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Detecting Target-Driven Earnings Management Based on the Distribution of Digits

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Abstract: We present a novel research design to detect target-driven earnings management in accounting data. As a particular concern in this line of research, information about the exact earnings target value of a given firm is often not available. We therefore develop an empirical strategy that does not require such information. To this end, we rely on the concept of the distribution of digits rather than the distribution of the earnings metric itself. We then theoretically derive that the mean of the distribution of digits, in particular, exhibits a specific pattern around the earnings target that can be exploited to investigate target-driven earnings management. This pattern arises regardless of the distribution of digits that obtains in unmanaged data. We extensively test our theoretical predictions using both simulated and archival data.

Keywords: distribution of digits, target-driven earnings management, Benford's Law

1. INTRODUCTION

The measurement of cross-sectional differences in earnings management continues to be one of the most relevant issues in accounting research (Jorgensen et al., 2014). Within this subject area, one important line of research focuses on earnings management activity intended to meet (or exceed) a given earnings target. Target-beating is a specific dimension of earnings quality and, consequently, requires its own proxies (Dechow et al., 2010). Previous research in this area largely focuses on three distinct earnings targets, namely (i) zero earnings, (ii) previous-period earnings, and (iii) analysts' forecasts (Dechow et al., 2010). However, numerous alternative (yet unobservable) earnings targets exist.

We develop a research design that allows the investigation of target-driven earnings management in accounting data when information concerning relevant earnings target values is not available. To this end, we rely on a concept that is well established

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in previous research on target-driven earnings management – although not among the most common measures – namely, the *distribution of digits* (e.g., Bhattacharya et al., 2010). The distribution of digits draws inferences not from the *total value* of a certain metric but instead from its *numerical structure*, i.e., the frequency of occurrence and the exact sequence of the digits '0' to '9' in the mantissa.

As a more technical aspect, previous research has relied on, as a benchmark, a certain set of theoretically derived distributions of digits that might be expected to obtain in accounting data in the absence of any earnings management (most notably, Benford's Law) – even though empirical evidence on the validity of such an approach is limited (e.g., Watrin et al., 2008). To the contrary, our empirical strategy does not rely on any theoretically derived distribution of digits. This advancement is made possible through the identification of a pattern in the mean of the distribution of digits in managed earnings that obtains regardless of the underlying distribution of digits in unmanaged earnings. This then enables reliance on relative comparisons of the distributions of digits between two or more groups of firms. We recognize that the advantage of not relying on a theoretically derived distribution of digits trades off against the requirement that data on at least two groups of firms must be available to the researcher. We argue that such a data requirement does not limit the applicability of our research design in practice, as most earnings management studies are already based on relative comparisons, with group allocations based on, for instance, listing status (e.g., Dechow et al., 2010), country of residence (e.g., Burgstahler et al., 2006) or periods of time (e.g., before and after the US 1986 Tax Reform Act, Shackelford and Shevlin, 2001).

We contribute in three ways. First, testing of target-driven earnings management is facilitated in settings that are not accessible with current methods. Specifically, our research design is applicable when information on earnings targets cannot be obtained and, moreover, even when the above-mentioned theoretically derived distributions of digits are suspected to be invalid in unmanaged data. It can even be applied when all groups under investigation manage earnings to a different degree. Second, our research design has low data requirements and thus low implicit costs of inference testing. Notably, it is applicable in simple cross-sectional analyses, whereas most other earnings management measures require panel data. Along the same lines, we require availability of only the earnings metric directly affected by target-driven earnings management. Building on these features, researchers can pool more firms into their samples with our research design than with designs that have more rigorous data requirements. Finally, we report superior statistical characteristics. To this end, we first note that the research design can be easily implemented and interpreted – once developed and well understood – as programming and inferential analysis are nearly trivial. More importantly, we report that our research design has higher power in small samples relative to the most closely related method developed in Carslaw (1988).

The paper proceeds as follows: Section 2 summarizes the relevant research in target-driven earnings management. We distinguish between research on observable earnings targets (i.e., zero earnings, previous-year earnings, analysts' forecasts) and research on non-observable earnings targets, where the latter relates to previous work on the distribution of digits. Section 3 combines these two research streams to develop our novel empirical strategy from a theoretical perspective. In this regard, we also elaborate on the general concept of the distribution of digits. In

Sections 4(i) and 4(ii), we test our research design based on simulated and archival data. We deliberately rely on a variety of data sources and settings to avoid sample selection bias. The study's limitations are discussed in Section 4(iii). We then extend the fundamental principle of this novel research design to applications in standard regression analysis in Section 5 and conclude in Section 6.

2. RELATED LITERATURE

(i) Observable Earnings Targets (Distribution of the Earnings Metric)

Previous research in the area of earnings management has identified asymmetries in the *frequency distribution of the earnings metric* near specific earnings target thresholds (essentially following seminal works by Hayn, 1995 and Burgstahler and Dichev, 1997). The most common thresholds employed are (i) zero (e.g., Burgstahler and Dichev, 1997; Degeorge et al., 1999; Bhattacharya et al., 2003; Burgstahler and Eames, 2006; Lang et al., 2006; Barua et al., 2010; and Dierynck et al., 2012), (ii) previous-period value (e.g., Burgstahler and Dichev, 1997; Degeorge et al., 1999; Beatty et al., 2002; Barua et al., 2010; and Frankel et al., 2011), and (iii) analysts' consensus forecasts (e.g., Degeorge et al., 1999; Brown and Higgins, 2001, 2005; Burgstahler and Eames, 2006; Koh et al., 2008; Barua et al., 2010; and Eames and Kim, 2012).

Three concerns are noteworthy in this line of research. First, the cut-off at which researchers consider a given value to be near the earnings target is arbitrary (Badertscher et al., 2012). Second, earnings targets must in fact be publicly observable. Lahr (2014) has provided a more flexible approach to the latter aspect, although it still requires information on potential earnings targets (Section 4(ii)(d)). Finally, technical aspects such as the effect of taxes (Beaver et al., 2007) and the effect of scaling (Degeorge et al., 1999; Durtschi and Easton, 2005, 2009; and Jorgensen et al., 2014; with a discussion by Burgstahler, 2014; Donelson et al., 2013; and Burgstahler and Chuk, 2015) have been criticized in the literature. The research design presented in this paper is not subject to these concerns.

(ii) Non-Observable Earnings Targets (Distribution of Digits)

Research investigating earnings management with non-observable earnings targets generally relies on the *distribution of digits*. The distribution of digits focuses on the occurrence of each digit from '0' to '9' within a given dataset. It technically does not allow investigation of the absolute size of a certain value but instead focuses on its numerical structure and hence on the frequency and the sequence of the digits.

Carslaw (1988) was the first to apply the distribution of digits to measure earnings management to meet non-observable earnings targets. For his analyses, he relies on a pattern called Benford's Law (Newcomb, 1881; and Benford, 1938). Benford's Law implies that the distribution of digits in large, unmanipulated datasets is not uniform, as one might intuitively expect, but logarithmic. Carslaw (1988) finds significantly more occurrences of digit '0' and significantly fewer occurrences of digit '9' in his data than Benford's Law would suggest, thus indicating upward-rounding behaviour in his sample of publicly listed New Zealand firms. Carslaw's findings have been confirmed in other world regions and for various types of earnings metrics by Thomas (1989), Niskanen and Keloharju (2000), van Caneghem (2002, 2004), Kinnunen and Koskela (2003),[1] Skousen et al. (2004), and Guan et al. (2006). Das and Zhang (2003) and Jorgensen et al. (2014) rely on an approach that is statistically similar to that of Carslaw (1988) but employ a uniform distribution to investigate target-driven earnings management behaviour in the distribution of digits for the ratio earnings per share, where Benford's Law might not hold.

All of these analyses demand specific assumptions regarding the distribution of digits that would be theoretically obtained in *unmanaged* earnings. However, research has not yet unambiguously identified such a distribution of digits. In particular, Benford's Law is not a law of nature but rather a frequently observed regularity (Watrin et al., 2008; Dlugosz and Müller-Funk, 2009; and Diekmann and Jann, 2010). Therefore, reliance on Benford's Law, or any other theoretically derived distribution of digits, may bias research findings. Consequently, we argue that using inter-group comparisons of the distribution of digits will often be more appropriate for the analysis of target-driven earnings management.

3. THEORETICAL DEVELOPMENT OF THE RESEARCH DESIGN

(i) Mantissa Notation and the Distribution of Digits

Our empirical strategy combines the research streams outlined in Sections 2(i) and 2(ii). Because we rely on the distribution of digits, we investigate the *numerical structure*, i.e., the frequency of occurrence and the sequence of digits from '0' to '9', rather than the total *value* of the underlying earnings metric. To appropriately isolate the effects on the distribution of digits, we convert the values of the earnings metric to scientific mantissa notation:

$$N = M \cdot 10^{\lambda} \tag{1}$$

where $N, M \in \mathbb{R}^{+}$, $\lambda \in \mathbb{Z}$, and $M \in [1, 10)$.

In non-technical terms, we shift the decimal point to the left in any value of the earnings metric until only one non-zero digit to the left of the decimal point remains and account for the magnitude of the earnings metric in λ. In notational terms, M is the mantissa of the *reported* value N of the earnings metric in question, with base 10 and exponent λ. We restrict the analysis to positive values of M because we are interested in earnings targets, which are likely greater than zero.[2] We correspondingly denote the *unmanaged earnings value* as $N^{+} = M^{+} \cdot 10^{\lambda+}$. Note that $N = N^{+}$ if no earnings management occurs. The *earnings target* value is denoted as $N^{*} = M^{*} \cdot 10^{\lambda^{*}}$.

Following Newcomb (1881) and Benford (1938), we assume the following:

A1: *The distribution of digits is not conditional on* λ.

1 Kinnunen and Koskela (2003) also present evidence that firms focus on 'behavioural' earnings targets, i.e., values that derive from relatively small upward rounding but that are conceived to be considerably larger than the unmanaged value.

2 Note that the subsequently described effect on the distribution of digits would simply be reversed with negative values.

An important consequence of A1 is that the magnitude of N, N^+, or N^* is not relevant to an analysis of the mantissa. We then make the following assumptions:

A2: *N^+ cannot be observed (or it is too costly to observe it).*

A3: *N^* cannot be observed (or it is too costly to observe it).*

Neither A2 nor A3 is a necessary condition; hence, factual observability of N^+ or N^* is obviously not problematic. However, being *able* to set A2 and A3 as they are set here decreases data requirements. Naturally, N must always be observable.

As further denotations, we refer to the leftmost digit within the mantissa, i.e., the position to the left of the decimal point, as the digit in the *first position*; we refer to the position directly to the right of the decimal point as the *second position*, and so forth. More generally, we denote all positions X as the *X^{th} position.* Note that the X^{th} position therefore never represents a particular digit but merely the position of a digit within the mantissa. The actual digit from '0' to '9' in the X^{th} position is denoted D_X, $D_X{}^*$, or $D_X{}^+$.[3] The *distribution of digits in the X^{th} position* consequently indicates the (expected or observed) frequency of occurrence of the digits from '0' to '9' conditional on X. We note that '0' may not occur in the first position with the specific mantissa notation selected above.

(ii) Distribution of Digits in the Event of Target-Driven Earnings Management

(a) Target-Driven Earnings Management

We investigate how target-driven earnings management affects the distribution of digits in a dataset. To derive these effects, we conjecture:

A4: *In managed earnings, the distribution of N exhibits a discontinuity such that there is a relatively small number of observations slightly below N^* and a relatively high number of observations at $N = N^*$ or slightly above N^*.*

Assumption A4 follows straightforwardly from the analysis of Burgstahler and Dichev (1997), who demonstrate that the distribution of N in managed earnings exhibits more values slightly above or exactly equal to the earnings target N^* than slightly below it. Conversely, with unmanaged earnings, no such pattern should occur because the earnings target N^* then has no effect on the distribution of N (i.e., a symmetric distribution of N around N^* results). Further empirical justification for A4 is provided by Kinney et al. (2002), who present evidence that large absolute earnings surprises yield considerably smaller capital market reactions per unit of earnings surprise than small absolute surprises, indicating decreasing marginal returns of upward earnings management once the earnings target is met. Conversely, the literature acknowledges that narrowly missing an earnings target has a disproportionately large impact in the capital markets (e.g., Bartov et al., 2002; Matsumoto, 2002; Skinner and Sloan, 2002; Jia, 2013; and Lacina et al., 2013). Consequently, the incentive to manage earnings upward is particularly high when the earnings target is close. Research even

3 Hence, for instance, a value of $N = 98.76$ has four positions X, which hold the digits $D_{X=1} = 9$, $D_{X=2} = 8$, $D_{X=3} = 7$ and $D_{X=4} = 6$.

demonstrates that managers manipulate earnings downward in cases in which an earnings target is exceeded by a large amount (e.g., Peasnell et al., 2005) or when credit rating thresholds are already met (e.g., Alissa et al., 2013) and thereby preserve the potential for upward earnings management for future periods.

We must then ask how the distributions of digits in the X^{th} positions within the mantissa M of reported earnings N are affected by earnings management. The answer depends on the mantissa M^* of the earnings target N^*. We conjecture:

A5: *M^* is a result of rounding.*

In other words, the accuracy of an earnings target N^* is lower than the accuracy of the 'real' earnings N^+. Earnings targets are rarely given to the units digits but rather are given to the thousands or millions digits. For instance, if the previous year's earnings amount to €129,394 and the next year's earnings are expected to be similar, the earnings target is unlikely to be set to €129,394 but instead will be set to, for example, €130,000; hence, $M^* = 1.30000$ (for a related discussion on target setting with respect to earnings per share, see Dechow and You, 2012). Regarding notation, we refer to a position X as a *target position* if – when considering M^* – the position contains a digit that is not '0' or if the position contains a digit that is '0' but is followed by a position that contains a digit that is not '0'. These positions and the digits contained therein are also often referred to as significant digits or significant figures. In our example above, the first position (with $D_1^* = 1$) and the second position (with $D_2^* = 3$) are target positions. All trailing positions are denoted *non-target positions*; thus, the rightmost target position in the mantissa M^* – the target position with the highest X – is exclusively followed by non-target positions.

Considering A2–A5, the intuition to this point is that the reported value N is managed upward until it meets the unobservable earnings target N^*, the mantissa M^* of which results from rounding.[4] Consequently, the effects on the mantissa M are those that result from rounding upward.

(b) Distribution of Digits in Target Positions

With regard to target positions, the effect of target-driven earnings management on the distribution of digits is ambiguous. At first glance, one may expect higher digits in target positions for managed earnings than for unmanaged earnings. In our example above, if the unmanaged value of the earnings metric were $N^+ = €115{,}867$ – and thus $M^+ = 1.15867$ – managing earnings upward to exactly meet $N^* = €130{,}000$ would increase the digit in position $X = 2$ from $D_2^+ = 1$ to $D_2 = D_2^* = 3$. However, managing earnings upward can also have the opposite effect on the mantissa in the target positions. In our example, if $N^+ = €99{,}329$ – and thus $M^+ = 9.9329$ – managing earnings upward to exactly meet $N^* = €130{,}000$ would decrease the digits in the target positions from $D_1^+ = D_2^+ = 9$ to $D_1 = D_1^* = 1$ and $D_2 = D_2^* = 3$. Consequently, the effects of target-driven earnings management on the distribution of digits in the target positions are ambiguous and therefore cannot be exploited.

4 For a discussion on the invariance of Benford's Law to rounding, refer, for instance, to Tödter (2009).

(c) Distribution of Digits in Non-Target Positions

Conversely, the distribution of digits in non-target positions of M can be investigated unambiguously when target-driven earnings management occurs. Referring again to our example above, the digits in non-target positions of the reported mantissa M for both unmanaged earnings values $N^{+} = 115{,}867$ and $N^{+} = 99{,}329$ decrease to '0' for all $X \geq 3$ when target-driven earnings management occurs to exactly meet N^{*} (or to relatively low digits when N^{*} is slightly exceeded). For unmanaged earnings N^{+}, a similar pattern would not be expected in the non-target positions, and M would contain exactly the same digits in exactly the same sequence as M^{+}. The 'real' value of the earnings metric N^{+}, however, results from mere business activity, not rounding. Consequently, the non-target positions of M should contain a relatively higher frequency of the digit '0' (or of relatively low digits) than they would when earnings management does not occur, and thus, the mean of the distribution of digits in non-target positions is negatively correlated with the degree of target-driven earnings management.

(iii) Classification of Position X as a Target Position or a Non-Target Position in Real Data

We acknowledge that it is not practically possible to distinguish between a target position and a non-target position in realistic data, i.e., without exact knowledge of M^{*}. Numerous researchers have previously solved this issue by postulating an assumption regarding the number of target positions in their particular datasets (Carslaw, 1988; Thomas, 1989; Niskanen and Keloharju, 2000; van Caneghem, 2002, 2004; Kinnunen and Koskela, 2003; Skousen et al., 2004; Guan et al., 2006; and Jorgensen et al., 2014, as discussed in Section 2(ii)). Empirical evidence from these studies indicates that firms set their earnings targets based either on only the first position or on the first two positions of M^{*}. Thus, one possible approach to the non-observability of the number of target positions is – in line with previous research – to postulate an explicit assumption concerning the characteristics of the data at hand. Nevertheless, cases of target positions $X > 2$ can occur. For instance, a greater number of target positions may be expected with greater total earnings target values (e.g., $N^{*} = 1.25$ billion instead of $N^{*} = 1.3$ billion).

Our research design does not require an explicit assumption regarding the exact number of target positions. Instead, we merely adopt the following assumption:

A6: *The propensity of observing a non-target position monotonically increases as X increases.*

The ambiguous effects of target-driven earnings management on the target positions that were described in Section 3(ii)(b) diminish as X increases because as a direct consequence of A6, the propensity of observing a target position decreases as X increases. Note that we do not assume that the number of target positions is similar for all firms in a given dataset or that the number of target positions is observable.

(iv) Research Design

Summarizing the above, we derive our main conclusions:

C1: *The mean of the distribution of digits in non-target positions is relatively lower for the group in which the level of target-driven earnings management is relatively higher.*

C2: *When an assumption concerning the number of target positions does not exist for the relevant data, C1 can be investigated by gradually extending the analysis to positions with higher X.*

When investigating C1, the non-observable characteristic of whether a position X in the mantissa M of the reported value N is either a target position or a non-target position must be taken into account. First, if the researcher has an economically founded assumption regarding the number of target positions in the relevant dataset(s), the mean of the distribution of digits may be selectively investigated in the corresponding non-target positions in reference to previous research. However, when no such information is available, C2 can be employed.[5]

We note that C1 and C2 hold even if M^*, λ^* and the number of target positions are different for each firm in the dataset. Moreover, none of these variables needs to be available to the researcher. This feature of our research design is crucial because it allows for the joint investigation of firms with different earnings targets. It also allows for samples with mixtures of categories of earnings targets, i.e., one sub-sample that focuses on previous-year values and another sub-sample that focuses on analyst forecasts. Finally, our research design is technically applicable to any earnings metric that would be subject to target-driven earnings management, such as net income (Carslaw, 1988; Niskanen and Keloharju, 2000; Kinnunen and Koskela, 2003; Skousen et al., 2004; and Guan et al., 2006 (quarterly net income)), earnings before taxes (van Caneghem, 2002, 2004), earnings before extraordinary items and discontinued operations (Carslaw, 1988; and Thomas, 1989), or earnings per share (Thomas, 1989; Das and Zhang, 2003; and Jorgensen et al., 2014).

Two implicit assumptions remain. First, the distribution of the number of target positions must be assumed to not *differ* between the groups of firms that are compared with respect to their earnings management activity (when earnings management can occur with both groups). This conjecture is similarly made by Carslaw (1988) and others, who additionally make an assumption regarding the exact number of target positions, which is not necessary here. Second, we assume that the distribution of digits in unmanaged earnings would be equal across the groups of firms compared. This conjecture evidently includes, but is not limited to, the respective assumptions made by the research stream related to Carslaw (1988) and Das and Zhang (2003).

5 To keep the analysis manageable, an assumption regarding the highest position X that may be a target position in the available dataset should be made, although such an assumption is not technically necessary. According to prior research discussed in Section 3(iii), $X \leq 2$ appears to be a reasonable assumption in this regard; hence, $X = 2$ and $X = 3$ are the most likely values for the leftmost non-target position. Consequently, limiting the analysis to $X \leq 4$ should generally be sensible.

4. EMPIRICAL ANALYSIS

(i) *Simulation Analysis*

(a) Simulation Approach

We use a two-period Monte Carlo simulation approach. Four factors must be accounted for in this simulation approach, namely (i) the distribution of unmanaged earnings N^+, (ii) the distribution of earnings targets N^*, (iii) the number of target positions, and (iv) managers' earnings management aggressiveness (similar to Degeorge et al., 1999).

We derive the distribution of N from the AMADEUS database for very large, large and medium-sized firms via Wharton Research Data Services (WRDS). Based on net income over 2009–2013 from all consolidated and unconsolidated statements reported in euros (3,306,508 firm-years), we use kernel density (Epanechnikov kernel) to estimate a continuous logarithmic distribution of N (model fit: $R^2_{\text{adj}} = 95.79\%$). From this, we generate N^* by rounding (refer to A5) and N^+ by building on the relative change in earnings data in Table 1, Panel A of Burgstahler and Dichev (1997). We set the number of target positions in N^* to be an independent random variable per firm that follows a discrete uniform distribution such that the number of target positions can take integer values of '1', '2' or '3'.

For the treatment group only, we define earnings management aggressiveness ϵ as the difference between N^* and N^+, scaled by N^*, that the manager is willing to bridge by means of target-driven earnings management. Finally, we set parameter υ as a boundary for exceeding the earnings target value N^* by means of target-driven earnings management in the treatment group with $\upsilon^{\min} = 0\%$ (mode) and $\upsilon^{\max} = 2\%$ in a triangular distribution. Figure 1 presents a detailed summary of the simulation approach.

Figure 1

Graphical Summary of the Simulation Approach

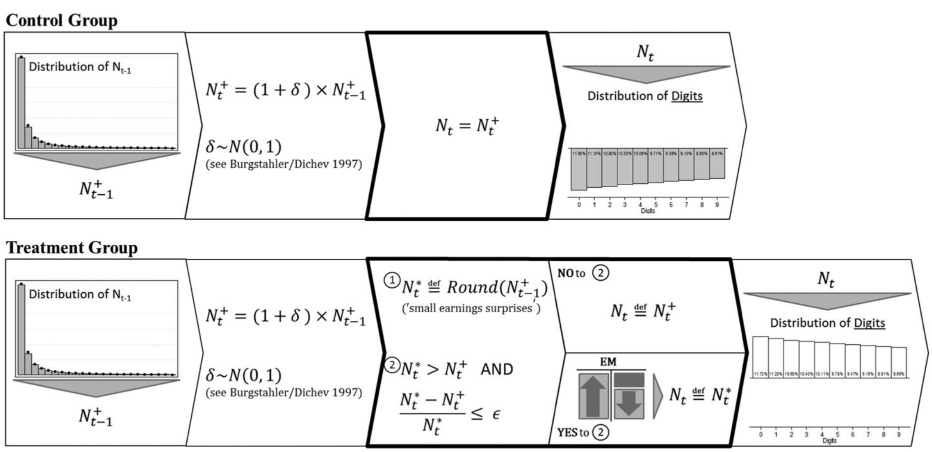


Table 1
Simulation Application

	Difference in Means for X^{th} position(s)				*Treatment Group*
Parameter ϵ	$\beta_{X=2}$	$\beta_{X=2\&3}$	$\beta_{X=3\&4}$	$\beta_{X=2\&3\&4}$	*Frequency of EM*
0%	0.001	0.000	0.000	0.001	0.000%
	(0.029)	(0.013)	(0.006)	(0.022)	[0.000%]
1%	−0.015	−0.016	−0.010	−0.011	0.402%
	(−0.358)	(−0.544)	(−0.335)	(−0.479)	[0.283%]
2%	−0.028	−0.028	−0.016	−0.020	0.787%
	(−0.701)	(−0.975)	(−0.553)	(−0.855)	[0.405%]
3%	−0.042	−0.039*	−0.021	−0.028	1.195%
	(−1.038)	(−1.349)	(−0.721)	(−1.187)	[0.497%]
4%	−0.054*	−0.049**	−0.025	−0.035*	1.582%
	(−1.336)	(−1.703)	(−0.864)	(−1.475)	[0.561%]
5%	−0.066*	−0.058**	−0.029	−0.042**	1.976%
	(−1.633)	(−2.015)	(−1.014)	(−1.768)	[0.631%]
6%	−0.078**	−0.069***	−0.035	−0.049**	2.385%
	(−1.921)	(−2.387)	(−1.223)	(−2.105)	[0.686%]
7%	−0.087**	−0.078***	−0.041*	−0.056***	2.770%
	(−2.127)	(−2.702)	(−1.428)	(−2.392)	[0.735%]
8%	−0.097***	−0.087***	−0.046*	−0.063***	3.157%
	(−2.377)	(−3.028)	(−1.583)	(−2.662)	[0.770%]
9%	−0.104***	−0.095***	−0.050**	−0.068***	3.557%
	(−2.558)	(−3.312)	(−1.751)	(−2.903)	[0.831%]
10%	−0.113***	−0.101***	−0.053**	−0.073***	3.936%
	(−2.781)	(−3.519)	(−1.829)	(−3.096)	[0.890%]

Notes:
The leftmost column shows different parameter settings ϵ for the simulation that present different levels of earnings management aggressiveness for the treatment group firms. The number of target positions is set randomly to be discretely uniformly distributed between 1 and 3. In the treatment group, earnings management can exceed the earnings target in a triangular distribution with parameter υ between $\upsilon = 0\%$ (mode) and $\upsilon = 2\%$. For all parameters, independent treatment and control groups are generated with 10,000 firms each and simulations are conducted with 3,000 iterations. All reported coefficients are mean values over these 3,000 iterations.
Coefficients β_X are the difference in means between treatment and control group for the digits contained in the *X*th position(s) as indicated. In cases where β_X is greater than zero, the mean of the digits in the *X*th position(s) is greater for the treatment group than for the control group and vice versa. *t*-Values of unpaired one-sided *t*-tests (unequal variance) are given in parentheses. ***, ** and * indicate (average) significance at the 1%, 5% and 10% levels, respectively. The rightmost column shows, for the treatment group of firms only, the percentage of firms that in fact engage in earnings management (Frequency of EM). Sample standard deviations are given in brackets.

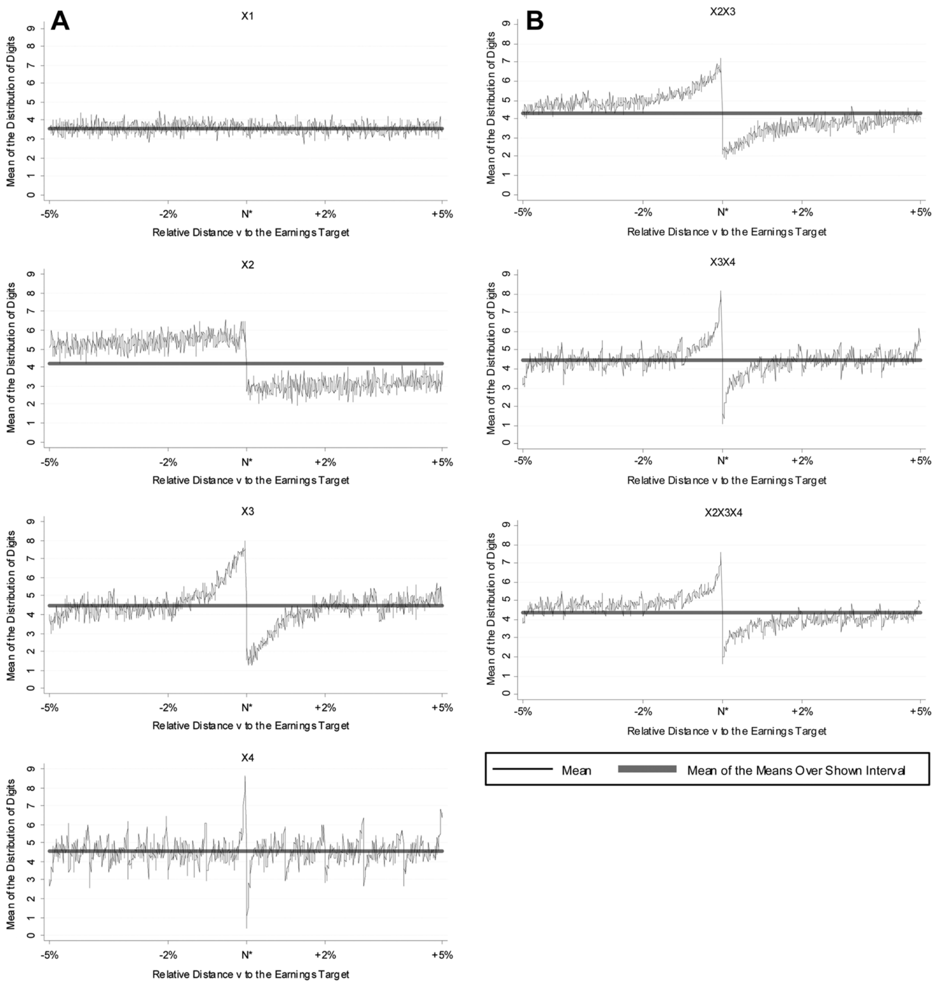
(b) Expected Patterns in Application

At the outset, we use the simulation approach to present expected patterns from the research design. First, we simulate earnings target N^* and reported earnings N for 1,500,000 control group firms. We therein measure υ as the observed difference between the (unmanaged) reported earnings value N and the earnings target N^*, scaled by N^*. Figure 2 shows the mean of the distribution of digits conditional on υ.

Figure 2 shows a distinct pattern around the earnings target N^* for all positions $X \geq 2$, i.e., for all potential non-target positions. Specifically, the mean of the distribution of digits (thin black solid line) slowly increases above its mean of means (thick grey solid line) until the earnings target N^* is nearly met ($\upsilon \rightarrow 0^-$). The

Figure 2

Panel A ($X = 1$, $X = 2$, $X = 3$, $X = 4$) Panel B ($X = 2\&3$, $X = 3\&4$, $X = 2\&3\&4$)
Mean of the Distribution of Digits in Unmanaged Earnings Conditional on v

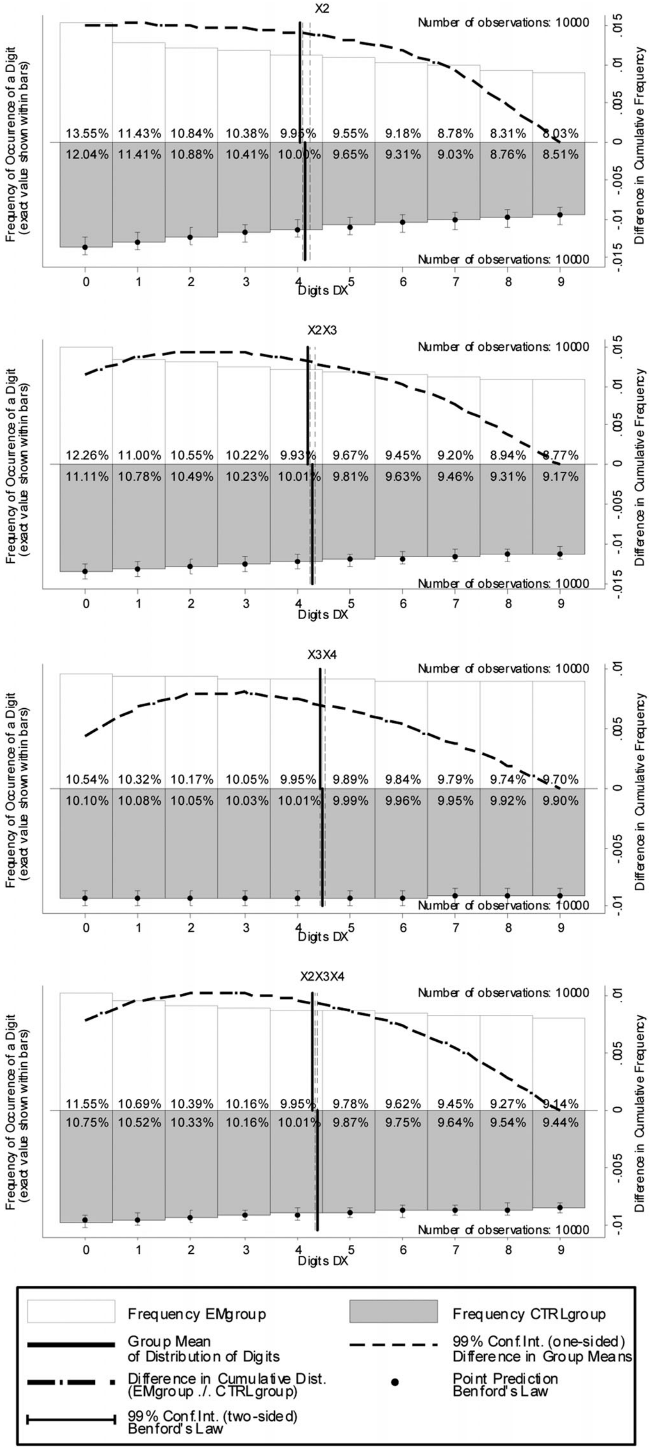


mean of the distribution of digits declines sharply when N^* is exactly met ($v = 0$), only to slowly return to the mean of means again when N^* is exceeded ($v > 0$). A similar pattern is present with $X = 2\&3$, $X = 3\&4$ and $X = 2\&3\&4$. Conversely, we observe no such pattern with $X = 1$, which is always a target position. Based on this graphical analysis, if A4 holds, the mean of the distribution of digits in non-target positions is systematically lower for managed earnings than for unmanaged earnings.

Second, to simulate real application of the research design, we generate pairs of one treatment group and one control group and compare them directly. Table 1 presents the results.[6]

6 Dichev et al. (2013) report that approximately 10% of earnings per share are typically managed when target-driven earnings management occurs on its merits, which directly translates into 10% of net income if

Figure 3
Graphical In-Depth Analysis with Regard to Table 1 ($\epsilon = 10\%$)



Interpreting Table 1, coefficients β_X indicate the difference in means between the treatment and the control groups for the position(s) X. Note that we do not report a column for $X = 1$ because $X = 1$ is always a target position and therefore not of interest (coefficients $\beta_{X=1}$ are non-significant for all ϵ). We do investigate the effect of varying windows of analysis that encompass more than one position X, particularly $X = 2\&3$, $X = 3\&4$ and $X = 2\&3\&4$.[7]

We observe that all β_X are negative for $\epsilon > 0\%$, although not always significantly so. Moreover, (i) the absolute value of the coefficients, (ii) the significance and (iii) the (relative) frequency of firms in the treatment group that in fact engage in target-driven earnings management increase with the level of earnings management aggressiveness ϵ.

As a peculiarity, we point out that the difference in means for $X = 3\&4$ is lower than that for $X = 2\&3$ in absolute terms for all $\epsilon > 0\%$ and consequently that significance is lower despite similar standard errors (not tabulated). This observation is explained by the results shown in Figure 2, where the mean of the distribution of digits strongly fluctuates around the mean of means for $X = 4$, with only one distinguishable spike in a narrow range of small absolute values of v, i.e., around $v = 0\%$. In contrast, for $X = 2$, the mean of the distribution of digits fluctuates to a lower degree and, moreover, shifts distinctively at $v = 0\%$. Consequently, substituting $X = 4$ for $X = 2$ decreases the significance of the results.

Third, as an exemplary graphical in-depth analysis of the distribution of digits, Figure 3 shows the frequency of D_X with digits '0' to '9' for both the treatment group (white) and the control group (gray) for the case of Table 1, $\epsilon = 10\%$.

Consistent with our expectations, we report for all X that the difference in the cumulative distribution of digits between the treatment group and the control group (dash-dotted line) is positive for all D_X and increases monotonically for smaller D_X while, after its unique global maximum, decreasing monotonically for greater D_X.[8] Hence, it holds for all X that the non-target positions of managed earnings contain a relatively higher frequency of relatively low digits than the non-target positions of unmanaged earnings (in agreement with C1 and C2).

(c) Simulation Diagnostics

Panel A (Panel B) of Table 2 reports the percentage of observations for which the null hypotheses of a smaller (greater) or equal mean of the distribution of digits in the control group relative to the treatment group is rejected at a 5% nominal significance level. With 3,000 iterations, the two-sided 95% confidence interval for the rejection rate ranges from 4.23% to 5.77%.

In Table 2, we report in both panels that rejection rates at $\epsilon = 0\%$ are largely not significantly different from the nominal significance level of 5%. Non-significance of rejection rates is also observed in both panels at $\epsilon > 0\%$ for $X = 1$. Hence, we conclude that our tests are well-specified under the null hypothesis.

the number of shares is assumed to be constant. We thus allow for distinct values of ϵ between 1% and 10% in 10 equally distanced steps.

7 We limit our analysis to the leftmost four positions in the mantissa ($X = 1, 2, 3, 4$) for computational convenience; however, no technical limitation exists in this regard.

8 A technical exception is $X = 2$, where the global maximum is the corner solution at $D_2 = 0$.

Table 2
Rejection Rates Conditional on Sample Size and ϵ

	Rejection Rates (%)				
ϵ	*X = 1*	*X = 2*	*X = 2&3*	*X = 3&4*	*X = 2&3&4*
Panel A					
250 firms					
0%	5.33	**5.83**	5.70	4.73	5.10
2%	4.97	**6.47**	**6.73**	**5.87**	**6.13**
4%	5.30	**7.40**	**7.47**	5.43	**7.17**
6%	5.13	**9.50**	**10.57**	**7.13**	**9.63**
8%	5.37	**10.17**	**12.10**	**8.43**	**10.67**
10%	4.97	**12.10**	**14.43**	**8.37**	**11.07**
1,000 firms					
0%	5.33	4.90	**5.77**	4.80	5.67
2%	4.87	**7.97**	**9.73**	**7.40**	**8.63**
4%	4.77	**10.60**	**13.43**	**8.40**	**13.00**
6%	4.73	**15.03**	**19.53**	**10.33**	**16.63**
8%	4.57	**18.30**	**24.40**	**13.10**	**20.77**
10%	5.07	**22.60**	**30.13**	**15.47**	**24.83**
5,000 firms per group					
0%	4.90	5.13	4.80	4.93	4.73
2%	5.70	**11.30**	**15.47**	**10.47**	**13.87**
4%	4.60	**24.43**	**32.20**	**14.47**	**27.90**
6%	5.17	**38.80**	**51.80**	**20.93**	**44.07**
8%	5.27	**50.97**	**68.70**	**28.17**	**58.77**
10%	4.90	**61.50**	**79.27**	**34.43**	**68.93**
10,000 firms					
0%	4.87	4.37	5.10	4.70	4.97
2%	5.33	**17.27**	**25.97**	**14.17**	**22.67**
4%	5.57	**37.30**	**52.27**	**20.57**	**43.17**
6%	5.17	**61.63**	**76.37**	**34.83**	**67.73**
8%	4.73	**75.60**	**91.50**	**48.33**	**85.73**
10%	5.03	**86.83**	**96.53**	**56.50**	**92.90**
Panel B					
250 firms					
0%	5.13	5.23	4.73	5.20	4.87
2%	5.03	***4.13***	***3.50***	***3.73***	***3.87***
4%	5.27	***3.30***	***3.13***	***3.83***	***3.53***
6%	4.60	***2.60***	***1.97***	***3.50***	***1.87***
8%	5.03	***2.17***	***1.93***	***3.67***	***2.03***
10%	4.73	***1.77***	***1.17***	***2.43***	***1.43***
1,000 firms					
0%	4.97	4.70	4.77	5.10	4.93
2%	**5.83**	***2.90***	***2.27***	***3.60***	***2.40***
4%	5.27	***1.70***	***1.53***	***2.67***	***1.67***
6%	4.93	***1.23***	***0.97***	***2.07***	***1.37***
8%	4.47	***0.80***	***0.47***	***1.50***	***0.57***
10%	***4.23***	***0.53***	***0.20***	***1.10***	***0.37***
5,000 firms					
0%	5.47	**6.00**	4.90	4.53	5.20
2%	4.63	***1.40***	***0.87***	***1.97***	***0.93***

(*Continued*)

Table 2
Continued

	Rejection Rates (%)				
ϵ	*X = 1*	*X = 2*	*X = 2&3*	*X = 3&4*	*X = 2&3&4*
Panel B					
4%	4.97	***0.50***	***0.27***	***1.53***	***0.47***
6%	4.90	***0.13***	***0.03***	***0.60***	***0.10***
8%	***4.20***	***0.03***	***0.00***	***0.17***	***0.00***
10%	5.27	***0.00***	***0.00***	***0.27***	***0.00***
10,000 firms					
0%	5.53	**6.20**	5.33	5.00	4.33
2%	4.87	***1.20***	***0.53***	***1.57***	***0.90***
4%	4.63	***0.10***	***0.07***	***0.70***	***0.10***
6%	4.50	***0.03***	***0.03***	***0.23***	***0.00***
8%	4.27	***0.00***	***0.00***	***0.07***	***0.00***
10%	4.73	***0.00***	***0.00***	***0.03***	***0.00***

Notes:
Panel A reports rejection rates (in %) for a one-sided, unpaired, unequal variance *t*-test with a nominal significance level of 5% and the alternative hypothesis that the mean of the distribution of digits is lower in the treatment group than in the control group. Panel B reports rejection rates (in %) for a one-sided, unpaired, unequal variance *t*-test with a nominal significance level of 5% and the alternative hypothesis that the mean of the distribution of digits is lower in the control group than in the treatment group. Data are generated by simulations using the number of firms shown in both the treatment group and the control group and different levels of earnings management aggressivenes ϵ in the treatment group. A total of 3,000 iterations are run per parameter setting. To facilitate interpretation, rejection rates that are significantly lower than the nominal significance level appear in bold italic type, while rejection rates that are significantly greater than the nominal significance level appear in bold type (at a 5% nominal significance level in a two-sided test).

In Panel A, we observe that rejection rates increase above the nominal significance level in both the sample size and ϵ for all $X \geq 2$ as expected. Corresponding to our previous findings from Table 1, we also observe that rejection rates are relatively low for $X = 3\&4$. Exactly mirroring Panel A, Panel B shows that rejection rates are significantly lower than 5% for all $\epsilon > 0\%$ and $X \geq 2$ and that they decrease with sample size and ϵ.

'Horse Race' against Carslaw (1988)

We replicate the analysis of the research stream that follows Carslaw (1988) (Section 2(ii)). Using the exact same dataset as in Tables 1 and 2, we employ a chi-squared goodness of fit test with the null hypothesis of Benford's Law to generate Table 3 (corresponds to Table 1) and Table 4 (corresponds to Table 2, Panel A).[9]

First, we find that the patterns of significance in Table 1 and Table 3 are largely identical, which indicates the validity of our research design. When considering Table 4 individually, we report that rejection rates are not significantly different from the nominal significance level for $\epsilon = 0\%$ with $X \geq 2$; thus, the unmanaged data do not contradict Benford's Law in the potential non-target positions (as already indicated in Figure 3 (black whiskers)). In contrast, we note that rejection rates are significantly above the nominal significance level for all $\epsilon \geq 0$ with the target position $X = 1$. We

9 By design, the chi-squared goodness of fit test does not allow replication of Table 2, Panel B.

Table 3
Horse Race against Carslaw (1988): Table 1 replicated

Parameter	*Chi-Squared Test for Fit to Benford's Law for X^{th} position(s)*			
ϵ	$\chi^2_{X=2}$	$\chi^2_{X=2\&3}$	$\chi^2_{X=3\&4}$	$\chi^2_{X=2\&3\&4}$
0%	9.342	9.374	9.082	9.299
1%	10.171	10.388	9.265	10.047
2%	11.606	12.334	9.793	11.514
3%	13.395	14.658	10.350	13.256
4%	15.249*	16.906*	10.653	14.769*
5%	17.943**	20.030**	11.228	17.244**
6%	20.887**	24.743***	12.515	20.886**
7%	24.201***	29.364***	13.703	24.497***
8%	27.711***	34.431***	14.732*	28.099***
9%	31.812***	40.591***	16.341*	32.878***
10%	36.038***	44.953***	16.914*	36.223***

Notes:
The leftmost column shows different parameter settings ϵ of the simulation that present different levels of earnings management aggressiveness of the treatment group firms. The number of target positions is set randomly to be discretely uniformly distributed between 1 and 3. In the treatment group, earnings management can exceed the earnings target in a triangular distribution with parameter υ between $\upsilon = 0\%$ (mode) and $\upsilon = 2\%$. For all parameters, independent treatment and control groups are generated with 10,000 firms each and simulations are conducted with 3,000 iterations. All reported coefficients are mean values over these 3,000 iterations.
Coefficients $\chi^2{}_X$ show the test value of a Chi^2 Goodness of Fit Test to Benford's Law in the treatment group for the digits contained in the *X*th position(s) as indicated. ***, ** and * indicate (average) significance at the 1%, 5% and 10% levels, respectively.

also observe a number of non-significant rejection rates with $X \geq 2$ for smaller $\epsilon > 0\%$ and for smaller sample sizes of 250 and 1,000 firms. Reconsidering Table 2, Panel A, in comparison with Table 4 (markers $^+$ and $^-$), we report that rejection rates in Table 4 are significantly lower for the majority of cases with $X \geq 2$ and hence for the potential non-target positions. More specifically, the rejection rates in Table 4 are significantly larger only for greater sample sizes of 5,000 and 10,000 firms with $X = 2$, $X = 2\&3$ and $X = 2\&3\&4$. We also observe that the tests applied by Carslaw (1988) have relatively higher rejection rates for $X = 1$ than does our research design, which corresponds to expectations for the reasons discussed in Section 3(ii)(b).

Finally, to gain deeper insight into the effect of the sample size on rejection rates, we perform an exemplary graphical in-depth analysis of Table 4 relative to Table 2, Panel A. Specifically, Figures 4 and 5 show a more granular analysis of rejection rates conditional on sample size, both for the method applied by Carslaw (1988) (thin black dashed line) and for our research design (thin black solid line), including the one-sided confidence interval at 5% level of significance (gray shaded area). We limit the analysis to the non-target positions and to the case of $\epsilon = 10\%$ (Figure 4), as in Figure 3 above, and to the case of $\epsilon = 0\%$ (Figure 5).

Figure 4 indicates that our research design has higher power in smaller samples. More specifically, the rejection rates of the (false) Null are significantly higher for $X = 2$ and $X = 2\&3$ ($X = 2\&3\&4$) in samples smaller than approximately 3,000 (4,700) firms. The two power functions also have exactly one intersection point for $X = 3\&4$, which occurs approximately at a sample size of 23,500 firms (not shown). We further report that intersection points between the two power functions observed in Figure 4

Figure 4

Graphical In-Depth Analysis with Regard to Table 4 ($\epsilon = 10\%$)

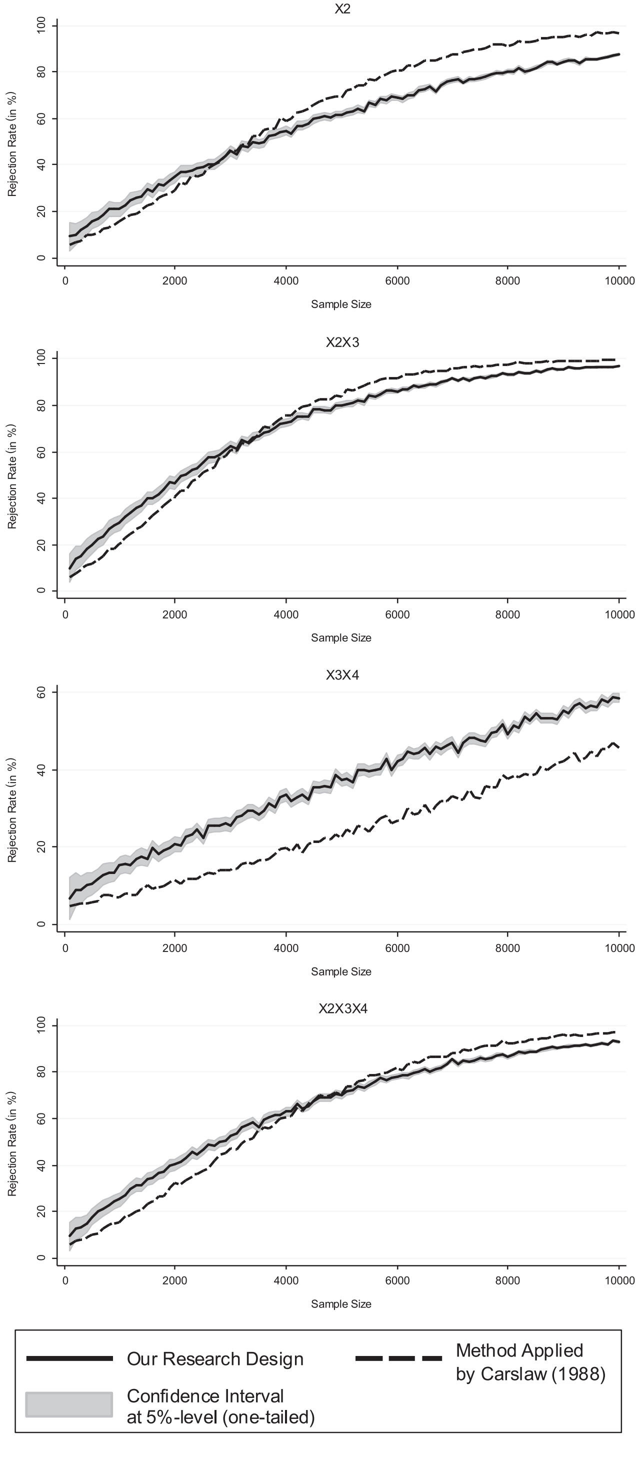


Figure 5

Graphical In-Depth Analysis with Regard to Table 4 ($\epsilon = 0\%$)

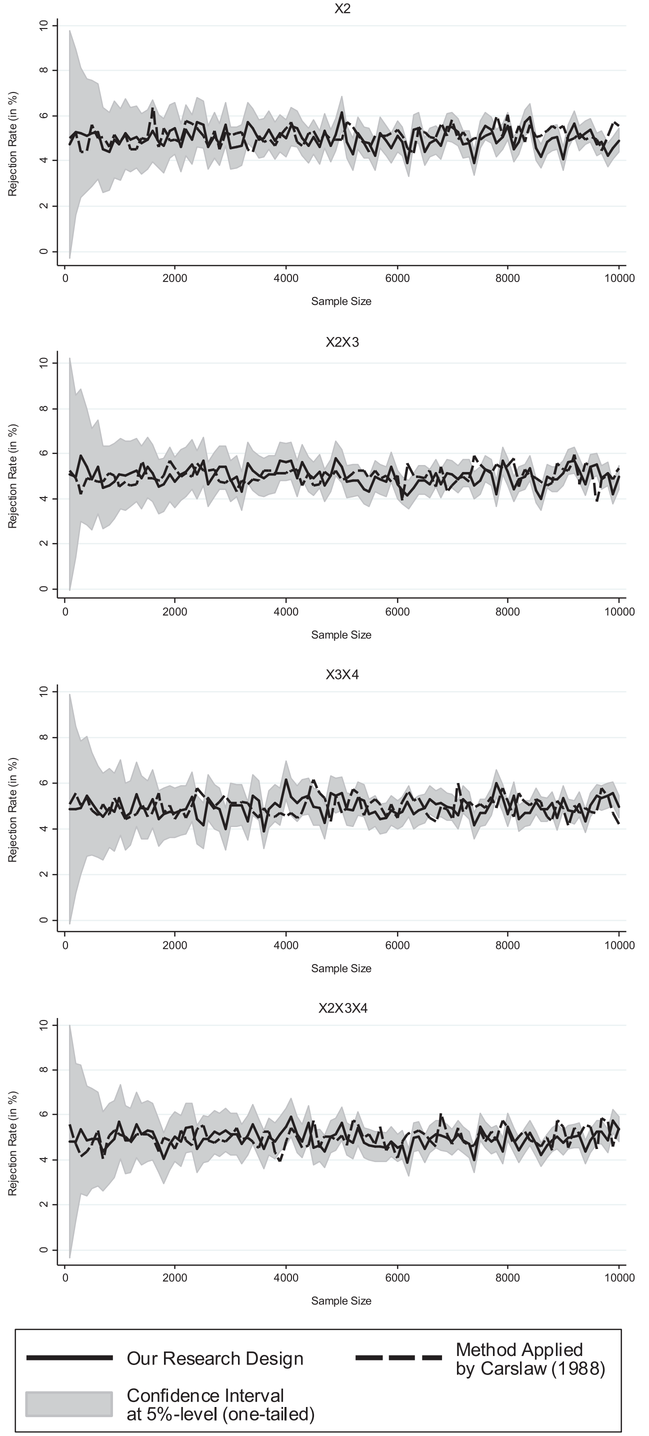


Table 4
Horse Race against Carslaw (1988): Table 2, Panel A, replicated

	Rejection Rates [%]				
ϵ	*X = 1*	*X = 2*	*X = 2&3*	*X = 3&4*	*X = 2&3&4*
250 firms					
0%	**7.67**	4.90	4.73	5.00	4.90
2%	**8.43**$^{+}$	4.93	5.63	5.43	**5.87**
4%	**7.80**	4.90	5.70	4.73	5.50
6%	**8.90**$^{++}$	**6.03**$^{-}$	**6.30**$^{--}$	5.33	**6.17**$^{-}$
8%	**9.43**$^{++}$	**6.33**$^{-}$	**7.33**$^{--}$	**6.27**	**6.87**$^{-}$
10%	**9.47**$^{++}$	**6.50**$^{--}$	**7.50**$^{---}$	5.43^{-}	**6.53**$^{--}$
1,000 firms					
0%	**8.13**$^{+++}$	5.17	5.27	5.07	5.37
2%	**8.50**$^{+++}$	5.07^{---}	5.40^{---}	5.03^{--}	5.30^{---}
4%	**10.50**$^{+++}$	**6.60**$^{---}$	**7.20**$^{---}$	4.60^{---}	**7.23**$^{---}$
6%	**13.37**$^{+++}$	**8.93**$^{---}$	**10.60**$^{---}$	**6.40**$^{---}$	**9.10**$^{---}$
8%	**16.20**$^{+++}$	**11.60**$^{---}$	**14.83**$^{---}$	**6.37**$^{---}$	**11.50**$^{---}$
10%	**21.37**$^{+++}$	**15.73**$^{---}$	**20.33**$^{---}$	**7.13**$^{---}$	**15.13**$^{---}$
5,000 firms					
0%	**7.93**$^{+++}$	4.97	4.87	4.50	4.97
2%	**11.50**$^{+++}$	**7.27**$^{---}$	**9.20**$^{---}$	**6.63**$^{---}$	**8.83**$^{---}$
4%	**23.63**$^{+++}$	**17.90**$^{---}$	**21.67**$^{---}$	**7.07**$^{---}$	**16.40**$^{---}$
6%	**39.70**$^{+++}$	**32.10**$^{---}$	**44.70**$^{---}$	**11.43**$^{---}$	**33.00**$^{---}$
8%	**60.87**$^{+++}$	**53.27**$^{++}$	**67.80**	**16.20**$^{---}$	**53.50**$^{---}$
10%	**76.20**$^{+++}$	**69.97**$^{+++}$	**83.90**$^{+++}$	**22.33**$^{---}$	**70.87**$^{++}$
10,000 firms					
0%	**8.50**$^{+++}$	5.33^{+++}	5.03	4.80	5.10
2%	**18.50**$^{+++}$	**13.53**$^{---}$	**15.60**$^{---}$	**7.00**$^{---}$	**12.97**$^{---}$
4%	**42.93**$^{+++}$	**34.67**$^{---}$	**44.73**$^{---}$	**11.53**$^{---}$	**32.53**$^{---}$
6%	**73.70**$^{+++}$	**66.07**$^{+++}$	**79.80**$^{+++}$	**20.47**$^{---}$	**64.80**$^{---}$
8%	**90.87**$^{+++}$	**87.13**$^{+++}$	**95.70**$^{+++}$	**32.67**$^{---}$	**87.60**$^{+++}$
10%	**97.47**$^{+++}$	**96.47**$^{+++}$	**99.53**$^{+++}$	**44.03**$^{---}$	**97.20**$^{+++}$

Notes:
The table reports rejection rates (in %) for a Chi^2 Goodness of Fit Test to Benford's Law with a nominal significance level of 5%. Data are generated by simulations using the number of firms shown in the treatment group and different levels of earnings management aggressivenes ϵ. A total of 3,000 iterations are run per parameter setting. To facilitate interpretation, rejection rates that are significantly lower than the nominal significance level appear in bold italic type while rejection rates that are significantly greater than the nominal significance level appear in bold type (at a 5% nominal significance level in a two-sided test). Markers +++, ++ and + (- - -, - - and -) indicate that the rejection rate is significantly higher (lower) than the comparable rejection rate in Table 2, Panel A, at the 1%, 5% and 10% levels, respectively, of a one-sided *t*-test of between sample differences in proportions with standard errors computed according to Fleiss et al. (2003).

occur similarly for smaller ϵ but shift to the right as ϵ is decreased toward 0% (not shown). Hence, the advantage of higher power in small samples is even amplified when earnings management activity in the data is lower. Figure 5 then compares occurrences of Type I errors in both methods ($\epsilon = 0\%$), and we observe that rejection rates of the (true) Null are neither significantly different from the nominal significance level of 5% nor significantly different between tests.

Overall, our research design reveals similar patterns to the methods applied by the research stream around Carslaw (1988), providing evidence of its validity. Moreover, we demonstrate that our research design offers relatively higher power in small samples and that this effect is amplified for small levels of earnings management activity – without a corresponding increase in Type I error rates. This analysis supports the view that our research design is adequate when earnings management research must rely on a small subsample of firms (e.g., a certain industry), on a limited number of years (e.g., new data after reform) or when the level of earnings management activity is low.

(ii) Archival Analysis

(a) Archival Approach

Archival accounting data are naturally associated with the limitation that they do not allow for observation of the unmanaged value of the earnings metric N^{+} or often even of the firm-level earnings target N^{*}; only the reported value N is certainly observable. Moreover, the degree of earnings management is unknown. Nevertheless, we apply our research design to three realistic settings in which target-driven earnings management has previously been demonstrated to exist. Our tests are independent of one another and deliberately rely on a variety of earnings metrics, accounting settings and databases to demonstrate that neither of these design choices drives the results.

(b) Positive vs. Negative Earnings per Share

As our first test, we replicate the analysis of Das and Zhang (2003). Their analysis reveals that when positive earnings per share are reported by firms, digits in the 1/10th cent position have a higher than 50% propensity to be equal to or greater than ‘5’. They find the opposite, i.e., that digits are mostly smaller than ‘5’, when negative earnings per share are reported. Assuming a uniform distribution of digits in the 1/10th cent position of unmanaged earnings, both of these findings indicate upward rounding with a focus on the cent position. We note that Dechow and You (2012) demonstrate that the process of setting an earnings target N^{*} in earnings per share corresponds to our assumptions, particularly A5.

We follow Das and Zhang (2003) in using data from Compustat for US firms in the fundamentals quarterly file over the period 1989 to 1998 and collect these data via WRDS. Consistent with their approach, we keep all observations with complete data regarding the following variables: income before extraordinary items available for common, extraordinary items and discontinued operations, net sales, operating income before depreciation, net cash flow from operating activities and common shares used to calculate basic earnings per share. We refrain from merging additional I/B/E/S data, as do Das and Zhang (2003) to facilitate their robustness tests, leaving us with a sample of 180,446 firm-quarter observations (relative to 103,994 firm-quarter observations in Das and Zhang, 2003). Our number of observations ranges from 13,764 for year 1989 to 22,265 for year 1998. At the outset, we replicate Figure 1 (Figure 2) from Das and Zhang (2003) using net income per share and find virtually the same distinct patterns (not shown). We then replicate the main results in Table 1 of Das and Zhang (2003) and show our findings in Table 5.

Table 5

Frequency of Rounding in the Cent Position for Different Earnings Metrics: Das and Zhang (2003), Table 1 replicated

	Positive		*Negative*		*Round*	
	$0 \leq D_{X=1} < 5$	$5 \leq D_{X=1}$	$0 \leq D_{X=1} < 5$	$5 \leq D_{X=1}$	*Yes*	*No*
Panel A: Net Income						
S	54,726	62,924	33,032	30,215	95,956	84,941
Actual Proportion	46.5	53.5	52.2	47.8	53.0	47.0
p-value	0.000		0.000		0.000	
Panel B: Earnings Before Extraordinary Items						
S	54,924	62,808	32,770	29,956	95,578	84,880
Actual Proportion	46.7	53.3	52.2	47.8	53.0	47.0
p-value	0.000		0.000		0.000	
Panel C: Sales						
S	74,812	75,371	0	0	75,371	74,812
Actual Proportion	49.8	50.2			50.2	49.8
p-value	0.075		–		0.075	
Panel D: Operating Income Before Depreciation						
S	71,342	70,673	20,601	19,372	91,274	90,714
Actual Proportion	50.2	49.8	51.5	48.5	50.2	49.8
p-value	0.962		0.000		0.189	
Panel E: Net Cash Flow from Operations						
S	56,776	56,169	34,698	33,886	90,867	90,662
Actual Proportion	50.3	49.7	50.6	49.4	50.1	49.9
p-value	0.965		0.001		0.630	

Notes:
The column 'Positive' ('Negative') hold distribution of digits analyses when the respective per share value is greater (smaller) zero. Column 'Round' shows cases of upwards-rounding. $D_{X=?}$ denotes the digit in position X as indicated, where $X = 1$ per definition describes 1/10th cent position in the per share value. S indicates the number of firm-quarters included. The *p*-values shown derive from a one-sided *t*-test of between sample differences in proportions with standard errors computed according to Fleiss et al. (2003). All values are per share values and computed according to Das and Zhang (2003). Specifically items are computed as follows. Panel A: net income per share = (income before extraordinary items available for common + extraordinary items and discontinued operations)/common shares used to calculate basic earnings per share; Panel B: earnings before extraordinary items per share = income before extraordinary items available for common/common shares used to calculate basic earnings per share; Panel C: sales per share = net sales/common shares used to calculate basic earnings per share; Panel D: operating income before depreciation per share = operating income before depreciation/common shares used to calculate basic earnings per share; Panel E: net cash flow from operations per share = net cash flow from operating activities/common shares used to calculate basic earnings per share.

Comparing Table 5 with the corresponding Table 1 in Das and Zhang (2003), we report nearly equivalent findings. First, we confirm that the propensity of digits $D_{X=1} \geq 5$ is higher than expected under the Null for positive reported values with net income per share (Panel A) and earnings before extraordinary items per share (Panel B) but not with operating income before depreciation per share (Panel D) and net cash flow from operations per share (Panel E). The differences in sales per share

are marginally significant (Panel C). Second, we observe the exact opposite effects when negative values are reported in Panel A and Panel B. We note that, contrary to Das and Zhang (2003), we also find significantly more digits $D_{X=1} < 5$ than expected under the Null in Panels D and E. Third, overall, we report significantly more firms rounding upward than firms rounding downward in Panels A and B, consistent with the prior of target-driven earnings management that builds on upward rounding in the cent position. We do not find any significant differences in terms of the propensity of rounding upward in Panels D and E.

Hence, target-driven earnings management of the specific pattern described by Das and Zhang (2003) is present in the data for the two earnings metrics of net income per share and earnings before extraordinary items per share. Consequently, we should observe a relatively high frequency of low digits in the positions $X \geq 2$ for positive values in these earnings metrics and vice versa for negative values. We test this proposition by applying our research design and directly comparing these two groups of observations. Note that the specific setting of Das and Zhang (2003) implicitly identifies the 1/10th cent position as the rightmost target position (see our discussion in Section 3(iii) and C2 above). This holds for both positive values and negative values, and hence, in light of Figure 2, we should expect strongest effects in the correspondingly established leftmost non-target position, i.e., in the 1/100th cent position ($X = 2$). Our results are reported in Table 6.[10]

Table 6

Comparison of Positive per Share Values and Negative per Share Values for Different Earnings Metrics as Shown in Table 5

	$\beta_{X=2}$	$\beta_{X=2\&3}$	$\beta_{X=3\&4}$	$\beta_{X=2\&3\&4}$
Panel A: Net Income	-0.046^{***}	-0.016	0.005	-0.012
	(-3.198)	(-1.617)	(0.488)	(-1.457)
Panel B: Earnings Before Extraordinary Items	-0.042^{***}	-0.016	-0.000	-0.014^{*}
	(-2.960)	(-1.591)	(-0.022)	(-1.736)
Panel D: Operating Income Before Depreciation	0.013	0.009	0.011	0.011
	(0.775)	(0.791)	(0.956)	(1.228)
Panel E: Net Cash Flow from Operations	-0.005	-0.011	-0.019^{*}	-0.014^{*}
	(-0.339)	(-1.141)	(-1.942)	(-1.781)

Notes:
All values are per share values and computed according to Das and Zhang (2003). Specifically items are computed as follows. Panel A: net income per share = (income before extraordinary items available for common + extraordinary items and discontinued operations)/common shares used to calculate basic earnings per share; B: earnings before extraordinary items per share = income before extraordinary items available for common/common shares used to calculate basic earnings per share; Panel D: operating income before depreciation per share = operating income before depreciation/common shares used to calculate basic earnings per share; Panel E: net cash flow from operations per share = net cash flow from operating activities/common shares used to calculate basic earnings per share. Coefficients β_X are the difference in means between positive and negative per share values in the *X*th position(s) as indicated. $X = 1$ per definition describes 1/10th cent position in the per share value. In cases where β_X is greater than zero, mean of the digits in the *X*th position(s) is greater for the negative per share values than for the negative per share values and vice versa. *t*-Values of two-sided unpaired *t*-tests (unequal variance) for the significance of β_X are given in parentheses. ***, ** and * indicates (average) significance at the 1%, 5% and 10% levels, respectively.

10 Note that sales per share (Panel C) cannot be investigated here, as in Das and Zhang (2003), because it is always equal to or greater than zero.

We observe the same patterns in Table 6, Panel A and Panel B as in Table 1, although the patterns in Table 6 are less pronounced for $X > 2$. Corresponding to our prior, the coefficients β_X are mostly negative, but often insignificant. Specifically, we find coefficients significantly smaller than zero in both panels for $X = 2$ and marginally so in Panel B for $X = 2\&3\&4$, which is overall consistent with our observations from Table 5. In Panel E, we observe marginally significantly negative coefficients for $X = 3\&4$ and $X = 2\&3\&4$, which are not supported by the results in Table 5.

In conclusion, the analysis based on our research design supports the conjecture of target-driven earnings management with a focus on the 1/10th cent position in earnings per share, and the comparison to the corresponding results of Das and Zhang (2003) yields additional indications of its validity.

(c) Types of Annual Statements

As our second test, we distinguish types of annual statements on the firm level based on the conjecture that each type provides information to a specific stakeholder group. Whereas financial statements provide information to the capital markets, tax statements provide information specifically to the tax authorities. Consequently, a common proposition is that incentives to manage earnings upward (downward) are more pronounced in the former (latter) (Hanlon and Heitzmann, 2010).

From a technical research perspective, tax statements are not publicly available. However, in the European Union (EU) accounting environment, firms publish both consolidated and unconsolidated financial statements, with the unconsolidated financial statements being closely related to a firm's tax statement. Watrin et al. (2014) correspondingly adapt the above-mentioned proposition to state that incentives to manage earnings upward are more (less) pronounced in consolidated (unconsolidated) financial statements. Additionally investigating the signed values of discretionary accruals as well as levels of book-tax conformity, Watrin et al. (2014) find that a higher degree of book-tax conformity is associated with more downward earnings management and less upward earnings management in the consolidated financial statement, thereby indicating that tax incentives have a considerable effect on the consolidated financial statement (through the unconsolidated financial statement). Consequently, target-driven earnings management in the consolidated statement is expected to decrease in the level of book-tax conformity.

Our first analysis investigates the proposition that target-driven earnings management is more pronounced in the consolidated statement than in the unconsolidated statement. We use the above-mentioned AMADEUS data on EU firms (Section 4(i)(a)) and include all firm-years of public firms for which both consolidated financial statements and unconsolidated financial statements are available (8,466 pairs of financial statements). In line with prior research, we expect target-driven earnings management with the earnings metrics (i) net income (Carslaw, 1988; Niskanen and Keloharju, 2000; Kinnunen and Koskela, 2003; Skousen et al., 2004; and Guan et al., 2006) and (ii) earnings before taxes (van Caneghem, 2002, 2004). We also investigate (iii) earnings before interest and taxes (EBIT), as it is a common indicator of firm operating performance. When analysing a specific earnings metric, we exclude all observations for which the earnings metric is negative or does not have a minimum accuracy of four positions in the mantissa M. The results are reported in Panel A of Table 7.

We observe the same patterns in Panel A of Table 7 as are reported in Table 1. Specifically, the analysis of net income yields significant negative differences in means for $X = 2$, $X = 3\&4$ and $X = 2\&3\&4$. Similar patterns, albeit less significant, are found for both earnings before taxes and earnings before interest and taxes. These results speak to the hypothesis that there is a higher degree of target-driven earnings management in the consolidated financial statements relative to the unconsolidated financial statements.

As a somewhat naïve reverse robustness test to this end, we repeat the analysis using three metrics for which target-driven earnings management would not be economically expected or would only be expected to a lesser degree, i.e., (iv) total revenue, (v) total cash flow and (vi) long-term liabilities. The results are reported in Panel B of Table 7. We find that the coefficients β_X are not significant for total revenue and long-term liabilities. Contrary to our prior, significant results are reported for total cash flow. Coherently, recent research demonstrates that firms do engage in cash flow management, specifically when analysts provide cash flow forecasts (e.g., McInnis and Collins, 2011; and Ayers et al., 2013).

We then conduct a second analysis to investigate the effect of book-tax conformity on target-driven earnings management in the consolidated financial statement. Following Watrin et al. (2014), we use the AMADEUS data from above and add both non-euro reported statements from AMADEUS and all available data from Compustat (Global) via WRDS for the 27 EU member states. Our sample now contains 31,844 consolidated financial statements over the period 2009 to 2013. We then separate

Table 7

Comparison of Consolidated Financial Statements and Unconsolidated Financial Statements for Different Earnings Metrics

	$\beta_{X=2}$	$\beta_{X=2\&3}$	$\beta_{X=3\&4}$	$\beta_{X=2\&3\&4}$	S
Panel A: Target-Driven Earnings Management is Expected					
Net Income	-0.148^{***}	-0.045	-0.109^{***}	-0.122^{***}	5,934
	(-2.619)	(-1.139)	(-2.668)	(-3.683)	
Earnings Before Taxes	0.029	0.032	-0.103^{**}	-0.059^{*}	6,040
	(0.527)	(0.809)	(-2.537)	(-1.791)	
Earnings Before Interest and Taxes	-0.050	-0.024	-0.083^{*}	-0.072^{**}	6,232
	(-0.840)	(-0.580)	(-1.948)	(-2.079)	
Panel B: Target-Driven Earnings Management is not Expected					
Total Revenue	0.041	-0.016	0.025	0.030	8,394
	(0.915)	(-0.499)	(0.768)	(1.153)	
Total Cash Flow	-0.031	0.008	-0.084^{**}	-0.066^{**}	6,576
	(-0.564)	(0.207)	(-2.152)	(-2.087)	
Long-Term Liabilities	0.018	0.044	-0.004	0.003	8,336
	(0.389)	(1.376)	(-0.126)	(0.119)	

Notes:
Coefficients β_X are the difference in means between the consolidated financial statements and the unconsolidated financial statements in the Xth position(s) as indicated. In cases where β_X is greater than zero, mean of the digits in the Xth position(s) is greater for the consolidated financial statements than for the unconsolidated financial statements and vice versa. t-Values of two-sided unpaired t-tests (unequal variance) for the significance of β_X are given in parentheses. ***, ** and * indicates (average) significance at the 1%, 5% and 10% levels, respectively. S indicates the number of firm-years included.

this sample into two sub-samples based on the Watrin et al. (2014) ranking of book-tax conformity and their nominal identification of accounting systems. Specifically, relying on Table 4 of Watrin et al. (2014), we label all countries above the median rank of book-tax conformity and with nominal identification 'one-book' or 'one/two-book' as high book-tax conformity and all countries below the median rank of book-tax conformity and with nominal identification as 'two-book', 'two/three-book' or 'three-book' as low book-tax conformity. Corresponding to Watrin et al. (2014), we then hypothesize that target-driven earnings management in the consolidated financial statement is relatively more pronounced for firms from a country of low book-tax conformity. The results are reported in Table 8.

The results presented in Panel A of Table 8 indicate that target-driven earnings management in consolidated financial statements is indeed systematically more pronounced for firms in countries of low book-tax conformity. Comparing Panel A in Table 8 and Panel A in Table 7, we find structurally similar results in both, but the results on net income are weaker in Table 8. We argue that, even in countries with low book-tax conformity, book-tax conformity is still strongest with net income relative to earnings before taxes and earnings before interest and taxes. Consequently, differences in target-driven earnings management between low book-tax conformity countries and high book-tax conformity countries would be relatively weakest in net income. Finally, considering Panel B of Table 8, which contains the metrics for which

Table 8

Comparison of Consolidated Financial Statements for Firms from low Book-Tax Conformity Countries and from High Book-Tax Conformity Countries for Different Earnings Metrics

	$\beta_{X=2}$	$\beta_{X=2\&3}$	$\beta_{X=3\&4}$	$\beta_{X=2\&3\&4}$	S
Panel A: Target-Driven Earnings Management is Expected					
Net Income	0.015	0.054	−0.117**	−0.073*	8,701
	(0.214)	(1.080)	(−2.254)	(−1.733)	
Earnings Before Taxes	−0.182***	−0.079	−0.176***	−0.178***	9,123
	(−2.626)	(−1.612)	(−3.482)	(−4.356)	
Earnings Before Interest and Taxes	−0.136**	−0.126***	−0.247***	−0.210***	9,146
	(−1.990)	(−2.633)	(−4.985)	(−5.232)	
Panel B: Target-Driven Earnings Management is not Expected					
Total Revenue	−0.035	0.001	0.044	0.018	15,399
	(−0.663)	(0.019)	(1.180)	(0.584)	
Total Cash Flow	0.078	0.025	−0.037	0.002	8,194
	(0.980)	(0.451)	(−0.629)	(0.035)	
Long-Term Liabilities	−0.051	−0.002	−0.035	−0.040	14,344
	(−0.940)	(−0.058)	(−0.877)	(−1.255)	

Notes:
Coefficients β_X are the difference in means between the consolidated financial statements for the low book-tax conformity country firms and the high book-tax conformity country firms in the *X*th position(s) as indicated. In cases where β_X is greater than zero, mean of the digits in the *X*th position(s) is greater for the low book-tax conformity country firms than for the high book-tax conformity country firms and vice versa. *t*-Values of two-sided unpaired *t*-tests (unequal variance) for the significance of β_X are given in parentheses. ***, ** and * indicates (average) significance at the 1%, 5% and 10% levels, respectively. S indicates the number of firm-years included.

target-driven earnings management is not expected, we find no significant results at all, supporting the conjecture that there are no between-country differences in the distribution of digits per se.

In conclusion, our results support the findings of Watrin et al. (2014) that target-driven earnings management is conditional on both the type of annual statement and the accounting environment.

(d) Globally Smoothed Kernel Density

As our third test, we use the novel identification strategy proposed by Lahr (2014), who estimates a kernel density distribution that is *globally* indistinguishable from the underlying empirical distribution of the metric and which then serves as a reference distribution for *local* deviations. The key for optimal smoothing (based on a given kernel function) lies in the estimation of bin width by means of bootstrap simulations (bootstrap KDE). Lahr (2014) demonstrates that his approach yields structurally equivalent, but generally more conservative, results than the established analysis by Burgstahler and Dichev (1997).

Replicating his setting, we use Compustat for US firms in the fundamentals annual file via WRDS for the years 1976 to 2010. We rely, for identification, on standardized changes in net income as applied by Lahr (2014), but we round the previous year value earnings target to the first two positions of the mantissa M, corresponding to A5, and hence we compute $(\text{NetIncome}_t - \text{round}(\text{NetIncome}_{t-1}))/\text{MarketValue}_{t-2}$. Net income in t and market value in t–2 are as reported. We further follow Lahr (2014) in excluding firms with NAICS in ranges 4400–5000 and 6000–6500 as well as firm-year observations with standardized changes in net income smaller than -1, greater than $+1$ and exactly 0. We drop all observations with negative NetIncome_t and require a minimum accuracy of four positions in the mantissa. All observations in bootstrap KDE bins of $(\text{NetIncome}_t - \text{round}(\text{NetIncome}_{t-1}))/\text{MarketValue}_{t-2}$ above the earnings target with significant divergence from the reference distribution at a 10% significance level are then pooled and compared in their NetIncome_t to observations in the mirrored bins just below the threshold (with a maximum of six bins as set by Lahr, 2014). Table 9 shows the results.

We observe the same patterns in Table 9 as observed in Table 1 for all three kernel functions and for different nominal significance levels α applied with the bootstrap KDE. Corresponding to expectations, the coefficients are non-significant for $X = 2$, which is the rightmost target position in this setting. We observe relatively high t-values relative to previous analyses as a direct result of the small bin width generated by the bootstrap KDE, which leads to observations relatively close to the earnings target. The results are unchanged when (i) using an extended range of 12, 18 or 24 bins around the earnings target, (ii) comparing all bins with significantly higher observed frequency to bins with significantly lower observed frequency relative to the reference distribution, and (iii) rounding *down* the previous year net income earnings target.

In conclusion, we find that our research design yields results structurally comparable to those derived by the novel method of Lahr (2014). More generally, the tests conducted also provide evidence that our research design is applicable in earnings discontinuity settings, which also sets it in relation to the important research stream surrounding Burgstahler and Dichev (1997).

Table 9

Globally Smoothed Kernel Density as Reference Distribution

A	$\beta_{X=2}$	$\beta_{X=2\&3}$	$\beta_{X=3\&4}$	$\beta_{X=2\&3\&4}$	S	$BinWidth$
Epanechnikov Kernel (MaxDiff = 0.0001)						
1%	−0.060	−0.299***	−0.343***	−0.249***	19,445	0.0062
	(−1.414)	(−9.883)	(−11.466)	(−10.122)		
2.5%	−0.061	−0.332***	−0.385***	−0.277***	16,189	0.0051
	(−1.307)	(−10.075)	(−11.825)	(−10.354)		
5%	−0.102	−0.683***	−0.741***	−0.528***	7,229	0.0046
	(−1.499)	(−14.226)	(−15.577)	(−13.497)		
10%	–	–	–	–	–	0.0035
Uniform Kernel (MaxDiff = 0.0001)						
1%	−0.054	−0.345***	−0.406***	−0.289***	14,445	0.0045
	(−1.094)	(−9.940)	(−11.835)	(−10.238)		
2.5%	−0.069	−0.377***	−0.443***	−0.318***	12,667	0.0040
	(−1.327)	(−10.192)	(−12.120)	(−10.608)		
5%	−0.037	−0.505***	−0.582***	−0.400***	10,532	0.0033
	(−0.637)	(−12.387)	(−14.434)	(−12.081)		
10%	−0.092	−1.093***	−1.217***	−0.842***	4,329	0.0027
	(−1.050)	(−17.743)	(−19.969)	(−16.723)		
Gaussian Kernel (MaxDiff = 0.0001)						
1%	−0.046	−0.557***	−0.660***	−0.455***	8,512	0.0026
	(−0.730)	(−12.348)	(−14.798)	(−12.429)		
2.5%	−0.151	−1.320***	−1.414***	−0.993***	3,628	0.0023
	(−1.579)	(−19.685)	(−21.227)	(−18.055)		
5%	−0.119	−1.426***	−1.550***	−1.073***	3,276	0.0021
	(−1.182)	(−20.159)	(−22.125)	(−18.516)		
10%	−0.102	−1.752***	−1.930***	−1.321***	2,523	0.0016
	(−0.893)	(−21.685)	(−24.224)	(−19.933)		

Notes:
Coefficients β_X are the difference in means between firms in bins above the threshold with significant local divergence from the global reference distribution and firms in the exact same bins mirrored below the threshold in the *X*th position(s) as indicated. In cases where β_X is greater than zero, mean of the digits in the *X*th position(s) is greater for bins above the threshold than for bins below the threshold and vice versa. *t*-Values of two-sided unpaired *t*-tests (unequal variance) for the significance of β_X are given in parentheses. ***, ** and * indicates (average) significance at the 1%, 5% and 10% levels, respectively. α indicates the one-sided nominal significance level for the creation of the bootstrap KDE, and S indicates the number of firm-years included. Cases without significant bins are indicated as '–'. BinWidth reports the bin width as it results from the bootstrap KDE as presented by Lahr (2014), and MaxDiff reports the respective point of maximum difference between the kernel distribution estimate and the underlying empirical distribution.

(iii) Robustness and Limitations

Any analysis of the distribution of digits follows a fundamentally different rationale from that for the analyses most typically applied in accounting research. Consequently, our research design is occasionally not immediately intuitive. Nonetheless, methods investigating the distribution of digits are valuable to the research community and have been demonstrated to be applicable in the earnings management context. Based on these considerations, we include a rather extensive discussion below.

First, the distribution of digits prevailing in the raw AMADEUS data used for our simulation analysis in Section 4(i) may already be affected by earnings management. Recall that converting the discretely distributed raw data to a continuous distribution based on the kernel density estimation should sufficiently control for these effects because we ultimately rely on AMADEUS only for the *magnitude* of the earnings metric, whereas the resulting *numerical structure* is a direct result of simulated random number generation. Moreover, we note that our research design can be applied even if the control group firms also engage in target-driven earnings management because merely relative differences in the degree of target-beating activity are exposed. Lastly, because the value of unmanaged earnings in our simulations is generated using an identical mechanism for both the control group and the treatment group, any differences between groups must be attributed to the treatment of target-driven earnings management.

Second, for the application of our research design, identifying the earnings metric on which managers actually focus with respect to their earnings management activity and measuring its exact reported value are vital. Obtaining this value may be particularly problematic in samples that include different types of firms or firms from different jurisdictions (e.g., earnings targets might be based on local GAAP, whereas reported earnings are in IFRS or US GAAP). Selecting the correct earnings metric seems to be an obvious requirement. However, we emphasize this requirement nonetheless because even finding a reasonable proxy for the correct earnings metric – which is often sufficient in positive accounting research – would not suffice for investigating the distribution of digits because any investigation in this regard relies on the exact mantissa M. Similarly, researchers must consider the accuracy of the distribution of digits in databases and when performing currency conversions. Positions within the mantissa of the reported value N that are affected by rounding or approximate currency conversion may not be analysed using our research design.

Third, firm size may theoretically influence the distribution of digits in very specific circumstances.[11] However, the effect of firm size on target positions decreases as X increases, and thus, such effects primarily affect the target positions. As we discuss above, target positions should, in any case, be treated with caution when target-driven earnings management is analysed. Nonetheless, researchers may need to control for differences in firm size in certain settings. Controlling for such differences in the context of a distribution of digits analysis can be achieved by drawing random subsamples with firms of similar size and rerunning the analysis.

Finally, managers may not actually face an earnings threshold N^* that is rounded to a certain value. Instead, managers may receive private benefits per unit of managed earnings (e.g., a bonus based on a given percentage of the reported net income). Straightforwardly, our research design would not work under such circumstances because it investigates only earnings management to meet a rounded earnings target. Managers may also face an earnings target that is based on some form of target growth rate. In this case, the earnings metric to be investigated must be the growth rate rather

11 For instance, assume that the reported earnings in one group are 10% higher than those of firms in another group, independent of whether target-driven earnings management occurs. Whereas reported incomes of 1.20 million and 1.32 million have identical values of λ, D_2 and D_3 are greater to account for the greater total value. Because the researcher cannot observe whether positions $X = 2$ and $X = 3$ are target positions, size might affect the results.

than the underlying annual statement item.[12] Similar to our investigation of earnings per share from Section 4(ii)(b), a natural rightmost target position in these settings might be the second position or third position after the decimal. Our research design is not limited to monetary values.

5. APPLICATION IN REGRESSION ANALYSIS

We derive that the mean of the distribution of digits in the non-target positions is negatively correlated with the degree of target-driven earnings management (refer to C1). Naturally, this theoretical result can also be straightforwardly employed to proxy for target-driven earnings management in regression analysis. To do so, researchers must capture the mean of the distribution of digits in any position(s) X that is deemed a non-target position(s). Such a variable could be created on both the firm level and the group level.

6. CONCLUSIONS

We present a novel empirical strategy to detect differences in target-driven earnings management activity between two or more groups of firms. Specifically, we find that the mean of the distribution of digits in non-target positions is systematically lower for managed earnings than for unmanaged earnings and provide extensive tests for the utilization of this finding. It can also be extended to applications in standard regression analysis, which are arguably the most prevalent in positive accounting research.

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