Accounting Choices and the Legal Environment: the Impact of the *Ex Post* Loss Rule

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**Abstract**

Using a landmark Supreme Court decision as a natural experiment, I examine the impact of a fundamental requirement in securities litigation—the *ex post* loss rule—on income-decreasing accounting choices. *Dura Pharmaceuticals v. Broudo* (2005) established that plaintiffs must show that the alleged misrepresentations caused an actual economic loss. The case resolved a circuit split, allowing me to identify a treatment jurisdiction affected by *Dura*, and control jurisdictions in which the rule was already the prevailing legal standard. Motivated by legal analyses suggesting that *Dura* incentivizes firms to withhold or delay negative corrections, I hypothesize and find that treatment firms in high-litigation industries became more likely to delay write-downs and avoid income-decreasing accrual error reversals at the firm level after *Dura*, relative to matched control firms. This study sheds light on the relationship between securities law and accounting practices, and informs policy makers on the accounting impact of a key feature of the legal environment.

*Keywords:* Write-downs, Accruals, Litigation, Legal environment

*JEL:* K22, M41

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1. Introduction

“Dura’s transformative effect has been undeniable.” (Sullivan et al., 2010)

“As one might expect, securities lawyers regularly counsel their clients that, if they must disclose a piece of bad news, they should wait if necessary so as to be able to release good news at the same time. Finally, when firms have bad news to report that can be delayed no longer, they may as well report as much bad news as possible. Dura’s elevation of the ex post loss rule may exacerbate such trends.” (Spindler, 2007, p. 684-685)

Accounting choices and disclosures play an important role in securities litigation: over a third of securities class action lawsuits to date allege financial statement misrepresentations, and over a quarter explicitly allege GAAP or GAAS violations. In recent years, for example, Harley-Davidson, HP, IBM, Xerox, and Yahoo! have each been sued following accounting changes related to write-downs and working capital.

In a securities class action lawsuit, the plaintiff investors must demonstrate loss causation by showing that the firm’s alleged misconduct caused a corrective disclosure that resulted in a stock price decline. This is known as the ex post loss rule (see Spindler, 2007). This rule links securities litigation inextricably with accounting because downward corrections are fundamental to the accounting process. For example, accounting standards such as ASC 320 and ASC 350 generally require an impairment or further impairment tests when an asset’s carrying value exceeds its fair value, and income-increasing working capital accrual estimation errors should reverse downwards within a year at least at the transaction level (Allen et al., 2013).

However, legal analysis suggests that the ex post loss rule increases incentives to withhold or delay bad news. Spindler (2007) concludes that the rule incentivizes firms to “obscure or delay negative information” (p. 656–657) because a turnaround in fortunes, news about other projects, or exogenous events can disrupt the causal link between alleged misconduct and a price decline, or prevent a price decline altogether:

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1Based on lawsuits recorded in Stanford Law School’s Securities Class Action Clearinghouse database. The database has recorded over 4,300 lawsuits filed since 1996.

“A firm may choose to undertake multiple projects (e.g., conglomerate), and can then lie about one of the projects in the hope that the other project will ultimately make up for it. Similarly, exogenous events, such as market fluctuations, can interrupt the chain of causation and deny plaintiffs a recovery. Or a firm may fraudulently withhold news of bad performance in the hopes of turning it around in the future, preventing an ex post market decline.” (Spindler, 2007, p. 657)

I argue in this paper that the analysis in Spindler (2007) applies to the choice of recognizing required income-decreasing write-downs and accrual reversals, both of which can trigger litigation but are subject to discretion at the firm level. Write-downs are subject to managerial judgment for example in the estimation of asset fair values, and the literature (see Allen et al., 2013) suggests that working capital accrual errors do not reverse within one year at the firm level despite generally needing to do so at the transaction level. The primary prediction of this study is therefore that the rule causes firms at high risk of litigation to delay income-decreasing write-downs and avoid working capital accrual error reversals at the firm level, respectively.

To identify the causal impact of the ex post loss rule on these accounting practices, I exploit Dura Pharmaceuticals v. Broudo, 544 U.S. 336 (2005), henceforth Dura, a landmark Supreme Court case that established the rule in one legal jurisdiction, with little or no expected impact on most other jurisdictions. Before Dura, the Ninth Circuit did not require plaintiffs to plead that the firm’s misconduct caused a price decline, while the majority of the circuits did. In Dura, the Supreme Court overturned the Ninth Circuit, establishing that a causal link between the misconduct and a price decline is required in order to demonstrate loss causation. Dura was described by the Financial Times as “the most important securities case in a decade” (Waldmeir, 2005).

I use triple difference designs to examine whether firms in the Ninth Circuit became more likely to delay required write-downs and avoid income-decreasing accrual error reversals after Dura, relative to firms in control circuits. For the post-Dura period relative to the pre-period, and for treatment relative to control firms, I examine the extent to which a book-to-market greater than one predicts a write-down the following year, and the extent to which a highly positive working capital accrual error predicts a highly negative working capital accrual error the following year.

I find that firms in high-litigation industries in the Ninth Circuit became more likely to delay required write-downs and avoid income-decreasing working capital accrual
error reversals at the firm level after Dura relative to matched control firms. In addition, when write-downs do occur, they are larger in treatment firms after Dura relative to control firms, consistent with Spindler (2007, p. 684-685), who suggested that Dura may increase delays of bad news until they “can be delayed no longer”. Finally, I find that the probability of being sued generally declined more in treatment firms post-Dura than control firms, in the overall sample of firms in industries at high risk of litigation, and in the subsamples in which a write-down or accrual error error reversal is likely to be required.

By exploiting Dura’s resolution of a circuit split to examine the causal impact of the ex post loss rule on accounting choices, I aim to contribute to the growing literature on the impact of court rulings on financial reporting, and more generally to the literature examining the relationship between the legal environment and accounting decisions. This study also contributes to the literature on litigation risk and financial reporting. In particular, it builds on Watts’ (2003) influential litigation explanation by providing evidence that in the current legal environment, managers attempt to reduce the litigation costs of overstatements by disrupting the causal relationship between the overstatement and a subsequent ex post loss. Finally, this study informs academics, policy makers, and practitioners by shedding light on how a change in the legal environment can have an impact on accounting practices that are fundamental to GAAP.

2. Literature and contribution

In this study I aim to contribute to two overlapping streams of research. The first is the growing literature on the impact of court rulings on financial reporting, a rich arena for testing fundamental questions at the intersection of accounting and law. The second is the literature examining the relationship between litigation and financial reporting, particularly the stream of research relying on the litigation explanation spelled out by Watts (2003)—the idea that managers understate net assets because “expected litigation costs of overstatement are higher than those of understatement” (p. 216).

2.1. Accounting and changes in the legal environment

Both of these streams of research examine the relationship between the legal environment and financial reporting. A firm’s legal environment is the all-encompassing “sea of law” through which it navigates, as described by Edelman & Suchman (1997):
“Modern organizations are immersed in a sea of law. They are born through the legal act of incorporation, and they die through the legal act of bankruptcy. In between, they raise capital under securities law, hire employees under labor and antidiscrimination law, exchange goods and services under contract law, develop public identities under trademark law, innovate under patent and copyright law, and engage in production under environmental, and health and safety law.” (p. 480)

In particular, I have in mind what Edelman & Suchman (1997) call the facilitative facet of the legal environment, in which the law “appears as a system of procedural rules” (p. 483) that are exogenous to the firm.

Taking this definition of the legal environment to its broadest extent, the accounting literature has long examined the relationship between financial reporting and the legal environment. The many streams of research examining accounting policies and methods are of fundamental importance to the profession (e.g. Sunder, 1973; Biddle, 1980; Barth et al., 1996; Beatty & Weber, 2006; Barth et al., 2012), as are the closely-related studies examining other regulatory changes, such as those introduced by the Private Securities Litigation Reform Act (e.g. Johnson et al., 2001), the Sarbanes-Oxley Act (e.g. Zhang, 2007; Cohen et al., 2008) and the Dodd-Frank Act (e.g. Christensen et al., 2017). The recent literature has also begun examining the impact of the microfoundations of the legal environment, including individuals’ legal expertise (e.g. Krishnan et al., 2011), general counsel (e.g. Hopkins et al., 2015), external counsel (e.g. Bozanic et al., 2016), and law firms (e.g. Dechow & Tan, 2017).

A growing stream of research has also examined the impact of court rulings on accounting decisions. Court rulings can have a profound and sweeping effect on the legal environment. Decisions by the United States courts of appeals (that is, the circuit courts) can establish legal precedents across multiple states at once, while Supreme Court decisions in turn often resolve circuit splits, establishing precedents across one or more circuit courts’ jurisdictions at once.\(^3\)

\(^3\)For example, Shapiro (2006) writes that the Supreme Court’s “primary mechanism for maintaining uniformity is to resolve circuit splits—areas of law in which different federal courts of appeals (and state supreme courts) disagree about what rule or standard governs. In resolving these circuit splits, the Court often announces rules and standards to be applied by the lower courts” (p. 272–273, internal quotation marks omitted).
Earlier accounting studies examining court rulings include Simon (1956), Little et al. (1995), and Dhaliwal & Erickson (1998), and in recent years a growing number of studies have exploited court rulings to answer questions at the intersection of accounting and law. Furchtgott & Partnoy (2015) and Bliss et al. (2016), for example, examine the impact of Dura on the bundling of restatement news with other news, and their findings provide support for the arguments by Spindler (2007) that motivate this study. Hopkins (2014) and Cazier et al. (2017) use In re Silicon Graphics, 183 F.3d 970 (9th Cir. 1999) as an exogenous shock to examine the impact of changes in litigation risk on earnings management and non-GAAP reporting respectively. Finally, Chy & Hope (2017) exploit court decisions that changed auditor legal liability to examine the impact of auditor conservatism on myopic underinvestment in R&D.

2.2. Accounting and securities litigation

Litigation is “perhaps the most frequently studied aspect of the facilitative legal environment” (Edelman & Suchman, 1997, p. 485), and a large body of research examines the relationship between securities litigation and financial reporting. I identify three major subsets of this literature—studies that examine guidance, accounting quality, and conservatism, respectively.

Early studies on accounting and litigation examined earnings guidance as a determinant of shareholder litigation, supported by evidence on the high cost of negative earnings news (e.g. Skinner, 1994). For example, both Francis et al. (1994) and Skinner (1997) find, counterintuitively, that litigation likelihood increases in the frequency of guidance. More recent studies find support for a negative relation between guidance and litigation (e.g. Field et al., 2005; Donelson et al., 2012; Billings & Cedergren, 2015); Field et al. (2005), in particular, find that guidance is negatively relative to lawsuits when they use a simultaneous equations framework to control for endogeneity, and after excluding dismissed lawsuits. Several recent studies have also examined the consequences of litigation or litigation risk on guidance (e.g. Rogers & Van Buskirk, 2009; Houston et al., 2010; Billings et al., 2016).\footnote{In addition, several studies have examined the relationship between litigation and disclosure tone: Rogers et al. (2011) find a positive relation between earnings announcement optimism and litigation and find evidence that plaintiffs target optimistic language, and Cazier et al. (2016) find that tone is only associated with litigation risk for non-forward-looking statements, consistent with safe harbor protection for forward-looking statements.}

Next, a line of research has examined the relationship between accounting quality
and litigation risk; for example, DuCharme et al. (2004), Gong et al. (2008), Grimm (2009), and Chalmers et al. (2012) find evidence suggesting that litigation risk increases with abnormal accruals or decreases with accruals quality; and Palmrose & Scholz (2004) find that litigation risk increases with core earnings restatements. In particular, Gong et al. (2008) find in the context of merger announcements that the market does not fully price the variation in litigation risk attributable to abnormal accruals and other observables.

Finally, a line of research examines the relationship between litigation and conservatism. Basu (1997) provided initial evidence by showing that conditional conservatism is greater in periods of high auditor legal liability, and Watts (2003) subsequently spelled out a litigation explanation for conservatism:

“Since the expected litigation costs of overstatement are higher than those of understatement, management and auditors have incentives to report conservative values for earnings and net assets.” (p. 216)

Motivated in part by Watts (2003), the subsequent literature has found that conservatism is increasing in litigation risk at the firm level (e.g. Qiang, 2007; Khan & Watts, 2009), and that firms with greater conditional conservatism have more favorable litigation outcomes (Ettredge et al., 2016). Furthermore, in a well-identified cross-country study, Huijgen & Lubberink (2005) find that conservatism is greater in the jurisdiction with greater exposure to legal liability, consistent with the litigation explanation for conservatism.

Conceptually, my study builds on Watts’ (2003) litigation explanation. I explain that in the current legal environment, it is the ex post loss when an overstatement is corrected that gives rise to the litigation costs borne by defendants, and not the overstatement per se (see Section 3.1), and present arguments due to Spindler (2007) that the costs of overstatement may not be fully internalized if managers can distort the causal relation between the overstatement and a price decline (Section 3.2). My empirical tests then examine whether there is evidence that firms use accounting choices to distort the causal relationship between the overstatement and an ex post loss.

3. Legal motivation

3.1. The circuit split in the interpretation of loss causation

In securities class action lawsuits, plaintiffs are required to demonstrate loss causation—that the defendant’s violation caused the plaintiff’s loss. The requirement was
codified in the Private Securities Litigation Reform Act of 1995, henceforth PSLRA, which was designed to reduce frivolous lawsuits:

“the plaintiff shall have the burden of proving that the act or omission of the defendant alleged to violate this chapter caused the loss for which the plaintiff seeks to recover damages.” (15 U.S.C. §78u-4(b)(4))

While the PSLRA codified the requirement of loss causation, until the Dura decision in 2005, the United States Courts of Appeals (that is, the circuit courts) were divided in their interpretations of the requirement.

By the time of Dura, the differing interpretations could broadly be divided into a majority view—the interpretation held by the majority of circuits—and a minority view. The majority view held that loss causation was established only if plaintiffs could demonstrate a causal link between the defendant’s misconduct and actual economic losses to the plaintiff. In contrast, the minority view held that loss causation was established if plaintiffs could demonstrate that the fraud caused the defendant’s stock price to be inflated at the time of purchase. Spindler (2007) refers to the contrasting interpretations as the ex post and ex ante loss rules respectively.

As detailed in Escoffery (2000), the difference in interpretation arose because the concept of loss causation “developed exclusively out of case law and was never expressly recognized by the Supreme Court” (p. 1781). The split in legal opinion was evident as early as the mid-1990s. For example, in Knapp v. Ernst & Whinney, 90 F.3d 1431 (9th Cir. 1996), the Ninth Circuit said that “plaintiffs establish loss causation if they have shown that the price on the date of purchase was inflated because of the misrepresentation” (p. 1438). The Eleventh Circuit rejected this decision in Robbins v. Koger Props., 116 F.3d 1441 (11th Cir. 1997), stating that

“Our decisions explicitly require proof of a causal connection between the misrepresentation and the investment’s subsequent decline in value”.


6See, for example, Escoffery (2000); Prezioso et al. (2004).

7See also Ferrell & Saha (2007) (“Has not such an investor suffered a loss, in an economic sense, from the fraudulent statement? The answer turns on whether one looks at the situation ex post or ex ante”, p. 172.)

8These and other cases were discussed in an amicus brief for Dura (Prezioso et al., 2004). See the amicus brief for further details on the split in the Circuits prior to Dura.
By 2003, the majority view had also been held by the influential Second Circuit. In *Emergent Capital Inv. Mgmt. v. Stonepath Group*, 343 F.3d 189 (2nd Cir. 2003), henceforth *Emergent*, the Second Circuit said:

“We think that the second amended complaint contains legally sufficient allegations of a causal connection between the subject matter of these omissions and the ultimate decline in NETV’s stock value, that is, loss causation.”

Notably, the position of the Second Circuit appears to have been unclear or misunderstood prior to 2003: its 2001 decision in *Suez Equity Investors v. Toronto-Dominion Bank*, 250 F.3d 87 (2nd Cir. 2001), was cited by several courts in support of the minority view. The Second Court later clarified the *Suez Equity* decision in *Emergent*.

By 2003, the minority view was held almost exclusively by the Ninth Circuit. The Ninth Circuit said in *Broudo v. Dura Pharmaceuticals*, 339 F.3d 933 (9th Cir. 2003), henceforth *Broudo*, that:

“Ninth Circuit cases hold that: in a fraud-on-the-market case, the plaintiffs establish loss causation if they have shown that the price on the date of purchase was inflated because of the misrepresentation.”

The Supreme Court argued in *Dura* that the Ninth Circuit’s perspective was unique, and that “other Courts of Appeals have rejected the Ninth Circuit’s inflated purchase price approach to proving causation and loss” (p. 344, internal quotation marks omitted). The Ninth Circuit itself contrasted its view with the majority view as follows:

“By contrast, other circuits [...] do require demonstration of a corrective
disclosure followed by a stock price drop to be alleged in the complaint.”
(Broudo, footnote 4)

In its 2005 decision in Dura, the Supreme Court reversed the Ninth Circuit’s decision in Broudo. The Supreme Court held that it is insufficient for a plaintiff only to prove that the defendant’s security price was inflated at the date of purchase, arguing that the plaintiff “has suffered no loss” at the time of the transaction (p. 342), and that “the Ninth Circuit’s holding lacks support in precedent” (p. 343). In addition, the Supreme Court expressed agreement with the majority view, for example citing the plaintiffs’ “failure to claim that Dura’s share price fell significantly after the truth became known” (p. 347).

Dura therefore resolved the Circuit split, establishing definitively that plaintiffs in securities class action lawsuits need to allege that the defendant’s violation caused an actual economic loss to the plaintiffs. Table 1 summarizes the legal environments pre- and post-Dura by legal jurisdiction.

Table 1: Loss causation standards by jurisdiction before and after Dura

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<thead>
<tr>
<th>Jurisdiction</th>
<th>Pre-Dura</th>
<th>Post-Dura</th>
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<tbody>
<tr>
<td>Ninth Circuit</td>
<td>Show price inflation on purchase</td>
<td>Show actual economic loss</td>
</tr>
<tr>
<td>Majority opinion</td>
<td>Show actual economic loss</td>
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Before Dura, the circuit courts were divided in their interpretations of the loss causation standard in securities class action lawsuits. The Ninth Circuit held that plaintiffs were only required to establish that the defendant’s stock price was inflated, while the majority opinion was that plaintiffs must demonstrate a causal link between the misconduct and actual economic losses to the plaintiff. In Dura, the Supreme Court agreed with the majority opinion.

3.2. Impact of the ex post loss rule on negative corrections

Dura was described as “the most important securities case in a decade” (Waldmeir, 2005). The courts began applying the ex post loss rule immediately, interpreting the rule to mean that a stock price decline is required: “cases [since Dura] appear to be almost universally in line with the interpretation that Dura requires a market decline” (Spindler, 2007, p. 671). The case also sparked a series of studies in the legal academia that examine the legal context, potential consequences, and criticisms of the decision (e.g. Fox, 2005; Dutton, 2006; Olazabal, 2006; Cross, 2007; Ferrell & Saha, 2007; Spindler, 2007).
Spindler (2007), in particular, argues that the rule “fails to adequately internalize the costs of fraud onto the firm” (p. 657). Given an overstatement, a firm can bundle the negative correction with other news, or an exogenous event or turnaround in fortunes could occur. These can distort the causal relationship between the overstatement and subsequent price declines, or avoid a price decline altogether. Without an ex post loss that is attributable to alleged fraud, plaintiffs would not be able to sue for damages.

Specifically, Spindler (2007) examines three settings—when a firm has multiple projects, when exogenous events occur, and when there are multiple periods—and analyses in each setting a hypothetical project with some probability of success (see p. 677–685). To summarize his arguments, focusing on the case in which an overvalued project has failed and the manager is contemplating a negative correction that could cause a stock price decline:

**Multiple projects:** The losses from the project’s failure can be made up by gains from other projects, potentially avoiding ex post losses entirely. Even if multiple projects fail sufficiently for plaintiffs to suffer ex post losses, determining the amount of damages attributable specifically to the overstatement may be problematic.

**Exogenous events:** The correction can be bundled with a negative exogenous event, minimizing legal liability. Because a firm is not liable for ex post losses that investors would have suffered even in the absence of fraud, legal liability may be reduced if an exogenous event occurred that would have caused a stock price decline even if the project succeeded.

**Multiple periods:** If the project spans multiple periods, a negative correction in one period can be delayed in order to bundle it with future information about the project: “the marginal benefit of good news [in the second period] is quite high, because it reduces fraud liability, whereas the marginal cost of additional bad news is zero, since the loss causation rule limits fraud liability to the damages actually caused by the fraud.” (p. 684)

Incentives to delay bad news over multiple periods are particularly important because firms often have projects and assets that span multiple reporting periods. In his discussion of the multiple-period setting, Spindler (2007, p. 684) in fact suggests examining whether the likelihood of delaying bad news varied by legal jurisdiction before the Dura decision unified the circuits:
“It would be interesting to see whether evidence of delays is greater in jurisdictions utilizing *ex post* loss causation rules prior to *Dura*. In any event, *Dura* should exacerbate the tendencies to delay that already exist.”

Furthermore, he suggests that when the bad news can no longer be delayed, firms “may as well report as much bad news as possible” (p. 685), consistent with big bath incentives.

To apply these arguments to accounting choices in broad terms (see Section 4 for a detailed discussion), the *ex post* loss rule incentivizes managers to avoid or delay income-decreasing reversals of inflated financials. For example, income-increasing working capital accrual errors should reverse at the transaction level, but the reversals can be bundled with other income-increasing working capital accruals at the firm level (e.g. Allen et al., 2013), obscuring the impact of the reversal of the positive error specifically. In addition, assets like goodwill span multiple fiscal periods, allowing managers to delay required write-downs until they can be bundled with other news or until an exogenous event or a turnaround occurs.

3.3. Supporting evidence and tension

The opinions of *Dura* and subsequent courts on loss causation, and some empirical evidence from the literature, generally support the argument that the causal link between alleged misconduct and a subsequent price decline can be distorted. In *Dura* itself the Supreme Court discussed the strength of the relationship between inflated share prices and subsequent price declines, noting that even if there is a price decline,

> that lower price may reflect, not the earlier misrepresentation, but changed economic circumstances, changed investor expectations, new industry-specific or firm-specific facts, conditions, or other events, which taken separately or together account for some or all of that lower price.” (p. 343)

Subsequent courts’ opinions support the arguments in *Dura* and Spindler (2007). To cite several examples from dismissed lawsuits:

In *Leykin v. AT&T Corp.*, 423 F. Supp. 2d 229 (S.D.N.Y. 2006), the court dismissed the complaint in part because the plaintiffs did not show that the price decline was due to the alleged misconduct rather than an industry-wide price decline, illustrating the point that defendants are not liable for *ex post* losses that investors would have faced in the absence of fraud.
In *Lattanzio v. Deloitte*, 476 F.3d 147 (2nd Cir. 2007), the Second Circuit said that the plaintiffs would have had to allege facts that allow “some rough proportion” (p. 26) of the *ex post* loss to be attributed to the defendant’s misstatements, as opposed to the misstatements by another party.

In *Wilamowsky v. Take-Two*, 818 F. Supp. 2d 744 (S.D.N.Y. 2011), the court said that in order for the plaintiff to rely on certain misstatements to show loss causation, he would have had “to disaggregate their impact on his loss from prior misstatements and legitimate news affecting Take-Two stock prices” (p. 34).

In *Kuriakose v. Freddie Mac*, 2011 U.S. Dist. LEXIS 34285 (S.D.N.Y. 2011), the court said that “there is a decreased probability that Plaintiffs’ losses were caused by fraud” (p. 42) because the defendant’s stock was “clearly linked” to marketwide conditions.

These cases support the idea that under the *ex post* loss rule, loss causation requires price declines to be disentangled from marketwide conditions and other news.\(^\text{13}\)

Spindler (2007) is also supported by a number of empirical studies. Furchtgott & Partnoy (2015) and Bliss et al. (2016) together show that *Dura* increased the likelihood that a restatement is announced on the same day as other disclosures, including 10-K and 10-Q filings and earnings announcements. Bliss et al. (2016) further find that the likelihood of a lawsuit within a year of the restatement declined after *Dura* for restatements bundled with other bad news. These studies therefore provide some evidence that *Dura* incentivized managers to bundle bad news with other news, consistent with the arguments in Spindler (2007).

Intriguingly, a recent study found evidence contrary to the idea that the *ex post* loss rule incentivizes bundling with bad news. Donelson & Hopkins (2016) show that the courts do not fully disentangle large market declines and the impact of firm-specific news: they find that litigation and settlements are more likely after earnings disclosures when the disclosures occurred during large short-window market declines. This suggests that bundling with other bad news may in fact *increase* litigation risk. Furthermore, additional tests in Donelson & Hopkins (2016) suggest that this phenomenon may be driven by judicial expertise: when a judge has more specialized experience in securities litigation, large market declines are more likely to lead to dismissals, and vice versa.

\(^\text{13}\)I note, as a caveat, that these cases were not dismissed on the basis of loss causation alone.
The results in Donelson & Hopkins (2016) highlight an area of tension in motivating this study: that the justice system is not perfect. In a study of district and appellate court civil cases over 1988 to 2000, Eisenberg (2004) finds that 21 percent of cases with definitive judgments are appealed, and that defendants achieve reversals about 40 percent of the time if the appeal is not settled or withdrawn. These figures indicate that mistakes (at least by district courts) are not uncommon. A manager making a costly accounting choice to avoid a lawsuit would have to consider the possibility of being sued anyway, and of the suit not being dismissed despite his best efforts.

An additional layer of tension is that delaying bad news may itself increase litigation costs in the long run if a lawsuit it not successfully avoided or dismissed. An exogenous event or a turnaround of fortunes may not happen, for example. Delaying a correction increases litigation risk because it is likely to lengthen the time during which the firm’s stock price was allegedly inflated by misconduct. This increases the number of statements that would be scrutinized for misrepresentations, and increases the number of putative class members. Field et al. (2005) writes, for example, that the “longer the stock trades at too high a price, the greater the potential damages from a lawsuit and the more likely the firm is to be sued” (p. 496, internal quotation marks omitted).

As a counterargument, however, Spindler (2007) suggests that it is commonplace for lawyers to recommend delaying bad news, suggesting that the benefits to the firm of delaying must usually outweigh the costs:

“As one might expect, securities lawyers regularly counsel their clients that, if they must disclose a piece of bad news, they should wait if necessary so as to be able to release good news at the same time.” (p. 684)

Given the legal and empirical evidence for and against, whether managers exploit the *ex post* loss rule affirmed by *Dura*—and if so, to what extent—is an empirical question.

4. Hypothesis development

My overall research question is whether the *ex post* loss rule incentivizes firms at high risk of litigation to withhold or delay income-decreasing accounting choices. Specifically, I hypothesize that firms in the legal jurisdiction most affected by *Dura*—the Ninth Circuit—became more likely to delay write-downs and avoid downward accrual error reversals at the firm level after *Dura*, relative to control firms.
My hypotheses are motivated primarily by the arguments in Spindler (2007) suggesting that under an *ex post* loss regime, managers can reduce the cost of overstated financial results by distorting the causal relationship between the overstatement and subsequent price declines. As discussed in detail in Section 3.2, this distortion can be achieved by bundling downward corrections with other news, by the impact of exogenous events, or by withholding bad news in the hopes of a positive turnaround. In an *ex ante* loss regime, in contrast, these actions would be less effective at reducing litigation risk because plaintiffs are able to show loss causation on the basis of the alleged overstatement.

*Dura* would therefore have an impact on income-decreasing accounting choices that are closely linked to prior periods of observably inflated financials. In addition, *Dura* would have an impact on income-decreasing accounting choices that are expected to lead to litigation, but that are subject to managerial discretion.

### 4.1. Write-downs

GAAP rules require that “most non-financial assets must be written down when their fair values drop sufficiently below their carrying values” (Lawrence et al., 2013, p. 112). Write-downs are charged against earnings, and frequently contribute substantially to losses. Among loss firms over the past decade that recorded write-downs, the write-downs accounted for more than half of losses in about 40% of cases, and were greater than total losses in about 20% of cases.\(^{14}\)

Write-downs expose firms to securities litigation risk not only because they contribute to losses, but in particular because they reveal that financial results were inflated in the past. Companies that have been sued in recent years following write-downs include HP, IBM, Xerox, and Yahoo!.\(^{15}\) In *In re HP Securities Litigation*, plaintiffs sued HP after the firm announced an $8.8 billion impairment due in part to accounting fraud inflating financial results. I describe the events leading to the case in more detail

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\(^{14}\)Without including write-downs included in cost of goods sold. These descriptives are based on comparing the sum of non-goodwill pretax write-downs and impairments (\(wdp\)) and pretax goodwill impairments (\(gdwlip\)) against net income (\(ni\)), for all Compustat firm-years with strictly negative \(ni\) and strictly negative \(wdp\) or \(gdwlip\) between 2007 and 2016 inclusive. \(wdp\) and \(gdwlip\) are set to zero if missing in Compustat.

Because a write-down is usually required when an asset’s fair value drops below its carrying value, an asset book-to-market ratio above one—*market-implied impairment*—can be used as an indicator that a write-down is very likely to be required.\(^\text{16}\) I note that market-implied impairment is not necessarily grounds for litigation *per se* even if it is accompanied by declining stock prices, and a book-to-market less than one does not necessarily imply that a write-down is not required. In *In re HP Securities Litigation*, HP’s stock price declined substantially after the acquisition of Autonomy, driving HP’s book-to-market close to one, but shareholders sued only after the write-down announcement (see Appendix A for details).

Finally, write-downs have long been known to be subject to managerial discretion (e.g. Elliott & Hanna, 1996; Francis et al., 1996; Wilson, 1996; Ramanna & Watts, 2012; Lawrence et al., 2013). Elliott & Hanna 1996 write that

> “consistent with claims made in the business press, management might be using write-offs to accomplish strategic earnings management objectives.”

(p. 154)

Judgement is often required even within the constraints of GAAP, and even if strict fair value tests are required. For example, SFAS 142 (now codified as ASC 360) required goodwill to be tested for impairment at least annually in two steps: first, potential impairment is determined by comparing the fair value of a reporting unit with its carrying value; second, the implied fair value of goodwill within the reporting unit is compared its carrying value. Ramanna & Watts (2012) argues that managerial discretion exists in the allocation of goodwill to reporting units, the estimation of the reporting units’ fair values, and the measurement of the fair values of net assets within reporting units.\(^\text{17}\)

In summary, write-downs may trigger securities litigation, but are subject to managerial discretion. The arguments in Spindler (2007) that the *ex post* loss rule may incentivize managers to delay bad news therefore applies: by exercising discretion in delaying a required write-down, a manager can wait for a positive turnaround (thus

---

\(^\text{16}\) Although the threshold may effectively be slightly above one for certain assets for which the fair value test is less stringent. See Lawrence et al. (2013, p. 115) for a summary of accounting principles on write-downs by asset class.

\(^\text{17}\) In addition, ASU 2011-08 has introduced additional room for discretion by allowing managers to bypass the two-step impairment test entirely depending on the outcome of a qualitative assessment.
avoiding the write-down entirely), or wait for additional value-relevant news that can be bundled with the write-down announcement. My first hypothesis, stated formally in alternate form, is therefore as follows:

**Hypothesis 1.** *Firms at high risk of litigation under the jurisdiction of the Ninth Circuit became more likely to delay required write-downs post-Dura, relative to matching control firms.*

In addition, assuming that not all firms are able to delay a write-down indefinitely, a delay is likely to lead to a larger write-down when it is eventually recorded. This would be consistent with firms being able to delay write-downs only up to a point, or firms reporting “as much bad news as possible” (Spindler, 2007, p. 685) by taking larger write-downs or by writing-down more assets, once they are unable to delay a write-down.

4.2. Downward accrual error reversals

More generally, write-downs are reversals of positive accruals. An inventory write-down, for example, is a correction of positive inventory accrual errors in the past, and goodwill impairments reverse previously-recognized goodwill as its estimated fair value decreases. My second set of tests focuses on downward reversals of working capital accrual estimation errors. This provides additional evidence on the impact of the *ex post* loss rule because income-decreasing changes in working capital can trigger litigation, but their effect would generally not be reflected in my tests of write-downs.18

As in the examples in Section 4.1 and Appendix A of lawsuits following write-downs, there are recent examples of class action lawsuits following downward corrections related to working capital. For example, Xerox was sued in 2000 after recording a $78 million charge in part for improper recognition of uncollectible receivables, among other issues, and Harley-Davidson was sued in 2005 for channel stuffing after it announced a reduction in production and shipment targets.19

Accrual estimation errors “arise from lack of perfect foresight or from the application of aggressive or conservative accounting mandated under generally accepted

---

18For example, inventory write-downs reverse inventory accruals (Allen et al., 2013), but would not be tested under Hypothesis 1 because they are usually reflected in costs of goods sold (Lawrence et al., 2013).
accounting principles” (p. 118), or from earnings management. (Allen et al., 2013) Examining estimation errors specifically in working capital accruals has the advantage that under the constraints of GAAP they generally reverse within one year at the transaction level. This follows from the definition of accrual estimation errors in Allen et al. (2013):

“An accrual estimation error is an ex post characterization of an accrual based on the difference between the accrual and the subsequently realized benefit.” (p. 115)

Since the benefits of positive working capital accruals are intended to be realized within one year, associated estimation errors should also reverse at the transaction level within a year. This allows me to use a highly positive error in the previous year as an indicator that a downward reversal is likely to be required in the current year.

While the estimation errors should reverse within one year at the transaction level, they may not do so at the firm level. Allen et al. (2013, see Table 3, Panel B), for example, find the surprising result that firm-level working capital accrual estimation errors—the component of working capital accruals not attributable to growth or temporary fluctuations in working capital requirements—are weakly positively autocorrelated. They suggest that the reversals may be offset by new estimation errors, or simply that estimation errors “often take longer than one year to reverse” (p. 115).

I therefore hypothesize that the arguments in Spindler (2007) apply to working capital accrual estimation errors; specifically, that the ex post loss rule incentivizes managers to bundle income-decreasing reversals with new income-increasing errors. This obscures the relationship between inflated financial results in the previous period and downward corrections in the current period, and potentially avoids a price decline, reducing the risk of litigation in an ex post loss regime. My second hypothesis, stated formally in alternate form, is therefore as follows:

**Hypothesis 2.** Firms at high risk of litigation under the jurisdiction of the Ninth Circuit became more likely to avoid required income-decreasing working capital accrual estimation errors at the firm level post-Dura, relative to matching control firms.

I also examine the extent to which the impact of the ex post loss rule on the timeliness of income-decreasing accrual error reversals drives its impact on overall accrual error reversals (income-decreasing or income-increasing). This would provide evidence for
a potential relationship between a key feature of the legal environment and overall accrual reversals, which has been a focus of much of the prior literature on, for example, earnings management and fraud detection (e.g. Dechow et al., 1995, 2011, 2012).

In addition, I test the prediction that *Dura* reduced the *ex post* probability of litigation, particularly for firms where a write-down or income-decreasing accrual reversal is likely to be required. I would expect to observe this given the motivation of this paper, but a counterargument is that delaying income-decreasing accounting choices may in fact increase litigation risk in the long run: it lengthens the time the firm’s stock price was allegedly inflated (see Section 3.3), and delaying bad news may lead to a firm subsequently reporting “as much bad news as possible” (Spindler, 2007, p. 684–685). I examine this in additional analyses in Section 9.\(^{20}\)

5. Research design

5.1. Treatment and control samples

I test Hypotheses 1 and 2 using regression models that exploit the fact that the *Dura* reversed the legal precedent of the Ninth Circuit. As discussed in Section 3, the split between the Ninth Circuit and other circuits was evident by 2003, with the minority view on loss causation being held almost exclusively by the Ninth Circuit. In *Dura* the Supreme Court ruled in favor of the majority view, reversing the Ninth Circuit and resolving the circuit split.

Consistent with prior literature (e.g. Furchtgott & Partnoy, 2015; Bliss et al., 2016; Cazier et al., 2017), I assign firms to Circuit Court jurisdictions based on the state in which the firm is headquartered. Appendix D shows a map of states under each Circuit Court jurisdiction. The use of headquarters location is grounded in legal reasoning; Cazier et al. (2017), for example, write that a suit filed outside the district in which a firm is headquartered is “highly vulnerable” to dismissal or removal to the headquarters district because

> “Due to the nature of the specific types of claims in private securities class action litigation and the fraud on the market presumption […], substantially all of the witnesses and evidence are likely to be located at the firms headquarters.” (p. 9)

\(^{20}\)I include this in additional analyses rather than as a formal hypothesis because it is not necessarily specific to the accounting choices I am studying in this paper.
Nevertheless, because *Dura* resolved a circuit split, there would be a bias against rejecting my null hypotheses to the extent that firms headquartered in the Ninth Circuit are expected to be sued in control circuits, and vice versa, during the pre-*Dura* period. I examine this further in untabulated analyses using data from Stanford’s Class Action Lawsuit Clearinghouse. I find that the substantial majority—about 91%—of lawsuits against firms located in treatment or control states were tried in treatment or control states respectively.\(^{21}\)

I therefore use firms headquartered in states under the jurisdiction of the Ninth Circuit in the treatment sample. I begin my analysis in 2003, the year the Ninth Circuit stated its legal position on loss causation in *Broudo* and contrasted it with that of other circuits (as outlined in Section 3.1). I define the pre-treatment period as 2003 to 2005 and the post-treatment period as 2006 to 2008 in order to use the same number of years pre- and post-treatment.\(^{22}\) My control sample comprises firms headquartered in states under the jurisdictions of all circuits other than the Eighth and Ninth Circuit.\(^{23}\)

I restrict the samples to firms in high-litigation industries, defined based on industry representation in actual lawsuit filings in the three years pre-*Dura*, and definitions from prior research (e.g. Donelson & Hopkins, 2016). Figure 1 shows the top industries during the three-year period based on Stanford’s Class Action Clearinghouse database. I define high-litigation industries as pharmaceuticals and biological; computers, elec-
Figure 1: Industry representation in lawsuit filings pre-\textit{Dura}

This figure shows the distributions of lawsuits filed in the three years pre-\textit{Dura}, sorted by the defendants’ industries. The lawsuits data is obtained from Stanford’s Securities Class Action Clearinghouse database (SCAC). In Panel A, lawsuits are sorted by the SCAC’s industry definitions; and in Panel B, the data is restricted to defendants with prior Compustat coverage and the lawsuits are sorted by the defendants’ three-digit SIC code. Only the top fifteen industries are shown, and financial industries are depicted in light grey and other industries are in dark blue.
tronics, and software; and telephone communications and electric services.\textsuperscript{24}

5.2. Testing Hypothesis 1

Hypothesis 1 concerns the timing of required asset write-downs; in other words I need to examine the changes in the likelihood of a write-down conditional on a write-down being required.

My strategy is to examine the extent to which an asset book-to-market greater than one predicts a write-down during the year. GAAP rules generally require a write-down when an asset’s carrying value exceeds its fair value, although there is some noise in operationalizing this empirically because in the case of tangible assets, the threshold may not be strict or Compustat may not capture the write-down separately.\textsuperscript{25} I mitigate this issue by focussing on firms with material intangible assets when testing Hypothesis 1.

A highly positive relationship between write-downs and a high book-to-market in a firm with material intangible assets then indicates that the firm records GAAP-required write-downs in a timely manner.\textsuperscript{26}

\textsuperscript{21}Based on lawsuit filings in the three years pre-\textit{Dura} with recent Compustat data available. The proportion is even higher (about 93\%) for firms in control states, despite the reduced hurdles to plaintiffs in the treatment jurisdiction pre-\textit{Dura}. For analyses in the legal literature on lawsuit filing location, see, for example, Cox et al. (2009) and Cain & Solomon (2015). In addition, see Appendix A for a case study in which the plaintiff company was sued in its headquarters state (California) and not its incorporation state (Delaware).

\textsuperscript{22} \textit{Dura} was decided in April 2005, which would have been in the second or fourth quarter of fiscal 2005 for most firms. If firms changed their accounting policies immediately, within fiscal 2005 itself, as a result of the decision, this would bias against rejecting my null hypotheses. In any case, for my main analyses I show the effect sizes for every year in my sample period.

\textsuperscript{23}I omit firms under the Eighth Circuit because its legal position appeared to be between the treatment and control groups. On the one hand the Ninth Circuit cited the Eighth Circuit in support of its interpretation (\textit{Broudo v. Dura Pharmaceuticals}, 339 F.3d 933, 9th Cir. 2003), but on the other hand an amicus brief for \textit{Dura} authored in part by the General Counsel of the Securities and Exchange Commission and the Solicitor General Counsel of Record of the Department of Justice stated that “the Eighth Circuit’s position on this issue is less than clear” (Prezioso et al., 2004, p. 9).

\textsuperscript{24}Specifically, I use the following SIC codes ranges: 2833–2836 and 8731–8734 for pharmaceuticals and biological; 3570–3577, 3600–3674, and 7370–7374 for computers, electronics, and software; and 4810–4813 and 4911–4931 telephone communications and electric services.

\textsuperscript{25}See Lawrence et al. (2013, p. 115-118) for a detailed analysis of GAAP rules and write-downs. Lawrence et al. (2013) show that there is a nonlinearity in the relation between write-downs and book-to-market ratios around a book-to-market ratio of one. They also show that the relationship between write-downs and beginning book-to-market increases with intangibles intensity. See also Beaver & Ryan (2005) and Ramanna & Watts (2012).

\textsuperscript{26}In untabulated analyses, I find that a significantly negatively average stock price reaction to earnings announcements in write-down quarters in my sample even when the asset book-to-market
The regression model for Hypothesis 1 is as follows:

\[
\text{logit}(\text{wdd}_t) = \alpha + \beta \times \text{abtmd}_{t-1} \times \text{post}_t \times \text{treat}_t + \gamma \times \Gamma_t + e_t
\]  

(1)

where \(\text{wdd}_t\) is a dummy variable indicating a write-down during \(t\), \(\text{abtmd}_{t-1}\) is a dummy variable indicating an asset book-to-market ratio greater than one at the start of \(t\), \(\text{post}_t\) is a dummy variable indicating the post-treatment period, \(\text{treat}_t\) is a dummy variable indicating firms in the Ninth Circuit, and \(\Gamma_t\) is a vector of second-order interactions, main effects, and controls.

A significantly negative estimate of \(\beta\) would reject the null hypothesis, and I would interpret this as evidence evidence that firms in the treatment sample avoid required write-downs to a greater extent after \(\text{Dura}\), relative to firms in the control sample.

Similarly, I examine the impact of \(\text{Dura}\) on the level of write-downs when they occur by examining the relationship between the level of write-downs and the level of firms’ beginning asset book-to-market. This model would estimate the amount of write-down a firm records, controlling for the extent to which its assets are overvalued relative to the market.

The regression model is as follows:

\[
\text{wd}_t = \alpha + \beta \times \text{abtm}_{t-1} \times \text{post}_t \times \text{treat}_t + \gamma \times \Theta_t + e_t
\]  

(2)

where \(\text{wd}_t\) is the scaled level of write-downs at \(t\), \(\text{abtm}_{t-1}\) is the asset book-to-market ratio at the start of \(t\), and \(\Theta_t\) is a vector of second-order interactions, main effects and controls.

Because write-downs are coded as negative values in Compustat, a significantly negative estimate of \(\beta\) would indicate that treatment firms record larger write-downs relative to beginning book-to-markets after \(\text{Dura}\), relative to firms in the control sample.

5.3. Testing Hypothesis 2

To test Hypothesis 2, I examine the extent to which income-increasing accrual errors in the previous period predict income-decreasing accrual errors in the current period.

is greater than one at the start of the year. This suggests that the market-implied impairment is incomplete on average, or that the market overreacts to impairment announcements.
Similar to Allen et al. (2013), I decompose working capital accruals into components attributable to growth, temporary fluctuations in working capital requirements, and errors.\textsuperscript{27} I then assign the signed error components for the current and previous years to quintiles, and examine the extent to which high-quintile accruals in the previous year predict accruals in the lowest quintile in the current year. I estimate two regression models for Hypothesis 2, as follows:

\[ \text{logit}(I(q_{acc} = 1)) = \alpha + \beta \times I(q_{acc_{t-1}} \geq 4) \times \text{post}_t \times \text{treat}_t + \gamma \times \Lambda_t + \epsilon_t \]  

(3)

\[ \text{logit}(I(q_{acc} = 1)) = \alpha + \beta \times I(q_{acc_{t-1}} = 5) \times \text{post}_t \times \text{treat}_t + \gamma \times \Lambda_t + \epsilon_t \]  

(4)

where \(q_{acc_t}\) is the quintile of the signed accrual error relative to the distribution at \(t\), and \(\Lambda_t\) is a vector of second-order interactions, main effects, and controls.

The estimates of \(\beta\) then measure the impact of \textit{Dura} on income-decreasing accrual reversals. Specifically, it captures the likelihood that a firm records highly negative accruals in the current year when accruals were highly positive in the previous year, relative to the likelihood when accruals was not highly positive. This is important because the underlying motivation of the paper is that \textit{Dura} incentivizes treatment firms specifically to avoid \textit{corrective} disclosures—disclosures that correct firm performance downwards.

Next I examine the impact of \textit{Dura} on accrual reversals in general using the following regression model:

\[ q_{acc_t} = \alpha + \beta \times q_{acc_{t-1}} \times \text{post}_t \times \text{treat}_t + \gamma \times \Pi_t + \epsilon_t \]  

(5)

where \(\Pi_t\) is a vector of second-order interactions, main effects, and controls. Significantly positive estimates of \(\beta\) would suggest that relative to control firms, year-on-year accrual reversals declined in treatment firms after \textit{Dura}.

\textsuperscript{27}See Appendix C for details on the construction of the accrual error variables.
5.4. Matching methodology

I use two matching methods to control for differences between the treatment and control subsamples:

- **Industry matching**: The control group comprises all firm-years in the same high-litigation industries as the treatment group.

- **Propensity matching**: The treatment and control observations are also from the same industries, but they are propensity-matched each year to minimize differences in potential confounding variables.

The propensity matching is carried out in three steps. First, I use logistic regressions to estimate the propensity that an observation is in the treatment subsample given a set of potential confounding variables. Second, I discard treatment and control observations that are outside the support of the propensity score. Third, I match treatment and control observations using full matching (Rosenbaum, 1991).

For the write-downs analyses, I match along \( abtm_{t-1}, \text{int}_{t-1}, \text{roa}_{t}, \text{log}_\text{age}_{t}, \text{log}_\text{at}_{t-1}, \text{log}_\text{mv}_{t-1} \) and two-digit SIC fixed effects. Matching by intangibles intensity (\( \text{int}_{t-1} \)) and performance (\( \text{roa}_{t} \)) is particularly important since Lawrence et al. (2013) find that the relationship between write-downs and book-to-market is more negative when intangibles intensity is higher and performance is poorer; and matching by age (\( \text{log}_\text{age}_{t} \)) controls for the possibility that accounting conservatism changes with firm age (e.g. as suggested by Khan & Watts, 2009).

For the accruals reversals analyses, I match along \( \text{acc.error}_{t-1}, \text{roa}_{t}, \text{growth}_{t-1}, \text{ebtm}_{t-1}, \text{log}_\text{age}_{t}, \text{log}_\text{mv}_{t-1} \) and two-digit SIC fixed effects. Matching by performance (\( \text{roa}_{t} \)) is particularly important due to the relationship between performance and accruals (e.g. Dechow et al., 1995; Kothari et al., 2005), and matching by growth and age (\( \text{growth}_{t-1}, \text{ebtm}_{t-1}, \text{log}_\text{age}_{t} \)) controls for the potential relationship between accruals persistence and a firm’s growth and operating cycle.28

I match treatment and control observations using the full matching procedure introduced by Rosenbaum (1991) (see also Rosenbaum, 2002; Hansen, 2004), which uses all available observations to generate an optimal match between treatment and control observations. I carry out the matching procedure after sample attrition and after winsorizing. I winsorize accrual estimation errors at ±50%, and other non-discrete variables are winsorized each year at the top and bottom percentiles.

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28Please refer to Appendix B for variable definitions.
groups.\footnote{For example, see Hansen (2004, p. 609): “Among matching techniques for observational studies, full matching is in principle the best, in the sense that its alignment of comparable treated and control subjects is as good as that of any alternate method, and potentially much better.” I implement the propensity matching using the \textit{MatchIt} package (Ho et al., 2007, 2011) in R.}

Full matching “is optimal in terms of minimizing a weighted average of the estimated distance measure between each treated subject and each control subject within each subclass.” (Ho et al., 2011, p. 7). The procedure matches treatment and control observations within subclasses in which a treatment observation is matched to one or more control observations, or a control observation is matched to one or more treatment observations. A set of weights is produced that I use in the subsequent analyses. In particular, I show (in Tables 2 and 3) that the differences in key confounders between treatment and control are insignificant after weighting, and I use weighted regressions when estimating the models under propensity matching.

6. Sample and descriptives

My sample period begins in 2003 and ends in 2008. As I discuss in Section 3, the split between the Ninth Circuit and other circuits was clear by 2003, when the Ninth Circuit stated its position in \textit{Broudo} and contrasted it with the majority view. Beginning the sample in 2003 also allows me to avoid the impact of changes attributable to the Sarbanes-Oxley Act.

Panels A of Tables 2 and 3 show the sample selection for the write-downs and accruals reversals tests respectively. For both tests I require firms to be located in the treatment and control jurisdictions and to be in high-litigation industries. The treatment sample comprises firms in states under the jurisdiction of the Ninth Circuit, and the control sample comprises firms in states under the jurisdictions of the circuits other than the Eighth or Ninth Circuit.\footnote{I omit firms under the jurisdiction of the Eighth Circuit because its legal position appeared to be between the majority and minority views (see Footnote 23).}

Next, I omit firms with beginning assets of less than $1 million, and for the write-downs tests I require firms to have material beginning intangibles, defined as beginning intangibles of at least 1% of beginning assets. I omit firms with low beginning assets because Hypothesis 1 examines asset write-downs, and to reduce the frequency of small denominators in the accrual measures used to test Hypothesis 2. Finally, for each set of tests I require availability of key variables used in the analyses.
Table 2: Descriptive statistics: write-downs analyses

Panel A: Sample selection

<table>
<thead>
<tr>
<th></th>
<th>All</th>
<th>Treatment</th>
<th>Control</th>
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</thead>
<tbody>
<tr>
<td>Firm-yrs. Firms</td>
<td>47,377</td>
<td>10,580</td>
<td>10,732</td>
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<tr>
<td>Treatment &amp; control jurisdictions</td>
<td>47,377</td>
<td>10,580</td>
<td>10,732</td>
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<tr>
<td>High-litigation industries</td>
<td>11,233</td>
<td>2,445</td>
<td>3,916</td>
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<tr>
<td>Minimum starting assets</td>
<td>9,621</td>
<td>2,187</td>
<td>3,348</td>
</tr>
<tr>
<td>Material starting intangibles</td>
<td>5,911</td>
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<td>Require variable availability</td>
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<tr>
<td>Propensity-matched</td>
<td>5,264</td>
<td>1,397</td>
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Panel B: Descriptive statistics

<table>
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<td>Firm-yrs. Firms</td>
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<td>1,854</td>
</tr>
<tr>
<td>Firms</td>
<td>513</td>
<td>506</td>
</tr>
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</table>

This table lists the sample selection steps for the write-downs analyses (Panel A), and descriptive statistics of the key variables (Panel B). I begin with Compustat observations between 2003 and 2008 that are headquartered (Compustat: loc) in the United States and located in a state (state) under the treatment or control jurisdictions. Treatment firms are located in the jurisdiction of the Ninth Circuit, while control firms are located in the jurisdictions of the Eighth or Ninth Circuits. I then reduce the sample to firms in high-litigation industries: pharmaceuticals and biological (sic 2833–2836, 8731–8734); computers, electronics, and software (sic 3570–3577, 3600–3674, 7370–7374); and telephone communications and electric services (sic 4810–4813, 4911–4931), and omit firms with beginning total assets (at) less than $1 million and beginning intangibles (intan) of less than 1% of beginning total assets. Finally, I require availability of variables used in the main regression analyses and abtm for the additional analyses, and construct a propensity-matched sample as detailed at Section 5.4. Panel B shows descriptive statistics including the differences between treatment and control for two subsamples. Variables other than discrete variables are winsorized each year at the top and bottom percentiles. The industry-matched sample comprises the treatment sample and all firms in the control sample, which are from the same industries. The propensity-matched sample comprises treatment and control observations that are successfully matched; the statistics are reweighted using the weights generated by the matching method described at Section 5.4. The t-statistics are based on the differences between the treatment and control means (weighted means, in the case of the propensity-matched sample), and t-statistics that indicate significant two-tailed differences at the 10% significance level (|t| > 1.645) are bolded.
### Table 3: Descriptive statistics: accruals reversals analyses

#### Panel A: Samples for analysis

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<td>Minimum starting assets</td>
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<td>Require variable availability</td>
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#### Panel B: Descriptive statistics

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#### Panel C: Accrual quintiles

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<td>Observations</td>
<td>1,314</td>
<td>1,315</td>
<td>1,313</td>
<td>1,315</td>
<td>1,314</td>
</tr>
<tr>
<td>Mean acc_t</td>
<td>-0.143</td>
<td>-0.026</td>
<td>-0.001</td>
<td>0.023</td>
<td>0.124</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>acc_{t-1} quintile</th>
<th>Q1</th>
<th>Q2</th>
<th>Q3</th>
<th>Q4</th>
<th>Q5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Observations</td>
<td>1,314</td>
<td>1,315</td>
<td>1,313</td>
<td>1,315</td>
<td>1,314</td>
</tr>
<tr>
<td>Mean acc_{t-1}</td>
<td>-0.148</td>
<td>-0.029</td>
<td>-0.003</td>
<td>0.024</td>
<td>0.130</td>
</tr>
</tbody>
</table>

This table lists the sample selection steps for the write-downs analyses (Panel A), and descriptive statistics of the key variables (Panels B and C). As in the write-downs analyses (Table 2) I restrict the sample to firms in the treatment and control jurisdictions and high-litigation industries, and require beginning total assets (at) to be at least $1 million. Next, I require availability of variables for the main regression analyses and construct a propensity-matched sample as detailed at Section 5.4. Panel B shows descriptive statistics including the differences between treatment and control for two subsamples. The accrual error variables are winsorized at ±50% and other non-discrete variables are winsorized each year at the top and bottom percentiles. The industry-matched sample comprises the treatment sample and all firms in the control sample, which are from the same industries. The propensity-matched sample comprises treatment and control observations that are successfully matched; the statistics are reweighted using the weights generated by the matching method described at Section 5.4. The t-statistics are based on the differences between the treatment and control means (weighted means, in the case of the propensity-matched sample), and t-statistics that indicate significant two-tailed differences at the 10% significance level ($|t| > 1.645$) are bolded. Panel C shows the means of the current and previous years’ accrual error measures within each quintile.
The above steps result in a sample of 1,882 treatment firm-years and 3,499 control firm-years for the write-downs analyses and 2,383 treatment firm-years and 4,188 control firm-years for the accruals reversals analyses. These are the industry-matched samples, in which treatment and control firm-years are from the same set of industries.

I construct the propensity-matched samples by applying the matching methodology described in Section 5.4 to the industry-matched samples. Treatment and control observations that are outside the support of the propensity score are dropped, resulting in a slight decline in the sample sizes for the propensity-matched sample. The methodology results in a set of weights that are used in the subsequent analyses.

Panels B of Tables 2 and 3 show descriptives of key variables by treatment and control group and matching method. In the propensity-matched columns, the means are weighted by the weights produced by the propensity-matching procedure. The treatment and control samples are significantly different along several variables; in particular, treatment firms are younger, have higher valuations, and have higher growth. All the differences become insignificant after propensity-matching.

Finally, Panel C of Table 3 shows the means of the current and previous years’ accrual errors within each quintile. The average accrual error at $t$ varies between $-14.3\%$ and $12.4\%$ of average assets over the five quintiles, and the average accrual error at $t-1$ varies between $-14.8\%$ and $13.0\%$ of average assets over its five quintiles.

7. Write-downs

7.1. Avoidance of write-downs

The results from estimating Equation 1 are shown at Table 4. I estimate the model using logistic regressions, and I use a quasibinomial link function for the propensity-matched sample because the data is weighted according to the matching methodology described in Section 5.4. In columns 1, 2, 4, and 5, I estimate the model for specific time periods.

The significantly negative coefficient estimates for $abtmd_{t-1} \times post_t \times treat_t$ in columns 3 and 6 suggest that treatment firms become more likely to avoid required write-downs post-$Dura$ relative to control firms. The estimated effect is larger in statistical and economic significance in the propensity-matched sample. Columns 1, 2, 4, and 5 show that the result is driven largely by the pre-period. In other words, firms in the Ninth Circuit are significantly less likely to delay write-downs than firms in control.
Table 4: Odds of writing down and beginning book-to-market

<table>
<thead>
<tr>
<th>Model:</th>
<th>Logistic (binomial)</th>
<th>Logistic (quasibinomial)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Matching:</td>
<td>Industry-matched</td>
<td>Propensity-matched</td>
</tr>
<tr>
<td>Period:</td>
<td>Pre</td>
<td>Post</td>
</tr>
<tr>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>(abtmd_{t-1} \times treat_t)</td>
<td>0.695**</td>
<td>(-0.234)</td>
</tr>
<tr>
<td></td>
<td>(0.292)</td>
<td>(0.418)</td>
</tr>
<tr>
<td>(abtmd_{t-1})</td>
<td>0.039</td>
<td>0.664***</td>
</tr>
<tr>
<td></td>
<td>(0.199)</td>
<td>(0.241)</td>
</tr>
<tr>
<td>(treat_t)</td>
<td>(-0.169)</td>
<td>0.177*</td>
</tr>
<tr>
<td></td>
<td>(0.108)</td>
<td>(0.107)</td>
</tr>
<tr>
<td>(abtmd_{t-1} \times post_t \times treat_t)</td>
<td>(-0.871^*)</td>
<td>(-1.074^**)</td>
</tr>
<tr>
<td></td>
<td>(0.500)</td>
<td>(0.504)</td>
</tr>
<tr>
<td>(abtmd_{t-1} \times post_t)</td>
<td>0.931***</td>
<td>1.144***</td>
</tr>
<tr>
<td></td>
<td>(0.288)</td>
<td>(0.289)</td>
</tr>
<tr>
<td>(post_t \times treat_t)</td>
<td>0.372***</td>
<td>0.470***</td>
</tr>
<tr>
<td></td>
<td>(0.143)</td>
<td>(0.145)</td>
</tr>
<tr>
<td>(post_t)</td>
<td>(-0.064)</td>
<td>(-0.172^*)</td>
</tr>
<tr>
<td></td>
<td>(0.086)</td>
<td>(0.089)</td>
</tr>
</tbody>
</table>

Year FEs | Yes | Yes | No | Yes | Yes | No |
Controls & Industry FEs | Yes | Yes | No | Yes | Yes | Yes |

Observations | 2,793 | 2,588 | 5,381 | 2,742 | 2,522 | 5,264 |
McFadden R² | 0.075 | 0.103 | 0.079 | 0.087 | 0.106 | 0.081 |
Nagelkerke R² | 0.120 | 0.165 | 0.127 | 0.139 | 0.169 | 0.130 |

This table shows the results from estimating Equation 1. I estimate the model using logistic regressions, and use a quasibinomial link function for the propensity-matched regressions because weights from the propensity-matching methodology described in Section 5.4 are applied to the model. In columns 1, 2, 4, and 5, I estimate the model for specific time periods. The control variables are \(int_{t-1}, roa_t, log\_age_t, log\_at_{t-1},\) and \(log\_mv_{t-1},\) and variable definitions are at Appendix B. Standard errors are shown in parentheses and the p-values are labeled as follows: *p<0.1; **p<0.05; ***p<0.01.
circuits before *Dura*. This is consistent with Ninth Circuit firms having lower incentives to avoid write-downs pre-*Dura* because its legal environment did not emphasize income-decreasing corrective disclosures.

The effects are also highly significant economically. From column 4, the coefficient of 0.597 implies that during the pre-*Dura* period, a book-to-market greater than one is associated with an 81.7 percentage point larger increase in the odds of a write-down in treatment firms than control firms. From column 5, this becomes 37.4 percentage points smaller post-*Dura*.

Figure 2 shows the difference in effect sizes between the treatment and control groups for each year of the sample period. In other words, beginning with Equation 1, I drop post*$_t$* and the year fixed effects, and estimate the following regression model each year:

$$\text{logit}(\text{wdd}_t) = \alpha + \beta \times abtm_{t-1} \times \text{treat}_t + \gamma \times \Gamma_t + \epsilon_t$$  \hspace{1cm} (6)

where $\Gamma_t$ is vector of main effects and controls. Figure 2 plots the estimates of $\beta$ each year for the industry-matched sample (Panel A) and the propensity-matched sample (Panel B). Figure 2 shows that treatment firms recorded required write-downs in a more timely manner for every year in the pre-*Dura* period compared to control firms, and that this reverses in the post-*Dura* period.

### 7.2. Level of write-downs when they occur

Next, I examine the level of write-downs when they occur by estimating Equation 2 for observations where $\text{wdd}_t = 1$. As in Table 4 I show regression results for the full model and for the model estimated within specific time periods, and I weight the propensity-matched sample using the same weights as before.

The results are at Table 5. From columns 3 and 6, the estimated coefficient on $abtm_{t-1} \times \text{post}_t \times \text{treat}_t$  is significantly negative, suggesting that write-downs by treatment firms became larger post-*Dura* relative to control firms, for a given level of beginning book-to-market. Columns 1, 2, 4, and 5 show that treatment firms recorded smaller write-downs than control firms pre-*Dura*, but larger write-downs post-*Dura*, on average.

The results are also significant economically. From columns 4 and 5, before *Dura*, a one standard deviation increase in the beginning book-to-market is associated with 4.5 percentage point smaller write-downs in treatment firms, as a proportion of market value.
This figure plots the estimated coefficients for $abtd_{t-1} \times treat_t$ from estimating Equation 1 each year without post$_t$ and year fixed effects. A coefficient of $\kappa$ implies that the increase in the odds of writing down when a firm's book-to-market becomes greater than one is $e^\kappa$ times as much in a treatment firm relative to a control firm in a given year, on average.
Table 5: Level of write-downs when they occur

<table>
<thead>
<tr>
<th>Dependent variable: $wd_t$</th>
<th>Model:</th>
<th>Ordinary least squares</th>
<th>Weighted least squares</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Matching:</td>
<td>Industry-matched</td>
<td>Propensity-matched</td>
</tr>
<tr>
<td>Period:</td>
<td>Pre</td>
<td>Post</td>
<td>DID</td>
</tr>
<tr>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
</tr>
<tr>
<td>$abtm_{t-1} \times treat_t$</td>
<td>0.114***</td>
<td>-0.032</td>
<td>0.113***</td>
</tr>
<tr>
<td></td>
<td>(0.035)</td>
<td>(0.039)</td>
<td>(0.034)</td>
</tr>
<tr>
<td>$abtm_{t-1}$</td>
<td>-0.003</td>
<td>-0.096***</td>
<td>-0.051*</td>
</tr>
<tr>
<td></td>
<td>(0.031)</td>
<td>(0.036)</td>
<td>(0.027)</td>
</tr>
<tr>
<td>$treat_t$</td>
<td>-0.067**</td>
<td>0.009</td>
<td>-0.068***</td>
</tr>
<tr>
<td></td>
<td>(0.027)</td>
<td>(0.027)</td>
<td>(0.025)</td>
</tr>
<tr>
<td>$abtm_{t-1} \times post_t \times treat_t$</td>
<td>-0.144***</td>
<td>-0.226***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.054)</td>
<td>(0.054)</td>
<td></td>
</tr>
<tr>
<td>$abtm_{t-1} \times post_t$</td>
<td>0.009</td>
<td>0.076**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.032)</td>
<td>(0.031)</td>
<td></td>
</tr>
<tr>
<td>$post_t \times treat_t$</td>
<td>0.072*</td>
<td>0.119***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.038)</td>
<td>(0.038)</td>
<td></td>
</tr>
<tr>
<td>$post_t$</td>
<td>-0.019</td>
<td>-0.061***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.023)</td>
<td>(0.022)</td>
<td></td>
</tr>
</tbody>
</table>

Year FEs | Yes | Yes | No | Yes | Yes | No |
Controls & Industry FEs | Yes | Yes | Yes | Yes | Yes | Yes |
Observations | 705 | 716 | 1,421 | 689 | 702 | 1,391 |
Adjusted R² | 0.417 | 0.494 | 0.433 | 0.471 | 0.511 | 0.459 |

This table shows the results from estimating Equation 2 for observations where $wdd_t = 1$. I estimate the model using least squares, and use weighted least squares for the propensity-matched regressions because weights from the propensity-matching methodology described in Section 5.4 are applied to the model. In columns 1, 2, 4, and 5, I estimate the model for specific time periods. The control variables are $int_{t-1}$, $roa_t$, $log_{age_t}$, $log_{at_{t-1}}$, and $log_{mv_{t-1}}$, and variable definitions are at Appendix B. Standard errors are shown in parentheses and the p-values are labeled as follows: *$p<0.1$; **$p<0.05$; ***$p<0.01$. 

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value at $t-1$; however, after Dura, it is associated with a 2.2 percentage point larger write-down in treatment firms.\(^{31}\)

### 7.3. Additional tests and sensitivity analyses

In untabulated analyses, I examine the impact of Dura on ending asset book-to-market ratios as a simple proxy for the degree of asset overvaluation. The ending book-to-market is significantly lower in the treatment group than the control group in the pre-period, and insignificantly different in the post-period. Using raw values, the difference in means between treatment and control in the pre-period is $-3.4$ percentage points ($t = -3.15$); using annual quintiles scaled from zero to one, it is $-5.3$ percentage points ($t = -3.78$).

Next, I examine the market reaction to write-downs, because my research design assumes that write-downs induce declines in stock prices that firms would have greater incentive to avoid under the Dura decision. I examine the three-day market reaction to earnings announcements for quarters in my sample during which a write-down occurred and for which data is available. Using earnings announcements understates the stock price reaction because write-downs may be announced beforehand.

I find that the size-adjusted return over the three trading days beginning on the earnings announcement day is $-1.6\%$ on average ($t = -5.77$). When the annual book-to-market ratio is greater than one at the start of the year, the size-adjusted return is $-2.1\%$ on average ($t = -2.09$). This suggests that the market impairment implied by the high beginning book-to-market is generally incomplete, or that the market overreacts to impairments.

Finally, I replicate my estimation of Equation 1 under different thresholds for high book-to-market ratios. I find that the main triple difference result at columns 3 and 6 of Table 4 become more significant economically and statistically when the book-to-market threshold is moderately greater than one (1.05 or 1.10), and statistically insignificant when the book-to-market threshold is moderately smaller than one (0.90 or 0.95).

The former result would be consistent with GAAP rules allowing the carrying value of certain assets classes to exceed their fair values (see Lawrence et al., 2013, p. 115), so incentives to avoid GAAP-required write-downs may only apply at higher thresholds.

---

\(^{31}\)This is based on the standard deviation of $abtm_{t-1}$ in the write-downs sample (0.306).
for certain firms. The latter result could be due to the introduction of excessive noise as more firms are erroneously assumed to require write-downs under GAAP.

8. Accrual reversals

8.1. Income-decreasing accrual error reversals

The results from estimating Equations 3 and 4 are at Tables 6 and 7 respectively. As in Table 4, I estimate the model using logistic regressions, and I use a quasibinomial link function for the propensity-matched sample because the data is weighted according to the matching methodology described in Section 5.4. In columns 1, 2, 4, and 5, I estimate the model for specific time periods.

From columns 3 and 6, the estimated coefficients on $I(q_{acc_{t-1}} \geq 4) \times post_t \times treat_t$ and $I(q_{acc_{t-1}} = 5) \times post_t \times treat_t$ are significantly negative, suggesting that treatment firms avoid income-decreasing accrual reversals more after Dura, relative to control firms. The effect sizes are also significant economically. From columns 4 and 5 of Table 3, in the pre-Dura period, having highly positive accruals in the previous year is associated with 80.2 percentage points higher odds of having highly negative accruals in the current year in treatment firms relative to control firms; but in the post-Dura period it is associated with 49.7 percentage points lower odds. Unlike the write-downs analyses, columns 1, 2, 4, and 5 show that the result is generally driven by both the pre- and post-Dura periods.

Figures 3 and 4 show the difference in effect sizes between the treatment and control groups for each year of the sample period. In other words, I estimate the following regression models each year:

$$\text{logit}(I(q_{acc_t} = 1)) = \alpha + \beta \times I(q_{acc_{t-1}} \geq 4) \times treat_t + \gamma \times \Lambda_t + \epsilon_t \quad (7)$$

$$\text{logit}(I(q_{acc_t} = 1)) = \alpha + \beta \times I(q_{acc_{t-1}} = 5) \times treat_t + \gamma \times \Lambda_t + \epsilon_t \quad (8)$$

where $\Lambda_t$ is a vector of main effects, and controls. Figures 3 and 4 plot the estimates of $\beta$ each year for Equations 7 and 8 respectively. The figures show that treatment firms were less likely to avoid income-decreasing accruals before Dura, but became more likely to avoid it after Dura.

Figures 5 and 6 provide additional details on the economic significance of Dura on accrual reversals. These figures show the percentage of firms with highly positive
Table 6: Income-decreasing accrual error reversals, highest two starting accrual quintiles

<table>
<thead>
<tr>
<th>Dependent variable: $I(q_{acc_t} = 1)$</th>
<th>Model: Logistic (binomial)</th>
<th>Logistic (quasibinomial)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Matching: Industry-matched</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Period:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pre</td>
<td>Post</td>
<td>DID</td>
</tr>
<tr>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>$I(q_{acc_{t-1}} \geq 4)$</td>
<td>$-0.678^{**}$</td>
<td>$0.589^{***}$</td>
</tr>
<tr>
<td>$\times treat_t$</td>
<td>$(0.205)$</td>
<td>$(0.206)$</td>
</tr>
<tr>
<td>$I(q_{acc_{t-1}} \geq 4)$</td>
<td>$0.040$</td>
<td>$-0.103$</td>
</tr>
<tr>
<td>$\times treat_t$</td>
<td>$(0.127)$</td>
<td>$(0.128)$</td>
</tr>
<tr>
<td>$treat_t$</td>
<td>$-0.291^{**}$</td>
<td>$-0.293^{**}$</td>
</tr>
<tr>
<td></td>
<td>$(0.126)$</td>
<td>$(0.134)$</td>
</tr>
<tr>
<td>$I(q_{acc_{t-1}} \geq 4)$</td>
<td>$1.067^{***}$</td>
<td>$1.251^{***}$</td>
</tr>
<tr>
<td>$\times post_t \times treat_t$</td>
<td>$(0.279)$</td>
<td>$(0.280)$</td>
</tr>
<tr>
<td>$I(q_{acc_{t-1}} \geq 4)$</td>
<td>$0.537^{***}$</td>
<td>$0.742^{***}$</td>
</tr>
<tr>
<td>$\times post_t$</td>
<td>$(0.169)$</td>
<td>$(0.171)$</td>
</tr>
<tr>
<td>$post_t \times treat_t$</td>
<td>$0.681^{***}$</td>
<td>$0.717^{***}$</td>
</tr>
<tr>
<td></td>
<td>$(0.181)$</td>
<td>$(0.180)$</td>
</tr>
<tr>
<td>$post_t$</td>
<td>$-0.281^{**}$</td>
<td>$-0.346^{***}$</td>
</tr>
<tr>
<td></td>
<td>$(0.115)$</td>
<td>$(0.114)$</td>
</tr>
<tr>
<td>Year FEs</td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td>Controls &amp; Industry FEs</td>
<td>Yes, No</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>3,544</td>
<td>2,992</td>
</tr>
<tr>
<td>McFadden R$^2$</td>
<td>0.109</td>
<td>0.124</td>
</tr>
<tr>
<td>Nagelkerke R$^2$</td>
<td>0.163</td>
<td>0.184</td>
</tr>
</tbody>
</table>

This table shows the results from estimating Equation 3. I estimate the model using logistic regressions, and use a quasibinomial link function for the propensity-matched regressions because weights from the propensity-matching methodology described in Section 5.4 are applied to the model. In columns 1, 2, 4, and 5, I estimate the model for specific time periods. The control variables are $roa_t$, $growth_t$, $ebtm_{t-1}$, $log_{age_t}$, and $log_{mv_{t-1}}$, and variable definitions are at Appendix B. Standard errors are shown in parentheses and the p-values are labeled as follows: *$p<0.1$; **$p<0.05$; ***$p<0.01$. 
Table 7: Income-decreasing accrual error reversals, highest starting accrual quintile

| Dependent variable: $I(q_{acc_t} = 1)$ | Model: Logistic (binomial) | Logistic (quasibinomial) | Matching: Industry-matched | Propensity-matched | Period: Pre | Post | DID | Pre | Post | DID |
|--------------------------------------|----------------------------|---------------------------|---------------------------|-------------------|------------|------|----|-----|------|----|-----|----|-----|-----|----|-----|----|-----|-----|----|-----|----|-----|-----|
| $I(q_{acc_{t-1}} = 5)$ × $treat_t$   | 0.278                      | −0.482**                  | 0.287                     | 0.442**           | 0.696***   | 0.439**|
|                                      | (0.217)                    | (0.230)                   | (0.216)                   | (0.223)           | (0.232)    | (0.221)|
| $I(q_{acc_{t-1}} = 5)$ $treat_t$    | 0.309**                    | 0.827***                  | 0.309**                   | 0.229*           | 1.098***   | 0.209 |
|                                      | (0.129)                    | (0.140)                   | (0.128)                   | (0.137)           | (0.143)    | (0.135)|
| $treat_t$                            | −0.177                     | 0.211*                    | −0.194*                  | −0.160           | 0.327***   | −0.149|
|                                      | (0.112)                    | (0.121)                   | (0.110)                   | (0.108)           | (0.118)    | (0.108)|
| $I(q_{acc_{t-1}} = 5)$ × $post_t$ × $treat_t$ | −0.766**                  | −1.131***                 |                          |                   |            |      |
|                                      | (0.316)                    | (0.320)                   |                          |                   |            |      |
| $I(q_{acc_{t-1}} = 5)$ × $post_t$ × $treat_t$ | 0.525***                  | 0.925***                  |                          |                   |            |      |
|                                      | (0.188)                    | (0.194)                   |                          |                   |            |      |
| $post_t$ × $treat_t$                 | 0.417***                   | 0.467***                  |                          |                   |            |      |
|                                      | (0.160)                    | (0.160)                   |                          |                   |            |      |
| $post_t$                             | −0.187*                    | −0.266***                 |                          |                   |            |      |
|                                      | (0.100)                    | (0.100)                   |                          |                   |            |      |
| Year FEs                             | Yes                        | Yes                       | No                       | Yes              | Yes        | No    |
| Controls & Industry FEs              | Yes                        | Yes                       | No                       | Yes              | Yes        | Yes   |
| Observations                         | 3,544                      | 3,027                     | 6,571                     | 3,514             | 2,992      | 6,506 |
| McFadden $R^2$                       | 0.111                      | 0.129                     | 0.118                     | 0.116             | 0.137      | 0.122 |
| Nagelkerke $R^2$                     | 0.166                      | 0.191                     | 0.176                     | 0.175             | 0.202      | 0.183 |

This table shows the results from estimating Equation 4. I estimate the model using logistic regressions, and use a quasibinomial link function for the propensity-matched regressions because weights from the propensity-matching methodology described in Section 5.4 are applied to the model. In columns 1, 2, 4, and 5, I estimate the model for specific time periods. The control variables are $roa_t$, $growth_t$, $ebtm_{t-1}$, $log_{age_t}$, and $log_{mv_{t-1}}$, and variable definitions are at Appendix B. Standard errors are shown in parentheses and the p-values are labeled as follows: *p<0.1; **p<0.05; ***p<0.01.
Figure 3: Accrual reversals by year, highest two starting accrual quintiles

Panel A: Industry-matched

Panel B: Propensity-matched

This figure plots the estimated coefficients for $I(q_{acc_{t-1}} \geq 4) \times treat_t$ from estimating Equation 7 each year without $post_t$ or year fixed effects.
Figure 4: Accrual reversals by year, highest starting accrual quintile

This figure plots the estimated coefficients for \( I(q_{acc_{t-1}} = 5) \times treat_t \) from estimating Equation 8 each year without \( post_t \) or year fixed effects.
accruals in the previous year that are in each quintile of accruals in the current year. For example, in Panel A of Figure 5, the top left data point indicates that in the pre-\textit{Dura} period, about 24% of treatment firms with highly positive accruals last year are in the lowest quintile of accruals this year. Figure 5 is based on firm-years with previous-year accruals in the highest two quintiles, while Figure 6 is based on the highest quintile. The figures show that in the pre-\textit{Dura} period, treatment firms were more likely than control firms to reverse accruals downwards to the lowest quintile. However, after \textit{Dura} they became less likely than control firms to do so.

\textbf{8.2. \textit{All accrual error reversals}}

Finally, the results from estimating Equation 5 are at Table 8. From columns 3 and 6, the significantly positive coefficient on $q_{\text{acc}_{t-1}} \times \text{post}_t \times \text{treat}_t$ indicates that accrual error reversals declined after \textit{Dura} in treatment firms, relative to control firms.

Since both $q_{\text{acc}_{t-1}}$ and $q_{\text{acc}_t}$ are quantile bins, a coefficient estimate of $\hat{\beta}$ indicates that an increase in the explanatory variable from the lowest to the highest quantile is associated with a $\hat{\beta} \times 100$ percentage point increase in the outcome variable along its distribution, on average. From columns 4 and 5, in the pre-\textit{Dura} period, an increase in starting accruals from the lowest to the highest quintile decreased ending accruals by 7.5 percentage points more in treatment than control firms, but in the post-\textit{Dura} period it decreased it by 10.1 percentage points less.

In untabulated analyses I find that the estimated coefficient on $q_{\text{acc}_{t-1}} \times \text{post}_t \times \text{treat}_t$ becomes insignificant and close to zero when I omit firms in the lowest quintile of accrual errors at $t$. This indicates that the change in overall accruals error reversals after \textit{Dura} is driven almost entirely by income-decreasing accruals.

\textbf{9. Additional analysis: probability of litigation}

In this section I examine the impact of \textit{Dura} on the probability of securities litigation in treatment relative to control firms. A primary motivation of this paper is that delaying or avoiding disclosure of bad news became an effective strategy for reducing litigation risk post-\textit{Dura} in treatment firms. However, the possibility that firms attempt to delay bad news but are ultimately ineffective at obfuscating or avoiding the negative market reaction would work in the opposite direction.

I proxy for litigation risk using a dummy variable $\text{sued}_t$ that is equal to one if the
Figure 5: Accrual reversals by ending quintile, highest two starting accrual quintiles

These figures plot the percentage of firms with previous-year accrual errors in the highest two quintiles that are in each quintile of accrual errors in the current year.
These figures plot the percentage of firms with previous-year accrual errors in the highest quintiles that are in each quintile of accrual errors in the current year.
Table 8: All accrual error reversals

<table>
<thead>
<tr>
<th>Dependent variable: $q_{acc_t}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model: Ordinary least squares</td>
</tr>
<tr>
<td>Matching: Industry-matched</td>
</tr>
<tr>
<td>Period: Pre</td>
</tr>
<tr>
<td>(1)</td>
</tr>
<tr>
<td>$q_{acc_{t-1}} \times treat_t$</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>$q_{acc_{t-1}}$</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>$treat_t$</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>$q_{acc_{t-1}} \times post_t \times treat_t$</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>$q_{acc_{t-1}} \times post_t$</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>$post_t \times treat_t$</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>$post_t$</td>
</tr>
<tr>
<td></td>
</tr>
</tbody>
</table>

Year FEs | Yes | Yes | No | Yes | Yes | No |
| Controls & Industry FEs | Yes | Yes | Yes | Yes | Yes | Yes |

Observations | 3,544 | 3,027 | 6,571 | 3,514 | 2,992 | 6,506 |
Adjusted $R^2$ | 0.047 | 0.055 | 0.051 | 0.058 | 0.065 | 0.057 |

This table shows the results from estimating Equation 5. I estimate the model using least squares, and use weighted least squares for the propensity-matched regressions because weights from the propensity-matching methodology described in Section 5.4 are applied to the model. In columns 1, 2, 4, and 5, I estimate the model for specific time periods. The control variables are $roa_t$, $growth_t$, $ebtm_{t-1}$, $log_{age_t}$, and $log_{mv_{t-1}}$, and variable definitions are at Appendix B. Standard errors are shown in parentheses and the p-values are labeled as follows: *p<0.1; **p<0.05; ***p<0.01.
firm was sued for alleged wrongdoing during $t$ and zero otherwise.\footnote{To be precise, I retrieve the first and reference class periods for each class action lawsuit in Stanford’s Class Action Clearinghouse database. For a given firm, $sued_t$ then takes the value of one if the firm has a lawsuit in the data whose first or reference class period overlaps with $t$, and zero otherwise.} I use a measure of litigation incidence that restricts the time of wrongdoing to $t$ because the timing of disclosures is endogenous in my study.\footnote{For example, if my dependent variable captures lawsuits filed only within $t + 1$, a firm that is accused of wrongdoing at $t$ but only sued in $t + 2$ because the bad news was delayed would be erroneously classified as not facing litigation. A greater delay in disclosing bad news would then be mechanically related to a reduced incidence of litigation.} I then examine the following regression model:

$$sued_t = \alpha + \beta \times treat_t \times post_t + \gamma \times \Sigma_t + \epsilon_t$$ (9)

where $\Sigma_t$ is a vector of control variables and main effects. I estimate this model in several subsamples: the subsample used in the write-downs analyses (Section 7), and the subsample used in the accrual reversals analyses (Section 8); and I use the same control variables as in the respective main regressions (see Tables 4, 6, and 7). I also estimate the model in the intersection of the two subsamples, for which I use the union of the two sets of control variables.

While I expect litigation to decline in all high-litigation treatment firms, I also estimate the model in subsamples of firms with inflated financials at the start of the year—that is, firms with beginning book-to-market greater than one or firms with high beginning accruals error quintiles—to examine the change in litigation in firms that are more likely to record the accounting corrections studied in this paper. Among firms with beginning book-to-market greater than one, $Dura$ was so effective at reducing litigation risk than no treatment firms were sued in the post-$Dura$ period.\footnote{In contrast, about 9% of treatment firms with book-to-market greater than one were sued in the pre-$Dura$ period.} This precludes the use of a logit model due to perfect separation, so for consistency I use a linear probability model when estimating Equation 9.

The results are shown at Table 9. Panels A to C show the results from estimating Equation 9 in the write-downs subsample, the accrual reversals subsample, and the intersection of the two subsamples respectively. From column 3, the coefficients on $post_t \times treat_t$ are significantly negative, suggesting that the probability of litigation declined in treatment firms relative to control firms post-$Dura$. The relative decline
of 3.3 to 4.1 percentage points is highly significant economically, since the overall probability of litigation over the three subsamples is about 5 percent. In addition, columns 1 and 2 suggest that the decline is driven by treatment firms having a higher probability of being sued in the pre-\textit{Dura} period, consistent with the split in the legal environment pre-\textit{Dura}.

Columns 4 and 5 show the change in incidence of litigation among firms with inflated financials at the start of the year. From Panel C, the probability of litigation in firms with high beginning book-to-market or highly positive accrual errors declined by over four percentage points, consistent with \textit{Dura} increasing the set of strategies for avoiding litigation risk when a downwards accounting correction is likely to be required. An exception is in firms with the most extreme positive accruals (column 5 of panel B): the coefficient is in the expected direction but is not statistically significant, which could be due to some firms being less successful at avoiding litigation subsequent to highly positive accrual errors.

10. Conclusions

Under the \textit{ex post} loss rule, plaintiffs in securities lawsuits are required to show that the firm’s alleged misconduct caused a corrective disclosure that resulted in a stock price decline. Firms at high risk of litigation would therefore be incentivized to avoid or delay bad news in the hope of a turnaround or the occurrence of other news that can be bundled with the bad news (see Spindler, 2007; Bliss et al., 2016). The question I aim to answer in this study is whether this applies to the avoidance or delaying of income-decreasing accounting choices, which would demonstrate a fundamental link between corrective disclosures in the context of securities litigation, and downwards corrections of financials as required by GAAP.

My research design exploits the fact that the Supreme Court’s decision in \textit{Dura} caused the \textit{ex post} loss rule to be exogenously adopted in the Ninth Circuit, when it was already the \textit{de facto} prevailing legal standard in the majority of circuits. I find that after \textit{Dura}, firms under the jurisdiction of the Ninth Circuit and in high-litigation industries became more likely to delay GAAP-required write-downs and avoid income-decreasing reversals of working capital accrual estimation errors at the firm level, relative to matched control firms. This suggests that the current loss causation standard in securities litigation affects income-decreasing accounting choices.

In addition, I find that when write-downs do occur, they are larger after \textit{Dura}.
Table 9: Incidence of litigation before and after *Dura*

<table>
<thead>
<tr>
<th>Period</th>
<th>Pre</th>
<th>Post</th>
<th>DID</th>
<th>DID</th>
<th>DID</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td>(5)</td>
</tr>
</tbody>
</table>

*Panel A: Write-downs sample*

<table>
<thead>
<tr>
<th></th>
<th>Full sample</th>
<th>abtm(_{t-1}) &gt; 1</th>
</tr>
</thead>
<tbody>
<tr>
<td>treat(_t)</td>
<td>0.042***</td>
<td>0.014</td>
</tr>
<tr>
<td></td>
<td>(0.010)</td>
<td>(0.009)</td>
</tr>
<tr>
<td>post(_t) × treat(_t)</td>
<td>-0.033***</td>
<td>-0.074**</td>
</tr>
<tr>
<td></td>
<td>(0.012)</td>
<td>(0.036)</td>
</tr>
</tbody>
</table>

Observations 2,793 2,588 5,381 410
Adjusted R\(^2\) 0.044 0.040 0.042 0.036

*Panel B: Accrual reversals sample*

<table>
<thead>
<tr>
<th></th>
<th>Full sample</th>
<th>I((q_{acc}) (≥) 4)</th>
<th>I((q_{acc}) = 5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>treat(_t)</td>
<td>0.039***</td>
<td>0.010</td>
<td>0.044***</td>
</tr>
<tr>
<td></td>
<td>(0.008)</td>
<td>(0.008)</td>
<td>(0.008)</td>
</tr>
<tr>
<td>post(_t) × treat(_t)</td>
<td>-0.041***</td>
<td>-0.035**</td>
<td>-0.027</td>
</tr>
<tr>
<td></td>
<td>(0.011)</td>
<td>(0.017)</td>
<td>(0.021)</td>
</tr>
</tbody>
</table>

Observations 3,544 3,027 6,571 2,629 1,314
Adjusted R\(^2\) 0.053 0.040 0.046 0.035 0.028

*Panel C: Combined sample*

<table>
<thead>
<tr>
<th></th>
<th>Full sample</th>
<th>abtm(<em>{t-1}) &gt; 1 or I((q</em>{acc}) (≥) 4)</th>
<th>abtm(<em>{t-1}) &gt; 1 or I((q</em>{acc}) = 5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>treat(_t)</td>
<td>0.046***</td>
<td>0.050***</td>
<td>0.047***</td>
</tr>
<tr>
<td></td>
<td>(0.011)</td>
<td>(0.010)</td>
<td>(0.010)</td>
</tr>
<tr>
<td>post(_t) × treat(_t)</td>
<td>-0.039***</td>
<td>-0.049**</td>
<td>-0.043*</td>
</tr>
<tr>
<td></td>
<td>(0.014)</td>
<td>(0.020)</td>
<td>(0.024)</td>
</tr>
</tbody>
</table>

Observations 2,349 2,100 4,449 1,961 1,072
Adjusted R\(^2\) 0.050 0.037 0.043 0.029 0.018

Panels A to C show the result from estimating Equation 9 in three subsamples respectively: the write-downs subsample (from Section 7), the accrual reversals subsample (from Section 8), and the intersection of the two subsamples. Equation 9 is estimated using a linear probability model as explained in Section 9. In columns 4 and 5, the samples are further reduced to firms with inflated beginning financials. In Panels A and B, I include the same control variables as in the respective main regressions (see Tables 4, 6, and 7), and I use the union of the two sets of control variables in Panel C. The accrual error quantiles in Panel C are based on the cutoffs used in the more complete sample in Panel B. Variable definitions are at Appendix B. Variables other than treat\(_t\) and post\(_t\) × treat\(_t\) are suppressed for brevity, standard errors are shown in parentheses, and the p-values are labeled as follows: *p<0.1; **p<0.05; ***p<0.01.
relative to the firm’s beginning book-to-market ratio, in treatment firms relative to control firms. This is consistent with firms being able to delay write-downs only up to a point, or firms reporting “as much bad news as possible” (Spindler, 2007, p. 684–685) by recording larger write-downs or write-downs to more assets in the same period, once they are unable to delay a write-down. I also find that the impact of *Dura* on income-decreasing working capital accrual error reversals is large enough to drive a significant change in *overall* working capital accrual error reversals after *Dura*.

Finally, I find in additional analyses that the probability of securities litigation declined in treatment firms relative to control firms post-*Dura*. The change is driven by treatment firms being more likely to face litigation than control firms pre-*Dura*, consistent with the split in the legal environment pre-*Dura*. In particular, the decline in litigation is also observed in the set of treatment firms with high beginning book-to-market ratios or highly positive beginning accrual errors, driven largely by the former.

This study contributes to the literature on the relationship between the legal environment and accounting, and in particular to the growing literature on the impact of court rulings on financial reporting. I believe that this paper is informative to policy makers and legal and accounting practitioners because downward corrections to a company’s financials are fundamental to GAAP and are useful for example in the detection of fraud (e.g. Dechow et al., 2012). If, as my findings suggest, the *ex post* loss rule increases incentives to delay or avoid income-decreasing accounting choices, this fundamental feature of the legal environment may be introducing distortions to firms’ financial disclosures.
Appendix A. HP, Autonomy, and *In re HP Securities Litigation*

“Some consider the Autonomy acquisition to be the worst corporate deal ever.” (Stewart, 2015, *The New York Times*)

**Appendix A.1. Overview and timeline**

In June 2015, Hewlett-Packard reached a $100 million agreement with plaintiffs to settle *In re HP Securities Litigation*. Over the past two decades, the amount has been the largest class action settlement paid by HP, and the suit is one of only two class action lawsuits against HP that was not successfully dismissed. The first complaint in the consolidated suit was filed just six days after HP announced a write-down largely related to its acquisition of Autonomy Corporation plc in 2011. Figure Appendix A.1 shows a timeline of key events related to the case.

Figure Appendix A.1: Timeline of events related to *In re HP Securities Litigation*

**Appendix A.2. Acquisition of Autonomy**

On August 18, 2011, HP announced that it had offered to acquire Autonomy, an enterprise software company. In its press release, HP explained that the acquisition would allow the company to exploit the growth in the enterprise information management and business analytics software and services sectors, and that Autonomy complements HP’s existing product offerings. (HP, 2011b)

The stock market reacted negatively to the acquisition announcement: HP’s stock price declined about 28% (22% market-adjusted) over the three trading days centered on the announcement day. The media also expressed uncertainty over the acquisition.

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35Based on data from Stanford Law School’s Securities Class Action database.
in the days following the announcement. The Economist (2011), for example, advised readers to “be wary of their plan to buy Autonomy”, citing several reasons including the difficulty in HP’s apparent attempt to use Autonomy to establish a software platform.

The acquisition was completed on October 3, 2011, at £25.50 per share for 213,421,299 shares of Autonomy, about 87.34% of Autonomy’s share capital, in cash. (HP, 2011a)

![Graph showing cumulated returns from July 2011 to December 2012 inclusive.](image)

**Figure Appendix A.2:** Cumulated returns from July 2011 to December 2012 inclusive.

*Appendix A.3. Financial results subsequent to acquisition*

After the 28% stock price decline around the acquisition announcement in August 18, 2011, HP’s stock price declined a further 40% (65% market-adjusted) until the end of fiscal 2012, as can be seen in Figure Appendix A.2. HP reported declining quarter-on-quarter revenues in the first, second and third quarters of fiscal 2012 (HP, 2012a,c,d). Furthermore, its third-quarter earnings announcement included an $8 billion goodwill impairment charge “associated with the Services segment” (HP, 2012d), and was accompanied by a 12% stock price decline (11% market-adjusted) over the three trading days centered on the earnings announcement day.
The stock price declines associated with the acquisition announcement and over fiscal 2012 contributed to a substantial increase in HP’s asset book-to-market ratio to 0.90 and 0.96 at the end of 2011 and 2012 respectively, much higher than the average of 0.61 over the previous five years (see Table Appendix A.1).

Finally, on November 20, 2012, in its fourth-quarter earnings announcement, HP announced a $8.8 billion write-off, the majority of which were “linked to serious accounting improprieties, disclosure failures and outright misrepresentations at Autonomy” prior to acquisition (HP, 2012b). HP’s stock price fell about 7% (about 9% market-adjusted) over the three trading days centered on the announcement day.

Table Appendix A.1: Selected annual financials for HP, fiscal years 2006 to 2012

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Total assets ($'M)</td>
<td>108,768</td>
<td>129,517</td>
<td>124,503</td>
<td>114,799</td>
<td>113,331</td>
<td>88,699</td>
<td>81,981</td>
</tr>
<tr>
<td>Common equity ($'M)</td>
<td>22,436</td>
<td>38,625</td>
<td>40,449</td>
<td>40,517</td>
<td>38,942</td>
<td>38,526</td>
<td>38,144</td>
</tr>
<tr>
<td>Shares outstanding ('M)</td>
<td>1,963</td>
<td>1,991</td>
<td>2,204</td>
<td>2,365</td>
<td>2,415</td>
<td>2,580</td>
<td>2,732</td>
</tr>
<tr>
<td>Closing stock price ($)</td>
<td>13.85</td>
<td>26.61</td>
<td>42.04</td>
<td>47.46</td>
<td>38.28</td>
<td>51.68</td>
<td>38.74</td>
</tr>
<tr>
<td>Pretax write-downs ($'M)</td>
<td>-4,330</td>
<td>-72</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Pretax goodwill imp. ($'M)</td>
<td>-13,705</td>
<td>-813</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Pretax income ($'M)</td>
<td>-11,933</td>
<td>9,056</td>
<td>11,083</td>
<td>9,415</td>
<td>10,473</td>
<td>9,177</td>
<td>7,191</td>
</tr>
<tr>
<td>Market capitalization ($'M)</td>
<td>27,185</td>
<td>52,967</td>
<td>92,652</td>
<td>112,234</td>
<td>92,458</td>
<td>133,320</td>
<td>105,839</td>
</tr>
<tr>
<td>Asset book-to-market ratio</td>
<td>0.958</td>
<td>0.900</td>
<td>0.705</td>
<td>0.615</td>
<td>0.679</td>
<td>0.483</td>
<td>0.548</td>
</tr>
</tbody>
</table>

Selected financial results for HP for fiscal years 2006 to 2012 inclusive, retrieved from Compustat. Market capitalization each year is the product of the closing stock prices and the number of shares outstanding, and the asset book-to-market is as defined at Appendix B.

Appendix A.4. The lawsuits and their outcomes

On November 26, 2012, just days after the announcement of the $8.8 billion write-down, Nicolow v. Hewlett-Packard was filed in the Northern District of California. The class action lawsuit was filed in the state in which HP was headquartered (and not the state in which it was incorporated, Delaware). An additional lawsuit, Pokoik v. Hewlett-Packard, was filed on November 30, 2012 in the same district, and the two suits were later consolidated as In re HP Securities Litigation.

The initial complaint (Nicolow v. Hewlett-Packard, No. C-12-5980 CRB) alleged that the defendants—HP and certain executives—concealed their knowledge that Autonomy’s financial results at the time of acquisition “were the product of accounting improprieties”; that they “were looking to unwind the deal in light of the accounting irregularities” even after HP had agreed to acquire Autonomy; and that the Enterprise Services business was performing poorly (para. 54).
The defendants subsequently filed a motion to dismiss the class action on the bases of scienter and falsity (but not loss causation). The motion was only partially granted by the District Court, and the Court’s responses to the motion highlight some of the key legal issues of the case. In particular, the Court cited a whistleblower “who raised concerns about Autonomy’s accounting improprieties with HP’s General Counsel” (p. 14) possibly as early as May 2012, and then-CEO “Whitman’s decision to put forward entrepreneurial challenges as an explanation [for Autonomy’s poor performance] while choosing not even to mention the alternative possibility of accounting fraud, which she knew to be plausible” (p. 15). The Court also cited a false statement in a 10-Q filing concerning the value of Autonomy at the time of acquisition (p. 19).

HP eventually settled the securities class action lawsuit for $100 million. The acquisition and alleged misconduct also had repercussions for HP’s and Autonomy’s top executives: HP reported the termination of its CEO in a Form 8-K filing on September 22, 2011, even before the acquisition was completed, and Autonomy’s former CFO was recently charged by the Department of Justice (Department of Justice, 2016).

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36 See No. C-12-5980 CRB, “Order re Motion to Dismiss”, on November 26, 2013
37 See No. C-12-5980 CRB, “Stipulation of Settlement and Release”, on June 9, 2015
### Variable definitions

<table>
<thead>
<tr>
<th>Variable</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>(abtm_{t-1})</td>
<td>Total assets ((at)) at the end of (t - 1) divided by the market value of equity plus total assets minus common equity ((csho \times prcc.f + at - ceq)) at the end of (t - 1).</td>
</tr>
<tr>
<td>(abtm_{t-1}d)</td>
<td>An indicator variable equal to one if (abtm_{t-1} &gt; 1), and zero otherwise.</td>
</tr>
<tr>
<td>(acc_t)</td>
<td>The component of working capital accruals at (t) that is attributable to estimation error. See Appendix C for details on the construction of this variable.</td>
</tr>
<tr>
<td>(ebtm_{t-1})</td>
<td>Common equity ((ceq)) at the end of (t - 1) divided by the market value of equity ((csho \times prcc.f)) at the end of (t - 1).</td>
</tr>
<tr>
<td>(growth_t)</td>
<td>Change in total revenue ((rext)) during (t) scaled by total revenue during (t - 1).</td>
</tr>
<tr>
<td>(int_{t-1})</td>
<td>Total intangible assets ((intan)) at the end of (t - 1) scaled by total assets ((at)) at the end of (t - 1).</td>
</tr>
<tr>
<td>(log_{age_t})</td>
<td>The natural logarithm of firm age, defined as (t) minus the first fiscal year at which the firm appears in Compustat plus one.</td>
</tr>
<tr>
<td>(log_{at_{t-1}})</td>
<td>The natural logarithm of total assets ((at)) at end of (t - 1).</td>
</tr>
<tr>
<td>(log_{mv_{t-1}})</td>
<td>The natural logarithm of the market value of equity ((csho \times prcc.f)) at the end of (t - 1).</td>
</tr>
<tr>
<td>(post_t)</td>
<td>An indicator variable equal to one if (t) is after 2005, and zero otherwise.</td>
</tr>
<tr>
<td>(q_{acc_t})</td>
<td>The quintile of (acc_t) relative to its distribution each year.</td>
</tr>
<tr>
<td>(roa_t)</td>
<td>Income before extraordinary items ((ib)) during (t) scaled by average assets ((at)) during (t).</td>
</tr>
<tr>
<td>(sued_t)</td>
<td>An indicator variable equal to one if the firm faced a class action lawsuit with a class period that overlaps with (t), based on both the first and reference class period recorded in Stanford’s Class Action Clearinghouse database.</td>
</tr>
<tr>
<td>(treat_t)</td>
<td>An indicator variable equal to one if the firm is located in a state ((state)) under the jurisdiction of the Ninth Circuit at (t), and zero otherwise. See Appendix D for a map of states by legal jurisdiction.</td>
</tr>
<tr>
<td>(wd_t)</td>
<td>The level of write-downs during (t) ((wdp + gdwlip)) scaled by the market value of equity ((csho \times prcc.f)) at the end of (t - 1). Larger write-downs are coded as more negative values.</td>
</tr>
<tr>
<td>(wdd_t)</td>
<td>An indicator variable equal to one if the firm took a write-down at (t) ((wdp &lt; 0) or (gdwlip &lt; 0)), and zero otherwise.</td>
</tr>
</tbody>
</table>

Unless otherwise stated, variables in parentheses refer to Compustat Fundamentals Annual variable names.
Appendix C. Accrual estimation errors

In my accrual reversals tests I use \(acc_t\), a proxy for the estimation error component of working capital accruals. I construct this variable using a method similar to Allen et al. (2013), who use the Dechow & Dichev (2002) model as modified by Bushman et al. (2012) to decompose accruals into “good accruals”—the component explained by growth and temporary fluctuation in working capital requirements—and accrual estimation errors.

I model the non-error component of working capital accruals at \(t\) as a function of operating cash flows at \(t - 1\), \(t\), and \(t + 1\), employee growth at \(t\), and sales growth at \(t\), and include a scaled intercept:

\[
\frac{wca_t}{a_t} = \beta_0 \frac{1}{a_t} + \beta_1 \frac{cfo_{t-1}}{a_t} + \beta_2 \frac{cfo_t}{a_t} + \beta_3 \frac{cfo_{t+1}}{a_t} + \beta_4 \frac{\Delta emp_t}{emp_{t-1}} + \beta_5 \frac{\Delta rev_t}{rev_{t-1}} + \epsilon
\]

where \(wca_t\) is working capital accruals (Compustat: \(\Delta (act - che - lct + dlc + txp)\)) during \(t\); \(cfo_t\) is operating cash flow (\(oancf\)) during \(t\); \(emp_t\) is the number of employees (\(emp\)) at \(t\); \(rev_t\) is total revenue (\(revt\)) during \(t\); and \(\bar{a}_t\) is average of the starting and ending total assets (\(at\)) at \(t\).

I estimate the coefficients of the model every industry-year, where industries are defined according to two-digit SIC codes. To reduce the impact of outliers and small sample sizes on the coefficient estimates, when estimating the coefficients I use only firm-years with average assets greater than $5 million, require at least ten observations each industry-year, and winsorize each term at the top and bottom percentile each industry-year.

I then merge the estimated coefficients \(\hat{\beta}_i\) for each industry-year back into the data, and compute the accrual estimation error as the component of working capital accruals not explained by the model:

\[
acc_t = \frac{wca_t}{a_t} - (\hat{\beta}_0 \frac{1}{a_t} + \hat{\beta}_1 \frac{cfo_{t-1}}{a_t} + \hat{\beta}_2 \frac{cfo_t}{a_t} + \hat{\beta}_3 \frac{cfo_{t+1}}{a_t} + \hat{\beta}_4 \frac{\Delta emp_t}{emp_{t-1}} + \hat{\beta}_5 \frac{\Delta rev_t}{rev_{t-1}})
\]

\(53\)
Appendix D. Circuit court jurisdictions

This map, reproduced in full from United States Courts (n.d.), shows the jurisdiction of each U.S. Court of Appeal. The Ninth Circuit, which is the treatment jurisdiction in this study, comprises firms located in Alaska, Arizona, California, Guam, Hawaii, Idaho, Montana, Nevada, the Northern Mariana Islands, Oregon, or Washington.
References


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Lattanzio v. Deloitte, 476 F.3d 147 (2nd Cir. 2007).


Robbins v. Koger Props., 116 F.3d 1441 (11th Cir. 1997).


*Suez Equity Investors v. Toronto-Dominion Bank*, 250 F.3d 87 (2nd Cir. 2001).


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