Seeing red, keeping watch: Loss-induced vigilance and CEO investment judgments

Abstract

Prior research on losses emphasizes preference-based channels—changes in risk aversion, loss aversion, or reference dependence. We argue instead that realized losses do not make CEOs uniformly risk-averse or risk-seeking; they make them more selective. In a survey experiment with 2,720 Danish SME CEOs linked to verified accounting data, we compare firms just below versus just above the zero-earnings benchmark and exploit randomized variation in expected returns across investment vignettes to test how recent losses shape investment judgments. CEOs who recently experienced small losses place greater weight on expected returns, rejecting low-IRR projects and favoring high-IRR projects more than similar profit firms. The results are robust to alternative earnings windows, donut-style exclusions, entropy balancing, and placebo timing tests, and are consistent with an attention-based vigilance mechanism. More broadly, loss-induced vigilance suggests a behavioral channel through which performance can rebound after small losses as CEOs reallocate attention and capital toward higher-value projects.

1. INTRODUCTION

Earnings performance is a central signal in corporate finance: it shapes capital allocation, monitoring, and managerial evaluation. While scrutiny from investors, lenders, and the media generally intensifies as earnings decline, the shift from a small profit to a small loss is commonly viewed as triggering disproportionate attention. Consistent with this view, firms exert considerable effort to avoid reporting even economically trivial losses (Burgstahler & Dichev, 1997; Degeorge, Patel, & Zeckhauser, 1999; Roychowdhury, 2006).

Because crossing the zero-earnings benchmark is a salient performance event, it is likely to shape how executives evaluate and screen subsequent investment opportunities. Yet despite a large experimental literature on post-loss behavior, field evidence from corporate decision makers remains scarce: realized losses are endogenous to fundamentals and often confounded with financial distress. We therefore tackle this identification challenge and test whether realizing a small loss causally alters CEOs' screening of investment opportunities, and through which channel.

Competing theories predict sharply different investment responses to losses. Constraint- and wealth-based accounts imply that losses reduce risk capacity and increase conservatism in project screening (Arrow, 1965; Pratt, 1964), and disappointment/regret-based preferences predict caution after unfavorable outcomes (Gul, 1991; Loomes & Sugden, 1982). Reference-dependent models instead predict break-even seeking when performance falls below a salient benchmark, increasing willingness to accept risk to return to the reference point (Thaler & Johnson, 1990; Tversky & Kahneman, 1992; Kőszegi & Rabin, 2006, 2007). Consistent with these opposing mechanisms, the evidence is mixed: some settings show post-loss de-risking (e.g., Gneezy & Potters, 1997), while others show post-loss risk seeking / loss-recovery behavior (e.g., Coval & Shumway, 2005; Imas, 2016) and, in corporate settings, risk shifting in distress (e.g., Eisdorfer, 2008; Li, Lockwood, & Miao, 2017), suggesting that realized losses need not shift risk appetite uniformly.

We propose a screening-based mechanism. A realized loss is a salient performance shock that can increase screening intensity and managerial vigilance, shifting attention toward value-relevant signals used in capital budgeting rather than inducing a uniform change in risk appetite. In this view, losses raise the weight managers place on expected investment returns and on downside and upside states of the payoff distribution—information that is diagnostic for investment efficiency—so that managers reject negative- or low-value projects more aggressively while responding more strongly to high-quality opportunities (Kahneman, 1973; Gehring & Willoughby, 2002; Erev, Ert, & Yechiam, 2008; Hochman & Yechiam, 2011; Yechiam & Hochman, 2013; Gabaix, 2019). This mechanism implies a change in screening sensitivity, a steeper mapping from payoff-relevant fundamentals to evaluations, rather than a uniform shift in average risk-taking.

We test these predictions in a survey experiment linked to administrative accounting records. In September 2019, 2,720 Danish SME executives evaluate standardized investment proposals described by three-point return distributions (worst/base/best case). This vignette design randomizes expected internal rate of return (IRR) and tail outcomes while holding other features constant across respondents. We merge survey responses to verified ORBIS financial statements and focus on firms in a narrow neighborhood around the zero-earnings benchmark, comparing respondents from firms just below versus just above zero earnings. We use RD-style local-polynomial tools to summarize patterns around the benchmark and implement sensitivity checks that address potential sorting (density diagnostics and donut-style exclusions). Because expected returns are experimentally varied, our identification comes from differences in how near-threshold loss versus profit firms map randomized payoff information into investment judgments, rather than from cutoff-based treatment assignment per se.

We find that crossing from a small profit to a small loss sharply steepens the relation between expected returns and investment attractiveness: managers in loss firms are about **4** percentage points more likely to rate high-IRR projects as attractive and **8** percentage points more

likely to rate low-IRR projects as unattractive, consistent with more selective screening rather than a uniform shift in risk appetite.

This symmetric response—stronger rejection of low-IRR projects and stronger endorsement of high-IRR projects—provides evidence that realized losses increase the weight placed on value-relevant signals. Crossing into the loss domain steepens the mapping from expected returns to investment evaluations, consistent with more selective screening rather than a uniform shift in risk appetite. In other words, losses change *how* managers translate payoff-relevant information into ratings, increasing discrimination across the opportunity set.

These effects are robust across a wide range of identification and specification checks. We obtain comparable estimates using local-polynomial RD specifications and alternative bandwidth choices, and we detect no discontinuities at placebo cutoffs (e.g., prior- or subsequent-year earnings). The results also remain stable when we address modest covariate imbalance around the threshold—most notably in liquidity and solvency—by reweighting observation using entropy balancing. Taken together, the evidence is consistent with crossing from a small profit to a small loss increasing managerial selectivity in investment evaluation. More broadly, the findings suggest that small losses do not primarily shift risk-taking; instead, they operate as a disciplining device that sharpens attention to value-relevant information and aligns capital allocation more closely with fundamentals—a "disciplining signal" that improves investment efficiency.

We contribute to three strands of research. First, we show that the experience of a small loss—distinct from the anticipation of one—has real economic consequences for subsequent investment behavior. Prior work documents that managers act to avoid losses through value-destroying earnings management (Burgstahler & Dichev, 1997; Roychowdhury, 2006), consistent with theories emphasizing loss aversion and reference dependence (Thaler & Johnson, 1990; Barberis & Huang, 2001). We extend this literature by showing that once a loss is realized, it can sharpen managerial attention and improve investment selection. Managers who have recently experienced a loss become more discriminating—favoring high-return projects and avoiding low-

return ones. Thus, whereas anticipated losses induce distortionary actions, experienced losses appear to foster more selective decision-making. Second, we offer behavioral microfoundations for the well-documented mean reversion in firm profitability. Rather than stemming solely from competition or accounting reversals (Fama & French, 2000; Nissim & Penman, 2001; Wiggins & Ruefli, 2002), we show that realized losses trigger vigilance and more selective investment, improving resource allocation. Conversely, small profits may reduce attention and foster complacency, allowing inefficiencies to persist. Thus, managerial attention and vigilance help explain why firm performance naturally reverts toward the mean. Third, our results contribute to behavioral corporate finance (Baker, Ruback, & Wurgler, 2007) by identifying an attention-based channel through which prior performance affects real decisions. They also complement research on real earnings management and post-performance adaptation (Pinnuck & Lillis, 2007; Roychowdhury et al., 2019), showing that the same accounting benchmark that triggers distortionary behavior before year-end can promote selective, value-preserving investment choices thereafter.

Together, these results challenge the frictionless benchmark of classical finance under which all positive-NPV projects should be undertaken (Modigliani & Miller, 1958). Instead, we show that small accounting losses serve as psychologically meaningful reference points that reallocate managerial attention (Kahneman, 1973; Gabaix, 2019), linking cognitive mechanisms to real economic outcomes.

2. THEORY

Losses are salient performance signals in corporate finance and accounting. In owner-managed SMEs, posting a loss can affect financing and stakeholder relationships, not just reported performance. A loss can weaken the firm's bargaining position with banks and other capital providers, constrain financing flexibility (e.g., renewal and terms of credit lines and overdrafts), and raise scrutiny because SME lending is conducted under high information opacity and monitoring costs, making recent profitability a salient input in screening and ongoing oversight

(Berger and Udell, 1995, 2006; Boot, 2000). It may also affect relationships with suppliers and customers if the loss is interpreted as a signal of elevated default risk or reduced capacity to honor commitments; theories and evidence on trade credit emphasize that suppliers adjust terms when buyers' risk and outside financing conditions deteriorate (Petersen and Rajan, 1997; Wilner, 2000), and research on financial distress highlights indirect costs such as impaired product-market relationships when counterparties become concerned about continuity or performance (Opler and Titman, 1994). These consequences make the profit–loss boundary potentially relevant for subsequent investment decisions.

A large literature documents that firms exert considerable effort to avoid reporting even small accounting losses, implying that the zero-earnings threshold is a psychologically and economically meaningful benchmark (Hayn, 1995; Burgstahler and Dichev, 1997; Degeorge, Patel, and Zeckhauser, 1999). The salience of this threshold is amplified by the manager's direct control over the firm's bottom line. Because these managers can often avoid a reported loss through discretionary "real activities"—such as reducing owner remuneration or delaying personal payouts—reporting a loss can indicate that these discretionary buffers were insufficient or that managers chose not to draw on them. Real-activities evidence suggests that managers are willing to distort operating and investment decisions to remain just above zero (Roychowdhury, 2006).

To the extent that owner-managers can use discretionary adjustments to buffer small shocks, a reported loss near zero can signal that these buffers were insufficient or that managers chose not to draw on them, leaving the firm in a more constrained state than an otherwise similar firm just above zero. Thus, among firms near the zero threshold, being just below zero constitutes a qualitatively different state than being just above zero: it reflects buffer exhaustion rather than merely an unfavorable draw.

Taken together, the zero threshold is both behaviorally salient and economically consequential in owner-managed SMEs. These patterns align with reference-dependent preferences: outcomes evaluated relative to a benchmark carry disproportionate weight in the loss

domain (Tversky and Kahneman, 1991). For an owner-manager, crossing into the loss domain is not just an accounting outcome but a "hard" signal that the economic shock has exceeded their capacity to manage it. Similar reference-point effects appear in other high-stakes performance settings (Pope and Schweitzer, 2011; Allen et al., 2017).

Standard preference-based models yield contrasting predictions about behavior after a realized loss. In expected-utility frameworks with decreasing absolute risk aversion, losses reduce wealth and thereby lower willingness to bear risk (Arrow, 1965; Pratt, 1964), and disappointment- or regret-based preferences similarly predict more conservative choices following unfavorable outcomes (Gul, 1991; Loomes and Sugden, 1982). In contrast, reference-dependent models predict break-even motives when performance falls below a salient benchmark, increasing risk taking through the reflection effect and loss-recovery behavior (Thaler and Johnson, 1990; Tversky and Kahneman, 1992; Kőszegi and Rabin, 2006, 2007). Dynamic formulations further distinguish realized from unrealized losses and imply different subsequent risk-taking responses (Barberis and Xiong, 2009; Imas, 2016).

Empirically, however, post-loss behavior is not uniform: losses are associated with both de-risking and loss-chasing across laboratory and field settings (Gneezy and Potters, 1997; Coval and Shumway, 2005; Denis and Kruse, 2000; Eisdorfer, 2008). This heterogeneity suggests that realized losses need not operate primarily through a single, uniform shift in risk preferences. We therefore develop an alternative mechanism in which losses affect information processing and screening intensity, changing how managers weight payoff-relevant fundamentals when evaluating investment opportunities.

2.2. Attention and loss-induced vigilance

To reconcile divergent post-loss risk-taking patterns, we shift from preference-based explanations to an attention-based perspective in which losses primarily affect information processing. Evidence from psychology and behavioral economics shows that losses trigger an orienting response and elevate on-task attention (Gehring and Willoughby, 2002; Hochman and

Yechiam, 2011). Synthesizing this work, Yechiam and Hochman (2013) argue that losses increase sensitivity to payoffs: rather than producing a uniform shift in valuation, losses sharpen responsiveness to payoff-relevant information and increase choice consistency (Erev, Ert, and Yechiam, 2008).

This mechanism maps naturally to economic models of limited attention and selective processing. When attention is scarce, decision makers allocate weight to a subset of signals (Kahneman, 1973; Sims, 2003; Gabaix, 2019). A realized loss is a salient performance shock that can tighten the attention constraint and increase the weight placed on diagnostic cues. In corporate settings, this implies heightened managerial vigilance: after a loss, managers devote more attention to value-relevant inputs when screening investment opportunities, rather than experiencing a uniform change in risk appetite.

This prediction is consistent with organizational theories of response to performance shortfalls. Behavioral theories of the firm emphasize that negative feedback triggers problemistic search and reallocates attention toward diagnosing and correcting underperformance (Cyert and March, 1963; Greve, 2003). Relatedly, threat-rigidity accounts predict heightened monitoring and tighter control under adverse conditions (Staw, Sandelands, and Dutton, 1981).

A key empirical implication distinguishes vigilance from standard alternatives. If losses operate mainly through tighter constraints or greater risk aversion, they should shift investment evaluations downward on average. In contrast, loss-induced vigilance predicts a change in the mapping from fundamentals to evaluation: managers should respond more strongly to payoff-relevant project signals—most directly, expected returns—leading to sharper discrimination between high- and low-quality projects.

2.3. Implications for risk allocation

A vigilance-based account implies that realized losses primarily change how managers map project fundamentals into evaluations. In owner-managed firms, where managers often have discretion to buffer small shocks, crossing from a small profit to a small loss can represent a

qualitatively different performance state—one that plausibly triggers heightened scrutiny of discretionary decisions. Accordingly, we expect screening intensity to increase sharply around the zero-earnings benchmark.

The key empirical distinction is between a level effect and a slope effect. If losses operate mainly through tighter constraints or a uniform shift in risk appetite, investment evaluations should shift downward on average. In contrast, loss-induced vigilance predicts a change in the mapping from payoff-relevant information to evaluation: managers place greater weight on expected returns, rejecting low-return projects more aggressively while responding more strongly to high-return opportunities.

Importantly, reporting discretion around zero does not undermine the benchmark's relevance in our setting. If anything, it strengthens the interpretation of the realized earnings sign as a salient performance outcome: observed earnings reflect both underlying performance and managers' discretionary efforts to avoid reporting a loss. As a result, firms reporting small profits near zero may include "managed" firms that faced negative shocks but successfully used discretionary buffers. This mixing should attenuate differences between firms just above and just below zero, biasing against finding a discontinuity in screening intensity. Therefore, any increase in return sensitivity among firms just below zero is conservative with respect to manipulation.
In our setting, these arguments imply that the relationship between a project's Expected IRR and its attractiveness rating should be steeper when prior-year earnings fall just below zero than when they fall just above zero. We therefore test:

H1: *The sensitivity of project evaluations to Expected IRR is greater for loss firms than for profit firms, in a local neighborhood around the zero-earnings benchmark.*

3. RESEARCH DESIGN

3.1. Experimental data

Our hypothesis pertains to investment preferences that are difficult or arguably impossible to

collect from archival sources. First, even though some implications of undertaken investments are reflected in the financial statements, these implications are impossible to disentangle from other drivers of firm financials. Second, implications are ex-post and do not reflect the ex-ante expectations underlying the decisions and preferences. Third, even if ex-ante expectations for all undertaken investments were publicly disclosed, we could observe only the accepted investments of those available to the firm. Therefore, our hypotheses call for collecting non-archival data, specifically, data collected via a field experiment used to collect dependent variables, i.e., reactions to ex-ante investment information.

Our field experiment was a large-scale, unincentivized online experiment with SME managers in Denmark. Each participant was asked to assess (on a 7-point Likert scale) the attractiveness of a hypothetical business investment opportunity, portrayed in a vignette including ex-ante information about several attributes deemed relevant by managers in interviews made during the development of the instrument. See Table 1 below for an example. See Appendix 1 for the full parameterization and for how this parameterization translates into the specific hypothetical investment opportunity of Example 1[1].

----------Insert Table 1 here----------

The vignette information of primary relevance to this study are the *Yearly returns (IRR)* and *Likelihood of scenario* of each of the three scenarios: *worst case*, *base case,* and *best case,* which together determine likelihood-weighted Expected IRR (= worst case IRR * worst case likelihood + base case IRR * base case likelihood + best case IRR * best case likelihood). The instrument included a range of other parameters for two reasons. One was the possibility of using the instrument to address other research questions. Another reason was the ambition to enhance the external validity

[1] This experiment was embedded in a broader study focusing on corporate investment choices and their subsequent management. The comprehensive survey encompassed a total of 72 questions, with only a limited portion being relevant to this paper. The vast majority of the data were primarily gathered for the development of a practical online investment management tool, a request made by the funding organization. The complete survey can be obtained upon request. See also Christoffersen, Holzmeister and Plenborg, 2023 using the same data for a different set of research questions

of the experiment by portraying a vignette with information representing information that would be seen in a real-world investment proposal. Consequently, the parameters to present and the ranges of the parameter values were based on an iterative pilot process. We tested different parameters and value ranges with firm managers and subsequently adjusted these before testing the instrument on different managers. We strived to choose the estimated values to strike a satisfactory balance between wide variation in the variables and managers still perceiving the values as within the range relevant to their managerial decision-making. For instance, this approach resulted in the scaling of amounts with a firm-specific size factor – based on the company's gross profits and total equity obtained from its financial statements – to ensure that the investment project is at reasonable stakes. In total, the pilot phase drew on the help of 50 SME managers.

We performed our experiment in the context of Danish SMEs, typically owner-managed, who are subject to no or minimal pressure from media, analysts, and equity investors. We chose all Danish limited liability SMEs that were at least five years old, were not holding companies, were not within the financial sector, were not part of a larger group, and had executives who were not involved in other companies. This gave rise to a sample of 19,759 companies. We hired Danmarks Statistik (the Danish governmental statistical bureau) to identify (via unique personal identifiers tied to unique firm identifiers) the most senior executive (most had just one) for each of these 19,759. Following this identification, Danmarks Statistik sent survey invitations to these individuals' e-boks, which are strictly personal government-granted e-mail accounts. For the survey item relevant to this paper, we received 4507 responses, which translates into a response rate of 22.8%.

3.2. Archival data

We hypothesize that earnings realizations moderate the relationship between the hypothetical investment IRR and managers' attractiveness assessment. Specifically, we hypothesize that firms react to prior experiences with small profits vs. losses, most notably recent experiences with these.

Because the experiment was conducted in September 2019, we focus on fiscal-year 2018 earnings for firms with December year-ends. For these firms, the 2018 financial statements would typically have been finalized and filed before the experiment, implying that the 2018 profit/loss status was known to the firm at the time respondents completed the survey. However, to conduct a placebo test on a future non-realized benchmark, we use 2019 earnings and thus also require firms to have financials available for that year.

With these additional restrictions of relevance for this particular study the sample size available for our analyses drops to 2,720. The majority (98%) of this drop from 4507 responses to a sample size of 2720 is caused by firms with financial years that do not end in December. The financials were obtained from ORBIS.

4. RESULTS

4.1. Descriptives and correlations

Table 2 presents descriptive statistics of the individual parameters in the experimental instrument and the resulting *Expected IRR,* which is this study's primary independent variable. Furthermore, we include descriptives for the dependent variable, *ATTRACTIVENESS,* as well as $EARNINGS_{t-1}$ (available to the firm at the time of the experiment; filed prior to the survey) and (for placebo testing) $EARNINGS_t$ (realized after the experiment; used for placebo tests). Table 3 presents correlations between the variables in Table 2.

----------Insert Table 2 here----------

Beyond showing how our parametrization transforms into variation in the parameters shown in the vignette of the experiment (i.e., Investment Size through Likelihood Best Case), Table 2 demonstrates satisfactory variation in the resulting *Expected IRR* as well as in the response variable *ATTRACTIVENESS*. Importantly, earnings are concentrated around the zero benchmark, yielding a sizeable number of observations on both sides of zero. Figure 1 (presented at the end of this section) portrays the distribution around zero.

----------Insert Table 3 here----------

Table 3 serves two purposes. First, it shows that the instrument has face validity as ATTRACTIVENESS is positively correlated with Expected IRR and with the key scenario parameters that mechanically determine Expected IRR (scenario IRRs and scenario probabilities). Second, Table 3 shows that *ATTRACTIVENESS* is not significantly related to *Investment size*, *First Year with Income from Investment*, *Last Year with Income from Investment*, *Years till Break-Even Base Case*, *Years till Break-Even Best Case,* which by design (see parametrization Appendix 1) are uncorrelated with *Expected IRR*. Table 3 also demonstrates negative correlations between *Investment size* and *CURRENT ASSETS* as well as *LIABILTIES* because *Investment size* is by design positively related to firm assets, while *CURRENT ASSETS* and *LIABILTIES* are both deflated with firm assets.

----------Insert Figure 1 here----------

The final item in this section is Figure 1, which plots the distribution of $EARNINGS_{t-1}$ in the neighborhood of the zero-earnings benchmark. The figure shows visible bunching around zero, consistent with incentives and discretion to avoid reporting small losses documented in prior work (e.g., Burgstahler & Dichev, 1997). Importantly, our mechanism is framed around managers' responses to the realized and salient *reported* performance signal—whether the firm ends up reporting a small loss or a small profit—regardless of whether this status reflects fundamentals alone or is partly shaped by reporting discretion. Our identification does not rely on cutoff-based treatment assignment; instead, we leverage randomized variation in vignette payoffs to test whether firms just below versus just above zero differ in how they map expected returns into investment evaluations. As a sensitivity check, we nevertheless complement the baseline specifications with donut-style estimates that exclude a narrow window around zero (Barreca, Guldi, Lindo, & Waddell, 2011).

4.2.1. Main results

4.2.1.1 Hypothesis test

We hypothesize that the sensitivity of project evaluations to expected IRR is higher in firms with recent past losses than in firms with recent past profits. Figure 2 shows the relation between expected IRR and ATTRACTIVENESS for loss firms (red line and dots) and profit firms (blue line and dots) for a sample of firms with $EARNINGS_{t-1}$ between -0.10 and +0.10. The steeper slope for loss firms visually suggests that evaluations are more sensitive to changes in expected IRR among firms with recent losses. Formally, this slope difference is captured by the interaction term IRR × NEGATIVE $EARNINGS_{t-1}$ in Table 4. In addition, the relative positions of the two curves show that loss firms evaluate low-IRR projects as less attractive, while evaluating high-IRR projects as more attractive within the near-zero earnings window. Notably, the two curves intersect between an IRR of 13% and 14%, which is in the ballpark of corporate investment hurdle rates reported in CFO survey evidence (Graham and Harvey, 2001; Brounen et al., 2004). This is reassuring as it suggests that firms with negative earnings rate negative NPV projects lower than firms with positive earnings do while still rating positive NPV projects higher. This supports the notion of heightened vigilance.

---------- Insert Figure 2 here----------

Table 4 presents formal tests of our hypothesis using ordered logistic regressions for a sample of firms $EARNINGS_{t-1}$ between -0.10 and +0.10. In column 1, there are no controls, column 2 controls for liquidity ($CURRENT\ ASSETS_{t-1}$) and (lack of) solvency ($LIABILITIES_{t-1}$), while column 3 controls for the possibility that liquidity and solvency may affect the way that *IRR* influences the assessment of *ATTRACTIVENESS*. We do this as we acknowledge that losses may also entail changes in liquidity and solvency, which may influence assessments and decision-making.

Across all specifications, the coefficient on the interaction between IRR and $NEGATIVE\ EARNINGS_{t-1,}$ is positive and statistically significant at the 5% level. Furthermore, the magnitude of the interaction term is substantial relative to the main effect of IRR, indicating that expected

returns have a markedly stronger influence on project evaluations among loss firms than among profit firms. In the ordered logit framework, this implies that increases in IRR raise the odds of assigning higher attractiveness ratings more strongly for firms with recent losses.

Although coefficients from ordered logit models cannot be interpreted in terms of linear changes in the Likert-scale outcome, the consistently positive and significant interaction indicates a meaningful difference in return sensitivity. Specifically, for loss firms, increases in expected IRR translate into a much steeper shift in the probability mass toward higher attractiveness categories compared to profit firms.

---------- Insert Table 4 here----------

These estimates imply that a recent small loss steepens the mapping from expected returns to project attractiveness. Relative to near-threshold profit firms, loss firms rate low-return projects less favorably and high-return projects more favorably, consistent with sharper screening rather than a uniform shift in risk appetite. To illustrate economic magnitudes, we convert the main-specification estimates into predicted probabilities (controls set to sample means). For projects at the 90th percentile of Expected IRR (0.28), the predicted probability of an "attractive" rating (6–7) is about 4 percentage points higher for loss firms than for profit firms (≈13.6% vs. ≈9.8%). For projects at the 10th percentile of Expected IRR (−0.01), the predicted probability of an "unattractive" rating (1–2) is about 8 percentage points higher for loss firms than for profit firms (≈48.3% vs. ≈40.7%).

5. ROBUSTNESS

5.1. Sensitivity to bandwidth choice and donut exclusions

Our main estimates could be sensitive to the earnings window used to define "near-zero" firms. A wider window risks comparing firms that differ in fundamentals; a narrower window improves comparability but reduces precision. We therefore assess bandwidth sensitivity in Table 5, Panel A by progressively narrowing the earnings interval, ultimately to [−0.02,0.02]. Across these specifications, the interaction between IRR and NEGATIVE EARNINGS t−1 remains positive

and is statistically significant in all but one window (the [−0.04,0.04] interval), indicating that the main finding is not driven by a particular bandwidth choice.

---------- Insert Table 5 here----------

Table 5, Panel B reports donut-style estimates that exclude observations in progressively larger windows around zero. The point estimates remain positive across all exclusion radii, but statistical significance varies as the donut widens. This pattern is expected: the benchmark-triggered mechanism is most diagnostic in the immediate neighborhood of zero, and mechanically removing those observations reduces power—especially because the number of loss-firm observations drops quickly as the exclusion window expands. Importantly, the donut specifications do not change the qualitative conclusion: across exclusion choices, loss firms continue to exhibit greater return sensitivity than profit firms, consistent with the benchmark-triggered vigilance mechanism.

5.2. Placebo tests with Earnings$_{t-2}$ and Earnings$_t$

Our study fundamentally applies a 2x2 quasi-experimental design in which we vary randomly between high and low IRR investments on one dimension but could not randomly vary on the profit vs. loss dimension and, therefore, had to rely on given variation in firms' actual earnings numbers for that dimension. Hence, the condition of being a loss or a profit firm is not assigned to the firms at random. Therefore, loss and profit firms will likely differ on other parameters than their earnings. These differences may drive their differences in investment project ratings. If this is the case and the differences are more stable than earnings, we would expect results from the main analysis to prevail even when using earnings from the year before and the year after.

We, therefore, conduct placebo tests by repeating the main analysis for these years. Figure 3 and Table 6 provide the relevant results. Focusing on Panel A of Figure 3 and the corresponding Panel A of Table 6, we see results indicating that the experience of a loss two years previously is unrelated to the assessment of current-year investment proposals. This reduces the likelihood that our results are driven by time-invariant, unobserved differences between loss and profit firms.

Similarly, Panel B of Figure 3 and the corresponding Panel B of Table 6 indicate that the (yet to be realized) loss in the current year is not related to the assessment of current-year investment proposals in the same manner as the experience of a loss last year, adding credence to that observation.

Noteworthy is also that Panel B of Figure 3 indicates findings in line with past empirical archival literature investigating the relationship between current-year earnings and current-year investment decisions, suggesting that managers (plausibly) anticipating a loss shy away from bad as well as good projects in an attempt to reach the short-term zero-earnings benchmark (Roychowdury 2006). Indeed untabulated results from regressing ATTRACTIVENESS on NEGATIVE EARNINGS$_t$ (and control variables CURRENT ASSETS$_t$ and LIABILITIS$_t$) suggests at the 5% significance level that the upcoming loss is negatively related to ATTRACTIVENESS. Therefore, Panel B of Figure 3 not only alleviates concerns about unobserved differences driving results but also adds credibility to our experimental instrument by providing results in line with results previously obtained via other methodologies.

In sum, our placebo tests provide confidence that our results do not arise because of firm fixed effects. We do, however, caution that these placebo tests only address unobserved factors that are stable over more than one accounting period, and therefore, the tests do not rule out that unobserved single-period factors are driving our results.

----------Insert Figure 3 here----------

----------Insert Table 6 here----------

5.3. Test of worst case, base case, and best case scenarios

Expected IRR is mechanically determined by scenario-specific returns and their probabilities (worst, base, and best case). The higher return sensitivity we document could therefore be driven disproportionately by one particular scenario component, which would matter for how broadly the results generalize across investment settings. If, for instance, worst case returns are the only

drivers of our results, investment proposals without any negative returns would produce different results. Therefore, we repeat the test of H1 using the worst case, base case, and best case contributions to the *IRR*. Table 7 repeats the full model regression of Table 4, however with *IRR* replaced by the likelihood-weighted IRRs from the three scenarios, *worst case*, *base case,* and *best case* in each of the three columns 1, 2, and 3, respectively, while column 4 include all at the same time. Results indicate that loss and profit firms differ most in their attention paid to worst and best scenarios, but more importantly they indicate the main results from Table 4 are not driven solely by one scenario.

----------Insert Table 7 here----------

5.4. Local comparison around the zero-earnings benchmark

The main results in Table 4 rely on the choice of an earnings range around zero. Restricting the sample to a narrow range increases comparability between loss and profit firms but reduces the number of observations and may make the estimates sensitive to idiosyncratic observations. Conversely, using a broader range increases statistical power but reduces the likelihood that firms below and above zero earnings are economically similar. To address this trade-off and reduce reliance on discrete bandwidth choices, we complement the main analysis with a local comparison approach centered on the zero-earnings benchmark.

In this analysis, we follow the visualization and local-smoothing conventions of the regression discontinuity literature (Lee & Lemieux, 2010) and implement robust bias-corrected local-polynomial methods using the rdplot and rdrobust commands developed by Calonico, Cattaneo, and Titiunik (2014). Importantly, although we use RD-style tools to summarize patterns locally around the zero-earnings benchmark, our identification does not rely on cutoff-based treatment assignment. Instead, identification comes from the randomized allocation of investment vignettes with different expected returns.

Because RD-style tools are primarily designed to characterize local relationships between a running variable and an outcome, they are not well suited for directly assessing differences in sensitivity to expected returns across project types. We therefore construct a local treatment contrast of high-IRR versus low-IRR vignettes among firms with similar earnings, using 1-to-1 nearest-neighbor matching on earnings distance, matching exactly within each side of the cutoff (loss with loss; profit with profit). Specifically, we split the sample into firms assigned high-IRR (above-median) and low-IRR (below-median) investment vignettes. Within each subsample, firms are matched without replacement based on the absolute distance of $EARNINGS_{t-1}$. from zero, separately for firms with negative and positive earnings. For each matched pair, we compute the difference in investment attractiveness between the high-IRR and low-IRR firms, denoted $\Delta ATTRACTIVENESS_{\text{high IRR-low IRR}}$. This measure captures the local difference in responsiveness to project returns for firms at a given level of $EARNINGS_{t-1.}$

---------- Insert Figure 4 here----------

Figure 4 plots $\Delta ATTRACTIVENESS_{\text{high IRR-low IRR}}$ against $EARNINGS_{t-1}$ for firms within the baseline interval of $EARNINGS_{t-1} \in [-0.10, 0.10]$. The figure presents binned scatterplots constructed using a quantile-spaced binning procedure to ensure that individual observations do not unduly influence the visual patterns (Calonico et al., 2014). The line is fitted using a local linear regression estimated separately on either side of the zero-earnings benchmark.

Figure plots indicate a pronounced decrease in $\Delta ATTRACTIVENESS_{\text{high IRR-low IRR}}$ just above the zero-earnings benchmark. This pattern suggests that firms with recent losses differentiate more strongly between high- and low-IRR projects than firms with recent profits, particularly in the vicinity of the benchmark. Notably, relatively large values of $\Delta ATTRACTIVENESS_{\text{high IRR-low IRR}}$ appear immediately below zero earnings, consistent with heightened sensitivity to expected returns following a loss. In the lower right corner of Figure 4 we report local-polynomial estimates corresponding to the graphical analysis. We note that the robust Z statistics -2.933 indicate statistically different (at the 1% level) reactions to high vs. low

IRR projects when firms are above vs. below the zero earnings benchmark. These results are consistent with the main findings reported in Table 4 and reinforce the conclusion that recent losses amplify sensitivity to project returns.

5.5. Untabulated robustness tests on experimental data

We conduct two additional robustness tests for which we do not tabulate results. First, to address the concern that non-linear responses to IRR may affect results based on the continuous specification, we rerun all the regessions in Table 4 with the continuous IRR replaced by a simple dichotomous indicator for high versus low IRR (above versus below the sample median). The untabulated results show that the coefficient for the relevant interaction term is significant at the same or higher levels than the corresponding coefficient in the main test.

Second, we address concerns that the control variables for liquidity and solvency in the main test do not ensure covariate balance between the firms above and below zero making it possible that effects of the covariates are not fully controlled for. This concern is particularly salient given modest differential response rates in our main sample: 21.9% for profit firms versus 19.5% for loss firms (Table 4). Therefore, we seek to obtain covariate balance using entropy-balancing (Hainmueller, 2012; McMullin & Schonberger, 2020). We base the balancing on our control variables from Table 4, liquidity ($CURRENT\ ASSETS_{t-1}$) and (lack of) solvency ($LIABILITIES_{t-1}$). We obtain a control group with balanced covariates that do not differ significantly from the covariates in the treatment group (negative earnings) (t values all below 0.06). Subsequently, we run the regressions of Table 4 with weights produced by the entropy balancing and obtain results for the variable of interest that are all significant at the same level as in the original tests.

5.6. Archival evidence (complementary)

As an additional robustness test on non-experimental data, we investigate archival data to see whether firm investments and firm profitability are related to the experience of a recent prior loss

vs. gain. Specifically, we analyze the variables $ASSETS_t$ and $EARNINGS_t$ which are current year total assets and current year earnings both scaled by prior year total assets. Results for $ASSETS_t$ are presented in Panel A of Figure 5, while results for $EARNINGS_t$ are shown in Panel B of Figure 5.

Because both outcome variables, particularly $EARNINGS_t$, are likely strongly correlated with $EARNINGS_{t-1}$ due to underlying relations in fundamental economics, we focus on local comparisons around the zero-earnings benchmark to limit extrapolation across economically dissimilar firms. To do so, we apply the same RD-style local-polynomial visualization and estimation tools used in Section 5.4, treating $EARNINGS_{t-1}$ as the running variable and examining local patterns in $ASSETS_t$ and $EARNINGS_t$ in the vicinity of zero earnings. As in earlier analyses, these tools are used to summarize local relationships rather than to claim cutoff-based identification. Figure 5 presents the corresponding graphical evidence and reports the associated local-polynomial estimates in the lower right corner of each panel.

----------Insert FIGURE 5 here----------

The estimates indicate no statistically significant difference in $ASSETS_t$ around the zero-earnings benchmark, while the coefficient for $EARNINGS_t$ is negative with robust z statistics at -1.747 which corresponds to significance at the 10% level. Although these archival results are naturally influenced by a wide range of factors beyond firms' investment decisions, they do not contradict the main implications of our theory and experimental findings. In particular, the archival results do not indicate a discrete contraction in asset growth around the zero-earnings benchmark. While earnings exhibit a small negative discontinuity that is marginally significant, the estimates are economically small and statistically weak. Accordingly, we interpret these patterns as broadly consistent with, but not definitive evidence of, the vigilance mechanism documented in the experimental setting.

6. CONCLUSION

This paper examines how crossing the zero-earnings benchmark shapes managerial investment screening. Prior work shows that firms cluster around zero earnings and exert effort to avoid reporting even small losses, consistent with the benchmark's salience (Hayn, 1995; Burgstahler and Dichev, 1997; Degeorge, Patel, and Zeckhauser, 1999). We predict that experiencing a small realized loss—relative to a small profit—induces heightened vigilance and increases the weight managers place on payoff-relevant project fundamentals when evaluating investments. Using an online survey experiment with 2,720 manager evaluations from SMEs, we find that managers from firms with prior-year earnings just below zero discriminate more sharply between high- and low-quality projects than managers from firms just above zero. The effect is not a uniform downward shift in project ratings. Instead, managers with recent losses penalize weak projects more and respond more strongly to attractive projects, consistent with a change in information processing rather than generalized pessimism or a uniform shift in risk preferences.

The findings contribute to the literature on earnings thresholds and real effects by highlighting a post-loss channel. Existing work emphasizes that the prospect of avoiding a small loss can induce real actions that may be value-reducing (Roychowdhury, 2006; Gunny, 2010). Our evidence complements this view by showing that the experience of a realized loss is associated with more discriminating screening of subsequent projects. The results also connect to performance feedback theories in which performance shortfalls trigger problemistic search and heightened attention (Cyert and March, 1963; Greve, 2003), and to evidence that losses increase attention and responsiveness to incentives (Gehring and Willoughby, 2002; Hochman and Yechiam, 2011; Yechiam and Hochman, 2013). More broadly, the results fit within behavioral corporate finance research emphasizing that psychological mechanisms shape corporate decisions (Barberis, 2013; Baker and Wurgler, 2013). In our setting, the key behavioral margin is a slope effect: crossing into the loss domain steepens the sensitivity of evaluations to expected returns, sharpening discrimination between good and bad projects.

Several limitations point to extensions. First, our evidence comes from a hypothetical (unincentivized) survey experiment; future work could examine whether similar slope effects arise in incentivized designs or settings with real stakes. Second, while project attributes are randomized, loss status is not experimentally assigned; although we focus on local comparisons around zero and implement extensive robustness checks, sorting around near-zero earnings cannot be fully ruled out. Third, our sample focuses on SMEs, and it remains an open question whether benchmark-triggered vigilance operates similarly in large firms with more distributed decision rights and formal capital budgeting systems.

Overall, the evidence indicates that small losses—relative to small profits—are associated with more discriminating investment screening in the subsequent period. The results suggest that crossing the zero-earnings benchmark can shape internal capital allocation by changing how managers process and weight information, opening paths for future research on benchmark-driven attention and investment efficiency.

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APPENDIX

Appendix A. Parametrization and example

Experimental participants were presented with a hypothetical business opportunity, varying in several key attributes that may enter managers' assessment of risk and attractiveness of the business opportunity. In particular, managers faced an investment project with three scenarios (worst-case, base-case, and best-case), for which they were informed about the size of the initial investment and the time with income from the investment. For each of the three scenarios, participants were informed about four key performance indicators: *(i)* the likelihood of the scenario, *(ii)* the net loss or gain from the investment, *(iii)* the yearly internal rate of return (IRR), and *(iv)* the number of years to break-even (B/E). Each participant received information about the same variables but with randomly drawn values (within a pre-specified range), giving rise to researcher-controlled variation in explanatory variables. Importantly, the estimates of the key characteristics were scaled by a firm size factor – based on the company's gross profits and its total equity, obtained from the company's financial statements – to ensure that the investment project is at reasonable stakes. The estimated values were chosen in such a way that they could strike a satisfactory balance between wide variation in the variables and managers still perceiving the values as being within the range relevant for their managerial decision-making. These values were based on iterative pilot approach where we tested different ranges of the parameters with firm managers. Table A1 provides an example of variables shown to a participant which Table A2 summarizes the parametrization.

Table A1 *Example of hypothetical investment opportunity shown*

	Worst Case	***Base Case***	***Best Case***
Size of initial investment	DKK 1,700,000	DKK 1,700,000	DKK 1,700,000
Net loss (-) or gain (+) from the investment	DKK –1,105,000	DKK 1,200,000	DKK 4,000,000
Yearly return (IRR)	–24%	18%	51%
Time period with income from the investment	2020–2028	2020–2028	2020–2028

Number of years until break-even	n.a.	4.7	2.2
Likelihood of scenario	45%	40%	15%

Table A2. Parametrization of the three scenarios of the investment project presented to participants in the online experiment. All parameters determining the business opportunity's attributes (i.e., i, s_A, t_A, r_A, s_B, t_B, r_B, p,) – as defined in the table – were randomly drawn from uniform distributions. The scenarios were scaled by a factor (f), based on the gross return and total equity obtained from the company's accounting data, ensuring that the investment opportunity faced by managers is at reasonable stakes.

	Worst Case (c=1)	*Base Case (c=2)*	*Best Case (c=3)*
Investment size (I)	$I = i \cdot f$ with $i \in \{1\%, 2\%, \ldots, 100\%\}$ and $f = 0.25 \cdot$ gross return $+ 0.50 \cdot$ total equity		
Time A (s_A-e_A)	*From* $s_A \in \{2020,2021\}$ *until* e_A $[=s_A+t_A]$ *with* $t_A \in \{2, 3, \ldots, 10\}$		
Net loss/gain (π_i)	$\pi_1 = I \cdot r_{1A}$ with $r_{1A} \in \{-0.95, -0.90, \ldots, -0.25\}$	$\pi_2 = I \cdot r_{2A} \cdot (e_A - 2019)$ with $r_{2A} \in \{0.010, 0.011, \ldots, 0.100\}$	$\pi_3 = I \cdot r_{3A} \cdot (e_A - 2019)$ with $r_{3A} \in \{0.11, 0.12, \ldots, 0.75\}$
Rate of return (irr_i)	$irr_1 \in \{-83\%, -82\%, \ldots, -4\%\}$ (determined by r_{1A}, s_A and t_A)	$irr_2 \in \{3\%, 4\%, \ldots, 20\%\}$ (determined by r_{2A}, s_A and t_A)	$irr_3 \in \{15\%, 16\%, \ldots, 133\%\}$ (determined by r_{3A}, s_A and t_A)
Time B (s_B-e_B)	*From* $s_B \in \{2020,2021\}$ *until* e_B $[=s_B+t_B]$ *with* $t_B \in \{2, 3, \ldots, 10\}$		
Break-even (b_i)	b_1 = "n.a."	$b_2 \in \{1.5, 1.6, \ldots, 9.1\}$ (determined by r_{2B}, s_B and t_B)	$b_3 \in \{0.6, 0.7, \ldots, 5.4\}$ (determined by r_{3B}, s_B and t_B)
Likelihood (p_i)	$p_1 \in \{5\%, 10\%, \ldots, 55\%\}$ if $p_2 = 40\%$ $p_1 \in \{5\%, 10\%, \ldots, 45\%\}$ if $p_2 > 50\%$ $p_1 \in \{5\%, 10\%, \ldots, 40\%\}$ if $p_2 > 55\%$ etc.	$p_2 \in \{40\%, 45\%, \ldots, 70\%\}$	$1 - p_2 - p_1$

EXAMPLE

We demonstrate our procedure for arriving at the different values in the Table A2 with an example of a firm with gross profit of DKKm 6.186 and equity of DKKm 4.461. As we want to present numbers that are within a plausible range for firms we use this accounting information to determine a size factor (*f*) which we let depend on Gross profit (multiplied with 0.25) as well as Equity (multiplied with 0.5). In this case the size factor is DKKm 3.777 (0.25*DKKm 6.186+0.50*DKKm 4.461).

Size of initial investment

In order to estimate *investment size*, we multiply the size factor by 46% (*s*) which is drawn randomly from $i \in \{1\%, 2\%, \ldots, 100\%\}$. The resulting investment size is DKKm 1.737420 which we round to DKKm 1.7 (*I*).

Net loss (-) or gain (+) from the investment

The next item appearing in the table seen by the participant is *Net loss (-) or gain (+) from the investment* which is a loss in the Worst Case scenario and a gain in the Base and Best Case scenarios. For the Base and Best Case we let this depend on a *Time Frame A* (s_A-e_A). In this example the cash inflows start by the end in 2020 (drawn randomly from $s_A \in \{2020, 2021\}$ and end in 2026 (e_A) which we arrive at by adding 6 years (t_A) drawn randomly from $t_A \in \{2, 3, \ldots, 10\}$. We treat cash flows as if they took place at the midpoint of a year. For the Base Case we multiply the number of years from the investment is taken (2019 for all firms) till it ends (e_A-2019) with 10% (r_{2A}) drawn randomly from $r_{2A} \in \{0.010, 0.011, \ldots, 0.100\}$ and the investment size *I* to arrive at a Base Case *Net Gain* of DKKm 1.19 [=1.7*10%*(2026-2019)] which we round to DKKm 1.2. Similarly for the Best Case, we multiply the number of years from the investment is taken till it ends (e_A-2019) with 34% (r_{3A}) drawn randomly from $r_{3A} \in \{0.11, 0.12, \ldots, 0.75\}$ and the investment size (*I*) to arrive at a Best

Case *Net Gain* of DKKm 4.046(=1.7*34%*(2026-2019) which we round to DKKm 4. For the Worst Case *Net Loss* we simply multiply the investment size *I* with -65% (r_{1A}) drawn randomly from $r_{1A} \in \{-0.95, -0.90, \ldots, -0.25\}$ to arrive at a Worst Case *Net Loss* of DKKm -1.105.

Yearly return (IRR)

To arrive at the respective *IRRs* we assume that a negative cash flows (-*I*) falls in 2019, while for the positive cash flows (I+ π_i) for the three scenarios (Worst Case (i=1), Base Case (i=2), Best Case (i=3)) are evenly distributed over a time range specified above, hence the Base Case cash flows (in DKKm) simulated for the IRR calculation are as follows:

2019: -1.7, 2020-2023: (1.7+1.2)/6 = 0.483333

using the formula

2019: -*I*, 2020-2023: $(I+\pi_2)/t_A$

We then calculate the IRR of this cash flows stream which results in IRR_2=18%.

We do similarly for the Worst Case to arrive at the following simulated cash flow (in DKKm):

2019: -1.7, 2020-2023: (1.7-1.105)/6 = 0.99167

using the formula

2019: -*I*, 2020-2023: $(I+\pi_1)/t_A$

We then calculate the IRR of this cash flows stream which results in IRR_1=-24%.

Finally, for the Best Case we arrive at the following simulated cash flow (in DKKm):

2019: -1.7, 2020-2023: (1.7+4)/6 = 0.950

using the formula

2019: -*I*, 2020-2023: $(I+\pi_3)/t_A$

We then calculate the IRR of this cash flow stream which results in IRR_3=51%.

As noted in the table, IRRs are determined solely by $r_{1A\ (r_{2A\ and}\ r_{3A})}$, s_A and t_A and IRRs are thus uncorrelated with the investment size *I,* however we include *I* and resulting *Net Gain/Loss* (π_1, π_2, π_3) here for the sake of exemplification.

Time period with income from the investment

We simulate a new time frame, Time Frame B in Table 2 which we present in the table. In this example we draw s_B=2020 and t_B=*8* resulting in e_B=2028 and hence the time period 2020-2028 presented to the participant.

Time Frame B differs from Time Frame A which means that it is uncorrelated with the absolute and relative returns (*Net loss (-) or gain (+)* and *Yearly return (IRR)*).

Number of years until break-even

Base Case and Best Case Years till Breakeven are based on a simulation of cash flows generated by the same process as explained above in relation to *Net loss (-) or gain (+) from the investment* but with other values of the different parameters including timing parameters from Time Frame B and new return parameters, r_{2B} *and* r_{3B}. In this example we randomly draw r_{2B}=8% r_{3B}=29%.

This process gives rise to *Years till Breakeven* that are correlated with time period seen be participants but uncorrelated with the absolute and relative returns (*Net loss (-) or gain (+)* and *Yearly return (IRR)*).

The specific calculation of *Years till Breakeven*, in the following illustrated for the Base Case, depends on the time from the investment is undertaken (2019) till it starts (s_B) and then the ratio between the investment *I* and the yearly cash flows $(I+I*r_{2B}*(e_B-2019))/t_B$ as stipulated by the following formula $[s_A-2019+I/((I+I*r_{2B}(e_B-2019))/t_B)-1]$ which can be rewritten independent on investment size *I* as $[s_A-2019+1/((1+1*r_{2B}*(e_B-2019))/t_B)-1]]$. With the specific parameters drawn in our example this results in Base Case *Years till Breakeven* of 4.7 [=2020-2019+1/((1+1*8%*(2028-2019))/8)-1]. Using the same approach but with r_{3B}=29%, we get Best Case *Years till Breakeven* of 2.2[=2020-2019+1/((1+1*8%*(2028-2019))/8)-1]

Likelihood of scenario

The final parameter estimated was the *likelihoods* of the three cases. First we estimate the likelihood of the base case scenario p_2 with likelihoods drawn from $p_2 \in \{40\%, 45\%, \ldots, 70\%\}$. The remaining

1- p_2 are distributed between the worst and base case likelihoods p_1 and p_3 randomly in chunks of 5 percentage points drawn from $p_1 \in \{5\%, 10\%, \ldots, 55\%\}$ and $p_3 = 1 - p_2 - p_1$ which results in p_1 and p_3 with same underlying distributions. In this example we have $p_1 = 40\%$, $p_2 = 45\%$, $p_3 = 15\%$.

FIGURES

Figure 1: Distribution of $EARNINGS_{t-1}$. This figure plots the density of $EARNINGS_{t-1}$. The histogram is normalized so that the total area equals one. The horizontal axis reports $EARNINGS_{t-1}$ and the vertical axis reports probability density.

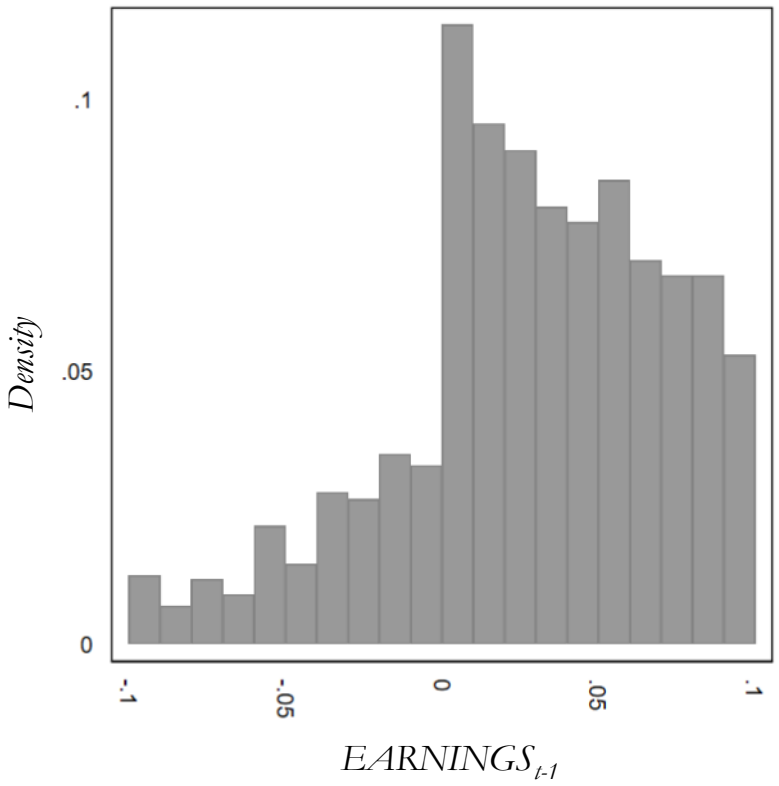


Figure 2: Losses and sensitivity of investment evaluations to expected returns. This figure plots the relationship between expected internal rate of return (IRR) and managers' ratings of investment attractiveness (ATTRACTIVENESS) for firms with negative earnings (loss firms) and positive earnings (profit firms) in year t − 1. The sample is restricted to firms with $EARNINGS_{t-1} \in [-0.10, 0.10]$. Points represent binned averages, and lines represent fitted linear relationships. Red (blue) dots and lines represent loss (profit) firms.

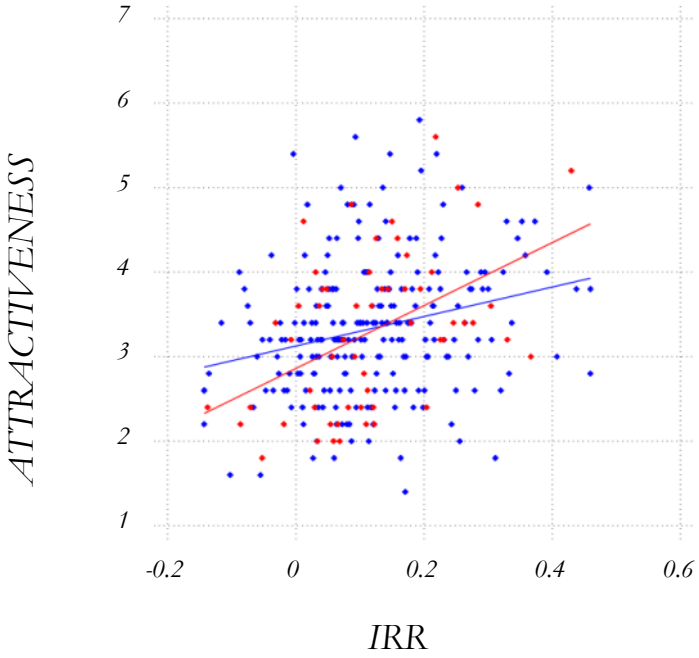
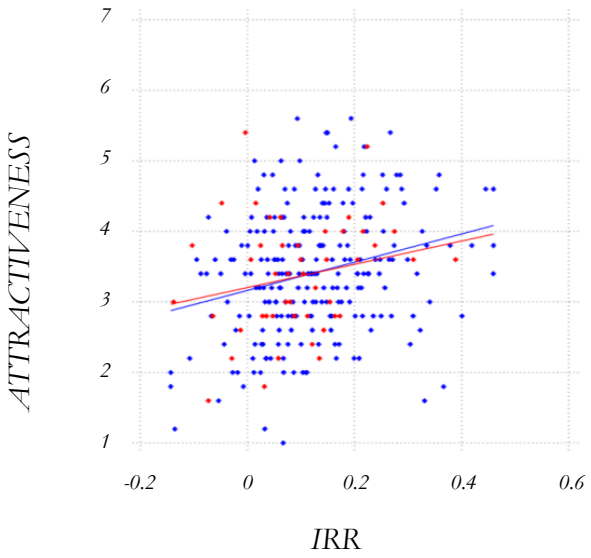


Figure 3: Placebo tests using past and future earnings. Panel A plots the relationship between expected IRR and ATTRACTIVENESS using earnings from year t − 2 to classify firms as loss or profit firms. Panel B repeats the analysis using earnings from year t. The sample in both panels is restricted to firms with earnings within ±10 percentage points of zero ($EARNINGS_{t-2} \in [-0.10, 0.10]$ in Panel A; $EARNINGS_t \in [-0.10, 0.10]$ in Panel B). Lines represent fitted relationships for loss and profit firms. Red (blue) dots and lines represent loss (profit) firms.

Panel A:



Panel B:

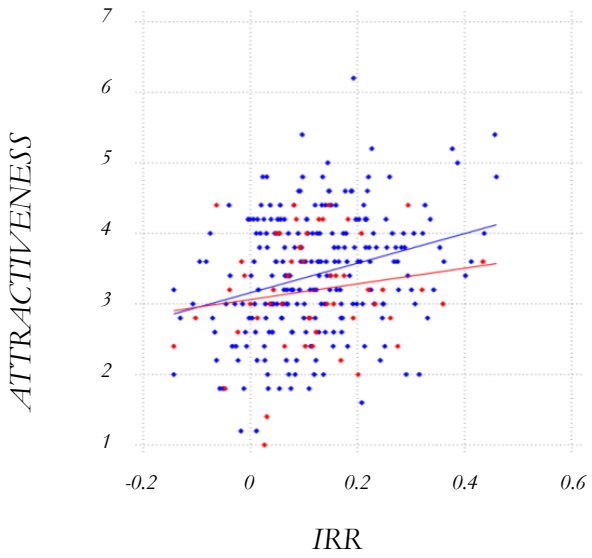


Figure 4: Local comparison of return sensitivity around the zero-earnings benchmark. This figure plots the local difference in investment attractiveness between high-IRR and low-IRR projects (ΔATTRACTIVENESS_{high IRR − low IRR}) against prior-year earnings ($EARNINGS_{t-1}$). The sample is restricted to firms with $EARNINGS_{t-1} \in [-0.10, 0.10]$. Binned scatter points are constructed using quantile-spaced bins, and lines represent local linear fits estimated separately on either side of the zero-earnings benchmark using regression-discontinuity visualization tools. The figure also reports the estimated discontinuity at the cutoff and the corresponding robust test statistic.

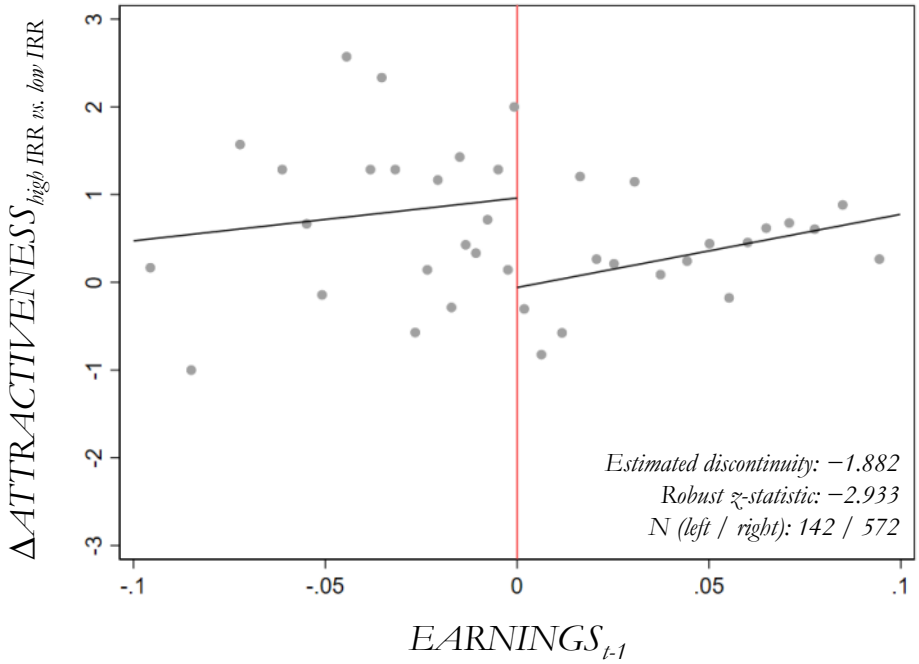
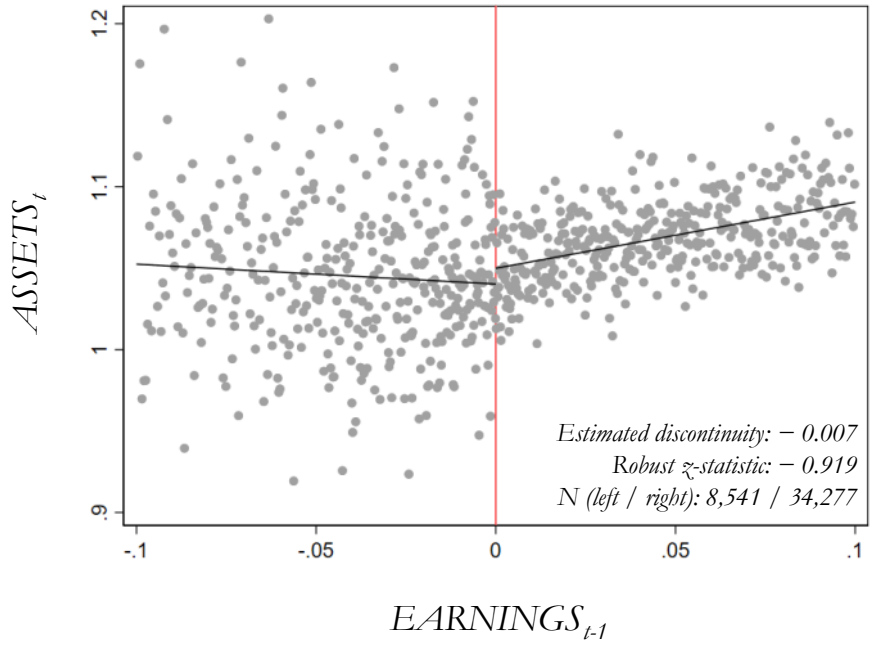
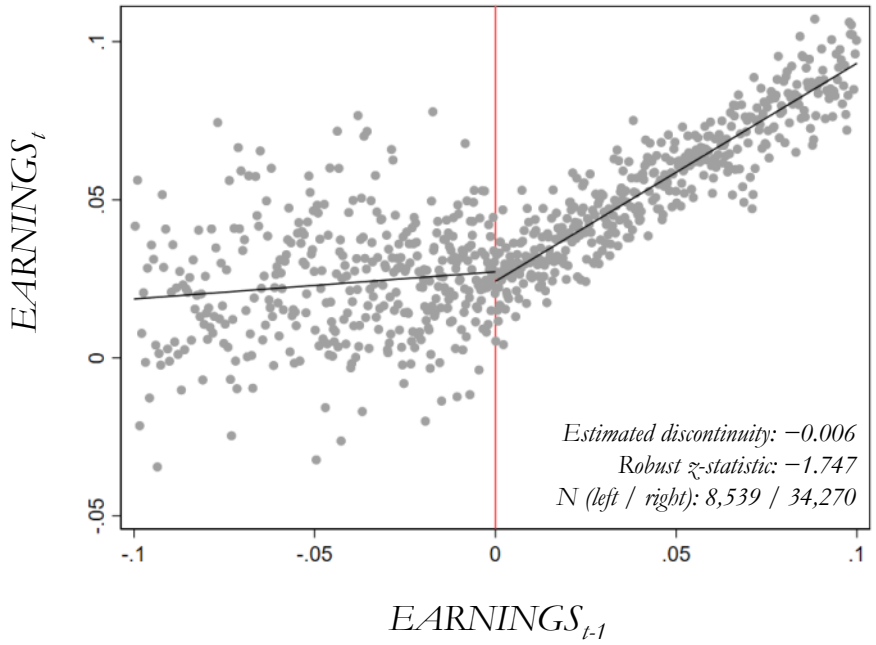


Figure 5: Local comparison of assets and earnings outcomes around zero earnings. This figure presents local polynomial estimates of current-year total assets ($ASSETS_t$) and earnings ($EARNINGS_t$), both scaled by prior-year assets, around the zero-earnings benchmark. Binned scatter points are constructed using quantile-spaced bins, and lines represent local linear fits estimated separately on either side of the zero-earnings benchmark using regression-discontinuity visualization tools. The figure also reports the estimated discontinuity at the cutoff and the corresponding robust test statistic.





TABLES

Table 1: Example of hypothetical investment opportunity shown to managers. This table presents an example of the investment vignette used in the field experiment. Managers evaluate a hypothetical project characterized by three scenarios (worst case, base case, best case), each defined by investment size, net gain or loss, internal rate of return (IRR), break-even time, and scenario likelihood. Values are scaled by firm size to ensure economically plausible stakes.

	V nqrs B`rd	***A`rd B`rd***	***Adrs B`rd***
Size of initial investment	DKK 1,700,000	DKK 1,700,000	DKK 1,700,000
Net loss (-) or gain (+) from the investment	DKK –1,105,000	DKK 1,200,000	DKK 4,000,000
Yearly return (IRR)	–24%	18%	51%
Time period with income from the investment	2020–2028	2020–2028	2020–2028
Number of years until break-even	n.a.	4.7	2.2
Likelihood of scenario	45%	40%	15%

Table 2: Descriptive statistics. This table reports descriptive statistics for the experimental parameters, expected IRR, investment attractiveness (ATTRACTIVENESS), and accounting variables, including $EARNINGS_{t-1}$. All accounting variables are scaled by total assets.

	N	mean	sd	p10	p25	p50	p75	p90
Investment Size (DKKm)	2720	3.99	8.76	0.23	0.58	1.45	3.60	8.75
Outcome Worst Case (DKKm)	2720	-2.38	5.44	-5.25	-2.04	-0.80	-0.31	-0.12
Outcome Base Case (DKKm)	2720	1.83	4.68	0.08	0.20	0.56	1.50	3.70
Outcome Best Case (DKKm)	2720	12.92	31.65	0.50	1.40	3.80	10.00	27.00
IRR Worst Case	2720	-0.24	0.16	-0.45	-0.32	-0.21	-0.12	-0.08
IRR Base Case	2720	0.10	0.04	0.05	0.07	0.10	0.13	0.15
IRR Best Case	2720	0.55	0.24	0.26	0.36	0.53	0.68	0.89
First Year with Income from	2720	2020.51	0.50	2020	2020	2021	2021	2021
Last Year with Income from	2720	2025.49	2.68	2022	2023	2025	2028	2029
Years till Break-Even Base Case	2720	4.57	1.65	2.50	3.30	4.50	5.80	6.80
Years till Break-Even Best Case	2720	2.05	0.85	1.10	1.40	2.00	2.50	3.20
Likelihood Worst Case	2720	23.02	13.03	5.00	10.00	20.00	30.00	40.00
Likelihood Base Case	2720	54.80	10.03	40.00	45.00	55.00	65.00	70.00
Likelihood Best Case	2720	22.18	13.13	5.00	10.00	20.00	30.00	40.00
Expected IRR	2720	0.12	0.12	-0.01	0.04	0.11	0.19	0.28
ATTRACTIVENESS	2720	3.40	1.78	1.00	2.00	4.00	5.00	6.00
$EARNINGS_{t-1}$	2720	0.10	0.25	-0.05	0.01	0.07	0.17	0.30
$EARNINGS_t$	2720	0.09	0.28	-0.06	0.01	0.07	0.16	0.29
$CURRENT\ ASSETS_{t-1}$	2720	0.73	0.26	0.31	0.57	0.82	0.94	0.98
$CURRENT\ ASSETS_t$	2720	0.73	0.26	0.31	0.57	0.82	0.94	0.98
$LIABILITIES_{t-1}$	2720	0.64	0.27	0.33	0.47	0.63	0.78	0.91
$LIABILITIES_t$	2720	0.64	0.29	0.31	0.45	0.62	0.77	0.91

The individual parameters in the vignette of the experimental (i.e. Investment Size through Likelihood Best Case) are defined and related as explained in Appendix 1.

Expected IRR is defined as IRR=IRR Worst Case*Likelihood Worst Case + IRR Base Case*Likelihood Base Case + IRR Best Case*Likelihood Best Case

ATTRACTIVENESS is managers' perception of the investment project attractiveness which was elicited using the question: "How attractive is this opportunity for your company?" to be answered on a Likert scale ranging from 1 ("not attractive at all") to 7 ("very attractive")

$EARNINGS_{t-1}$ is 2018 Earnings scaled by 2017 Total Assets. The denotation t-1 appears because the experiment was conducted in September 2019
$EARNINGS_t$ is 2019 Earnings scaled by 2018 Total Assets. The denotation t appears because the experiment was conducted in September 2019

$CURRENT\ ASSETS_{t-1}$ is 2018 Current Assets scaled by 2017 Total Assets. The denotation t-1 appears because the experiment was conducted in September 2019
$CURRENT\ ASSETS_t$ is 2019 Current Assets scaled by 2018 Total Assets. The denotation t appears because the experiment was conducted in September 2019

$LIABILITIES_{t-1}$ is 2018 Liabilities scaled by 2017 Total Assets. The denotation t-1 appears because the experiment was conducted in September 2019
$LIABILITIES_t$ is 2019 Liabilities scaled by 2018 Total Assets. The denotation t appears because the experiment was conducted in September 2019

Table 3: Correlations. This table presents pairwise correlations among experimental parameters, Expected IRR, ATTRACTIVENESS, and accounting variables.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
1 Investment Size (DKKm)																					
2 Outcome Worst Case (DKKm)	**-0.93**																				
3 Outcome Base Case (DKKm)	**0.87**	**-0.79**																			
4 Outcome Best Case (DKKm)	**0.85**	**-0.78**	**0.87**																		
5 IRR Worst Case	0.01	**0.11**	**0.08**	**0.09**																	
6 IRR Base Case	0.01	-0.01	**0.13**	0.00	**-0.08**																
7 IRR Best Case	-0.02	0.02	**-0.05**	**0.08**	**-0.18**	**0.1**															
8 First Year with Income from Invsmt.	0.02	-0.01	0.02	0.00	0.00	0.02	**-0.04**														
9 Last Year with Income from Invsmt.	0.02	-0.01	0.02	0.01	0.00	0.01	-0.03	**0.2**													
10 Years till Break-Even Base Case	0.02	-0.01	0.02	0.00	0.00	0.02	-0.04	**0.28**	**0.92**												
11 Years till Break-Even Best Case	0.02	-0.02	0.02	0.01	0.01	0.04	-0.03	**0.5**	**0.5**	**0.5**											
12 Likelihood Worst Case	-0.02	0.01	-0.02	-0.03	-0.01	0.02	-0.02	0.00	0.01	0.00	-0										
13 Likelihood Base Case	0.03	-0.03	0.02	0.03	-0.01	**-0.05**	0.00	0.00	0.01	0.01	-0	**-0.37**									
14 Likelihood Best Case	0.00	0.01	0.01	0.01	0.02	0.02	0.02	-0.01	-0.02	-0.01	0.01	**-0.71**	**-0.39**								
15 Expected IRR	0.01	**0.04**	**0.04**	**0.08**	**0.22**	**0.2**	**0.42**	-0.02	-0.02	-0.01	0.00	**-0.71**	**-0.06**	**0.76**							
16 ATTRACTIVENESS	0.00	0.02	0.02	0.02	**0.06**	**0.04**	**0.05**	0.01	-0.02	-0.01	0.00	**-0.14**	0.03	**0.12**	**0.16**						
17 $EARNINGS_{t-1}$	-0.01	0.01	-0.01	-0.01	-0.01	0.02	0.02	0.00	-0.01	0.00	-0.02	0.00	0.02	-0.02	0.01	-0.02					
18 $EARNINGS_t$	0.00	-0.01	0.01	0.00	-0.01	0.02	0.00	0.00	-0.02	-0.01	-0.02	-0.02	0.03	-0.01	0.00	0.01	**0.34**				
19 $CURRENT\ ASSETS_{t-1}$	**-0.11**	**0.09**	**-0.10**	**-0.10**	-0.03	0.00	-0.01	0.00	0.01	0.00	0.00	0.02	-0.01	-0.01	-0.03	-0.01	**0.10**	**0.05**			
20 $CURRENT\ ASSETS_t$	**-0.11**	**0.09**	**-0.10**	**-0.10**	-0.03	-0.01	-0.01	0.02	0.01	0.01	0.01	0.03	-0.01	-0.02	-0.03	-0.03	**0.09**	**0.07**	**0.93**		
21 $LIABILITIES_{t-1}$	**-0.15**	**0.14**	**-0.12**	**-0.11**	0.01	0.01	0.02	-0.02	**-0.04**	**-0.04**	0.02	**0.04**	**-0.05**	0.00	-0.01	-0.01	**-0.30**	**-0.22**	**-0.05**	-0.03	
22 $LIABILITIES_t$	**-0.15**	**0.15**	**-0.12**	**-0.11**	0.00	0.00	0.02	-0.01	-0.03	-0.03	0.03	0.03	**-0.04**	0.01	0.00	-0.01	**-0.27**	**-0.34**	-0.03	-0.02	**0.87**

Correlations significant at the 0.05 level are in bold

Table 4: Losses and sensitivity of investment evaluations to expected returns. Ordered logit regressions of *ATTRACTIVENESS* on expected *IRR*, an indicator for negative earnings in year t − 1, and their interaction. The sample includes firms with $EARNINGS_{t-1} \in [-0.10, 0.10]$. Specifications progressively control for liquidity ($CURRENT\ ASSETS_{t-1}$) and solvency ($LIABILITIES_{t-1}$), and their interactions with IRR.

	ATTRACTIVENESS		
	(1)	(2)	(3)
IRR	1.694***	1.692***	1.346
	(3.895)	(3.902)	(0.800)
NEGATIVE EARNINGS t-1	-0.269	-0.276^	-0.287^
	(-1.616)	(-1.649)	(-1.712)
IRR # NEGATIVE EARNINGS t-1	**2.236***	**2.239***	**2.356***
	(1.998)	**(1.995)**	**(2.094)**
CURRENT ASSETS t-1		-0.027	-0.183
		(-0.156)	(-0.802)
IRR # CURRENT ASSETS t-1			1.32
			(0.892)
LIABILITIES t-1		0.145	0.226
		(0.704)	(0.934)
IRR # LIABILITIES t-1			-0.847
			(-0.519)
Observations	1431	1431	1431

Notes: T values are provided in parentheses. ^ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 5. Main results with alternative intervals

Panel A: The same regressions as in column 3 of Table 4 (all controls included), estimated over progressively narrower earnings intervals around zero.

	ATTRACTIVENESS				
	(1)	(2)	(3)	(4)	(5)
EARNINGS $_{t-1}$ intervals framing the sample:	*[-0.10, 0.10]*	*[-0.08, 0.08]*	*[-0.06, 0.06]*	*[-0.04, 0.04]*	*[-0.02, 0.02]*
IRR	1.346	0.711	1.038	0.652	0.739
	(0.800)	(0.414)	(0.494)	(0.262)	(0.184)
NEGATIVE EARNINGS t-1	-0.287^	-0.278	-0.292	-0.126	-0.498
	(-1.712)	(-1.581)	(-1.514)	(-0.586)	(-1.635)
IRR # NEGATIVE EARNINGS t-1	**2.356***	**2.552***	**2.412^**	**1.553**	**4.416***
	(2.094)	**(2.216)**	**(1.892)**	**(1.097)**	**(2.091)**
CURRENT ASSETS t-1	-0.183	-0.3	-0.135	-0.061	0.3
	(-0.802)	(-1.239)	(-0.467)	(-0.182)	(0.689)
IRR # CURRENT ASSETS t-1	1.32	1.794	1.282	2.1	-1.572
	(0.892)	(1.163)	(0.676)	(0.932)	(-0.483)
LIABILITIES t-1	0.226	0.293	0.232	0.038	-0.221
	(0.934)	(1.143)	(0.648)	(0.086)	(-0.402)
IRR # LIABILITIES t-1	-0.847	-0.373	-0.679	-1.337	-0.939
	(-0.519)	(-0.223)	(-0.294)	(-0.468)	(-0.210)
Observations	1431	1231	1002	717	394

Notes: T values are provided in parentheses. ^ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Panel B: The same regressions as in column 3 of Table 4 (all controls included), estimated excluding observations progressively close to the zero-earnings benchmark (donut estimates), expanding the excluded window symmetrically around zero from 1%-åp..

	ATTRACTIVENESS				
	(1)	(2)	(3)	(4)	(5)
EARNINGS $_{t-1}$ intervals framing the sample:	*[-0.10, -0.10] excl. (-0.01, 0.01)*	*[-0.10, -0.10] excl. (-0.02, 0.02)*	*[-0.10, -0.10] excl. (-0.03, 0.03)*	*[-0.10, -0.10] excl. (-0.04, 0.04)*	*[-0.10, -0.10] excl. (-0.05, 0.05)*
IRR	1.069	1.283	1.186	0.993	1.21
	(0.592)	(0.711)	(0.703)	(0.526)	(0.695)
NEGATIVE EARNINGS t-1	-0.178	-0.23	-0.236	-0.253	-0.306
	(-0.979)	(-1.351)	(-1.314)	(-1.254)	(-1.525)
IRR # NEGATIVE EARNINGS t-1	**1.745**	**1.747**	**2.365***	**1.882**	**2.644^**
	(1.478)	**(1.540)**	**(2.014)**	**(1.370)**	**(1.925)**
CURRENT ASSETS t-1	-0.231	-0.205	-0.207	-0.343	-0.243
	(-0.927)	(-0.836)	(-0.898)	(-1.247)	(-1.033)
IRR # CURRENT ASSETS t-1	1.622	1.088	1.814	1.95	1.965
	(1.037)	(0.687)	(1.235)	(1.156)	(1.295)
LIABILITIES t-1	0.157	0.14	0.242	0.316	0.357
	(0.613)	(0.548)	(0.998)	(1.128)	(1.420)
IRR # LIABILITIES t-1	0.041	0.306	-1.131	-0.087	-1.335
	(0.024)	(0.179)	(-0.690)	(-0.050)	(-0.789)
Observations					

Notes: T values are provided in parentheses. ^ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 6: Placebo tests using alternative earnings years.
Panel A: Repeats the main analysis using earnings from year t − 2.

	ATTRACTIVENESS		
	(1)	(2)	(3)
IRR	1.954***	1.954***	-0.633
	(4.261)	(4.261)	(-0.361)
NEGATIVE EARNINGS t-2	0.034	0.019	0.015
	-0.199	-0.11	-0.085
IRR # NEGATIVE EARNINGS t-2	**-0.28**	**-0.281**	**-0.328**
	(-0.236)	**(-0.239)**	**(-0.270)**
CURRENT ASSETS t-2		-0.106	-0.417^
		(-0.624)	(-1.793)
IRR # CURRENT ASSETS t-2			2.627^
			(1.744)
LIABILITIES t-2		0.199	0.06
		(0.882)	(0.191)
IRR # LIABILITIES t-2			1.211
			(0.655)
Observations	1367	1367	1367

Notes: T values are provided in parentheses. ^ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 6, Panel B: Repeats the analysis using earnings from year t.

	ATTRACTIVENESS		
	(1)	(2)	(3)
IRR	2.135***	2.092***	3.235^
	(4.640)	(4.566)	(1.922)
NEGATIVE EARNINGS t	-0.109	-0.143	-0.144
	(-0.672)	(-0.868)	(-0.870)
IRR # NEGATIVE EARNINGS t	**-1.004**	**-0.98**	**-0.953**
	(-1.007)	**(-0.978)**	**(-0.930)**
CURRENT ASSETS t		-0.201	-0.042
		(-1.165)	(-0.173)
IRR # CURRENT ASSETS t			-1.298
			(-0.813)
LIABILITIES t		0.464*	0.508^
		(2.231)	(1.915)
IRR # LIABILITIES t			-0.37
			(-0.224)
Observations	1426	1426	1426

Notes: T values are provided in parentheses. ^ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 7: Decomposition of expected returns into scenario components.

This table reports ordered logit regressions analogous to Table 4, replacing expected IRR with the likelihood-weighted contributions from the worst-case, base-case, and best-case scenarios.

	ATTRACTIVENESS			
	(1)	(2)	(3)	(4)
LLH-weighted Worst Case IRR	1.847			0.661
	(0.483)			(0.164)
LLH-weighted Base Case IRR		1.472		0.94
		-0.163		-0.103
LLH-weighted Best Case IRR			1.666	1.579
			(0.750)	(0.674)
NEGATIVE EARNINGS t-1	0.257	0.196	-0.29	0.201
	(1.353)	(0.675)	(-1.450)	(0.512)
LLH-weighted Worst Case IRR # NEGATIVE EARNINGS t-1	**5.028^**			4.431
	(1.887)			(1.630)
LLH-weighted Worst Case IRR # CURRENT ASSETS t-1	2.901			3.008
	(0.818)			(0.785)
LLH-weighted Worst Case IRR # LIABILITIES t-1	-1.349			-0.861
	(-0.454)			(-0.278)
LLH-weighted Base Case IRR # NEGATIVE EARNINGS t-1		**-3.875**		-3.148
		(-0.814)		(-0.654)
LLH-weighted Base Case IRR # CURRENT ASSETS t-1		4.533		5.574
		(0.581)		(0.705)
LLH-weighted Base Case IRR # LIABILITIES t-1		1.158		1.51
		(0.112)		(0.145)
LLH-weighted Best Case IRR # NEGATIVE EARNINGS t-1			**2.407**	**1.715**
			(1.624)	**(1.132)**
LLH-weighted Best Case IRR # CURRENT ASSETS t-1			0.801	0.369
			(0.420)	(0.179)
LLH-weighted Best Case IRR # LIABILITIES t-1			-0.975	-0.746
			(-0.410)	(-0.297)
CURRENT ASSETS t-1	0.13	-0.311	-0.146	-0.197
	(0.492)	(-0.686)	(-0.550)	(-0.330)
LIABILITIES t-1	0.069	0.079	0.234	0.098
	(0.227)	(0.137)	(0.730)	(0.137)
Observations	1431	1431	1431	1431

Notes: T values are provided in parentheses. ^ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.