment and Control Samples

Table 2 reports summary statistics for our treatment and control samples in the year before the merger. The treatment sample consists of all stocks covered by two merging brokerage houses around the 1-year merger window. The control sample is the remainder of the Compustat universe with the required data. Panel A reports summary statistics for the earnings management variables. Panel B reports summary statistics for the control variables. All variables are defined in the Appendix.

	Treated Firms						Control Firms					
Variable	*N*	Mean	Q1	Median	Q3	Std. Dev.	*N*	Mean	Q1	Median	Q3	Std. Dev.
Panel A. Earnings Management Variables												
AM	1,266	0.180	0.021	0.062	0.175	0.376	29,455	0.243	0.034	0.086	0.216	0.472
RM_1	1,266	0.114	−0.154	0.102	0.312	0.894	29,455	0.061	−0.239	0.089	0.394	1.195
RM_2	1,266	0.098	−0.129	0.034	0.198	1.021	29,455	0.108	−0.166	0.049	0.260	1.366
RM_{CFO}	1,266	−0.100	−0.209	−0.095	−0.014	0.391	29,455	−0.038	−0.205	−0.074	0.034	0.533
RM_{PROD}	1,266	−0.083	−0.208	−0.045	0.054	0.265	29,455	−0.076	−0.205	−0.050	0.077	0.305
RM_{DISX}	1,266	0.197	0.007	0.130	0.302	0.801	29,455	0.145	−0.078	0.110	0.351	1.056
Panel B. Control Variables												
COVERAGE	1,264	22.868	14	22	31	11.333	29,115	7.269	2	5	10	7.181
ln(SIZE)	1,264	8.365	7.134	8.327	9.488	1.733	29,115	5.700	4.412	5.608	6.822	1.808
ROA	1,264	0.106	0.067	0.108	0.163	0.133	29,115	0.042	0.021	0.085	0.138	0.219
MTB	1,264	5.036	2.048	3.127	5.697	7.024	29,115	3.391	1.342	2.262	3.941	5.151
SALES_GR	1,264	0.044	0.119	0.239	0.155	0.228	29,115	0.025	0.126	0.271	0.132	0.321
Panel C. Cross-Sectional Analysis Variables												
EXPERIENCE	1,266	7.796	6.581	8	8.956	1.778	29,362	3.800	6.429	8.622	6.184	3.820
HOUSE_EXP	1,266	4.411	5.500	6.411	5.436	1.508	29,362	2.500	4.062	5.857	4.209	2.815
AUDITOR_TENURE	1,266	5.454	3	5	8	2.212	29,455	5.257	3	5	7	2.498
NOA	1,266	0.702	0.530	0.669	0.806	0.402	29,455	0.725	0.494	0.690	0.872	0.496

Treated firms are larger in size and have greater coverage than the average Compustat firm. These differences occur for two reasons. First, treated firms must be covered by at least two brokerage houses. Second, the majority of treated firms are involved with the large brokerage house mergers (i.e., mergers 1, 2, 3, 9, and 10, as detailed in Table 1) and large houses tend to cover large firms (Hong and Kacperczyk (2010)). In addition, the treatment and control samples differ along several other observable dimensions, as displayed in Table 2. To validate our empirical design, we demonstrate in tests below that our results are not driven by these ex ante differences.

III. Results

This section starts by confirming the validity of the quasi-experiment and then quantifies the average effect of an exogenous loss of analyst coverage on

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earnings management (Section III.A). In Section III.B, we conduct a series of cross-sectional tests to further assess what is driving the estimated average treatment effect. In particular, we investigate how this treatment effect varies with proximity to important earnings thresholds, analyst experience, and costs of earnings management. In Section III.C, we conclude our empirical analysis with a series of robustness tests.

A. Average Effect of Analyst Following on Earnings Management

Table 3 presents the main results and contribution of this article. We first validate the key premise of the experiment: On average, treated firms should lose analyst coverage relative to nontreated firms in the year following a brokerage house merger. We examine whether this is the case by replacing earnings

TABLE 3

Baseline Effects on Coverage, Accrual-Based, and Real Earnings Management

Table 3 reports results from the estimation of equation (1). POST is equal to 1 for the postmerger period and 0 for the premerger period. For each merger, we construct an indicator variable (TREATED) that is equal to 1 for each stock covered by both merging brokerage houses (treatment sample), and 0 otherwise. COVERAGE is the number of analysts covering a firm in the year before the merger. AM denotes our measure of accrual-based earnings management. RM_1 and RM_2 denote our measures for real earnings management. In Panel A, we present the baseline effects. In Panel B, we classify treated firm-years into two groups depending on whether a firm's premerger level of COVERAGE is above (LOW_COVERAGE = 0) or below (LOW_COVERAGE = 1) the median and allow the treatment effect to vary between these two groups. If indicated, the regressions include industry fixed effects, merger fixed effects, or firm fixed effects. The *t*-values (in parentheses) are robust to clustering at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in the Appendix.

Panel A. Baseline Effects

Independent Variable	COVERAGE 1	AM 2	AM 3	AM 4	AM 5	RM_1 6	RM_2 7
POST	−0.007	−0.022***	−0.022***	−0.024***	−0.024***	0.064***	0.049***
	(−0.264)	(−3.463)	(−3.468)	(−3.746)	(−3.637)	(8.591)	(7.021)
TREATED	15.624***	−0.112***	−0.068***	−0.040***	−0.021	0.067***	0.060***
	(30.508)	(−7.199)	(4.501)	(−2.847)	(−1.501)	(3.820)	(3.718)
POST × TREATED	−0.633***	0.043**	0.043**	0.043**	0.043**	−0.095***	−0.089***
	(−4.442)	(2.165)	(2.172)	(2.166)	(2.101)	(−3.457)	(−3.319)
Merger fixed effects	No	No	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	No	No	No	Yes	Yes	Yes	Yes
Firm fixed effects	No	No	No	No	Yes	Yes	Yes
No. of obs.	61,442	61,442	61,442	61,442	61,442	61,442	61,442
R^2	0.1389	0.001	0.058	0.156	0.354	0.332	0.297

Panel B. Conditional on Premerger Coverage Level

Independent Variable	AM 1	RM_1 2	RM_2 3
POST	−0.024***	0.064***	0.048***
	(−3.64)	(8.59)	(7.02)
TREATED	−0.022	0.068***	0.060***
	(−1.52)	(3.88)	(3.75)
POST × TREATED × 1{LOW_COVERAGE = 1}	0.055**	−0.122***	−0.099***
	(2.01)	(−3.98)	(−3.42)
POST × TREATED × 1{LOW_COVERAGE = 0}	0.029	−0.064	−0.076*
	(1.22)	(−1.56)	(−1.94)
Merger fixed effects	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes
No. of obs.	61,442	61,442	61,442
R^2	0.354	0.386	0.297

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management (EM) with analyst coverage (COVERAGE) on the left-hand side of equation (1). Column 1 of Table 3 confirms that our quasi-experiment is relevant. The estimated coefficient is −0.633 with a *t*-value of −4.44. This is consistent in terms of size and significance with research using a similar experimental design (e.g., Derrien and Kecskes (2013), Hong and Kacperczyk (2010)), in spite of sample differences occurring due to various data restrictions across these studies.

Next, we investigate the effects of this loss of coverage on the earnings management behavior of the firm. The remaining columns of Table 3 display these results. Column 2 shows the outcome of estimating equation (1) with accrual manipulation (AM) as the dependent variable without any fixed effects. The results indicate that the DiD coefficient, β_3, is positive and statistically significant. The point estimate on the DiD term in column 2 is 0.043, indicating that a drop in coverage among treated firms causes an increase in the use of abnormal discretionary accruals that is about 9% of 1 standard deviation. Thus, the effect we document is both statistically significant and economically meaningful.

In columns 3–5 of Table 3, we run the same analysis but now include a battery of fixed effects. These fixed effects mitigate the concern that time-invariant factors could be driving the observed relation between coverage and earnings management behavior between units. In column 3, we include merger fixed effects. We then additionally include industry and, finally, industry and firm fixed effects. None of these steps change the overall picture: For all of these specifications, the estimated partial effect of the merger on the treated firms remains statistically significant and on the same order of magnitude. This confirms that the estimated impact of coverage on accrual manipulation is not due to time-invariant heterogeneity between mergers, industries, or firms.

Thus, after the merger and coverage loss, consistent with greater accrual manipulation, treated firms' accounting figures reflect a higher amount of absolute abnormal accruals (i.e., a larger gap between cash flows and earnings relative to industry peers). This outcome mirrors prior empirical research that infers a monitoring role of securities analysts when studying their impact on accrual manipulation (Irani and Oesch (2013), Lindsey and Mola (2013), and Yu (2008)).

In columns 6 and 7 of Table 3, we examine the impact of coverage on real earnings management. We consider the two composite measures of real activities manipulation used in Cohen and Zarowin (2010) and defined in equations (11) and (12). The estimated DiD coefficient in the RM_1 equation is −0.095 with a *t*-value of −3.46. We arrive at this estimate when we include the full set of merger, industry, and firm fixed effects. A similar result holds when we exclude these fixed effects (omitted for brevity) and in the RM_2 equation, although the magnitude is slightly smaller in the latter case. Thus, the point estimate indicates that a loss of coverage causes a reduction in the use of real earnings management among treated firms. This reduction in real activities manipulation is both relative to control firms and relative to the level of real manipulation within firms in the period before the coverage shock.

These estimates are the key findings of this article. They indicate that managers decrease the use of real activities to manipulate reported earnings in response to an exogenous loss of coverage. This positive relation is consistent with analyst following pressuring managers to manage earnings and doing so via real

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activities manipulation. The use of real activities to manipulate reported earnings can be rationalized by observing that it may be harder to detect and punish such actions and may therefore be characterized by lower expected private costs for managers (Cohen et al. (2008), Graham et al. (2005)).

Consistent with the prior literature (e.g., Yu (2008)), we find a negative relation between analyst following and accrual-based earnings management. Although this relation is in line with analysts constraining accrual-based earnings management, by considering managers' overall earnings management strategy our results indicate that managers use real activities manipulation as a natural alternative way to handle pressure from analysts. Indeed, our findings indicate that a reduction in analyst following leads to a shift in managers' preferred mix of earnings management tools, in particular, a substitution from real activities manipulation to accrual-based earnings management. Thus, considering both methods of earnings management is informative and enables us to uncover a more complete picture of how securities analysts influence earnings management practices.

Next, we examine how the adjustment in earnings management varies with initial analyst coverage. We expect firms experiencing a large percentage reduction in coverage to adjust their earnings management behavior more sharply. Moreover, if securities analysts do affect earnings management, we would also expect to observe the greatest adjustment in reporting behavior among firms experiencing a large percentage loss in analyst coverage (i.e., firms with a low premerger level of coverage). This is an important way to test the validity of our identification strategy.

The results of this investigation are shown in Panel B of Table 3. We split our treatment sample into two groups and define an indicator variable that is equal to 1 depending on whether coverage in the year before the merger is above (LOW_COVERAGE = 0) or below (LOW_COVERAGE = 1) the median among treated firms. Mean coverage in the below- (above-) median premerger coverage subgroup is 12.1 (28.3). We then estimate our baseline model, allowing the treated effect to differ among these two groups. The point estimates indicate that the cross-sectional effect is concentrated among firms with low premerger coverage, which are firms where the loss of one analyst represents a larger percentage drop in analyst following. For this group, the estimated DiD coefficient for the accrual manipulation regression is positive and statistically significant, and for the real activities manipulation regression is negative and significant. This is not the case for the high coverage subgroup. We conduct two additional sample splits (unreported) that are based on the pre- and postmerger level of coverage, respectively. First, following Hong and Kacperczyk (2010), we compare treated firms that were covered by fewer than five analysts premerger with those that were covered by more than five. Using this alternative cutoff, we find a consistent result that treated firms with low premerger coverage experience a stronger treatment effect. Second, we condition on firms losing all coverage postmerger and once again find that the treatment effect is stronger for this subset of firms. Thus, the effect of coverage on earnings management is strongest among firms experiencing a large percentage drop in coverage, which is consistent with our expectation and reassures us that our experiment is well designed.

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In our next set of tests, we disaggregate our composite real activities manipulation measure and repeat our baseline tests on each separate component (RM_{PROD}, RM_{CFO}, and RM_{DISX}). Our aim is to understand which of the three methods of real manipulation described in Section II features most prominently.

These results can be found in Table 4. We reestimate equation (1) using each of the three real activities manipulation components as left-hand-side variables.[24] Panel A displays the results for RM_{DISX}, Panel B for RM_{CFO}, and

TABLE 4

Channels of Real Activities Manipulation

Table 4 reports results from the estimation of equation (1). POST is equal to 1 for the postmerger period and 0 for the premerger period. For each merger, we construct an indicator variable (TREATED) that is equal to 1 for each stock covered by both merging brokerage houses (treatment sample), and 0 otherwise. COVERAGE is the number of analysts covering a firm in the year before the merger. $-RM_{DISX}$, $-RM_{CFO}$, and RM_{PROD} denote measures of real earnings management based on abnormal discretionary expenses (Panel A), cash flows from operations (Panel B), and production costs (Panel C), respectively. If indicated, the regressions include industry fixed effects, merger fixed effects, or firm fixed effects. The *t*-values (in parentheses) are robust to clustering at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in the Appendix.

	1	2	3	4
Panel A. Abnormal Discretionary Expenses: $-RM_{DISX}$				
POST	0.049***	0.049***	0.048***	0.048***
	(7.654)	(7.639)	(7.536)	(7.180)
TREATED	0.0032**	0.061***	0.085***	0.056***
	(1.986)	(3.659)	(5.343)	(3.714)
POST × TREATED	−0.077***	−0.077***	−0.077***	−0.077***
	(−3.211)	(−3.214)	(−3.201)	(−3.071)
Merger fixed effects	No	Yes	Yes	Yes
Industry fixed effects	No	No	Yes	Yes
Firm fixed effects	No	No	No	Yes
No. of obs.	61,442	61,442	61,442	61,442
R^2	0.001	0.017	0.082	0.345
Panel B. Abnormal Cash Flows from Operations: $-RM_{CFO}$				
POST	0.011***	0.011***	0.010***	0.011***
	(3.439)	(3.450)	(3.300)	(3.312)
TREATED	−0.048***	−0.051***	−0.048***	0.012*
	(−5.586)	(−5.921)	(−5.643)	(1.758)
POST × TREATED	−0.017	−0.017	−0.018*	−0.018
	(−1.594)	(−1.592)	(−1.658)	(−1.624)
Merger fixed effects	No	Yes	Yes	Yes
Industry fixed effects	No	No	Yes	Yes
Firm fixed effects	No	No	No	Yes
No. of obs.	61,442	61,442	61,442	61,442
R^2	0.002	0.027	0.067	0.348
Panel C. Abnormal Production Costs: RM_{PROD}				
POST	0.010***	0.010***	0.011***	0.011***
	(5.741)	(5.742)	(6.081)	(5.834)
TREATED	−0.013	−0.021**	−0.021**	0.001
	(−1.358)	(−2.022)	(−2.301)	(0.191)
POST × TREATED	−0.001	−0.001	−0.001	−0.001
	(−0.087)	(−0.094)	(−0.134)	(−0.178)
Merger fixed effects	No	Yes	Yes	Yes
Industry fixed effects	No	No	Yes	Yes
Firm fixed effects	No	No	No	Yes
No. of obs.	61,442	61,442	61,442	61,442
R^2	0.000	0.005	0.093	0.665

[24]The left-hand-side variables in the regressions are $-RM_{DISX}$, $-RM_{CFO}$, and RM_{PROD}, respectively, for ease of interpretation.

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Panel C for RM_{PROD}. In columns 1–4 of each panel, we repeat the analysis starting with no fixed effects and then incorporating merger, industry, and firm fixed effects sequentially. This demonstrates the robustness of the point estimates to these potential sources of heterogeneity.

Looking across these panels and focusing on the POST × TREATED interaction, the point estimates indicate that the adjustment in real activities manipulation following the coverage drop comes primarily from abnormal discretionary expenses. The increase in abnormal discretionary expenses following the reduction in coverage is consistent with recent empirical evidence in He and Tian (2013), who argue that analysts impede innovative activity.

Overall, the key results presented here indicate that an exogenous reduction in analyst coverage causes greater use of accrual-based earnings management and less real activities manipulation, a substitution effect. These results indicate that managers substitute out of real activities manipulation and into accrual manipulation when they feel less scrutinized by financial analysts. This finding is consistent with managers rebalancing their mix of earnings management tools to reflect the lower likelihood of detection of accrual manipulation.

B. Cross-Sectional Analysis

Our findings so far indicate that managers trade off the costs and benefits of earnings management tools (real and accrual based) and that financial analysts have a causal impact on this trade-off. To bolster confidence in the plausibility of our results and the validity of our quasi-experimental research design, we now investigate how the treatment effect varies cross-sectionally. In particular, we seek to understand whether the treatment effect is stronger among firms with a greater incentive to manage earnings. We consider firms in close proximity to the zero-earnings threshold (Section III.B.1), firms losing experienced analysts (Section III.B.2), and firms with lower costs of earnings management (Section III.B.3). These factors have been identified by the accounting and finance literature as key determinants of incentives to manage earnings.[25] As we discuss in detail, the results from this section provide further support for a causal effect of analyst scrutiny on managers' mix of real and accrual-based earnings management.

1. Suspect Firms at the Zero-Earnings Threshold

In this section, we examine the earnings management behavior of firms in close proximity to an important earnings benchmark. We demonstrate that the estimated treatment effect is stronger for this subset of "suspect" firms.

Conceptually, if analysts pressure managers to meet short-run earnings benchmarks, this may incentivize managers to manipulate earnings. If this statement is true, it follows that managers should have a stronger incentive to manage earnings when earnings are expected to narrowly miss a short-run earnings

[25]For overviews of the literature on earnings management incentives, see Dechow and Skinner (2000), Fields, Lys, and Vincent (2001), and Healy and Palepu (2001).

target. Put differently, the effect of analyst scrutiny on earnings management and managers' mix of accrual and real activities manipulation should be more evident when a firm is in close proximity to an earnings target.

This line of thought is corroborated by previous empirical research. First, empirical evidence clearly demonstrates that firms with reported earnings either meeting or closely beating important targets manage earnings more frequently. This occurs both through accrual-based earnings management (Bartov et al. (2002)) and real activities manipulation (Bushee (1998)). Second, analyst coverage may exacerbate incentives to manipulate earnings near targets, as greater coverage is associated with a more severe market reaction to a firm missing an earnings target (Gleason and Lee (2003), Hong, Lim, and Stein (2000)).

In this section, we focus on the zero-earnings threshold. This benchmark has been shown to be particularly important in research based on both observational data and survey-based evidence. For instance, using a large sample of U.S. firms from 1984 to 1996, Degeorge et al. (1999) find that the positive earnings threshold is predominant in the sense that firms falling just short of this benchmark show a strong tendency to manage earnings upward (see also Burgstahler and Dichev (1997)). Moreover, in their survey of 401 U.S. financial executives, Graham et al. (2005) find that more than 65% agree or strongly agree that reporting a positive earnings per share is an important benchmark.

To identify firms near the zero-earnings threshold and conduct our empirical analysis, we proceed as follows. We label earnings management suspects as firm-years with earnings meeting or closely beating the zero-earnings threshold in the previous year. In particular, we classify treated firm-years as meeting or closely beating this threshold whenever reported earnings before extraordinary items divided by lagged assets fall between 0 and 0.05% (Roychowdhury (2006), Zang (2012)). We then define an indicator variable SUSPECT that reflects this partitioning of the treatment sample. Finally, we repeat the heterogeneous treatment effects analysis; that is, we reestimate our baseline model allowing the treatment effect to differ between the suspect and nonsuspect groups.

The results of this analysis are displayed in Table 5. The baseline treatment sample is partitioned into two groups depending on whether premerger earnings are in close proximity to the zero threshold (SUSPECT $= 1$) or not (SUSPECT $= 0$). We then estimate the differential treatment effect between these two groups by interacting this indicator variable with the POST $\times$ TREATED variable. In columns 1–3, we see that each of the point estimates of the treatment effect is larger in magnitude for the suspect firms relative to the nonsuspect firms. Moreover, for the suspect group, the estimated DiD coefficient in the accrual manipulation regression is positive and larger than the average treatment effect reported in Table 3. For the nonsuspect group, the estimated treatment effect is not statistically significant. A similar pattern emerges for the estimates from the real earnings management equations, where we find the estimated treatment effect to be larger for the suspect treated firms as compared to the nonsuspect firms.[26]

[26]We implement an F-test of the alternative hypothesis that the coefficient on the suspect firm triple interaction is bigger than the nonsuspect interaction (against the null hypothesis that they are equal).

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TABLE 5

Suspect Firms at the Zero Earnings Threshold

Table 5 reports results from estimating equation (1) with a heterogeneous treatment effect that accounts for whether a firm is suspect. Treated firms that just meet or beat the zero earnings benchmark in the premerger period are assigned "suspect" status. Accordingly, an indicator variable SUSPECT is set equal to 1 for treated firms with earnings before extraordinary items over lagged assets between 0 and 0.5%. We use our measures of accrual-based earnings management (AM) and real activities manipulation (RM_1 and RM_2) as dependent variables. POST is equal to 1 for the postmerger period and 0 for the premerger period. For each merger, we construct an indicator variable (TREATED) that is equal to 1 for each stock covered by both merging brokerage houses (treatment sample), and 0 otherwise. If indicated, the regressions include industry fixed effects, merger fixed effects, or firm fixed effects. The *t*-values (in parentheses) are robust to clustering at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in the Appendix.

	AM	RM_1	RM_2
Independent Variable	1	2	3
POST	−0.024***	0.064***	0.048***
	(−3.68)	(8.58)	(7.01)
TREATED	−0.021	0.067***	0.060***
	(−1.49)	(3.81)	(3.71)
POST × TREATED × 1{SUSPECT = 1}	0.108**	−0.206***	−0.157**
	(2.18)	(−3.03)	(−2.32)
POST × TREATED × 1{SUSPECT = 0}	0.033	−0.076***	−0.077***
	(1.56)	(−2.61)	(−2.77)
Merger fixed effects	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes
No. of obs.	61,442	61,442	61,442
R^2	0.354	0.388	0.297

These results are consistent with our expectation that treated firms close to the important zero-earnings benchmark have a greater incentive to manage earnings. For these firms the exogenous loss of coverage induces a greater response, consistent with analyst coverage having a compounding effect on earnings management incentives.

2. Impact of Analyst Experience

In this section, we test cross-sectionally how the experience of the analysts following the firm influences earnings management behavior following the merger-related coverage loss.

An established literature has found that analyst experience (or skill) matters for capital markets outcomes and has an important impact on earnings management outcomes. This research demonstrates that analysts with greater experience are more skillful in the sense that they provide more accurate forecasts that incorporate past information more quickly (Clement (1999), Mikhail, Walther, and Willis (1997), (2003)). These studies put forward two main explanations for the observed positive relation between analyst experience and skill. First, senior analysts have survived longer than junior analysts, and it is therefore plausible that they are endowed with more skill to begin with. Second, senior analysts may acquire more skill with time, for example, as a result of industry specialization,

We implement three such tests, one for each of the earnings management regressions in columns 1, 2, and 3 of Table 5. The respective *p*-values for these tests are 0.062, 0.037, and 0.127, indicating that the differences in coefficients are statistically significant (in columns 1 and 2) or borderline statistically insignificant (in column 3).

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training, or repeated interactions with management at a given company. On the relation between analyst skill and managerial behavior, Yu (2008) finds that accrual manipulation is negatively correlated with the average experience level of the analysts following the firm, conditional on the coverage level. This final piece of evidence is consistent with the scrutiny of experienced analysts incrementally constraining accrual-based earnings management.

In our context, we hypothesize that treated firms followed by highly experienced analysts will have less of an incentive to adjust earnings management behavior following a reduction in coverage. Empirically, this corresponds to a small average treatment effect of the merger-related coverage loss on earnings management for treated firms followed by highly experienced analysts. Our basic intuition is that, from the perspective of a firm covered by highly experienced analysts, losing one analyst at random is likely to have only a small effect on managerial incentives. For these firms, the remaining pool of analysts covering the firm is skillful. Thus, the nature of remaining analysts' forecasts, the market reaction to earnings announcements, and hence managers' incentives will likely be unaffected by the coverage loss.

We investigate this hypothesis empirically by first defining analyst experience at the firm level and then implementing a test in our heterogeneous treatment effects framework.

We measure analysts' experience at the firm level in the year before the merger. To this end, we first measure the level of experience of each analyst covering every firm in our treatment sample. We measure analyst-level experience in two complementary ways following Yu (2008). First, we consider "general experience," which is simply the number of years an analyst has worked as an analyst. We measure this as the number of years that an analyst identifier appears in the IBES database.

Second, we consider "house experience," which is the number of years that an analyst has worked at her current brokerage house. This is calculated by counting the number of years that an analyst and her current employer's identifier are matched in IBES. Firm-year-level analyst experience is then calculated as the simple average of the experience of analysts covering the firm in a given year. Table 2 provides relevant summary statistics for firm-level analyst experience.[27]

Next, we define an indicator variable, EXP, and use our heterogeneous treatment effects empirical framework. Our treatment sample is once again classified into two groups, this time depending on whether the premerger level of analyst experience is above (EXP = 1) or below (EXP = 0) the median level of firm-level experience in the sample. Our baseline model (1) is then reestimated allowing for a differential treatment effect across the two groups.[28]

[27]Note that for this analysis we lose a small number of control firms because a unique analyst identifier is not reported in IBES.

[28]Throughout Section III.B, we employ dichotomous variables and interact them with the POST × TREATED variable in our heterogeneous treatment effects regression specification. Although the analyst experience variables are continuous, we cannot cleanly incorporate them into a triple-differences specification. In the case of the analyst general and house experience variables, both variables are always $\geq$1 for treated firms (the premerger mean general experience is equal to 7.8 and minimum is equal to 1.5). This follows from treatment assignment requiring that a firm be covered by at least two

The results of this analysis are shown in Table 6. Looking across columns 1–3 and comparing the point estimates between the two groups, we see that the coefficient on POST × TREATED is larger in magnitude for the low-analyst-experience group as compared to the high-analyst-experience group. This is true for each of the accrual manipulation and real activities manipulation equations. Moreover, this is also the case when analyst experience is measured using house experience (see columns 4–6). However, although each of the point estimates is statistically significant at conventional levels, the differences are not significant in general.[29] Thus, we must interpret these results with caution given the weak evidence that the coefficients are statistically distinct.

TABLE 6

Impact of Analyst Experience

Table 6 reports results from estimating equation (1) with a heterogeneous treatment effect that accounts for whether treated firms are covered by experienced analysts. Treated firms are classified as having high or low analyst experience status using two schemes: first, the average number of years that analysts following the firm have worked as an analyst, and second, the average number of years that analysts following the firm have worked as an analyst at their current brokerage house. An indicator variable EXP is set equal to 1 for treated firms with above-median firm-level analyst experience in the premerger period, and 0 otherwise. We use our measures of accrual-based earnings management (AM) and real activities manipulation (RM_1 and RM_2) as dependent variables. POST is equal to 1 for the postmerger period, and 0 for the premerger period. For each merger, we construct an indicator variable (TREATED) that is equal to 1 for each stock covered by both merging brokerage houses (treatment sample), and 0 otherwise. If indicated, the regressions include industry fixed effects, merger fixed effects, or firm fixed effects. The *t*-values (in parentheses) are robust to clustering at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in the Appendix.

	General Experience			House Experience		
	AM	RM_1	RM_2	AM	RM_1	RM_2
Independent Variable	1	2	3	4	5	6
POST	−0.023***	0.064***	0.049***	−0.024***	0.064***	0.049***
	(−3.68)	(8.58)	(7.01)	(−3.68)	(8.58)	(7.01)
TREATED	−0.030**	0.072***	0.069***	−0.030**	0.072***	0.069***
	(−2.11)	(3.93)	(4.18)	(−2.12)	(3.92)	(4.19)
POST × TREATED × 1{EXP = 0}	0.094*	−0.154***	−0.180***	0.111**	−0.128**	−0.176***
	(1.66)	(−2.59)	(−3.11)	(2.18)	(−2.09)	(−3.06)
POST × TREATED × 1{EXP = 1}	0.053***	−0.111***	−0.102***	0.049**	−0.116***	−0.101***
	(2.79)	(−3.73)	(−3.59)	(2.51)	(−3.89)	(−3.56)
Merger fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	61,256	61,256	61,256	61,256	61,256	61,256
R^2	0.353	0.388	0.300	0.353	0.387	0.297

The results of these tests provide suggestive evidence that firms covered by highly experienced analysts do not adjust their earnings management behavior to

analysts before the merger. This leads to a tricky interpretation of the triple-interaction coefficient in such a regression, as there is not a clear baseline level of experience. In contrast, using dichotomous variables allows for a consistent interpretation of our estimated coefficients and permits hypothesis testing.

[29]We implement an *F*-test of the alternative hypothesis that the coefficient on the inexperienced triple interaction is bigger than the experienced interaction (against the null hypothesis that they are equal). We implement three tests, one for each of the earnings management regressions in columns 1–3 of Table 6. The respective *p*-values for these tests are 0.22, 0.23, and 0.09. We conduct equivalent *F*-tests for the house experience regressions, resulting in *p*-values of 0.10, 0.42, and 0.10 for columns 4, 5, and 6, respectively.

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the same extent as those followed by inexperienced analysts. This finding confirms our intuition that the random loss of an analyst from a highly experienced group covering a firm will not affect managerial incentives to engage in earnings management.

3. Impact of the Costs of Earnings Management

Differences in firms' accounting and operational environments give rise to differences in the relative costs of real and accrual-based earnings management methods.[30] In this section, we investigate two important costs of accrual manipulation: auditor quality and accounting flexibility. We hypothesize and find that when these costs are relatively high, firms are unable to substitute away from real activities toward accrual manipulation following the loss of analyst coverage. Thus, we provide causal evidence that the impact of analyst scrutiny on accrual-based earnings management matters less in the presence of an effective auditor (or where managers have little accounting flexibility).

The literature has emphasized two factors limiting the use of accrual manipulation: i) scrutiny from external monitors, including auditors and regulators, and ii) degree of accounting flexibility. We now briefly describe why these factors are important and then provide details on how we measure them for our empirical analysis.

We first focus on external scrutiny from auditors as a cost of accrual manipulation. The accounting literature has emphasized audit quality as an important constraint on accounting manipulation (e.g., Becker, DeFond, Jiambalvo, and Subramanyan (1998), DeFond and Jiambalvo (1991), Myers, Myers, and Omer (2003), and Stice (1991)). This literature has demonstrated that high-quality auditors constrain extreme accounting choices made by management when presenting the firm's financial performance. Conversely, when audit quality is low, auditors do not constrain such questionable choices, resulting in a failure to detect misreporting or material fraud.

In our tests, we follow this literature and use auditor tenure (AUDITOR_TENURE) as a proxy for auditor scrutiny, based on data obtained from Compustat. Empirical evidence supports the assertion that as auditor tenure increases so too does overall audit quality. Geiger and Raghunandan (2002) identify a lack of knowledge of client-specific risks as a key reason auditors are less effective early in their tenure and, as a consequence, audit failures occur more frequently. Along these lines, prior research demonstrates that a larger fraction of audit failures occur on newly acquired clients and that auditors' litigation risk is greater in the early years of an engagement (Palmrose (1991)). Moreover, Myers et al. (2003) find that longer auditor tenure is associated with higher earnings quality, using a broad cross section of firms and several measures of accrual manipulation as proxies for earnings quality.[31]

[30] See Zang (2012) and references therein for an in-depth analysis and discussion of the costs of real and accrual-based earnings management.

[31] The other side of this argument, which has been the subject of debate among academics, regulators, and policy makers, has been that longer auditor tenure could compromise independence and lead to auditors' support for accounting choices that "push the boundaries" of GAAP. Those in favor of the

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In addition to scrutiny from external monitors, accrual manipulation may also be constrained by the flexibility within the accounting systems and procedures of the firm. Barton and Simko (2002) argue that accrual manipulation occurring in previous periods should accumulate on the balance sheet. In particular, if managers have biased earnings up in previous periods, this will be reflected in an "overstatement" of net operating assets.[32] Indeed, the authors find a strong positive association between the current level of net operating assets (relative to sales) and reported cumulative levels of abnormal accruals over the past 5 years. Taking this logic a step further, the authors hypothesize that managers will be constrained in their ability to bias up earnings via accrual manipulation if net assets have already been overstated in the past. If managers wish to stay within the limits of GAAP, liberal choices made in the past regarding loss recognition and measurement should limit their ability to make similarly generous assumptions going forward. Consistent with this hypothesis, Barton and Simko find that the likelihood of narrowly meeting or beating analysts' consensus earnings forecasts is decreasing in the extent to which net operating assets are overstated on the balance sheet.

Following Barton and Simko (2002), we capture accounting flexibility using the beginning-of-year net operating assets relative to sales (NOA_{t-1}), where net operating assets are calculated as shareholders' equity less cash and marketable securities plus total debt.

We investigate how scrutiny from auditors and the degree of accounting flexibility affect the use of different types of earnings management in response to the loss of coverage. If these factors do constrain accrual manipulation, this would be evidenced by a smaller increase in accrual-based earnings management following the loss of coverage. Moreover, if these costs are particularly onerous, managers might not rebalance their earnings management strategies toward accrual-based methods at all. In this case, we expect to see no adjustment in earnings management behavior following the loss of coverage.

To test how the use of different types of earnings management is affected by each of these costs, we split our treatment sample into two groups, "high" and "low" costs, depending on whether the cost variable is above or below the median among treated firms, in the year before the merger. We then estimate our baseline model, for both accrual-based and real earnings management (i.e., AM and RM_1), on each group separately and examine how the treatment effect varies between groups.[33]

The results of this analysis are presented in Table 7. Columns 1–4 and 5–8 show how auditor tenure and accounting flexibility, respectively, affect both

mandatory rotation of auditors argue that capping auditor tenure limits concerns about auditor capture and deteriorating audit quality. See Myers et al. (2003) for a detailed discussion of these issues, as well as empirical evidence in support of our approach.

[32]"Overstatement" describes the extent to which reported net assets exceed some benchmark that would have been recorded under an unbiased application of GAAP. Following Barton and Simko (2002), we use current sales as this benchmark. Although current sales may also be subject to manipulation, as acknowledged by these authors, such a reporting bias would be present only in the current period. The results presented in this section are also robust to using the alternative definition of scaled net operating assets found in Hirshleifer, Hou, Teoh, and Zhang (2004).

[33]The results (omitted for brevity) are similar when we consider RM_2.

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TABLE 7

Impact of Costs of Accruals Management

Table 7 reports results from the estimation of equation (1), with the sample split based on the costs of accruals management. Treated firms are classified according to the cost of accrual manipulation. We divide the sample first based on the median of auditor tenure (AUDITOR_TENURE) of treated firms and then based on the median of accounting flexibility measured by net operating assets (NOA). Firms with above-median auditor tenure and below-median NOA are assigned to each of the "high"-cost subsamples. We use our measures of accrual-based earnings management (AM) and real activities manipulation (RM_1) as dependent variables. POST is equal to 1 for the postmerger period, and 0 for the premerger period. For each merger, we construct an indicator variable (TREATED) that is equal to 1 for each stock covered by both merging brokerage houses (treatment sample), and 0 otherwise. Regressions include industry fixed effects, merger fixed effects, and firm fixed effects. The *t*-values (in parentheses) are robust to clustering at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in the Appendix.

	Auditor Tenure				Accounting Flexibility			
	AM		RM_1		AM		RM_1	
Independent Variable	High 1	Low 2	High 3	Low 4	High 5	Low 6	High 7	Low 8
POST	−0.017**	−0.046***	0.021**	0.125***	0.012	−0.037***	0.017*	0.071***
	(−2.012)	(−4.718)	(2.023)	(9.531)	(1.263)	(−3.963)	(1.833)	(6.548)
TREATED	−0.037*	−0.044**	0.030	0.077***	−0.015	−0.048***	0.008	0.077***
	(−1.694)	(−2.501)	(1.102)	(2.931)	(−0.659)	(−2.613)	(0.358)	(3.544)
POST × TREATED	0.028	0.053*	−0.027	−0.146***	0.001	0.089***	−0.056	−0.122***
	(0.998)	(1.944)	(−0.661)	(−3.309)	(0.044)	(3.473)	(−1.386)	(−3.340)
Merger fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	31,848	29,594	31,848	29,594	30,085	31,357	30,085	31,357
R^2	0.168	0.162	0.476	0.473	0.413	0.402	0.354	0.367

real and accrual-based earnings management behavior. The results are consistent with the substitution effect being muted where the costs of accrual manipulation are high. We find that the cross-sectional effect is concentrated among firms in the low-cost subsamples. For this group, the estimated DiD coefficient is positive and statistically significant for accrual manipulation (AM) and negative and statistically significant for real activities manipulation (RM_1). In contrast, in the high-cost subgroup, the estimated treatment effects are indistinguishable from 0. Thus, we observe an adjustment in earnings management behavior, a substitution from real activities to accrual manipulation, only among firms where the costs of accrual manipulation are not prohibitive.

Overall, the results indicate that the extent of substitution from real to accrual-based earnings management varies systematically with accounting-based costs of earnings management tools that have been emphasized in the literature (e.g., Zang (2012)).

When taken together with the results of Section III.B, we show that the mix of real and accrual-based earnings management techniques depends on several factors known to influence managers' incentives to manage earnings. This analysis gives us greater confidence in our baseline estimates and strengthens our argument for the causal effect of analyst scrutiny on the trade-off between real and accrual-based earnings management.

C. Robustness of Average Treatment Effect

In this section we perform a series of tests to examine the validity of our quasi-experiment and robustness of our estimated average treatment effect

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in Section III.A. We first show that our results hold when we control for ex ante differences between treated and control firms, using both control variables in a linear framework and a matching estimator (Section III.C.1). Next, we investigate the validity of our research design by testing for pre- and posttrends in our earnings management variables (Section III.C.2). Finally, we consider several alternative measures of the manipulation of accruals and real activities and show that our baseline estimates are unaffected in terms of magnitudes and statistical significance (Section III.C.3).

1. Controlling for Ex Ante Differences

The identifying assumption of our quasi-experiment states that the average change in the earnings management behavior of treated firms across the merger date is not due to any factor aside from the merger leading to a drop in analyst following. There is substantial evidence in the literature corroborating this assumption. Notably, Wu and Zang (2009) investigate merger-related departures of financial analysts and find that they occur primarily among target analysts, especially those that have overlapping coverage with analysts in the merger counterparty. The evidence we present in Tables 1 and 3 is consistent with these findings (see our discussion in Sections II and III.A). In addition, Hong and Kacperczyk (2010) demonstrate that the loss of coverage is unrelated to changes in firms' characteristics across the merger date. Thus, the loss of coverage is unrelated to both analyst quality and changes in firm characteristics that might drive the observed adjustment in earnings management behavior.

Although this evidence supports our identification assumption, in this section we nevertheless rule out the possibility that our estimates merely capture ex ante differences in the characteristics of treated and control firms. To this end, we adopt two distinct approaches: We first incorporate control variables into our baseline linear regression model and then we use a matching estimator. We discuss these two approaches in turn.

First, we reestimate our baseline specification (1) controlling for the sources of firm-level heterogeneity discussed in Section II. These control variables include size and performance, both of which are known to vary predictably with earnings management behavior (e.g., Kothari et al. (2005)). Our panel regression specification easily allows us to control for such potential sources of differences across firms, time-varying firm-level characteristics that correlate with earnings management behavior, in addition to the numerous fixed effects we have included thus far.

Table 8 shows these results, indicating that our baseline estimate of the effect of analyst following on accrual and real activities manipulation is robust to controlling for a large set of time-varying observables. Both the effect of the mergers on coverage (column 1) and the magnitude and statistical significance of the estimated average treatment effect are largely unaffected.

Second, we implement a DiD matching estimator. This alternative approach is beneficial if treatment and control samples differ along unobservable dimensions. In particular, including control variables in a linear framework might not control for unobservable heterogeneity, especially if there exist nonlinearities in the data (Roberts and Whited (2013)).

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TABLE 8

Robustness: Average Treatment Effect with Control Variables

Table 8 reports results from the estimation of equation (1) with additional control variables. For each merger, we consider a 1-year window before the merger (premerger window) and a 1-year window after the merger (postmerger window). The dependent variables are COVERAGE in column 1, AM in column 2, RM_1 in column 3, and RM_2 in column 4. POST is equal to 1 for the postmerger period, and 0 for the premerger period. For each merger, we construct an indicator variable (TREATED) that is equal to 1 for each stock covered by both merging brokerage houses (treatment sample), and 0 otherwise. If indicated, the regressions include industry fixed effects, merger fixed effects, or firm fixed effects. The *t*-values (in parentheses) are robust to clustering at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in the Appendix.

Independent Variable	COVERAGE 1	AM 2	RM_1 3	RM_2 4
POST	0.054**	−0.008	0.051***	0.023***
	(1.978)	(−1.223)	(6.660)	(3.312)
TREATED	1.928***	−0.0150	0.055***	0.049***
	(11.417)	(−1.081)	(3.204)	(3.131)
POST × TREATED	−0.758***	0.040*	−0.094***	−0.087***
	(−5.104)	(1.954)	(−3.387)	(−3.261)
ln(SIZE)	1.402***	0.027***	0.033***	0.015*
	(21.145)	(3.572)	(3.608)	(1.869)
ROA	−1.188***	0.009	0.007	0.020
	(−5.004)	(0.0201)	(0.138)	(0.436)
MTB	−0.081***	−0.002	0.002	0.002
	(−8.368)	(−1.357)	(1.504)	(1.591)
SALES_GR	0.600***	−0.089*	0.141***	0.213***
	(7.458)	(−5.362)	(6.911)	(10.702)
COVERAGE		−0.002*	0.005***	0.005***
		(−1.811)	(3.293)	(3.384)
Merger fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
No. of obs.	60,758	60,758	60,758	60,758
R^2	0.884	0.301	0.337	0.305

We match each treated firm to a set of control firms on the basis of observable characteristics that are measured at the firm level in the year before the merger. Initially, we match on firm size (ln(SIZE)), then operating performance (ROA), then both size and operating performance. We match on these two characteristics for two reasons. First, the mergers in our sample involve large brokerage houses that tend to cover big stocks (see Table 2). Second, size and performance vary in a predictable way with the use of real and accrual-based earnings management (Kothari et al. (2005), Zang (2012)). In a final step, we match on all covariates.

We use a nearest neighbor propensity score matching procedure, originally proposed by Rosenbaum and Rubin (1983) and previously used in our context (e.g., Balakrishnan et al. (2014), He and Tian (2013), and Irani and Oesch (2013)). To implement this matching scheme, we first run a logit regression of an indicator variable for whether a particular firm-year is classified as treated (indicator equal to 1) or control (indicator equal to 0) on our matching variables.[34] The sample used to estimate this regression consists of 1,264 treatment and 29,117 candidate control premerger firm-years. This is the sample of treated and control firms with all control variables available. The estimated coefficients from the logit regression are used to estimate probabilities of treatment for each firm-year in the

[34]The results are very similar when we use a probit regression to predict propensity scores.

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sample. These probabilities (propensity scores) are then used to perform a nearest neighbor match. We match with replacement using a standard tolerance (0.005 caliper) and allowing for up to three unique matches per treated firm. We use multiple matches per treated firm to improve the accuracy of our estimated treatment effects, which is possible as the number of candidate control firms exceeds the number of treated firms.

Table 9 shows the results from the matching estimator. Panel A displays the summary statistics for the treatment and matched control samples. The number of successful matches drops slightly as we include more covariates in the

TABLE 9

Robustness: Difference-in-Differences Matching Estimator

Table 9 reports summary statistics and results of using a difference-in-differences matching estimator. The treatment sample consists of all stocks covered by two merging brokerage houses around the 1-year merger window with valid matching variables. The control sample is the remainder of the Compustat universe with valid matching variables. Treated firms are matched using a nearest neighbor logit propensity score match using a 0.005 caliper and matching up to three control firms. Panel A shows summary statistics for the treatment and matched control samples in the year before the merger. *N* and *M* represent the total number of treatment and matched control firms, respectively. Panel B estimates the effect of the brokerage house mergers on COVERAGE and EM variables. The *t*-values (in parentheses) are robust to clustering at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in the Appendix.

Panel A. Summary Statistics for Matched Samples

	Treated Firms			Matched Control Firms			Diff.	
Variable	Mean	Std. Dev.	Med.	Mean	Std. Dev.	Med.	in Means	*t*-Value
1. Matching on ln(SIZE) ($N = 1{,}255$; $M = 3{,}749$)								
ln(SIZE)	8.355	1.723	8.327	8.339	1.707	8.315	0.016	(0.292)
ROA	0.107	0.136	0.108	0.114	0.127	0.120	−0.007*	(−1.650)
COVERAGE	22.839	11.335	22	19.266	11.169	18	3.573***	(9.702)
MTB	5.869	6.811	3.109	7.960	6.244	3.728	−2.091	(−0.961)
SALES_GR	0.156	0.228	0.119	0.161	0.228	0.125	−0.005	(0.637)
2. Matching on ROA ($N = 1{,}258$; $M = 3{,}753$)								
ln(SIZE)	8.366	1.735	8.327	8.501	1.760	8.528	−0.154**	(−2.474)
ROA	0.107	0.136	0.108	0.116	0.131	0.117	−0.009*	(−1.800)
COVERAGE	22.728	11.168	22	21.994	11.086	21	0.734*	(1.836)
MTB	5.854	6.803	3.123	8.293	8.401	3.827	−2.438	(−0.902)
SALES_GR	0.154	0.226	0.120	0.162	0.226	0.125	−0.008	(1.001)
3. Matching on ln(SIZE)/ROA ($N = 1{,}255$; $M = 3{,}751$)								
ln(SIZE)	8.344	1.709	8.320	8.622	1.708	8.677	−0.277***	(−4.633)
ROA	0.107	0.136	0.108	0.116	0.134	0.123	−0.010**	(−2.034)
COVERAGE	22.759	11.230	22	22.121	11.091	21	0.638	(1.628)
MTB	5.841	6.819	3.091	9.500	7.823	3.845	−3.658	(−1.449)
SALES_GR	0.155	0.228	0.119	0.167	0.227	0.125	−0.011	(−1.329)
4. Matching on All Covariates ($N = 1{,}252$; $M = 3{,}748$)								
ln(SIZE)	8.344	1.709	8.320	8.638	1.715	8.717	−0.293***	(−4.895)
ROA	0.107	0.136	0.108	0.116	0.131	0.120	−0.009*	(−1.956)
COVERAGE	22.759	11.230	22	22.160	11.161	21	0.599	(1.524)
MTB	5.841	6.819	3.091	9.411	7.896	3.803	−3.569	(−1.411)
SALES_GR	0.154	0.226	0.119	0.162	0.329	0.125	−0.008	(−0.952)

Panel B. Average Treatment Effects for Matched Samples

	COVERAGE	AM	RM_1	RM_2
Independent Variable	1	2	3	4
ln(SIZE)-matched	−0.794***	0.085***	−0.084***	−0.098***
(standard error)	(0.141)	(0.019)	(0.026)	(0.024)
ROA-matched	−0.644***	0.040**	−0.106***	−0.109***
(standard error)	(0.128)	(0.018)	(0.024)	(0.022)
ln(SIZE)/ROA-matched	−0.860***	0.093***	−0.094***	−0.098***
(standard error)	(0.141)	(0.021)	(0.025)	(0.023)
ln(SIZE)/. . ./SALES_GR-matched	−0.835***	0.081***	−0.103***	−0.117***
(standard error)	(0.139)	(0.021)	(0.024)	(0.022)

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matching scheme. Importantly, the summary statistics indicate that, at least for the covariates we match on, the differences between treated firms and matched control firms are small in terms of economic magnitudes. This is a clear indication that the matching scheme performs well.

Panel B of Table 9 displays the impact of the mergers on coverage and earnings management. Column 1 verifies that the merger event continues to have a meaningful impact on the coverage of treated firms relative to the matched control sample. The remaining columns indicate that the DiD matching estimator produces quantitatively similar estimates of the average treatment effect, both in terms of economic magnitudes and statistical significance. The results in Panels B persist across all sets of matching variables.

Overall, these results indicate that our main results (see Table 3) are not driven by heterogeneity between treatment and control groups. We show that differences in size and operating performance between treatment and control samples do not drive our results. Our estimates are very similar in magnitude and statistical significance when we match on all covariates, thus providing further evidence in support of our empirical design.

Taking the results of both approaches together, this section provides strong evidence that the coverage loss is exogenous and the resulting adjustment in earnings management behavior is not a consequence of some form of omitted variables bias.

2. Validity of Quasi-Experiment

The validity of our DiD identification strategy hinges on the parallel trends assumption. This assumption requires that treated and control firms exhibit similar growth rates of earnings management behavior in the run-up to the merger.

To verify this assumption, we conduct a falsification analysis. We rerun our baseline analysis from Table 3 but mechanically shift each merger event date by 1 year forward (Panel A of Table 10) or backward (Panel B). To illustrate, for merger 1, we move the event date 1 year forward to Dec. 31, 1993 in Panel A and 1 year backward to Dec. 31, 1995 in Panel B. If our finding that firms adjust their behavior in response to the exogenous loss of coverage holds (and this adjustment is not simply part of an ongoing trend), we would expect to observe insignificant estimated DiD coefficients for both of these exercises.

The estimates shown in Panel A and Panel B of Table 10 are consistent with the interpretation that the mergers cause an adjustment behavior, and this behavior is not part of an ongoing trend. Regardless of specification and of whether we artificially shift the merger event dates by 1 year forward or backward, the estimated average treatment effects are not statistically significant. This demonstrates that the adjustment in earnings management behavior among the treated firms takes place only around the merger event dates and is not due to some trend in either the pre- or postevent window. This provides evidence that the parallel trends assumption holds in our setup. Moreover, this also directly addresses the potential concern that our results might simply be due to reversion to the mean in earnings management behavior among treated firms, as it is unlikely that mean reversion would happen only in the year of the merger and not in the years before or after.

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TABLE 10

Validity of the Quasi-Experiment: Placebo Regressions

Table 10 reports results from estimating equation (1). In Panel A, we shift the 1-year window before/after the merger window by 1 year into the future. In Panel B, we shift the 1-year window before/after the merger window by 1 year into the past. We use our measures of accrual-based earnings management (AM) and real activities manipulation (RM_1 and RM_2) as dependent variables. POST is equal to 1 for the (shifted) postmerger period, and 0 for the (shifted) premerger period. For each merger, we construct an indicator variable (TREATED) that is equal to 1 for each stock covered by both merging brokerage houses (treatment sample), and 0 otherwise. If indicated, the regressions include industry fixed effects, merger fixed effects, or firm fixed effects. The *t*-values (in parentheses) are robust to clustering at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in the Appendix.

	AM	RM_1	RM_2
Independent Variable	1	2	3
Panel A. Event Date Shifted 1 Year Forward			
POST	0.080***	0.130***	0.109***
	(9.153)	(17.301)	(13.732)
TREATED	0.025	0.004	0.044*
	(1.353)	(0.233)	(1.953)
POST × TREATED	−0.030	−0.000	−0.026
	(−1.143)	(−0.036)	(−0.918)
Merger fixed effect	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes
No. of obs.	60,292	60,292	60,292
R^2	0.353	0.292	0.237
Panel B. Event Date Shifted 1 Year Backward			
POST	0.049***	0.109***	0.025***
	(10.401)	(9.928)	(4.441)
TREATED	−0.018**	−0.012	−0.044**
	(−2.079)	(−0.548)	(−2.559)
POST × TREATED	0.012	−0.017	−0.009
	(0.847)	(−0.851)	(−0.436)
Merger fixed effect	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes
No. of obs.	53,196	53,196	53,196
R^2	0.342	0.293	0.284

3. Alternative Measures of Earnings Management

In this section, we show that our results are robust to several alternative measures of earnings management outlined previously in Section II.

The outcomes of these tests are reported in Table 11. We recalculate each of the main measures of real and accrual-based earnings management using the 2-digit SIC industry classification when calculating the normal level of accruals and real activities manipulation. In addition, following Sloan (1996), we consider three non-regression-based measures for accrual-based earnings management, which we broadly term as current accruals (CA). Each of these measures uses accounting data, but none use a regression model to compute abnormal accruals. In each case, a higher value of the measure indicates more accruals used in the firm's reporting.

We estimate equation (1) for each of these alternative measures of earnings management. The estimated β_3 in Table 11 indicate that our main results are robust across these measures. Following a loss of analyst coverage, for each of the current accruals measures, firms' total accruals increase, indicating a bigger wedge between a firm's cash flows and earnings, making it harder for an

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TABLE 11

Robustness: Alternative Measures of Earnings Management

Table 11 reports results from the estimation of equation (1). For brevity, we report only the estimated coefficient on the POST × TREATED interaction. The dependent variables are listed in column 1 and are alternative measures of earnings management. For each merger, we consider a 1-year window before the merger (premerger window) and a 1-year window after the merger (postmerger window). POST is equal to 1 for the postmerger period, and 0 for the premerger period. For each merger, we construct an indicator variable (TREATED) that is equal to 1 for each stock covered by both merging brokerage houses (treatment sample), and 0 otherwise. All regressions include industry fixed effects, merger fixed effects, or firm fixed effects. The *t*-values (in parentheses) are robust to clustering at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in the Appendix.

Independent Variable	AM (SIC2)	RM_1 (SIC2)	RM_2 (SIC2)	CA	CA (Cash_Flow)	CA (Excl_Depr)
	1	2	3	4	5	6
POST	0.019*	0.045***	0.020**	−0.021***	−0.018***	−0.020***
	(1.894)	(5.388)	(2.539)	(−3.418)	(−3.271)	(−3.324)
TREATED	−0.040**	0.048**	0.033*	−0.018	−0.021*	−0.017
	(−2.113)	(2.552)	(1.933)	(−1.621)	(−1.714)	(−1.598)
POST × TREATED	0.059*	−0.074**	−0.057*	0.010***	0.011***	0.011***
	(1.884)	(−2.524)	(−1.939)	(2.958)	(2.753)	(2.809)
Merger fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	60,718	60,718	60,718	61,822	61,822	61,822
R^2	0.264	0.372	0.286	0.194	0.171	0.110

investor to discern true performance. These findings are consistent with our key findings for real and accrual-based earnings management following the exogenous coverage loss. Likewise, the estimated treatment effect is robust to employing a 2-digit SIC industry classification.

Finally, we examine the negative and positive components of discretionary accruals. Positive discretionary accruals are consistent with income-increasing manipulations and vice versa for negative discretionary accruals. Managers may be incentivized to boost income by using positive discretionary accruals. However, managers may also use negative discretionary accruals in order (to smooth earnings) to make future earnings benchmarks easier to meet (as in Acharya and Lambrecht (2015)). Thus far, we have considered manipulations in both directions, as we are interested in the impact of analyst coverage on earnings management per se, but now we consider the use of positive and negative discretionary accruals separately.

The results from reestimating our baseline specification (including merger, firm, and industry fixed effects) indicate a reduction in the use of positive discretionary accruals in response to the coverage loss. The estimated DiD coefficient for positive discretionary accruals is 0.044 with a *t*-value of 2.35. The equivalent point estimate for the negative discretionary accruals regression is small in magnitude and not statistically significant. These results are consistent with analysts affecting the use of income-increasing discretionary accruals as opposed to earnings-smoothing behavior through managers' use of accrual manipulation.

D. Comparison with OLS Results

We wrap up our empirical analysis by estimating a series of pooled OLS regressions of each of our earnings management measures on analyst following

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and the collection of control variables detailed in Section III.C.1. More precisely, we estimate:

$$\text{EM}_{it} = \alpha_t + \alpha_j + \alpha_i + \beta\text{COVERAGE}_{it} + \gamma' \text{X}_{it} + \epsilon_{it}, \quad (13)$$

using our earnings management variables, AM, RM_1, and RM_2, as left-hand-side variables, where, depending on the specification we use, we also include year fixed effects (α_t), Fama–French (1997) industry fixed effects (α_j), firm fixed effects (α_i), and the same set of time-varying firm-level control variables used in the analysis thus far. To be comparable with the results from our natural experiment, we restrict our sample to the period from 1994 until 2005.

The OLS regression estimates are shown in Table 12.[35] We present the results without any fixed effects, and then gradually introduce year, industry, and firm fixed effects. Overall, the coefficients on COVERAGE are very small and approximately an order of magnitude lower than the estimates from our experiment. Moreover, these estimates depend on the fixed-effects specification we use and are generally unstable and imprecisely estimated.

As we mention throughout this study, these OLS estimates are tricky to interpret because of the endogenous relation between analyst following and earnings management. This identification problem potentially explains mixed evidence on the use of real activities manipulation to meet analyst forecasts

TABLE 12

Analyst Coverage and Earnings Management: Ordinary Least Squares Estimation

Table 12 reports results from panel regressions of earnings management measures on analyst coverage and control variables that do not account for the endogeneity of analyst coverage. We use our measures of accrual-based earnings management (AM) and real activities manipulation (RM_1 and RM_2) as dependent variables. If indicated, the regressions include industry fixed effects, year fixed effects, or firm fixed effects. The *t*-values (in parentheses) are robust to clustering at the industry level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All variables are defined the Appendix.

	Panel A. No Fixed Effects			*Panel B. Year Fixed Effects*		
Independent Variable	AM	RM_1	RM_2	AM	RM_1	RM_2
	1	2	3	4	5	6
COVERAGE	−0.003**	−0.002	−0.001	0.003***	−0.001	−0.001
	(−2.526)	(−1.475)	(−1.366)	(2.666)	(−0.546)	(−0.683)
ln(SIZE)	0.042***	0.020***	0.009**	−0.019***	0.010*	0.005
	(7.031)	(3.748)	(2.234)	(−3.535)	(1.896)	(1.387)
ROA	−0.622***	0.109***	−0.107***	−0.400***	0.124***	−0.137***
	(−15.455)	(2.777)	(−3.734)	(−10.523)	(3.153)	(−4.784)
MTB	0.007***	−0.016***	−0.009***	0.011***	−0.017***	−0.011***
	(3.027)	(−9.054)	(−7.078)	(5.693)	(−9.728)	(−8.188)
SALES_GR	−0.277***	0.185***	0.231***	−0.273***	0.167***	0.234***
	(−11.232)	(8.587)	(12.903)	(−11.772)	(7.789)	(13.415)
Year fixed effects	No	No	No	Yes	Yes	Yes
Industry fixed effects	No	No	No	No	No	No
Firm fixed effects	No	No	No	No	No	No
No. of obs.	25,125	25,125	25,125	25,125	25,125	25,125
R^2	0.023	0.013	0.019	0.184	0.060	0.080

(continued on next page)

[35] Notice that the estimation sample used in Table 12 is smaller than the sample of the regressions estimated in Table 8. For the sample used in Table 12, every firm-year appears once, whereas in Table 8, each firm-year can enter the sample multiple times. For example, a firm-year acts as a control firm-year for multiple mergers occurring within a short time frame.

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TABLE 12 (continued)

Analyst Coverage and Earnings Management: Ordinary Least Squares Estimation

	Panel C. Year and Industry Fixed Effects			*Panel D. Year, Industry, and Firm Fixed Effects*		
Independent Variable	AM	RM_1	RM_2	AM	RM_1	RM_2
	7	8	9	10	11	12
COVERAGE	0.002**	0.000	0.000	0.002	0.005**	0.003*
	(2.187)	(0.123)	(0.496)	(0.973)	(2.301)	(1.901)
ln(SIZE)	−0.019***	0.012**	0.003	0.016	0.019*	0.000
	(−3.688)	(2.280)	(0.717)	(1.297)	(1.809)	(0.007)
ROA	−0.162***	0.161***	−0.100***	0.314***	−0.025	−0.054
	(−4.302)	(4.132)	(−3.490)	(3.523)	(−0.391)	(−1.001)
MTB	0.004**	−0.019***	−0.012***	−0.003	−0.004**	−0.005***
	(1.995)	(−10.823)	(−9.210)	(−1.244)	(−2.098)	(−2.963)
SALES_GR	−0.199***	0.197***	0.260***	−0.056*	0.234***	0.308***
	(−8.524)	(9.197)	(14.879)	(−1.704)	(8.436)	(12.620)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	No	No	No	Yes	Yes	Yes
No. of obs.	25,125	25,125	25,125	25,125	25,125	25,125
R^2	0.247	0.090	0.105	0.501	0.464	0.391

(e.g., Roychowdhury (2006)), as this methodology treats both exogenous (e.g., due to brokerage house mergers) and endogenous changes in analyst coverage equally. In contrast, the quasi-experimental design we employ identifies a specific, although pervasive in both the cross section and time series, collection of exogenous reductions in coverage. We use these events to isolate an economically meaningful and statistically significant effect, which is stable over many specifications and robustness tests.

IV. Conclusion

We examine the causal effects of financial analyst coverage on earnings management. We use brokerage house mergers as a quasi-experiment to isolate reductions in analyst coverage that are exogenous to firm characteristics (Hong and Kacperczyk (2010), Wu and Zang (2009)). Using DiD methodology, we find that firms that lose analyst coverage reduce real activities manipulation and increase their use of accrual-based earnings management. An important implication of these results is that although analyst coverage may be associated with lower accrual-based earnings management (e.g., Irani and Oesch (2013), Lindsey and Mola (2013), and Yu (2008)), pressure to meet analysts' expectations may nevertheless lead managers to resort to real activities manipulation. Given that real activities manipulation may entail costly deviations from normal business practices (Graham et al. (2005)), this points to a potentially detrimental real effect of securities analyst coverage. Thus, our findings shed further light on how financial analysts affect firm value by providing a more complete picture of their influence on managers' overall earnings management strategy.

Finally, because analyst coverage and termination decisions correlate with firm characteristics for numerous reasons, the estimates found in existing studies tend to be biased because of endogeneity. The quasi-experiment we use addresses

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this identification problem by focusing on a large set of reductions in coverage, present throughout the time series and cross section of firms, that are orthogonal to the characteristics of the firm. This approach potentially has many other useful applications in the accounting and finance literature for studying the impact of analyst coverage on incentives and market outcomes. We look forward to future work along these lines.

Appendix. Variable Definitions

This appendix presents the definitions for the variables used throughout the article.

Earnings Management Variables

AM: Absolute abnormal accruals computed as the difference between a company's total accruals and its nondiscretionary accruals.

RM_{CFO}: Abnormal cash flows from operations calculated (Roychowdhury (2006)).

RM_{PROD}: Abnormal production costs calculated (Roychowdhury (2006)).

RM_{DISX}: Abnormal discretionary expenses calculated (Roychowdhury (2006)).

RM_1: Combined real earnings management measure computed as the sum of RM_{DISX} and RM_{PROD}.

RM_2: Combined real earnings management measure computed as the sum of RM_{DISX} and RM_{CFO}.

CA: Nonregression current accruals measure (Sloan (1996)).

CA(Cash_Flow): Current accruals measure (Hribar and Collins (2002)).

CA(Excl_Depr): Current accruals measure excluding depreciation (Barton and Simko (2002)).

Control Variables

COVERAGE: Number of analysts in Institutional Brokers' Estimate System (IBES) covering stock in current year.

ln(SIZE): Natural logarithm of market capitalization (price times shares outstanding).

ROA: Return on assets calculated as net income divided by total assets.

MTB: Natural logarithm of a firm's book value divided by its market capitalization.

SALES_GR: 1-year growth in a firm's sales.

Cross-Sectional Analysis Variables

SUSPECT: Earnings before extraordinary items divided by assets between 0 and 0.05%.

EXPERIENCE: Average number of years in IBES database for analysts covering firm.

HOUSE_EXP: Average number of years at current brokerage house for analysts covering firm.

AUDITOR_TENURE: Number of years a company has retained the same auditor.

NOA: Net operating assets computed from cash flow statement (Barton and Simko (2002)).

References

Acharya, V., and B. Lambrecht. "A Theory of Income Smoothing When Insiders Know More Than Outsiders." *Review of Financial Studies*, 28 (2015), 2534–2574.

Anantharaman, D., and Y. Zhang. "Cover Me: Managers' Responses to Changes in Analyst Coverage in the Post-Regulation FD Period." *Accounting Review*, 86 (2012), 1851–1885.

Armstrong, C. S.; K. Balakrishnan; and D. A. Cohen. "Corporate Governance and the Information Environment: Evidence from State Antitakeover Laws." *Journal of Accounting and Economics*, 53 (2012), 185–204.

Baber, W. R.; P. M. Fairfield; and J. A. Haggard. "The Effect of Concern about Reported Income on Discretionary Spending Decisions: The Case of Research and Development." *Accounting Review*, 66 (1991), 818–829.

Balakrishnan, K.; M. B. Billings; B. T. Kelly; and A. Ljungqvist. "Shaping Liquidity: On the Causal Effects of Voluntary Disclosure." *Journal of Finance*, 69 (2014), 2237–2278.

https://doi.org/10.1017/S0022109016000156 Published online by Cambridge University Press

Barton, J., and P. Simko. "The Balance Sheet as an Earnings Management Constraint." *Accounting Review*, 77 (2002), 1–27.
Bartov, E. "The Timing of Asset Sales and Earnings Manipulation." *Accounting Review*, 68 (1993), 840–855.
Bartov, E.; D. Givoly; and C. Hayn. "The Rewards to Meeting or Beating Earnings Expectations." *Journal of Accounting and Economics*, 33 (2002), 173–204.
Becker, C. L.; M. L. DeFond; J. Jiambalvo; and K. Subramanyan. "The Effect of Audit Quality on Earnings Management." *Contemporary Accounting Research*, 15 (1998), 1–24.
Bens, D. A.; V. Nagar; and M. F. Wong. "Real Investment Implications of Employee Stock Option Exercises." *Journal of Accounting Research*, 40 (2002), 359–393.
Burgstahler, D., and I. Dichev. "Earnings Management to Avoid Earnings Decreases and Losses." *Journal of Accounting and Economics*, 24 (1997), 99–126.
Bushee, B. J. "The Influence of Institutional Investors on Myopic R&D Investment Behavior." *Accounting Review*, 73 (1998), 305–333.
Chen, S.-S., and C.-W. Huang. "The Sarbanes-Oxley Act, Earnings Management, and Post-Buyback Performance of Open-Market Repurchasing Firms." *Journal of Financial and Quantitative Analysis*, 48 (2013), 1847–1876.
Chen, T.; J. Harford; and C. Lin. "Do Analysts Matter for Governance? Evidence from Natural Experiments." *Journal of Financial Economics*, 115 (2015), 383–410.
Clement, M. "Analyst Forecast Accuracy: Do Ability, Resources, and Portfolio Complexity Matter?" *Journal of Accounting and Economics*, 27 (1999), 285–303.
Cohen, D. A.; A. Dey; and T. Lys. "Real and Accrual-Based Earnings Management in the Pre- and Post-Sarbanes-Oxley Periods." *Accounting Review*, 83 (2008), 757–787.
Cohen, D. A.; S. Pandit; C. E. Wasley; and T. Zach. "Measuring Real Activity Management." Working Paper, University of Texas at Dallas (2013).
Cohen, D. A., and P. Zarowin. "Accrual-Based and Real Earnings Management Activities around Seasoned Equity Offerings." *Journal of Accounting and Economics*, 50 (2010), 2–19.
Collins, D.; R. Pungaliya; and A. Vijh. "The Effects of Firm Growth and Model Specification Choices on Tests of Earnings Management in Quarterly Settings." Working Paper, University of Iowa (2012).
Dechow, P. M.; S. P. Kothari; and R. L. Watts. "The Relation between Earnings and Cash Flows." *Journal of Accounting and Economics*, 25 (1998), 133–168.
Dechow, P. M.; S. A. Richardson; and I. Tuna. "Why Are Earnings Kinky? An Examination of the Earnings Management Explanation." *Review of Accounting Studies*, 8 (2003), 355–384.
Dechow, P. M., and D. J. Skinner. "Earnings Management: Reconciling the Views of Accounting Academics, Practitioners, and Regulators." *Accounting Horizons*, 14 (2000), 235–250.
Dechow, P. M., and R. G. Sloan. "Executive Incentives and the Horizon Problem: An Empirical Investigation." *Journal of Accounting and Economics*, 14 (1991), 51–89.
Dechow, P. M.; R. G. Sloan; and A. P. Sweeney. "Detecting Earnings Management." *Accounting Review*, 70 (1995), 193–225.
Dechow, P. M.; R. G. Sloan; and A. P. Sweeney. "Causes and Consequences of Earnings Manipulation: An Analysis of Firms Subject to Enforcement Actions by the SEC." *Contemporary Accounting Research*, 13 (1996), 1–36.
DeFond, M. L., and J. Jiambalvo. "Incidence and Circumstances of Accounting Errors." *Accounting Review*, 66 (1991), 643–655.
Degeorge, F.; J. Patel; and R. Zeckhauser. "Earnings Management to Exceed Thresholds." *Journal of Business*, 72 (1999), 1–33.
Derrien, F., and A. Kecskes. "The Real Effects of Financial Shocks: Evidence from Exogenous Changes in Analyst Coverage." *Journal of Finance*, 68 (2013), 1407–1440.
Derrien, F.; A. Kecskes; and S. Mansi. "Information Asymmetry, the Cost of Debt, and Credit Events." Working Paper, HEC Paris (2012).
Dyck, A.; A. Morse; and L. Zingales. "Who Blows the Whistle on Corporate Fraud?" *Journal of Finance*, 65 (2010), 2213–2253.
Fama, E. F., and K. R. French. "Industry Costs of Equity." *Journal of Financial Economics*, 43 (1997), 153–193.
Fields, T. D.; T. Z. Lys; and L. Vincent. "Empirical Research on Accounting Choice." *Journal of Accounting and Economics*, 31 (2001), 255–307.
Fong, K. Y. L.; H. G. Hong; M. T. Kacperczyk; and J. D. Kubik. "Do Security Analysts Discipline Credit Rating Agencies?" Working Paper, New York University (2013).
Fuller, J., and M. C. Jensen. "Just Say No to Wall Street: Putting a Stop to the Earnings Game." *Journal of Applied Corporate Finance*, 14 (2002), 41–46.
Geiger, M. A., and K. Raghunandan. "Auditor Tenure and Audit Reporting Failures." *Auditing: A Journal of Practice & Theory*, 21 (2002), 67–78.

https://doi.org/10.1017/S0022109016000156 Published online by Cambridge University Press

Gleason, C. A., and C. M. C. Lee. "Analyst Forecast Revisions and Market Price Discovery." *Accounting Review*, 78 (2003), 193–225.
Graham, J.; C. Harvey; and S. Rajgopal. "The Economic Implications of Corporate Financial Reporting." *Journal of Accounting and Economics*, 40 (2005), 3–73.
Grundfest, J., and N. Malenko. "Quadrophobia: Strategic Rounding of EPS Data." Working Paper, Stanford University (2012).
Hazarika, S.; J. M. Karpoff; and R. Nahata. "Internal Corporate Governance, CEO Turnover, and Earnings Management." *Journal of Financial Economics*, 104 (2012), 44–69.
He, J., and X. Tian. "The Dark Side of Analyst Coverage: The Case of Innovation." *Journal of Financial Economics*, 109 (2013), 856–878.
Healy, P. M.; A. P. Hutton; and K. G. Palepu. "Stock Performance and Intermediation Changes Surrounding Sustained Increases in Disclosure." *Contemporary Accounting Research*, 16 (1999), 485–520.
Healy, P. M., and K. G. Palepu. "Information Asymmetry, Corporate Disclosure, and the Capital Markets: A Review of the Empirical Disclosure Literature." *Journal of Accounting and Economics*, 31 (2001), 405–440.
Healy, P. M.; and J. M. Wahlen. "A Review of the Earnings Management Literature and Its Implications for Standard Setting." *Accounting Horizons*, 13 (1999), 365–383.
Hirshleifer, D.; K. Hou; S. H. Teoh; and Y. Zhang. "Do Investors Overvalue Firms with Bloated Balance Sheets?" *Journal of Accounting and Economics*, 38 (2004), 297–331.
Hong, H., and M. Kacperczyk. "Competition and Bias." *Quarterly Journal of Economics*, 125 (2010), 1683–1725.
Hong, H.; T. Lim; and J. C. Stein. "Bad News Travels Slowly: Size, Analyst Coverage, and the Profitability of Momentum Strategies." *Journal of Finance*, 55 (2000), 265–295.
Hribar, P., and D. W. Collins. "Errors in Estimating Accruals: Implications for Empirical Research." *Journal of Accounting Research*, 40 (2002), 105–134.
Irani, R. M., and D. Oesch. "Monitoring and Corporate Disclosure: Evidence from a Natural Experiment." *Journal of Financial Economics*, 109 (2013), 398–418.
Jensen, M. C., and W. H. Meckling. "Theory of the Firm: Managerial Behavior, Agency Costs and Ownership Structure." *Journal of Financial Economics*, 3 (1976), 305–360.
Jones, J. J. "Earnings Management during Import Relief Investigations." *Journal of Accounting Research*, 29 (1991), 193–228.
Karpoff, J. M.; D. S. Lee; and G. S. Martin. "The Consequences to Managers for Financial Misrepresentation." *Journal of Financial Economics*, 88 (2008a), 193–215.
Karpoff, J. M.; D. S. Lee; and G. S. Martin. "The Cost to Firms of Cooking the Books." *Journal of Financial and Quantitative Analysis*, 43 (2008b), 581–611.
Kedia, S., and T. Philippon. "The Economics of Fraudulent Accounting." *Review of Financial Studies*, 22 (2009), 2169–2199.
Kelly, B. T., and A. Ljungqvist. "The Value of Research." Working Paper, New York University (2007).
Kelly, B. T., and A. Ljungqvist. "Testing Asymmetric-Information Asset Pricing Models." *Review of Financial Studies*, 25 (2012), 1366–1413.
Kothari, S.; A. J. Leone; and C. E. Wasley. "Performance Matched Discretionary Accrual Measures." *Journal of Accounting and Economics*, 39 (2005), 163–197.
Lang, M. H., and R. J. Lundholm. "Cross-Sectional Determinants of Analyst Ratings of Corporate Disclosures." *Journal of Accounting Research*, 31 (1993), 246–271.
Leuz, C. "Discussion of ADRs, Analysts, and Accuracy: Does Cross-Listing in the United States Improve a Firm's Information Environment and Increase Market Value?" *Journal of Accounting Research*, 41 (2003), 347–362.
Li, F. "Annual Report Readability, Current Earnings, and Earnings Persistence." *Journal of Accounting and Economics*, 45 (2008), 221–247.
Lindsey, L., and S. Mola. "Analyst Competition and Monitoring: Earnings Management in Neglected Firms." Working Paper, Arizona State University (2013).
Matsunaga, S. R., and C. W. Park. "The Effect of Missing a Quarterly Earnings Benchmark on the CEO's Annual Bonus." *Accounting Review*, 76 (2001), 313–332.
Mergenthaler, R. D.; S. Rajgopal; and S. Srinivasan. "CEO and CFO Career Penalties to Missing Quarterly Earnings Forecasts." Working Paper, Harvard Business School (2012).
Mikhail, M. B.; B. R. Walther; and R. H. Willis. "Do Security Analysts Improve Their Performance with Experience?" *Journal of Accounting Research*, 35 (1997), 131–166.
Mikhail, M. B.; B. R. Walther; and R. H. Willis. "The Effect of Experience on Security Analyst Underreaction." *Journal of Accounting and Economics*, 35 (2003), 101–116.
Myers, J. N.; L. A. Myers; and T. C. Omer. "Exploring the Term of the Auditor-Client Relationship and the Quality of Earnings: A Case for Mandatory Auditor Rotation?" *Accounting Review*, 78 (2003), 779–799.

https://doi.org/10.1017/S0022109016000156 Published online by Cambridge University Press

Palmrose, Z.-V. "Trials of Legal Disputes Involving Independent Auditors: Some Empirical Evidence." *Journal of Accounting Research*, 29 (1991), 149–185.
Richardson, S.; R. Sloan; M. Soliman; and I. Tuna. "Accrual Reliability, Earnings Persistence and Stock Prices." *Journal of Accounting and Economics*, 39 (2005), 437–485.
Roberts, M. R., and T. Whited. "Endogeneity in Empirical Corporate Finance." In *Handbook of the Economics of Finance*, Vol. 2, G. Constantinides, M. Harris, and R. Stulz, eds. Amsterdam, Netherlands: Elsevier Science (2013), 493–572.
Rosenbaum, P., and D. Rubin. "The Central Role of the Propensity Score in Observational Studies for Causal Effects." *Biometrika*, 70 (1983), 41–55.
Roychowdhury, S. "Earnings Management through Real Activities Manipulation." *Journal of Accounting and Economics*, 42 (2006), 335–370.
Sloan, R. G. "Do Stock Prices Reflect Information in Accruals and Cash Flows about Future Earnings?" *Accounting Review*, 71 (1996), 289–315.
Stice, J. D. "Using Financial and Market Information to Identify Pre-Engagement Factors Associated with Lawsuits against Auditors." *Accounting Review*, 66 (1991), 516–533.
Wilkins, M. S., and M. L. Loudder. "Articulation in Cash Flow Statements: A Resource for Financial Accounting Courses." *Journal of Accounting Education*, 18 (2000), 115–126.
Wu, J., and A. Zang. "What Determines Financial Analysts' Career Outcomes During Mergers?" *Journal of Accounting and Economics*, 47 (2009), 59–86.
Yu, F. "Analyst Coverage and Earnings Management." *Journal of Financial Economics*, 88 (2008), 245–271.
Zang, A. Y. "Evidence on the Trade-Off between Real Activities Manipulation and Accrual-Based Earnings Management." *Accounting Review*, 87 (2012), 675–703.

https://doi.org/10.1017/S0022109016000156 Published online by Cambridge University Press