Risky Business: The Evolution of the Risk-Relevance of Earnings over Time

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ABSTRACT

In contrast to the well-documented decline in the value relevance of earnings, we show that earnings risk-relevance has significantly increased over the past 50 years. We find increases in risk-relevance for both bottom-line earnings and higher-level profit measures such as operating income. While we find that rising investments in intangibles are an important driver of these results, we also find that the risk-relevance of line items less affected by intangibles has significantly increased, suggesting that intangibles cannot exclusively explain risk-relevance trends. Industry-level tests reveal an upward trend also in the *systematic* risk-relevance of earnings. Moreover, we find an increase in the predictive power of earnings volatility for future return volatility, suggesting that the ability of earnings to provide *new* risk-relevant information has increased over time. These results are corroborated by out-of-sample machine learning analyses, which allow for non-linearities and interactions among line items. Our paper highlights risk relevance as an important attribute of earnings informativeness, especially in today's uncertain and intangible-driven business environment.

Keywords: Risk-Relevance, Earnings Informativeness

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1. Introduction

This paper examines how the risk-relevance of earnings has developed over the past 50 years. A substantial body of literature explores how the quality of earnings information and its relevance to investors have evolved over time. Several studies provide evidence consistent with a *decline* in the overall quality and relevance of accounting earnings (e.g., Collins et al., 1997). This decline has been attributed to the increasing reliance on intangible asset investments, shifts in the nature of publicly listed firms (Srivastava, 2014; 2023), and the growing complexity of business operations that has led to more frequent recognition of one-time special items (Donelson et al., 2011; Bushman et al., 2016). Other studies show that, while the relevance of bottom-line earnings has declined, other factors, particularly those that better reflect the complex business models of "new economy" firms, such as research and development (R&D) expenditures, intangible assets, and growth, have gained relevance, offsetting the decrease in the relevance of earnings (Barth et al., 2023).

The majority of studies that investigate how the properties and relevance of accounting information have evolved examine trends in the *value-relevance* of earnings, i.e., the extent to which earnings information is used by investors to assess firm value. Many arguments underlying the decline in the value relevance of bottom-line earnings emphasize the diminishing ability of current earnings to provide information about future performance, thereby reducing their usefulness to investors. Nevertheless, financial reporting serves multiple roles, including helping stakeholders assess firm risk. Standard setters, such as the FASB, explicitly emphasize this role of accounting, noting that it should inform users about the "amount, timing, and uncertainty of (the prospects for) future net cash inflows to the entity" (SFAC No. 8, FASB 2010).

Value-relevance and risk-relevance both capture distinct aspects of investor decision-making and, hence, may evolve differently. To illustrate, consider investments in R&D. Previous studies show that the value relevance of earnings has declined partly because R&D is expensed (Srivastava, 2014), which reduces reported earnings but does not reflect investors' pricing, who often view R&D as an asset (Joos and Plesko, 2005). This misalignment weakens the relation between earnings and stock prices. In contrast, as risk-relevance reflects the relation between earnings volatility and return volatility, R&D could possess risk-relevance as the variability of R&D expenditures is likely informative about the variability of future performance and stock prices.

Recent accounting literature has begun to emphasize the importance of financial reporting in providing investors with insights into firm risk (Penman, 2016; Penman and Zhang, 2020; 2021; Chang et al., 2021). This growing literature corroborates standard setters' views on the importance of risk information and highlights that accounting information conveys both performance- and risk-related insights to market participants. However, despite the increasing academic and regulatory attention to the risk-informing role of financial reporting, we know relatively little about its development and how factors that have contributed to the decline in the value-relevance of bottom-line earnings have affected (the development in) risk-relevance.

Our study provides comprehensive and systematic empirical evidence that the risk-relevance of earnings has increased considerably over time. Specifically, for every year, we regress the three-year volatility of firm stock returns on the volatility of quarterly earnings, scaled by total assets, over the same three-year period (i.e., 12 quarters). We then use this regression's R-squared as the annual earnings risk-relevance measure and show it increased from around 5-10 percent in 1975 to 35-40 percent in recent years. When we regress the R-squared on a linear time trend, we find that the trend variable is positive and statistically significant for both bottom-line earnings and operating income measures.

Next, we investigate how the risk-relevance of individual line items that comprise bottom-line earnings has developed over time. We find evidence of increasing risk-relevance for most line items, with steeper positive trends for line items capturing firms' investments in intangibles. However, we also document upward trends in the risk-relevance of earnings that exclude intangibles and for line items less affected by intangibles, such as cost of goods sold. Collectively, these findings suggest that while the growing prominence of intangible-intensive firms is an important driver of the increase in the risk-relevance of earnings, it only partially accounts for the overall trend. Moreover, they suggest that the current intangibles measurement model, which limits the usefulness of earnings for predicting future performance (e.g., Rajgopal et al., 2023; Rajgopal et al., 2024; Srivastava, 2023), does not lead to a decline in the risk-relevance of earnings.

To assess the extent to which earnings reflect current market perceptions of firm risk, we measure risk-relevance as the contemporaneous relation between earnings volatility and return volatility. However, this approach is inherently backward-looking and does not provide insight into whether this information is new to investors. Hence, to address this issue, we examine whether earnings volatility conveys forward-looking risk information. We find that the predictive power of earnings volatility for future return volatility has increased over time, and these results remain robust even after controlling for current return volatility. Overall, these results highlight the importance and validity of our primary findings and suggest that earnings can provide investors with incremental volatility-related information beyond what is captured in current return volatility.

While our primary analyses focus on a firm's total risk, which is largely driven by firm-specific risk, they do not shed light on the ability of earnings to inform investors about systematic risk factors. Hence, we also investigate how the *industry* risk-relevance of earnings has changed over time. We find that the industry risk-relevance of operating income, but not bottom-line income measures, has increased over time. Notwithstanding the strong increase in the industry risk-relevance of operating income, collectively, these results suggest that the over-time increase in industry risk-relevance is smaller than the corresponding increase in firm-specific risk-relevance. Moreover, different items drive the over-time increase in industry risk-relevance, with only a limited role for intangibles.

Our main tests rely on the R-squared obtained from Ordinary Least Squares (OLS) regressions to assess risk-relevance and are bound by the inherent limitations of linear modeling techniques. Hence, we extend our analyses and employ advanced machine learning methods that allow us to capture potential interdependencies and nonlinear relationships among the predictor variables. All methods corroborate our primary results by confirming the positive and significant trend in earnings risk-relevance.

Our study extends academic literature on the properties of accounting information and contributes to multiple research streams. Prior research has predominantly focused on the value-relevance of earnings and their ability to inform investors about firms' future cash flows and performance. We contribute to this literature by focusing on the risk-informing role of accounting and documenting the differential effects of accounting practices and economic trends on the risk-relevance relative to the value-relevance of accounting earnings. Specifically, we show that the risk-relevance of earnings, including bottom-line net income numbers, has significantly increased over time. Furthermore, we provide evidence of heterogeneous trends across various income statement line items, with R&D and SG&A expenses showing a notable increase in risk-relevance over time. In addition, we show how these results vary depending on the type of risk (firm-specific or industry risk). Collectively, these tests contribute to a growing stream of literature on the risk-informing role of accounting information (e.g., Penman, 2016; Heflin et al., 2024), which is important given that we know relatively little about how accounting can (differentially) inform about (different types of) risk (see, e.g., Barth, 2024).

Given the ongoing debate surrounding the accounting treatment of intangible assets, our findings are also of interest to financial statement preparers and users, as well as accounting standard setters. Previous literature has shown that intangible investments reduce the value-relevance of earnings (Srivastava, 2014) and has claimed the end of accounting (Lev and Gu, 2016). Our results suggest that the current measurement model that immediately expenses intangible investments and reduces the value-relevance of earnings does not harm their risk-relevance. While we do not investigate whether alternative accounting treatments would further enhance risk-relevance, our results do show that earnings that include intangible expenses exhibit greater upward trends in risk-relevance than earnings that exclude such expenses. Given that one of the primary objectives of financial reporting is to inform users about the "uncertainty of the prospects for future cash inflows" (SFAC No. 8, FASB 2010), our findings highlight the need to consider both value-relevance and risk-relevance in evaluating accounting practices and designing accounting standards.

Notwithstanding the unique impact of intangibles, we find increases in the risk-relevance of earnings line items less affected by intangibles and for earnings that exclude R&D and SG&A. These results provide important insights to the literature as they point towards a broader, more general increase in the risk-relevance of accounting that, moreover, cannot be explained by (trends in) other major factors identified in prior literature, such as the increase in one-time item recognition (Donelson et al., 2011), shifts in the accrual-cash flow correlation (Bushman et al., 2016), declines in revenue-expense matching (Dichev and Tang, 2008), increases in earnings volatility (Srivastava, 2014; Dichev and Tang, 2009), or new cohorts of firms listing on the stock market (Srivastava, 2014).

The remainder of the paper is structured as follows. Section 2 provides an overview of related literature. Section 3 describes our sample selection process and research design. Section 4 presents and discusses our findings, and Section 5 concludes.

2. Related literature

One of the primary objectives of financial reporting is to provide information that investors, creditors, and other stakeholders can use to assess a firm's performance, financial position, and prospects. Hence, not surprisingly, a large literature within accounting focuses on the value-relevance of accounting information, with Ball and Brown (1968) being among the first to highlight the fundamental link between accounting earnings and stock prices.

The evolution of the value-relevance of accounting information has been the subject of extensive research, with many studies documenting significant temporal changes in how accounting information relates to firm value. Collins et al. (1997) provide early evidence of a decrease in the value-relevance of earnings in the second half of the 20th century. However, they also note an offsetting increase in the value-relevance of book values over the same period, suggesting a shift in the source of value-relevant information rather than an overall decline. Francis and Schipper (1999) corroborate these results, while Brown et al. (1999) also document a shift from earnings to book values. However, they find that the overall value-relevance of accounting information has declined after controlling for scale effects. Comparing the usefulness of accounting against other information, Lev and Zarowin (1999) find that the overall relevance of accounting has been deteriorating. More recent studies (see, e.g., Balachandran and Mohanram, 2011) generally confirm the results from the early literature. In addition, Lev and Gu (2016) investigate the combined value-relevance of a broad set of accounting items, including earnings and book values, and find that the combined value-relevance of these items has declined considerably. More recently, Barth et al. (2023) argue that while the value-relevance of bottom-line earnings may have decreased over time, the overall relevance of accounting information has not declined when considering other financial statement items that better reflect the business models of "new economy" firms.

A related stream of research seeks to explain *why* the relevance of accounting, and particularly earnings, has changed over time. This literature proposes that the rise of “new economy” firms that invest heavily in intangibles is a major contributor to the decline in the value-relevance of earnings. Lev and Zarowin (1999) attribute the decline in value-relevance to the increasing rate of change in the business environment and argue that investments in intangibles are an important driver of change. Similarly, Srivastava (2014) finds that earnings quality has declined over time as new cohorts of increasingly intangible-intensive firms have entered the stock market. Other studies focus on (outcomes of) the accounting process to investigate reasons for the decline in earnings value-relevance. Consistent with the increasing importance of intangibles, Dichev and Tang (2008) and Donelson et al. (2011) find an over-time decline in the degree of matching between revenues and expenses, which Dichev and Tang (2009) argue, among other factors, contributes to the over-time increase (decrease) in earnings volatility (earnings predictability).[1]

[1] He and Shan (2016) extend the examination of revenue-expense matching to an international context and provide cross-country evidence that the decline in matching is a global phenomenon.

Several studies focus on non-intangible investment reasons for a decline in the quality and relevance of earnings. For example, Bushman et al. (2016) find an over-time reduction in the negative correlation between accruals and cash flows, which they find cannot be explained by rising investments in intangibles. Instead, they find that increases in the recognition of one-time non-operating items explain this trend, which Donelson et al. (2011) attribute to the frequency of economic events that give rise to the recognition of these items. Interestingly, Christensen et al. (2023) find that, after declining in the 1990s, accrual quality has improved since the 2000s. They demonstrate that this trend cannot be attributed to intangibles or changes in the recognition of non-operating items but instead can be explained by recent decreases in cash flow volatility.

Although value-relevance has been a central focus of accounting research, it captures only one dimension of accounting's decision-usefulness. The FASB conceptual framework emphasizes another important property of accounting information: its ability to convey information about the *uncertainty* of future net cash inflows (i.e., risk-relevance) (SFAC No. 8, FASB 2010). While value-relevance and risk-relevance are interconnected through their link to stock prices, value-relevance emphasizes the directional relation between earnings levels and stock prices or returns. In contrast, risk-relevance focuses on variability and the relation between earnings and return volatility, the latter being how risk manifests. This distinction matters because accounting numbers can signal risk through their variability regardless of whether they exhibit a clear directional relation with firm value. For example, the immediate expensing of R&D investments weakens the relation between earnings levels and stock prices, thereby reducing value-relevance. However, the volatility in R&D expenditures can still inform investors about underlying business risks and the uncertainty and variability of future economic outcomes.

The accounting literature has recently started to examine the importance of financial reporting in conveying information on firm risk to investors (Penman, 2016; Penman and Zhang, 2020; 2021). This research stream defines risk-relevance as the degree to which accounting constructs convey information about firms' equity risk (Baginski and Wahlen, 2003; Hann et al., 2007; Hodder et al., 2006; Heflin et al., 2024). Building on early evidence documenting associations between earnings volatility and contemporaneous and future equity risk (Beaver et al., 1970; Eskew, 1979), subsequent studies have explored how different earnings components contribute to risk-relevance (e.g., Heflin et al., 2024). Moreover, research has begun to focus on the dynamic nature of risk-relevance. For example, Dou et al. (2014) document how the risk-relevance of mortgage-related assets increased over the years leading up to the 2007-2008 financial crisis, suggesting that the risk-informing role of accounting evolves with economic conditions.

Investigating trends in the risk-relevance of accounting earnings is important as it can shed light on *how* and *why* the ability of accounting information to inform about risk has developed over time. Regarding *how*, our tests can inform not only about risk-relevance trends of overall earnings, but a detailed analysis of income statement line items can further uncover shifts in the relative importance of specific earnings components in conveying risk information. Regarding *why*, our analysis can shed light on which factors drive trends in risk-relevance and provide insight into how these factors differentially affect risk-relevance relative to, for example, value-relevance. As the ability of accounting to inform about the variability of future cash inflows (i.e., risk) is an important objective of financial reporting, such insights are not only useful to investors but can also inform future standard-setting decisions. Indeed, heterogeneity in trends across different properties of accounting documented in earlier studies highlights the need for a better understanding of how earnings and its components contribute to the decision-usefulness of accounting information in capital markets. Insights into the distinct development of risk-relevance are of particular importance given the debate about the declined informativeness and value-relevance of bottom-line earnings.

3. Research design

3.1 Sample selection

Table 1, Panel A summarizes our sample selection procedures. Specifically, we begin by selecting all firm-years with available data in the Compustat-CRSP merged database for the period 1975-2023, leading to an initial sample of 294,706 firm-year observations. Following previous literature (e.g., Srivastava, 2014), we drop observations in the financial industry (Fama-French industries #44-#47) and observations with a Fama-French #48 industry code. From the remaining 218,840 firm-year observations, we eliminate observations with assets equal to or less than zero (697 firm-year observations) and observations with a missing standard deviation of returns (15,097 firm-year observations). After truncating the standard deviation of returns at the 1 percent level by fiscal year, we have a final sample of 199,032 firm-year observations.[2] Table 1, Panel B, presents the industry composition of our final sample. Pharmaceuticals and Business Services are the most represented, with 7 and 11.5 percent of the observations, respectively. Few firms are in the Tobacco, Shipbuilding, Defense, and Coal industry.

[Table 1 here]

3.2 Variables

Consistent with extant research, we focus on a firm's total risk to infer the degree to which earnings are risk-relevant (e.g., Heflin et al., 2024). Specifically, we calculate the standard deviation of

[2] We find similar results if we winsorize the standard deviation of returns or if we neither truncate nor winsorize the return standard deviation.

returns using daily stock returns over a three-year period that ends three months after the fiscal year-end (*STDRET*). We end the return window three months after the fiscal year-end to align with the window that we use to calculate the standard deviation of accounting measures and to ensure that the financial statement information is publicly available. We require each observation to have at least 252 trading days with available data to calculate the return standard deviation. In robustness tests, we also measure the standard deviation of returns based on monthly data (requiring at least 12 months of return data) or weekly data (requiring at least 52 trading weeks with return data).

In line with how we measure return volatility, we use a three-year (12-quarter period) to estimate variation in accounting earnings. We employ three different earnings measures: (i) net income (*NI*: NIQ_t/ATQ_{t-1}), (ii) income before extraordinary items (*IB*: IBQ_t/ATQ_{t-1}), and (iii) operating income (*OPER*: $OIADPQ_t/ATQ_{t-1}$). We require a minimum of six quarterly observations in the estimation of earnings volatility. In subsequent analyses, we also investigate the risk-relevance of line items and estimate volatility in sales (*ATO*: $SALEQ_t/ATQ_{t-1}$), cost of goods sold (*COGS*: $COGSQ_t/ATQ_{t-1}$), depreciation expense (*DEP*: DPQ_t/ATQ_{t-1}), research and development expense (*R&D*: $\max(0, XRDQ_t) / ATQ_{t-1}$), selling, general, and administrative expense (*SG&A*: $\max(0, XSGAQ_t)/ATQ_{t-1}$), tax expense (*TAX*: $TXTQ_t/ATQ_{t-1}$), special items (*SPEC*: $SPIQ_t/ATQ_{t-1}$), and non-operating income (*NONOP*: $NOPIQ_t/ATQ_{t-1}$). Next to estimating the standard deviation of total SG&A, we also calculate the standard deviation of SG&A adjusted for R&D expenses (*MainSG&A*: $(\max(0, XSGAQ_t) - \max(0, XRDQ_t))/ATQ_{t-1}$). We scale each of these measures by lagged total assets to be consistent with our calculation of earnings volatility.[3]

We follow a two-step procedure to infer the extent to which the risk-relevance of accounting information has changed over time. First, we estimate annual cross-sectional regressions of the

[3] We truncate these measures at the top and bottom one percent by fiscal year prior to measuring the standard deviation.

standard deviation of stock returns on the standard deviation of the accounting measures (*STDACC* in equation (1) below) described above. Following the literature on the value-relevance of accounting, we use the R-squared of the annual cross-sectional regressions as our measure of risk-relevance (*Risk-Relevance - R^2*). In a second step, we regress *Risk-Relevance - R^2* on a time trend (*TIME*), which ranges from 0 in 1975 to 48 in 2023, to investigate whether the risk-relevance of accounting information has changed over time:

$$STDRET_{i,t} = \beta_0 + \beta_1 STDACC_{i,t} + \varepsilon_{i,t} \tag{1}$$

$$Risk\text{-}Relevance - R^2_t = \beta_0 + \beta_1 TIME_t + \varepsilon_t \tag{2}$$

Table 1, Panel C, presents the descriptive statistics. The mean *STDRET* is 3.8 percent. Among earnings measures, *OPER* exhibits the lowest standard deviation at 2.1 percent, while *NI* shows the highest at 2.5 percent, consistent with the latter incorporating more volatile one-time items. Regarding the line items, *ATO* and *COGS* exhibit the highest standard deviations, reflecting their larger underlying magnitudes, while *DEP* shows the lowest, reflecting the stable nature of depreciation expenses for firms with stable assets.[4]

4. Results

4.1 Main results

Figures 1A - 1C and Table 2 show evidence of a clear upward trend in risk-relevance for each of the three earnings measures that we investigate. The annual R-squared for *NI* rises from 11-19 percent in the period 1975-1979 to 33-40 percent in the period 2020-2023. Similarly, *IB* shows a correspondingly strong increase from 7-13 percent to 34-41 percent over the same period. Starting

[4] Note that these statistics represent quarterly data. Hence, deviations are smaller than those typically observed on equivalent measures calculated using annual data.

from a lower base of 1–7 percent during the period 1975–1979, *OPER* exhibits the largest increase in risk-relevance among the three earnings measures, reaching an R-squared of 29–34 percent in the period 2020–2023.

[Figures 1A-1D here]

Figures 1A–1C illustrate that the increases in risk-relevance are not monotonic but instead follow a waved pattern. Figure 1D plots the development in the annual risk-relevance of each of the three earnings measures and includes indicators for economic downturns (booms) in red (green). For all income metrics, the plots show considerable drops in risk-relevance during and following crisis periods, such as the 2007-2008 financial crisis and the COVID-19 pandemic.[5] However, these drops are less pronounced for net income and income before extraordinary items, potentially because the one-time items included in these metrics are increasingly risk-relevant in crisis periods.[6] While not our main focus, these visualizations suggest that the risk-relevance of earnings is not static but evolves with economic conditions.

Nevertheless, as shown in Table 2, Panel B, for each of the three regressions, we find strong positive and statistically significant coefficients on a linear time trend (*TIME*), which range from 0.0037 for *NI* to 0.0045 and 0.0049 for *IB* and *OPER*, respectively. Moreover, the R-squared of these regressions ranges from 0.56 to 0.65, indicating that a linear time trend explains much of the variation in risk-relevance over time. Collectively, these results document an economically strong increase in the risk-relevance of earnings.

[Table 2 here]

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[5] Note that risk-relevance can be lower for multiple years after a crisis event as we estimate it over a three-year period. Hence, risk-relevance estimates will be affected by a crisis period up to two years after.

[6] Additional analyses (untabulated) confirm that line items such as special items and non-operating items are generally more risk-relevant during and following crisis periods.

Brown et al. (1999) show that changes in R-squared can be driven by changes in scale. Note, however, that their criticism of R-squared applies to (unscaled) levels regressions, whereas our analysis is based on standard deviations of *returns* and *return on assets*, both of which are scale-invariant. Nevertheless, because the scalar of the standard deviation of returns (*market capitalization*) differs from that of earnings (*total assets*), we control for the annual coefficient of variation in market capitalization and total assets to ensure that our results are not driven by differences in their relative changes. We continue to find evidence of a positive and significant upward trend in risk-relevance for each of the three earnings measures (untabulated) even after including these controls. In addition, previous literature has also shown that earnings volatility itself has changed considerably over time (e.g., Srivastava, 2014). Hence, to mitigate concerns that our results merely reflect changes in earnings volatility over time, we control for the average earnings volatility in a year. As reported in Table 2, the coefficient of *TIME* remains positive and significant even after including this control variable.[7]

We next investigate how the risk-relevance of key income statement line items has changed over time. Prior literature on the value-relevance of accounting information has shown that there have been major changes in the value-relevance of various line items. For example, Barth et al. (2023) show that even though the value-relevance of bottom-line earnings has declined, the value-relevance of other items, such as intangibles and growth-related constructs, has increased.

[Table 3 here]

The results of the line-item analysis are reported in Table 3. Except for *ATO* and *DEP*, we find that the risk-relevance of each of the line items has increased over time. The increase in risk-relevance is lowest for *TAX*, with an estimated increase in the R-squared of 0.05 percent per year.

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[7] We also find that our results are robust to controlling for the average return volatility in a year (untabulated).

In contrast, we find strong increases of 0.30 (0.32) percent to 0.52 percent per year for *SG&A* (*MainSG&A*) and *R&D*, respectively.[8] However, we also find a rise in the risk-relevance of accounting measures that are less affected by intangible investments. For example, the coefficient on *TIME* in the regression with the risk-relevance of *COGS* as a dependent variable is positive and significant and, in terms of economic significance, is consistent with a 0.12 percent increase in *Risk-Relevance* - R^2 per year. This result suggests that, at least in terms of risk-relevance, traditional accounting metrics are not losing relevance in today's intangible-driven economy. While the coefficients on *TIME* in the *SPEC* and *NONOP* regressions are positive (0.15 and 0.10, respectively) and significant, they are comparable in magnitude to the coefficient on *TIME* in the regression with *COGS* and smaller than the coefficients in the regressions with *SG&A* and *R&D*. Thus, despite the prior evidence of significant increases in the recognition of non-recurring items over time (Donelson et al., 2011; Bushman et al., 2016; He and Shan, 2016), our results suggest that non-recurring items are not the primary driver of the increase in earnings' risk-relevance. Notably, we find that the risk-relevance of most line items increases, with only the risk-relevance of asset turnover (*ATO*) decreasing over time.

4.2 The role of intangibles

Our line-item analysis shows that the increase in risk-relevance is particularly pronounced for R&D and (main) SG&A, relative to the other income statement components, and suggests that intangibles play an important role in explaining changes in the risk-relevance of earnings over time. To explore this issue further, we investigate trends in the risk-relevance of pre-R&D and pre-

[8] As data on quarterly R&D expenses are missing for the years prior to 1989, tests involving *R&D* and *MainSG&A*, which require data on quarterly R&D, are only estimated from 1989 to 2023.

SG&A earnings, which add back to the income numbers, a firm's R&D and SG&A expenses, respectively.

[Table 4 here]

Table 4, Panel A, reports results based on Pre-R&D earnings. For comparison, we also include results for the non-adjusted income numbers.[9] We find that risk-relevance trends are considerably weaker for each of the income measures when earnings are adjusted for R&D expenses. Specifically, the risk-relevance trend roughly halves for *NI* and *IB*, whereas it decreases by two-thirds for *OPER*. Table 4, Panel B, and Panel C show results based on removing SG&A and main SG&A, respectively. Despite evidence that the increasing trend in risk-relevance is weaker for earnings that exclude (main) SG&A, the results are not as pronounced as those for earnings that exclude R&D. In the analyses with *NI* or *IB*, we find only a minor drop in the coefficient on *TIME* after excluding SG&A or main SG&A. Excluding (Main) SG&A leads to a stronger reduction in risk-relevance trends for *OPER*, where we document a drop in the coefficient on *TIME* from 0.0049 for unadjusted operating profit to 0.0011 for operating profit that excludes SG&A expense.

An alternative approach to investigate the importance of intangibles, is to partition the sample based on R&D and (main) SG&A intensity and to investigate whether risk-relevance trends are different for high- versus low-intensity firms. To measure R&D and (main) SG&A intensity, we use the average quarterly R&D and (main) SG&A intensity over the same 12 quarters that we use to estimate earnings volatility. The results are reported in Table 4, Panels D-F.

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[9] Because of missing quarterly data on R&D expenses, the regressions with *R&D* and *MainSG&A* have only 35 observations for the period 1989-2023. To properly compare the impact of using Pre-R&D and Pre-MainSG&A earnings, we re-estimate the regressions originally reported in Table 2, Panel B, on this restricted period. Hence, while the "*Original*" column in Panel B exactly matches with the coefficients and T-statistics in Table 2, Panel B, this is not the case in Panels A and C, in which the coefficients and T-statistics are re-estimated on this restricted sample.

We find strong evidence that the increasing trend in risk-relevance of earnings is more pronounced for firms with high R&D intensity. For all three metrics, we find that trends in risk-relevance are at least double in magnitude for firms with high R&D investments. These results cannot be attributed to these firms starting with a low level of risk-relevance as the intercept, which captures risk-relevance in 1989, is generally of a similar magnitude or greater for high R&D intensity firms. Regarding operating profits, we find no significant increase in risk-relevance for low R&D firms and a very strong increase in risk-relevance for high R&D firms.

In line with the results in Panel B and C, the results based on SG&A intensity are weaker, especially when looking at total SG&A. For total SG&A, we find that the coefficient on *TIME* is higher in the high SG&A intensity subsamples for all three earnings measures. However, the differences are small relative to the low SG&A intensity subsamples. Results for main SG&A are more in line with the R&D results and indicate that trends in risk-relevance are more pronounced for firms with high main SG&A intensity, with a coefficient on *TIME* that is roughly twice as large in the high-intensity subsamples. Overall, these results support the line-item analyses reported in Table 3 and confirm the important role of intangibles in explaining risk-relevance trends.[10]

4.3 Future risk-relevance

Although the contemporaneous relation between earnings volatility and return volatility informs about whether accounting captures risk-relevant information, it does not provide evidence on whether this information is new to investors. Hence, we also investigate how the *future* risk-

[10] In untabulated tests, we also investigate how trends in earnings risk-relevance change when we add the annual level of *R&D* and *SG&A* spending to the regressions reported in Table 2. In line with the importance of investments in intangibles, we find that the significance of *TIME* is considerably lower for all three earnings measures and even disappears in the regressions with *NI*.

relevance of accounting information has developed over time. In our primary analyses, we align the measurement window of earnings and return volatility and measure both over the same three-year window. In this section, we replace contemporaneous return volatility with the year-ahead volatility in returns estimated over the one-year period that begins in the fourth month of fiscal year *t+1* and ends three months after the year *t+1* fiscal year-end. We use raw year-ahead return volatility (*STDRET t+1*) and a return volatility measure that controls for the contemporaneous (three-year) return volatility (*STDRET t+1 – Residual*). Specifically, *STDRET t+1 – Residual* is the residual of an annual regression of *STDRET t+1* on the contemporaneous three-year *STDRET*, which we use in our primary analyses. This measure sets a high hurdle for accounting information to possess future risk-relevance, requiring it to predict future return volatility incrementally to the information captured by contemporaneous return volatility.

[Table 5 here]

[Table 6 here]

Table 5 reports results regarding the future risk-relevance of our three earnings measures, whereas Table 6 replicates the line-item analyses of Table 3 but focuses on their future risk-relevance. The results in both tables largely align with our main findings based on contemporaneous return volatility. Specifically, using *STDRET t+1*, we find trends of increasing risk-relevance of earnings and most of the income statement line items, with the results again being strongest for intangibles, such as *R&D* and (*Main*)*SG&A*. With some exceptions, results using *STDRET t+1 - Residual* are also comparable to those reported earlier, and we continue to find increases in future risk-relevance for two out of the three earnings measures and most of the income statement line items, with again particularly pronounced increases for items capturing intangibles.

Note that the average R-squared and, by extension, the average time trend in risk-relevance are much lower as we now investigate the informativeness for future return volatility incremental to the information in current return volatility. However, the magnitudes of the over-time increase in future risk-relevance are economically meaningful. Specifically, the coefficient of 0.0002 on *TIME* indicates that over the 49-year period, the R-squared increases by about 1 percent (49 x 0.0002 = 0.98). This suggests that future risk-relevance doubles over the sample period when we compare it to the starting levels of future risk-relevance (as captured by the regression intercepts, which are 0.011 and 0.0084 for *NI* and *OPER*, respectively). Overall, these results provide strong evidence that accounting information provides *new* risk-relevant information to investors and increasingly does so over time.

4.4 Industry risk-relevance

Our analyses thus far have focused on the ability of accounting information to inform about a firm's total risk, which is largely driven by firm-specific risk factors. However, our tests do not address whether the informativeness of accounting information for broader, *systematic* risks that affect entire markets or industries has changed. Hence, in this section, we investigate changes in the ability of accounting to inform about systematic risk factors. To this end, we investigate whether the volatility in industry-wide earnings and accounting measures is informative about industry return volatility. We calculate industry returns as the value-weighted average return of all firms within a Fama-French 48 industry. Similarly, we calculate industry earnings (and other accounting constructs) as the lagged asset-weighted average earnings (accounting construct) of all firms within a Fama-French 48 industry. To ensure that the quarterly information needed to aggregate firm-level information to the industry level aligns in time, we restrict the sample to firms with a fiscal year-end in March, June, September, or December and calculate industry-level measures for each calendar quarter. Consistent with our primary analyses, we then estimate a regression of industry-wide return volatility on accounting measure volatility.[11]

[Table 7 here]

Table 7 reports the results of the industry-level analyses. In contrast to our firm-level results, industry risk-relevance has increased over time only for *OPER*. For both *NI* and *IB*, we find that the starting level of industry risk-relevance is much higher than that of firm-level risk-relevance. However, we document no further increase in risk-relevance over time. Our line items analysis shows results that are consistent with this finding. While we find that, relative to our firm-level analyses, industry-level taxes, special items, and non-operating items are highly risk-relevant, there is no further increase in the industry risk-relevance of these items over time. Results regarding the other line items also reveal differences relative to our firm-level analyses. For example, we find that the negative trend in the risk-relevance of *ATO* is absent at the industry level. Notably, although our firm-level analyses show a very strong increase in the risk-relevance of intangible asset-related items, the importance of intangibles at the industry level is much smaller. Despite documenting evidence of an increase in the industry risk-relevance of *R&D*, we find that the over-time increase is much smaller. Moreover, we do not find that *SG&A* or *MainSG&A* exhibit an increase in industry risk-relevance over time.

Overall, our analyses at the industry level provide evidence that the ability of accounting to inform about systematic risk factors has increased over time. However, compared to our firm-level results, increases in industry risk-relevance are smaller, limited to operating income only, and driven by different line items. Importantly, while our firm-level tests show significant increases in

[11] To obtain valid estimates of R-squared, for every year, we require at least 10 industries with sufficient data. Hence, in some of our analyses, we drop 1975 as less than 10 industry observations are available.

risk-relevance for intangible asset-related items, these effects are markedly weaker at the industry level, suggesting that these items primarily reveal information about firm-specific risks rather than industry-wide systematic risks.

4.5 Risk-relevance of accruals and cash flows

In earlier tests, we decomposed earnings into different line items and examined the evolution of their risk-relevance. However, another way to decompose earnings is to separate the cash flow and accrual components. While some line items are likely mostly driven by accruals (depreciation, special items), others may be driven mostly by cash flows (e.g., COGS, R&D expense). Bushman et al. (2016) show that the negative correlation between accruals and cash flows has declined over time, which indicates that the role of accruals in earnings smoothing has changed. Hence, we also investigate whether risk-relevance trends differ for the accrual and cash flow components of earnings. This analysis should shed light on whether our results on trends in the risk-relevance of earnings can be explained by over-time changes in the correlation between accruals and cash flows, or by a changed role of accruals. Regarding the former, if changes in the accrual-cash flow correlation drive risk-relevance increases, we should not observe strong increases in either accruals or cash flows individually. Regarding the latter, if the entire increase in earnings' risk-relevance is driven by a changing role of accruals, we should not observe over-time increases in the risk-relevance of cash flows.

[Table 8 here]

As cash flow data are available from 1989 onwards, we conduct this analysis on data from 1989-2023. Table 8 presents our findings. We report results based on cash flow from operating activities (*CFO*), total accruals (*ACC - NI* and *ACC - IB*), and operating accruals (*ACC - OPER*).

Our analysis reveals that both accruals and cash flows exhibit significant increases in their risk-relevance over time. While the increase in the risk-relevance of *ACC - OPER* is slightly smaller than that of *CFO*, generally, we do not find notable differences in risk-relevance trends across the two components. Thus, our findings cannot be exclusively attributed to potential changes in the correlation between accruals and cash flows or to their relative roles within earnings.

4.6 Machine learning analysis of earnings risk-relevance trends

Thus far, we have measured risk-relevance as the R-squared from linear OLS regressions. However, prior literature on the value-relevance of accounting information finds that declines in value-relevance are less pronounced when allowing for non-linearities and interactions among earnings components. While we find evidence of increases in risk-relevance even with linear OLS models, we supplement our OLS-based tests with machine learning methods. Barth et al. (2023) use Classification and Regression Trees (CART), a nonparametric machine learning method, to investigate the evolution in the value-relevance of accounting information. Their findings demonstrate that machine learning methods can capture nuances in the value-relevance trends that were not apparent in traditional linear analyses. Along this line, Chen et al. (2022) use another popular decision tree method, stochastic gradient boosting, to predict one-year-ahead earnings changes and further highlight the ability of machine learning methods to capture complex predictor interactions.

We investigate risk-relevance trends using both Random Forests (Breiman, 2001) and a variant of Gradient Tree Boosting (Chen and Guestrin, 2016), eXtreme Gradient Boosting (XGBoost). These approaches provide additional insights into the evolution of earnings risk-relevance by capturing potential interdependencies and nonlinear relationships and by employing ensemble learning methods that enhance out-of-sample prediction accuracy.[12]

We expand upon our primary analysis and model the relation between return volatility and the volatility of various earnings components, including sales, gross margin, depreciation, (Main) SG&A, tax, special items, and non-operating income. In line with Barth et al. (2023), we include ten industry indicators based on the Fama–French classification. To reduce overfitting, in which a model becomes too closely fitted to the training data and performs poorly on unseen data, we follow standard procedures that ensure robust out-of-sample model performance. Specifically, we use a hyperparameter tuning process that systematically tests different model parameter combinations to find the configuration that yields the best predictive performance.[13] To ensure robustness and comparability across models, we apply 10-fold cross-validation, training the model on nine folds of the data and testing it on the remaining fold, rotating through all folds. This process offers a reliable estimate of each model's performance on unseen data. Additionally, we use the out-of-bag (OOB) score for Random Forests, an internal validation method that estimates performance without requiring a separate validation set. To connect this analysis to our primary

[12] We opt not to use CART because it is a single decision tree algorithm, and not an ensemble learning method. In contrast, Gradient Tree Boosting and Random Forests build upon the CART concept by relying on multiple trees to enhance predictive performance and reduce overfitting.

[13] For Random Forests, we allow the model to grow between 500 and 2,000 trees with an increment of 100. We set the minimum number of observations in a leaf from 1 to 4 and consider both 'sqrt' and 'log2' options for the maximum number of features at each split. For Gradient Tree Boosting, we focus on a similar range of 500 to 2,000 trees, with learning rates between 0.005, 0.01, and 0.05. We set the maximum tree depth to range from 1 to 4 and fix the minimum sum of observations required to split a node in the tree (i.e., the minimum child weight) at 10. For both methods, we use half of the sample to estimate each tree. This sampling process serves two purposes: (i) it introduces randomness that helps prevent overfitting, and (ii) it reduces the correlation between trees, thereby improving the model's generalization capability. We implement our analyses using the sklearn and XGBoost packages in Python. XGBoost provides a regularized Gradient Tree Boosting framework, optimizing what is typically a computationally intensive process. For hyperparameter tuning, we use RandomizedSearchCV, which randomly samples from the parameter space and evaluates each configuration using 5-fold cross-validation, repeating the process 100 times to ensure thorough evaluation.

findings and assess the performance of our machine learning methods, we use an OLS regression as a benchmark.

[Figure 2 here]

Figure 2 illustrates the evolution of R-squared over time for all three models. Gradient Tree Boosting consistently demonstrates the highest R-squared values, ranging from approximately 0.05 to 0.54, followed closely by Random Forests with values between 0.08 and 0.50. OLS shows evidence of a similar upward trend, but with lower R-squared values, which range from about 0.04 to 0.43. The performance gap between the machine learning methods and OLS appears to have widened from the 1990s. This superior performance of the machine learning methods suggests that they may be capturing more complex aspects of the relation between the volatility of earnings components and returns that the linear OLS model does not fully account for.

Table 9 presents the results of regressions in which we model the annual R-squared values against a time trend variable. All three models show a positive and statistically significant risk-relevance trend and corroborate our main findings. The estimated trend coefficient is highest for Gradient Tree Boosting (0.0057 per year), followed by Random Forests (0.0048) and OLS (0.0043). The out-of-sample (OOS) and out-of-bag (OOB) results for Random Forests are nearly identical, further supporting the validity of our cross-validation procedure and confirming the robustness of our results. Notwithstanding the OLS results, the stronger trend observed in the R-squared values from the machine learning models is consistent with these better capturing nonlinear relationships and complex interactions among earnings components.

[Table 9 here]

To further investigate the drivers of increasing earnings risk-relevance, we examine the feature importance of different earnings components over time, as determined by our machine learning models. Figures 3A and 3B display the feature importance of the different earnings components for the Gradient Tree Boosting and Random Forests models, respectively. Both models show similar patterns. Specifically, most earnings components demonstrate relatively stable levels of feature importance over time. SG&A volatility exhibits the most pronounced increase in feature importance from the 1990s onward, whereas depreciation and sales volatility show a moderate decrease over time. In line with our earlier results, these findings are consistent with the shift towards a more intangible-intensive economy affecting the evolution of the risk-relevance of earnings.

[Figure 3A here]

[Figure 3B here]

4.7 Relation with other trends in the prior literature

As discussed in Section 4.2, we find that intangibles are an important contributor to the increase in earnings risk-relevance over time. However, our results point towards a broader, more general increase in risk-relevance over time. In this section, we discuss whether factors that prior literature finds to affect changes in the quality attributes and relevance of earnings can explain the observed trends in risk-relevance, and we show that they cannot fully explain our results.

Dichev and Tang (2009) and Srivastava (2014), among others, document a rise in earnings volatility over time. However, our results remain robust after controlling for annual averages of earnings volatility (see Table 3), indicating that changes in earnings volatility cannot explain the increase in risk-relevance. Similarly, prior research (Dichev and Tang, 2008; Donelson et al., 2011) shows a significant decline in revenue-expense matching over time. In line with Dichev and Tang (2008), we find strong decreases in revenue-expense matching over time (untabulated). Yet, even after controlling for annual levels of matching in our trend analysis, we continue to find a positive and significant coefficient on *TIME*, suggesting that changes in matching do not subsume risk-relevance trends (untabulated).

Donelson et al. (2011) and Bushman et al. (2016) attribute declining earnings quality partly to increased recognition of non-operating, one-time items. However, we find that risk relevance has increased for operating income and most income statement line items, making non-operating items an unlikely sole explanation. This is further supported by the results in Table 4, which shows that trends in the risk-relevance of nonoperating items are not exceptionally strong and, in some cases, weaker than those observed for other line items.

Bushman et al. (2016) document a weakening negative correlation between accruals and cash flows over time, while Christensen et al. (2023) find that accruals quality has increased in recent years after an initial decline in the 1990s. Our findings are inconsistent with either of these factors being a main driver of risk-relevance trends. Specifically, as we find increases in the risk-relevance of cash flows and accruals individually, changes in the correlation between these components cannot fully explain the risk-relevance trend. Likewise, the strong growth in cash flow risk-relevance suggests that trends cannot be explained solely by shifts in accrual quality.

Finally, Srivastava (2014) shows that newer cohorts of firms are increasingly intangible-intensive. Hence, we investigate whether risk-relevance trends can be explained by cohort effects. To test this, we restrict the sample to firms that went public before 1975, the first year in our sample. Even within this constant sample, we observe strong positive trends in risk relevance, indicating that cohort effects do not fully drive our results (untabulated).

4.8 Robustness tests

To assess the robustness of our results, we conduct several additional analyses. We start by examining the sensitivity of our results to alternative return volatility estimations. While the daily return data used in our primary analyses can capture high-frequency stock price fluctuations, they are also more sensitive to the inclusion of noise in short-term price movements (e.g., Hou and Moskowitz, 2005; Riedl and Serafeim, 2011). Hence, we replicate our analyses using return volatility estimated from weekly and monthly data. These results (untabulated) are quantitatively similar to those of our primary analyses and indicate that our conclusions are not sensitive to the volatility measurement window.

We also re-estimate risk-relevance trends in which we replace a firm's total risk (*STDRET*) with market-model or Fama-French 4-factor model-adjusted returns. This analysis complements our earlier industry-level tests by further distinguishing between firm-specific risk factors and broader market or industry trends. Results using these alternative measures are consistent with our primary findings on total risk. Hence, they reinforce our earlier conclusion that even though industry risk-relevance has increased over time, firm-specific risk factors play an important role in driving risk-relevance trends.

Overall, our main analyses rely on minimal sample restrictions to ensure the generalizability of our findings. However, to mitigate the concern that our results are driven by thinly traded, highly volatile "penny stocks," we replicate our analyses after excluding firms with share prices below $5, a threshold commonly used in prior literature as a proxy for illiquid and highly volatile stocks. We continue to find strong evidence of an increase in earnings risk-relevance that is most pronounced for line items related to intangibles.

5. Conclusion

This paper investigates how the risk-relevance of (bottom-line) earnings has developed over the past 50 years. While a broad literature focuses on the development of earnings properties and the relevance of earnings over time (Collins et al., 1997; Srivastava, 2014; Barth et al., 2023), most studies focus on the value-relevance of earnings and their ability to inform about future performance levels. In contrast, we focus on the ability of earnings to capture and convey information about risk and overall performance volatility (i.e., risk-relevance), an increasingly important attribute of accounting information. This focus aligns with standard setters, such as the FASB, who explicitly highlight the risk-informing role of accounting information as it should help users understand the "amount, timing, and uncertainty of (the prospects for) future net cash inflows to the entity" (SFAC No. 8, FASB 2010).

Using the R-squared from annual regressions of return volatility on earnings volatility as a measure of risk-relevance, we document a substantial increase in R-squared from approximately 10 percent in the early years of our sample to about 40 percent in recent years. These results hold for bottom-line income measures, operating income, and most income statement line items. Moreover, they persist when we investigate the relation between current earnings volatility and *future* return volatility, which suggests that the ability of earnings to provide *new* risk-relevant information to investors has increased over time.

We also find that the risk-relevance of industry earnings for industry return volatility has increased over time, suggesting that earnings' ability to inform about systematic risk factors has also increased. Nevertheless, these results are generally weaker than our firm-level results, suggesting that particularly *firm-specific* risk-relevance has increased over time. Moreover, we find that intangibles are less important in explaining trends in industry risk-relevance.

We supplement our OLS analysis with machine learning methods, specifically Random Forests and Gradient Tree Boosting, that allow us to model nonlinear relationships and interactions among earnings components. Although machine learning methods outperform OLS in explaining the relation between earnings components' volatility and return volatility, of central importance to our study, these models confirm the positive and significant trend in earnings risk-relevance over time.

In line with previous studies on the development of earnings attributes and relevance, we also examine the impact of the rising importance of intangibles. While the literature on the value-relevance of earnings suggests that the increasing prominence of intangibles drives much of the decline in value-relevance, our findings indicate that intangibles are becoming increasingly risk-relevant. Specifically, we find that (i) line items such as R&D and SG&A show the strongest increases in risk-relevance over time, (ii) trends in risk-relevance of Pre-R&D and Pre-SG&A earnings are smaller than those for earnings that include R&D and SG&A, and (iii) upward trends in the risk-relevance of earnings are more pronounced for firms with high R&D and SG&A intensity. Although our results do not address whether alternative accounting treatments, such as capitalization (see Iqbal et al. 2024), would result in even stronger increases in risk-relevance, they suggest that intangibles under the current measurement model are becoming increasingly risk-relevant.

Notwithstanding the impact of intangibles, we also find increases in the risk-relevance of earnings line items less affected by intangibles and for earnings that exclude R&D and SG&A. These results are important as they point towards a broader, more general, increase in the risk-relevance of accounting that, moreover, cannot be explained by (trends in) other major factors identified in prior literature, such as the increase in one-time item recognition (Donelson et al., 2011), changes in the accrual-cash flow correlation (Bushman et al., 2016), declines in revenue-expense matching (Dichev and Tang, 2008), increases in earnings volatility (Srivastava, 2014; Dichev and Tang, 2009), or new cohorts of firms listing on the stock market (Srivastava, 2014).

Overall, our study contributes to the broader literature on the evolution of accounting quality and relevance over time. This literature includes an ongoing debate about the relevance of accounting information, particularly bottom-line earnings, with many studies suggesting that the quality and relevance of earnings have declined over the years, leading some to proclaim the "end of accounting." In contrast, we find evidence of a steady increase in the risk-relevance of accounting information, including bottom-line earnings, over time. Given that providing information about risk is one of the key objectives of financial reporting, our findings offer important insights into the changing relevance of accounting.

Moreover, while previous studies suggest that the rising prominence of intangibles has contributed to declines in other quality and relevance attributes, we find that intangibles are becoming increasingly risk-relevant. At the same time, our findings also point to broader increases in risk-relevance that are not exclusively driven by intangibles, suggesting that the overall ability of accounting information to inform about risk has improved over time.

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FIGURE 1A

Figure 1A: This figure plots annual risk-relevance (R-squared) values from 1975 to 2023. We obtain R-squared values by regressing firms' return volatility on net income volatility, with both volatilities measured over three-year periods using daily returns and quarterly earnings, respectively. The dots show annual R-squared values and the solid line shows the fitted trend.

FIGURE 1B

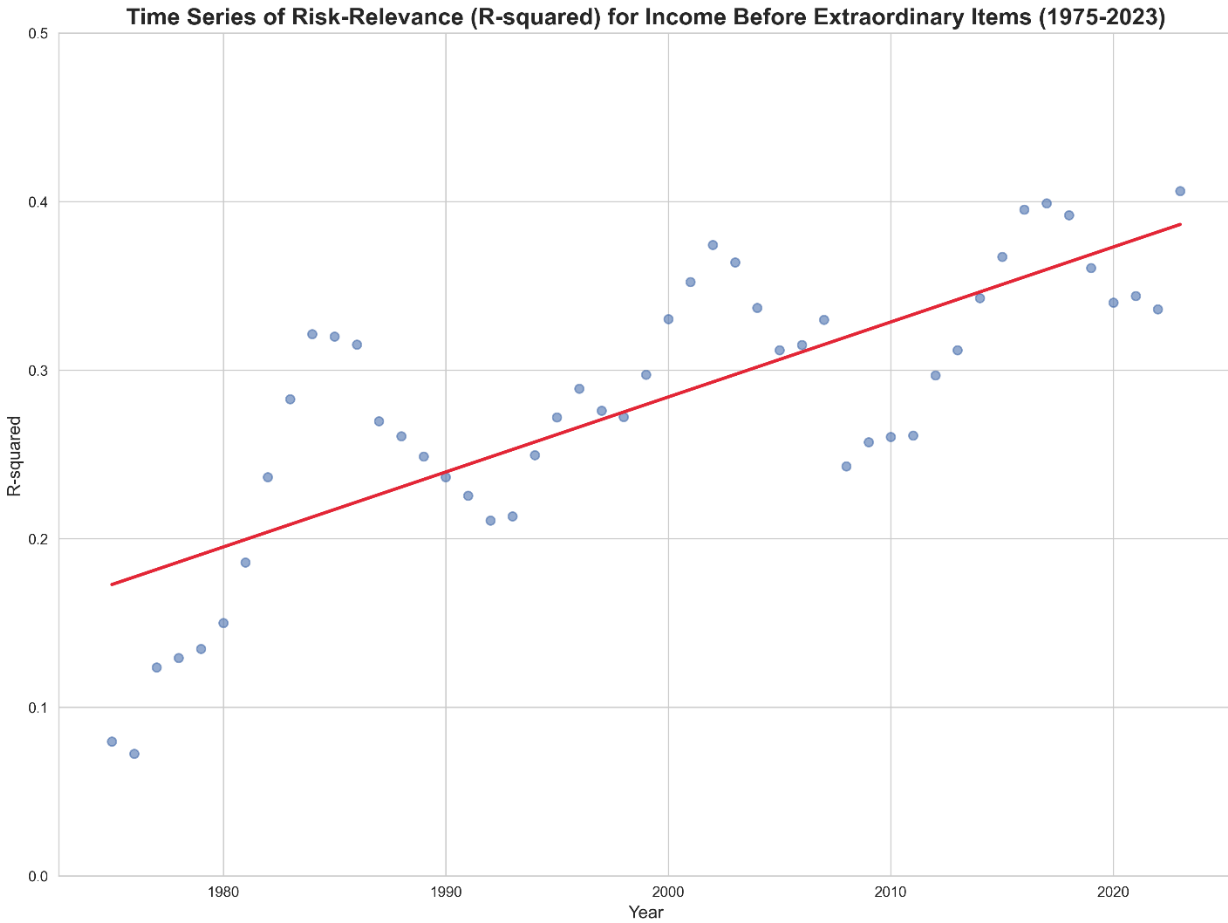

Figure 1B: This figure plots annual risk-relevance (R-squared) values from 1975 to 2023. We obtain R-squared values by regressing firms' return volatility on income before extraordinary items volatility, with both volatilities measured over three-year periods using daily returns and quarterly earnings, respectively. The dots show annual R-squared values and the solid line shows the fitted trend.

FIGURE 1C

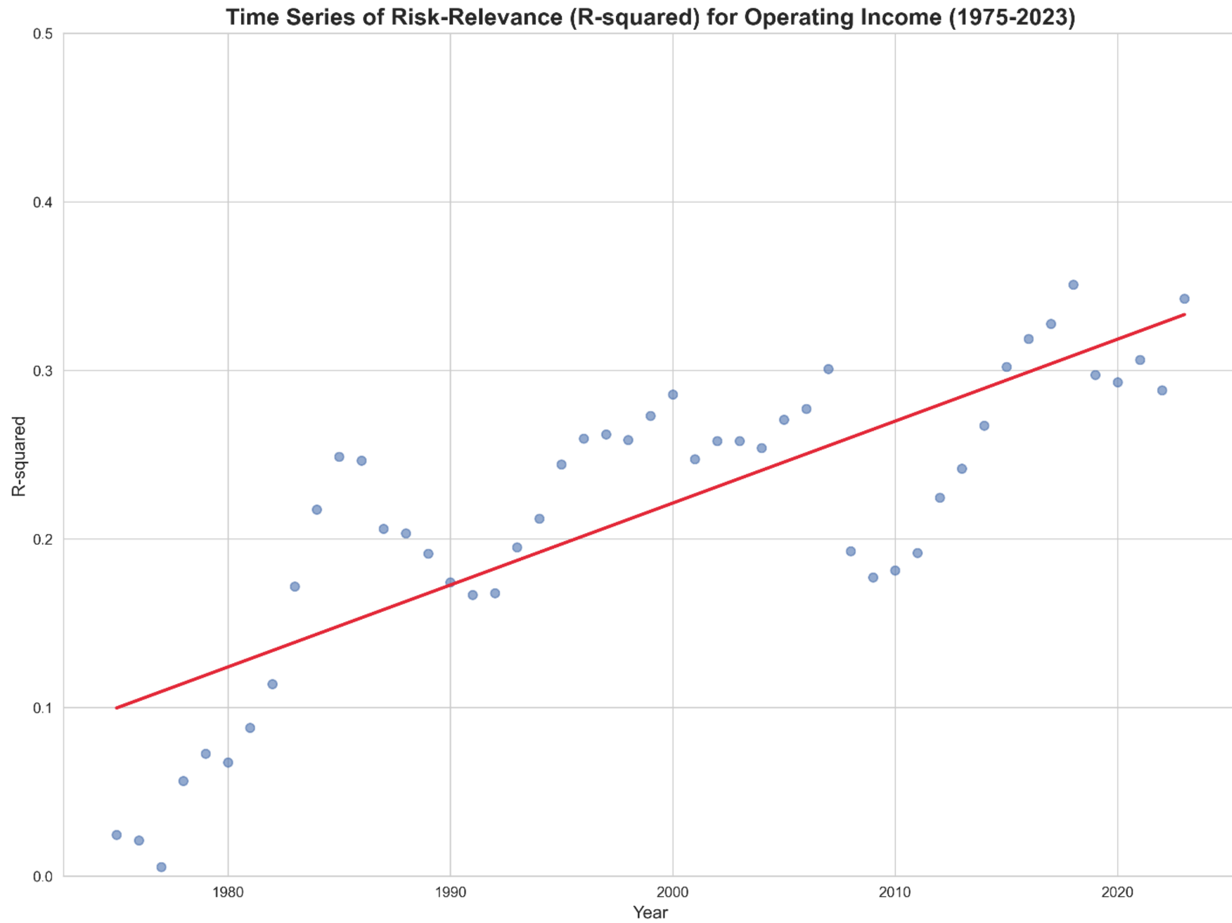

Figure 1C: This figure plots annual risk-relevance (R-squared) values from 1975 to 2023. We obtain R-squared values by regressing firms' return volatility on operating income volatility, with both volatilities measured over three-year periods using daily returns and quarterly earnings, respectively. The dots show annual R-squared values and the solid line shows the fitted trend.

FIGURE 1D

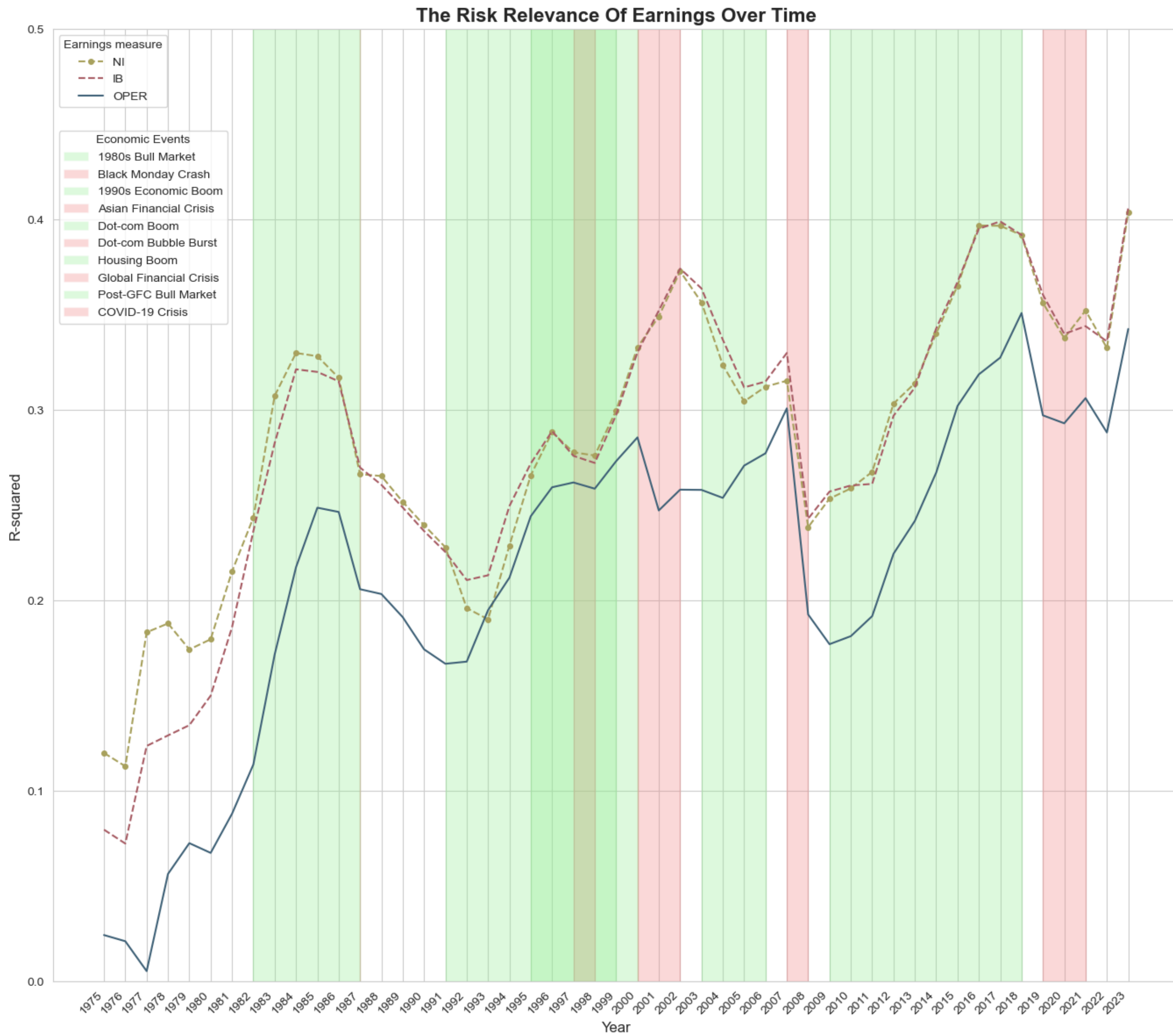

Figure 1D: This figure plots annual risk-relevance (R-squared) values from 1975 to 2023 for three earnings measures (net income, income before extraordinary items, and operating income). We obtain R-squared values by regressing firms' return volatility on the respective earnings measure volatility, with both volatilities measured over three-year periods using daily returns and quarterly earnings, respectively. Red and green shaded areas indicate economic downturns and booms.

FIGURE 2

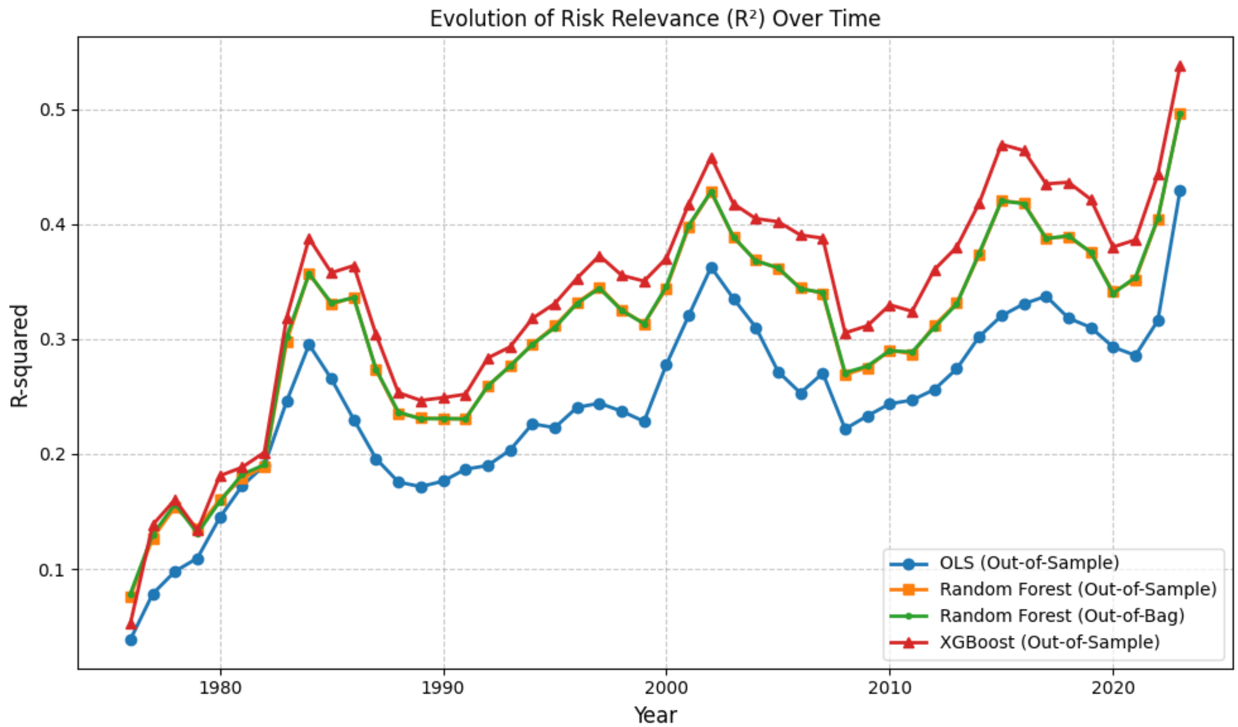

Figure 2: This figure plots out-of-sample R-squared values using Ordinary Least Squares regression and two machine learning approaches (Random Forests and Gradient Tree Boosting), from 1975 to 2023. R-squared values are calculated using 10-fold cross-validation, with an additional out-of-bag R-squared reported for Random Forests.

FIGURE 3A

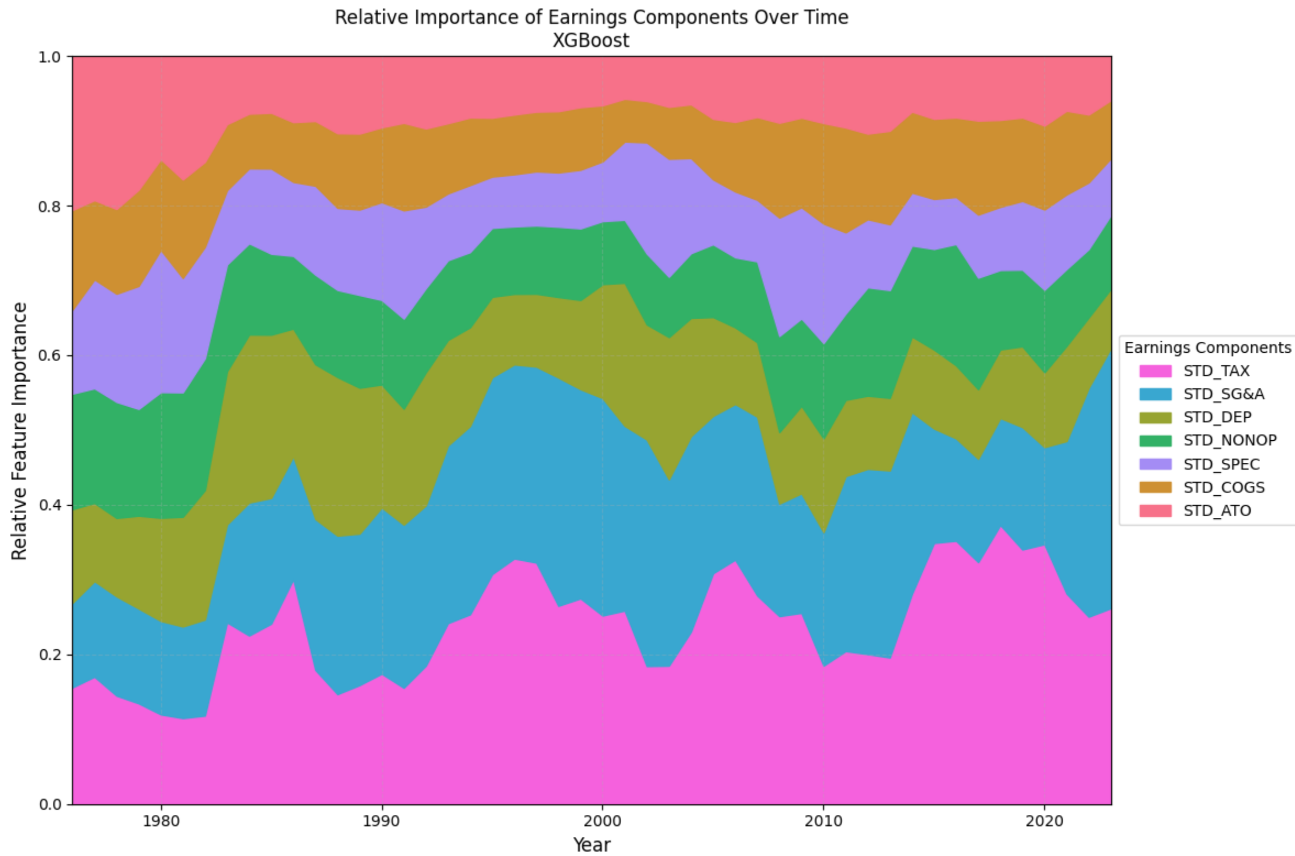

Figure 3A: This figure plots the relative contribution over time of seven earnings component volatilities 1975 to 2023: asset turnover (*STDATO*), cost of goods sold (*STDCOGS*), depreciation (*STDDEP*), non-operating income (*STDNONOP*), special items (*STDSPEC*), selling, general and administrative expenses (*STDSG&A*), and tax expense (*STDTAX*). The stacked area plot shows each component's importance from using Gradient Tree Boosting estimation.

FIGURE 3B

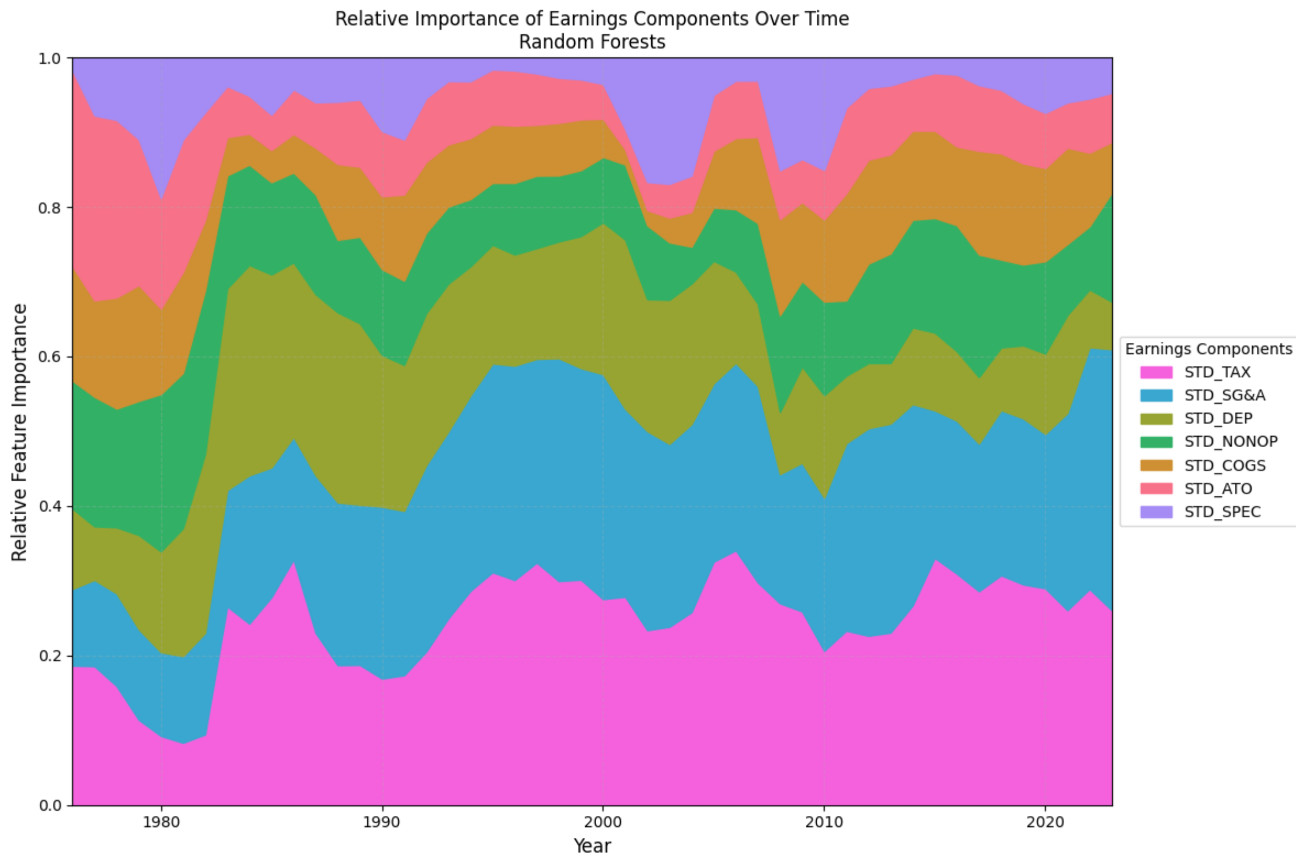

Figure 3B: This figure plots the relative contribution over time of seven earnings component volatilities from 1975 to 2023: asset turnover (*STDATO*), cost of goods sold (*STDCOGS*), depreciation (*STDDEP*), non-operating income (*STDNONOP*), special items (*STDSPEC*), selling, general and administrative expenses (*STDSG&A*), and tax expense (*STDTAX*). The stacked area plot shows each component's importance using Random Forests estimation.

TABLE 1

Sample and Descriptive Statistics

Panel A: Sample Selection

	No. Obs.
Firm-Years in the Compustat-CRSP (CCM) Universe	294,706
less: Firm-Years with Fama-French 48 Code in (44:48)	(75,866)
less: Firm-Years with total assets <= 0	(697)
less: Firm-Years with missing *STDRET*	(15,097)
Sample	**203,046**
Truncating *STDRET* at 1 percent per year	(4,014)
Final Sample for Analyses	**199,032**

Panel B: Fama-French 48 Industries

	Fama-French 48 – Code & Description	No. Obs.	Freq. Obs.
1	Agriculture	819	0.41%
2	Food Products	3,918	1.97%
3	Candy Soda	603	0.30%
4	Beer Liquor	826	0.42%
5	Tobacco Products	314	0.16%
6	Recreation	1,909	0.96%
7	Entertainment	3,325	1.67%
8	Printing and Publishing	1,946	0.98%
9	Consumer Goods	4,961	2.49%
10	Apparel	3,124	1.57%
11	Healthcare	3,556	1.79%
12	Medical Equipment	6,741	3.39%
13	Pharmaceutical Products	14,396	7.23%
14	Chemicals	4,341	2.18%
15	Rubber and Plastic Products	2,042	1.03%
16	Textiles	1,567	0.79%
17	Construction Materials	5,108	2.57%
18	Construction	3,198	1.61%
19	Steel Works Etc.	3,473	1.74%
20	Fabricated Products	1,008	0.51%
21	Machinery	8,188	4.11%
22	Electrical Equipment	3,352	1.68%
23	Automobiles and Trucks	3,497	1.76%
24	Aircraft	1,259	0.63%
25	Shipbuilding, Railroad Equipment	466	0.23%
26	Defense	476	0.24%
27	Precious Metals	2,362	1.19%
28	Non-Metallic & Industrial Metal Mining	1,703	0.86%
29	Coal	442	0.22%
30	Petroleum and Natural Gas	10,936	5.49%
31	Utilities	6,936	3.48%
32	Communication	6,088	3.06%
33	Personal Services	2,504	1.26%
34	Business Services	22,829	11.47%
35	Computers	8,604	4.32%
36	Electronic Equipment	12,975	6.52%
37	Measuring & Control Equipment	4,856	2.44%
38	Business Supplies	3,047	1.53%
39	Shipping Containers	829	0.42%
40	Transportation	6,411	3.22%
41	Wholesale	8,588	4.31%
42	Retail	11,392	5.72%
43	Restaurants, Hotels, Motels	4,117	2.07%

Panel C: Descriptive Statistics

Variable	No. Obs.	Mean	Std. Dev.	P25	Median	P75
STDRET	199,032	0.038	0.020	0.023	0.033	0.048
STDRET t+1	185,585	0.038	0.029	0.021	0.031	0.046
STDNI	169,956	0.025	0.026	0.008	0.016	0.033
STDIB	169,830	0.024	0.025	0.007	0.014	0.031
STDOPER	166,569	0.021	0.019	0.008	0.015	0.028
STDATO	169,642	0.054	0.050	0.021	0.040	0.071
STDCOGS	167,020	0.042	0.044	0.013	0.028	0.055
STDDEP	151,007	0.003	0.003	0.001	0.002	0.003
STDR&D	134,401	0.005	0.010	0.000	0.000	0.006
STDSG&A	171,681	0.015	0.021	0.003	0.008	0.019
STDMainSG&A	133,013	0.015	0.019	0.003	0.008	0.019
STDTAX	169,320	0.005	0.004	0.002	0.004	0.008
STDSPEC	163,326	0.006	0.009	0.000	0.002	0.008
STDNONOP	167,758	0.003	0.004	0.001	0.002	0.004

This table reports the sample selection process and descriptive statistics of the variables used in our main analyses. Panel A reports the various steps of our sample selection process, while Panel B provides an overview of the Fama-French 48 industries in our sample. Panel C reports descriptive statistics of the main variables. The sample includes all 199,032 firm-years with available data in the Compustat-CRSP universe after eliminating firms with a missing Fama-French 48 Industry code, firms in Fama-French industries 44-48, firms with total assets less than zero, and firms with a missing standard deviation of returns. Depending on data availability of the other variables, the number of observations for the other variables can vary. Due to missing quarterly data on R&D expenses, the sample for the tests involving *R&D* and *MainSG&A* includes the 35-year period from 1989-2023. The standard deviation of returns (*STDRET*) is measured as the standard deviation of daily returns over a three-year period that ends three months after the fiscal year-end. The year-ahead standard deviation of returns (*STDRET t+1*) is measured as the standard deviation of daily returns over the one-year period that ends three months after the *t+1* fiscal year-end. We use quarterly data (i.e., 12 quarters) from the same three fiscal years over which we estimate the standard deviation of returns to measure the standard deviation of the other variables (indicated with "*STD*"). *NI* is net income scaled by lagged total assets (NIQ / lag ATQ). *IB* is income before extraordinary items scaled by lagged total assets (IBQ / lag ATQ). *OPER* is operating income after depreciation scaled by lagged total assets (OIADPQ / lag ATQ). *ATO* is sales scaled by lagged total assets (SALEQ / lag ATQ). *COGS* is cost of goods sold scaled by lagged total assets (COGSQ / lag ATQ). *DEP* is depreciation expense scaled by lagged total assets (DPQ / lag ATQ). *R&D* is R&D expense scaled by lagged total assets (max(0, XRDQ) / lag ATQ). *SG&A* is SG&A expense scaled by lagged total assets (max(0, XSGAQ) / lag ATQ). *MainSG&A* is SG&A less R&D expense, scaled by lagged total assets ((max(0, XSGAQ) – max(0, XRDQ)) / lag ATQ). *TAX* is tax expense scaled by lagged total assets (TXTQ / lag ATQ). *SPEC* is special items scaled by lagged total assets (SPIQ / lag ATQ). *NONOP* is non-operating income scaled by lagged total assets (NOPIQ / lag ATQ).

TABLE 2

Risk-Relevance of Earnings over Time

Panel A: Annual Risk-Relevance

	Risk-Relevance - R^2				***Risk-Relevance - R^2***		
Fiscal Year	***NI***	***IB***	***OPER***	**Fiscal Year**	***NI***	***IB***	***OPER***
1975	0.120	0.080	0.024	2000	0.333	0.330	0.286
1976	0.113	0.072	0.021	2001	0.349	0.352	0.247
1977	0.183	0.124	0.005	2002	0.373	0.374	0.258
1978	0.188	0.129	0.057	2003	0.357	0.364	0.258
1979	0.174	0.135	0.073	2004	0.324	0.337	0.254
1980	0.180	0.150	0.068	2005	0.305	0.312	0.271
1981	0.215	0.186	0.088	2006	0.312	0.315	0.277
1982	0.244	0.236	0.114	2007	0.315	0.330	0.301
1983	0.308	0.283	0.172	2008	0.239	0.243	0.193
1984	0.330	0.321	0.218	2009	0.254	0.257	0.177
1985	0.328	0.320	0.249	2010	0.259	0.260	0.181
1986	0.317	0.315	0.247	2011	0.268	0.261	0.192
1987	0.266	0.270	0.206	2012	0.303	0.297	0.225
1988	0.265	0.261	0.203	2013	0.314	0.312	0.242
1989	0.252	0.249	0.191	2014	0.340	0.343	0.267
1990	0.240	0.237	0.174	2015	0.365	0.367	0.302
1991	0.228	0.225	0.167	2016	0.397	0.395	0.319
1992	0.196	0.211	0.168	2017	0.397	0.399	0.328
1993	0.190	0.213	0.195	2018	0.392	0.392	0.351
1994	0.229	0.250	0.212	2019	0.356	0.361	0.297
1995	0.266	0.272	0.244	2020	0.338	0.340	0.293
1996	0.288	0.289	0.260	2021	0.352	0.344	0.306
1997	0.278	0.276	0.262	2022	0.333	0.336	0.288
1998	0.276	0.272	0.259	2023	0.404	0.406	0.343
1999	0.300	0.297	0.273				

Panel B: Regression of *Risk Relevance* - R^2 on *TIME*

	Risk-Relevance - R^2			***Risk-Relevance - R^2***		
Variable	***NI***	***IB***	***OPER***	***NI***	***IB***	***OPER***
Intercept	0.1956***	0.1728***	0.0998***	0.1562***	0.1125***	-0.0836***
	(12.68)	(9.44)	(5.72)	(8.05)	(5.08)	(-3.54)
TIME	0.0037***	0.0045***	0.0049***	0.0028***	0.0029***	0.0045***
	(7.56)	(7.68)	(8.72)	(4.84)	(4.70)	(10.65)
EARNVOL_T				2.5268**	4.3972***	9.3769***
				(2.55)	(3.99)	(7.99)
N	49	49	49	49	49	49
R^2	0.56	0.60	0.65	0.60	0.68	0.80

This table reports the results of tests investigating how the risk-relevance of earnings has developed over the 49-year period from 1975 to 2023. The sample includes all 199,032 firm-years with available data in the Compustat-CRSP universe after eliminating firms with a missing Fama-French 48 Industry code, firms in Fama-French industries 44-48, firms with total assets less than or equal to zero, and firms with a missing standard deviation of returns. Depending on data availability of the other variables, the sample size for individual tests can vary. The standard deviation of returns (*STDRET*) is measured as the standard deviation of daily returns over a three-year period that ends three months after the fiscal year-end. We regress the standard deviation of returns annually on the standard deviation of earnings constructs and use the annual R-squared of this regression as the measure of risk-relevance (*Risk-Relevance* - R^2). We use quarterly data (i.e., 12 quarters) from the same three fiscal years over which we estimate the standard deviation of returns. *NI* is net income scaled by lagged total assets (NIQ / lag ATQ). *IB* is income before extraordinary items scaled by lagged total assets (IBQ / lag ATQ). *OPER* is operating income after depreciation scaled by lagged total assets (OIADPQ / lag ATQ). Panel A reports the risk-relevance (i.e., R-squared) per year for each of the three earnings constructs. Panel B reports the results of regressions in which we regress the annual risk-relevance on a time trend (*TIME*, which is equal to 0 in 1975 and 48 in 2023). *EARNVOL_T* is the average annual earnings volatility for each respective earnings construct. T-statistics are reported in parentheses under the coefficients. *, **, *** indicate statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively (two-tailed).

TABLE 3

Risk-Relevance of Earnings over Time – Income Statement Line Items

Variable	Risk-Relevance - R^2				
	ATO	***COGS***	***DEP***	***R&D***	***SG&A***
Intercept	0.0664***	0.0317***	0.0910***	0.0055	0.0451***
	(16.50)	(6.22)	(6.18)	(0.85)	(6.35)
TIME	-0.0009***	0.0012***	0.0002	0.0052***	0.0030***
	(-6.45)	(6.03)	(0.41)	(11.17)	(9.08)
N	49	49	49	35	49
R^2	0.46	0.52	0.00	0.78	0.67

Variable	Risk-Relevance - R^2			
	MainSG&A	***TAX***	***SPEC***	***NONOP***
Intercept	0.1034***	0.0038	0.0156***	0.0483***
	(11.77)	(0.69)	(3.46)	(7.26)
TIME	0.0032***	0.0005**	0.0015***	0.0010***
	(6.17)	(2.04)	(6.01)	(4.21)
N	35	49	49	49
R^2	0.56	0.13	0.37	0.35

This table reports the results of tests investigating how the risk-relevance of income statement line items has developed over the 49-year period from 1975 to 2023. The sample includes all 199,032 firm-years with available data in the Compustat-CRSP universe after eliminating firms with a missing Fama-French 48 Industry code, firms in Fama-French industries 44-48, firms with total assets less than or equal to zero, and firms with a missing standard deviation of returns. Depending on data availability of the other variables, the sample size for individual tests can vary. Due to missing quarterly data on R&D expenses, the sample for the tests involving *R&D* and *MainSG&A* includes the 35-year period from 1989-2023. The standard deviation of returns (*STDRET*) is measured as the standard deviation of daily returns over a three-year period that ends three months after the fiscal year-end. We regress the standard deviation of returns annually on the standard deviation of income statement line items and use the annual R-squared of this regression as the measure of risk-relevance (Risk-Relevance - R^2). We use quarterly data (i.e., 12 quarters) from the same three fiscal years over which we estimate the standard deviation of returns. *ATO* is sales scaled by lagged total assets (SALEQ / lag ATQ). *COGS* is costs of goods sold scaled by lagged total assets (COGSQ / lag ATQ). *DEP* is depreciation expense scaled by lagged total assets (DPQ / lag ATQ). *R&D* is R&D expense scaled by lagged total assets (max(0, XRDQ) / lag ATQ). *SG&A* is SG&A expense scaled by lagged total assets (max(0, XSGAQ) / lag ATQ). *MainSG&A* is SG&A less R&D expense, scaled by lagged total assets ((max(0, XSGAQ) – max(0, XRDQ)) / lag ATQ). *TAX* is tax expense scaled by lagged total assets (TXTQ / lag ATQ). *SPEC* is special items scaled by lagged total assets (SPIQ / lag ATQ). *NONOP* is non-operating income scaled by lagged total assets (NOPIQ / lag ATQ). *TIME* is a time trend that is equal to 0 in 1975 and 48 in 2023, except in the regressions with *R&D* and *MainSG&A*, where *TIME* is equal to 0 in 1989 and 34 in 2023. To investigate the development in risk-relevance, we regress the annual risk-relevance on *TIME*. T-statistics are reported in parentheses under the coefficients. *, **, *** indicate statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively (two-tailed).

TABLE 4

Risk-Relevance of Earnings over Time – Pre-R&D/SG&A Earnings & R&D/SG&A Intensity

Panel A: Pre-R&D Earnings

	Risk-Relevance - R^2					
	NI		***IB***		***OPER***	
Variable	***Original***	***Pre-R&D***	***Original***	***Pre-R&D***	***Original***	***Pre-R&D***
Intercept	0.2375***	0.2152***	0.2433***	0.2414***	0.1976***	0.1831***
	(20.01)	(12.59)	(23.26)	(19.79)	(19.66)	(18.32)
TIME	0.0040***	0.0018***	0.0039***	0.0018***	0.0033***	0.0011**
	(7.28)	(3.54)	(7.53)	(3.76)	(6.32)	(2.16)
N	35	35	35	35	35	35
R^2	0.51	0.20	0.50	0.20	0.42	0.10

Panel B: Pre-SG&A Earnings

	Risk-Relevance - R^2					
	NI		***IB***		***OPER***	
Variable	***Original***	***Pre-SG&A***	***Original***	***Pre-SG&A***	***Original***	***Pre-SG&A***
Intercept	0.1956***	0.1266***	0.1728***	0.1144***	0.0998***	0.0866***
	(12.68)	(7.10)	(9.44)	(6.61)	(5.72)	(6.50)
TIME	0.0037***	0.0031***	0.0045***	0.0034***	0.0049***	0.0011**
	(7.56)	(5.38)	(7.68)	(5.91)	(8.72)	(2.25)
N	49	49	49	49	49	49
R^2	0.56	0.43	0.65	0.47	0.65	0.13

Panel C: Pre-MainSG&A Earnings

	Risk-Relevance - R^2					
	NI		***IB***		***OPER***	
Variable	***Original***	***Pre-MainSG&A***	***Original***	***Pre-MainSG&A***	***Original***	***Pre-MainSG&A***
Intercept	0.2375***	0.1955***	0.2433***	0.1895***	0.1976***	0.1229***
	(20.01)	(17.89)	(23.26)	(18.21)	(19.66)	(15.48)
TIME	0.0040***	0.0035***	0.0039***	0.0036***	0.0033***	0.0025***
	(7.28)	(6.71)	(7.53)	(6.99)	(6.32)	(5.47)
N	35	35	35	35	35	35
R^2	0.51	0.45	0.50	0.47	0.42	0.39

Panel D: R&D Intensity

	Risk-Relevance - R^2					
	NI		***IB***		***OPER***	
Variable	***Low R&D***	***High R&D***	***Low R&D***	***High R&D***	***Low R&D***	***High R&D***
Intercept	0.2213***	0.2463***	0.2272***	0.2546***	0.1571***	0.2439***
	(21.32)	(19.15)	(22.83)	(24.04)	(15.62)	(21.40)
TIME	0.0023***	0.0044***	0.0021***	0.0042***	0.0005	0.0037***
	(4.17)	(7.08)	(4.02)	(7.33)	(0.94)	(6.83)
N	35	35	35	35	35	35
R^2	0.30	0.54	0.28	0.53	0.02	0.51

Panel E: SG&A Intensity

	Risk-Relevance - R^2					
	NI		***IB***		***OPER***	
Variable	***Low SG&A***	***High SG&A***	***Low SG&A***	***High SG&A***	***Low SG&A***	***High SG&A***
Intercept	0.1939***	0.1932***	0.1752***	0.1675***	0.0845***	0.1058***
	(11.61)	(11.17)	(9.43)	(8.08)	(5.97)	(4.91)
TIME	0.0030***	0.0037***	0.0037***	0.0045***	0.0039***	0.0052***
	(5.73)	(6.78)	(6.09)	(6.96)	(8.18)	(7.55)
N	49	49	49	49	49	49
R^2	0.43	0.54	0.51	0.58	0.60	0.63

Panel F: MainSG&A Intensity

	Risk-Relevance - R^2					
	NI		***IB***		***OPER***	
Variable	***Low MainSG&A***	***High MainSG&A***	***Low MainSG&A***	***High MainSG&A***	***Low MainSG&A***	***High MainSG&A***
Intercept	0.2421***	0.2200***	0.2481***	0.2253***	0.1735***	0.1877***
	(16.74)	(20.97)	(22.73)	(23.55)	(17.18)	(21.02)
TIME	0.0029***	0.0054***	0.0027**	0.0052***	0.0028***	0.0047***
	(4.22)	(9.00)	(4.29)	(9.06)	(5.65)	(7.73)
N	35	35	35	35	35	35
R^2	0.31	0.64	0.30	0.62	0.36	0.57

This table reports the results of tests investigating how (i) the risk-relevance of Pre-R&D and Pre-(Main)SG&A earnings has developed over the 49-year period from 1975 to 2023, and (ii) how the risk-relevance of earnings has developed over the 49-year period from 1975 to 2023, conditional on whether firms have above- or below-median R&D/(Main)SG&A intensity. The sample includes all 199,032 firm-years with available data in the Compustat-CRSP universe after eliminating firms with a missing Fama-French 48 Industry code, firms in Fama-French industries 44-48, firms with total assets less than or equal to zero, and firms with a missing standard deviation of returns. Depending on data availability of the other variables, the sample size for individual tests can vary. Due to missing quarterly data on R&D expenses, the sample for the tests involving *R&D* (Panel A and Panel D) and *MainSG&A* (Panel C and Panel E) includes the 35-year period from 1989-2023. The standard deviation of returns (*STDRET*) is measured as the standard deviation of daily returns over a three-year period that ends three months after the fiscal year-end. We regress the standard deviation of returns annually on the standard deviation of earnings constructs and use the annual R-squared of this regression as the measure of risk-relevance (Risk-Relevance - R^2). We use quarterly data (i.e., 12 quarters) from the same three fiscal years over which we estimate the standard deviation of returns. *NI* is net income scaled by lagged total assets (NIQ / lag ATQ). *IB* is income before extraordinary items scaled by lagged total assets (IBQ / lag ATQ). *OPER* is operating income after depreciation scaled by lagged total assets (OIADPQ / lag ATQ). Panel A reports results based on earnings, to which we add back quarterly R&D expenses. Panel B reports results based on earnings, to which we add back quarterly SG&A expenses. Panel C reports results based on earnings, to which we add back *MainSG&A*, where *MainSG&A* is equal to quarterly SG&A expenses less quarterly R&D expenses (max(0, XSGAQ) – max(0, XRDQ)). Panel D reports results based on R&D intensity, where R&D intensity is measured as the average R&D intensity (max(0, XRDQ) / lag ATQ) over the 12 quarters for which we calculate earnings volatility. Panel E reports results based on SG&A intensity, where SG&A intensity is measured as the average SG&A intensity (max(0, XSGAQ) / lag ATQ) over the 12 quarters for which we calculate earnings volatility. Panel F reports results based on *MainSG&A* intensity, where *MainSG&A* intensity is measured as the average *MainSG&A* intensity (*MainSG&A* / lag ATQ) over the 12 quarters for which we calculate earnings volatility. *TIME* is a time trend that is equal to 0 in 1975 and 48 in 2023, except in the regressions with *R&D* and *MainSG&A*, where *TIME* is equal to 0 in 1989 and 34 in 2023. To investigate the development in risk-relevance, we regress the annual risk-relevance on *TIME.* T-statistics are reported in parentheses under the coefficients. *, **, *** indicate statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively (two-tailed).

TABLE 5
Future Risk-Relevance of Earnings over Time

Variable	Future Risk-Relevance - R^2 STDRET t+1			Future Risk-Relevance - R^2 STDRET t+1 - Residual		
	NI	***IB***	***OPER***	***NI***	***IB***	***OPER***
Intercept	0.1599***	0.1462***	0.0872***	0.011***	0.0132***	0.0084***
	(16.33)	(10.88)	(5.40)	(5.44)	(5.15)	(2.99)
TIME	0.0020***	0.0025***	0.0031***	0.0002**	0.0001	0.0002**
	(5.47)	(5.47)	(5.74)	(2.21)	(1.43)	(2.31)
N	48	48	48	48	48	48
R^2	0.40	0.43	0.44	0.08	0.04	0.09

This table reports the results of tests investigating how the future risk-relevance of earnings has developed over the 48-year period from 1975 to 2022. The sample includes all 199,032 firm-years with available data in the Compustat-CRSP universe after eliminating firms with a missing Fama-French 48 Industry code, firms in Fama-French industries 44-48, firms with total assets less than or equal to zero, and firms with a missing standard deviation of returns. Depending on data availability of the other variables, the sample size for individual tests can vary. The standard deviation of returns (*STDRET t+1*) is measured as the standard deviation of daily returns over the one-year period that ends three months after the *t+1* fiscal year-end. We regress the standard deviation of returns annually on the standard deviation of earnings constructs and use the annual R-squared of this regression as the measure of future risk-relevance (Future Risk-Relevance - R^2). *STDRET t+1 – Residual* is equal to the residual of an annual regression of *STDRET t+1* on *STDRET*, where *STDRET* is the standard deviation of daily returns over a three-year period that ends three months after the fiscal year-end. We use quarterly data (i.e., 12 quarters) from the same three fiscal years over which we estimate the standard deviation of returns. *NI* is net income scaled by lagged total assets (NIQ / lag ATQ). *IB* is income before extraordinary items scaled by lagged total assets (IBQ / lag ATQ). *OPER* is operating income after depreciation scaled by lagged total assets (OIADPQ / lag ATQ). *TIME* is a time trend that is equal to 0 in 1975 and 47 in 2022. To investigate the development in risk-relevance, we regress the annual risk-relevance on *TIME*. T-statistics are reported in parentheses under the coefficients. *, **, *** indicate statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively (two-tailed).

TABLE 6

Future Risk-Relevance of Earnings over Time - Income Statement Line Items

Panel A: Future Risk-Relevance based on *STDRET t+1*

	Future Risk-Relevance – R^2								
Variable	***ATO***	***COGS***	***DEP***	***R&D***	***SG&A***	***MainSG&A***	***TAX***	***SPEC***	***NONOP***
Intercept	0.0517***	0.0244***	0.0684***	0.0028	0.0335***	0.0803***	0.0046	0.0190***	0.0357***
	(15.42)	(5.79)	(6.90)	(0.43)	(4.86)	(8.73)	(1.05)	(7.75)	(7.53)
TIME	-0.0008***	0.0008***	-0.0001	0.0040***	0.0022***	0.0021***	0.0002	0.0002**	0.0007***
	(7.46)	(5.38)	(-0.40)	(6.67)	(6.17)	(3.01)	(1.20)	(2.05)	(3.27)
N	48	48	48	34	48	34	48	48	48
R^2	0.46	0.37	0.01	0.62	0.53	0.30	0.06	0.04	0.20

Panel B: Future Risk-Relevance based on *STDRET t+1 - Residual*

	Future Risk-Relevance – R^2								
Variable	***ATO***	***COGS***	***DEP***	***R&D***	***SG&A***	***MainSG&A***	***TAX***	***SPEC***	***NONOP***
Intercept	0.0024***	0.0019***	0.0062***	-0.0040	-0.0007	0.0044	0.0006	0.0026***	-0.0001
	(3.67)	(2.95)	(3.72)	(-1.21)	(-0.33)	(1.17)	(0.66)	(2.72)	(-0.05)
TIME	-0.0000	0.0001**	-0.0000	0.0008**	0.0004***	0.0005*	0.0001	0.0000	0.0002**
	(-0.55)	(2.65)	(-0.78)	(2.56)	(3.18)	(1.70)	(0.96)	(0.31)	(2.32)
N	48	48	48	34	48	34	48	48	48
R^2	0.00	0.07	0.01	0.27	0.26	0.13	0.04	0.00	0.12

This table reports the results of tests investigating how the future risk-relevance of income statement line items has developed over the 48-year period from 1975 to 2022. The sample includes all 199,032 firm-years with available data in the Compustat-CRSP universe after eliminating firms with a missing Fama-French 48 Industry code, firms in Fama-French industries 44-48, firms with total assets less than or equal to zero, and firms with a missing standard deviation of returns. Depending on data availability of the other variables, the sample size for individual tests can vary. The standard deviation of returns (*STDRET t+1*) is measured as the standard deviation of daily returns over the one-year period that ends three months after the *t+1* fiscal year-end. We regress the standard deviation of returns annually on the standard deviation of earnings constructs and use the annual R-squared of this regression as the measure of future risk-relevance (*Future Risk-Relevance - R^2*). *STDRET t+1 – Residual* is equal to the residual of an annual regression of *STDRET t+1* on *STDRET*, where *STDRET* is the standard deviation of daily returns over a three-year period that ends three months after the fiscal year-end. We use quarterly data (i.e., 12 quarters) from the same three fiscal years over which we estimate the standard deviation of returns. *ATO* is sales scaled by lagged total assets (SALEQ / lag ATQ). *COGS* is cost of goods sold scaled by lagged total assets (COGSQ / lag ATQ). *DEP* is depreciation expense scaled by lagged total assets (DPQ / lag ATQ). *R&D* is R&D expense scaled by lagged total assets (max(0, XRDQ) / lag ATQ). *SG&A* is SG&A expense scaled by lagged total assets (max(0, XSGAQ) / lag ATQ). *MainSG&A* is SG&A less R&D expense, scaled by lagged total assets ((max(0, XSGAQ) – max(0, XRDQ)) / lag ATQ). *TAX* is tax expense scaled by lagged total assets (TXTQ / lag ATQ). *SPEC* is special items scaled by lagged total assets (SPIQ / lag ATQ). *NONOP* is non-operating income scaled by lagged total assets (NOPIQ / lag ATQ). *TIME* is a time trend that is equal to 0 in 1975 and 47 in 2022, except in the regressions with *R&D* and *MainSG&A*, where *TIME* is equal to 0 in 1989 and 33 in 2022. To investigate the development in risk-relevance, we regress the annual risk-relevance on *TIME*. T-statistics are reported in parentheses under the coefficients. *, **, *** indicate statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively (two-tailed).

TABLE 7
Risk-Relevance of Earnings over Time - Industry-Level Tests

	Industry Risk-Relevance – R^2					
Variable	***NI***	***IB***	***OPER***	***ATO***	***COGS***	***DEP***
Intercept	0.2820***	0.2915***	0.1266**	-0.0028	-0.015*	-0.0022
	(5.46)	(5.81)	(2.38)	(-0.28)	(-1.74)	(-0.15)
TIME	0.0026	0.0031	0.0083***	0.0011**	0.0015***	0.0028***
	(1.27)	(1.59)	(4.55)	(2.25)	(2.95)	(3.93)
N	49	49	48	49	48	48
R^2	0.03	0.05	0.26	0.17	0.24	0.24

	Industry Risk-Relevance – R^2					
Variable	***R&D***	***SG&A***	***MainSG&A***	***TAX***	***SPEC***	***NONOP***
Intercept	-0.0027	0.0103***	0.0129**	0.1944***	0.0845***	0.2505***
	(-0.26)	(3.19)	(2.66)	(4.14)	(3.36)	(5.44)
TIME	0.0009**	-0.0000	-0.0002	-0.0009	0.0003	-0.0018
	(2.23)	(-0.32)	(-1.24)	(-0.53)	(0.29)	(-1.20)
N	35	49	35	49	49	49
R^2	0.10	0.00	0.04	0.01	0.00	0.03

This table reports the results of tests investigating how the industry risk-relevance of industry-level earnings and income statement line items has developed over the 49-year period from 1975 to 2023. The sample includes all industry years with available data in the Compustat-CRSP universe. To facilitate the measurement of industry-level variables, we only include firms with a fiscal year-end in March, June, September, or December. We further eliminate firms with a missing Fama-French 48 Industry code, firms in Fama-French industries 44-48, firms with total assets less than or equal to zero, and firms with a missing standard deviation of returns. Depending on data availability of the other variables, the sample size for individual tests can vary. Due to missing quarterly data on R&D expenses, the sample for the tests involving *R&D* and *MainSG&A* includes the 35-year period from 1989-2023. The industry-wide standard deviation of returns (*STDRET_IND*) is measured as the standard deviation of daily industry-wide returns over a three-year period that ends in March of year *t*. We calculate industry-level returns as a value-weighted average daily return for all firms with the same Fama-French 48 industry code. We regress the standard deviation of industry returns annually on the standard deviation of industry-level earnings and income statement line items and use the annual R-squared of this regression as the measure of industry risk-relevance (*Industry Risk-Relevance - R^2*). We use quarterly data (i.e., 12 quarters) from the same three-year period over which we estimate the standard deviation of returns. *NI* is net income scaled by lagged total assets (NIQ / lag ATQ). *IB* is income before extraordinary items scaled by lagged total assets (IBQ / lag ATQ). *OPER* is operating income after depreciation scaled by lagged total assets (OIADPQ / lag ATQ). *ATO* is sales scaled by lagged total assets (SALEQ / lag ATQ). *COGS* is costs of goods sold scaled by lagged total assets (COGSQ / lag ATQ). *DEP* is depreciation expense scaled by lagged total assets (DPQ / lag ATQ). *R&D* is R&D expense scaled by lagged total assets (max(0, XRDQ) / lag ATQ). *SG&A* is SG&A expense scaled by lagged total assets (max(0, XSGAQ) / lag ATQ). *MainSG&A* is SG&A less R&D expense, scaled by lagged total assets ((max(0, XSGAQ) – max(0, XRDQ)) / lag ATQ). *TAX* is tax expense scaled by lagged total assets (TXTQ / lag ATQ). *SPEC* is special items scaled by lagged total assets (SPIQ / lag ATQ). *NONOP* is non-operating income scaled by lagged total assets (NOPIQ / lag ATQ). For each calendar-quarter and each variable, we calculate an industry average. To align with the measurement of industry-level returns, which are based on value-weighted returns, we use an (lagged) asset-weighted average to measure industry-level variables. We require each Fama-French 48 industry to have at least 10 firms with available data to calculate industry averages. *TIME* is a time trend that is equal to 0 in 1975 and 48 in 2023, except in the regressions with *R&D* and *MainSG&A*, where *TIME* is equal to 0 in 1989 and 34 in 2023. To investigate the development in risk-relevance, we regress the annual risk-relevance on *TIME*. T-statistics are reported in parentheses under the coefficients. *, **, *** indicate statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively (two-tailed).

TABLE 8

Risk-Relevance of Accruals & Cash Flows over Time

	Risk-Relevance – R^2			
Variable	***CFO***	***ACC - NI***	***ACC - IB***	***ACC - OPER***
Intercept	0.0720***	0.1386***	0.1330***	0.1082***
	(7.95)	(14.15)	(14.58)	(12.68)
TIME	0.0032***	0.0025***	0.0026***	0.0014***
	(5.78)	(5.54)	(6.08)	(3.40)
N	35	35	35	35
R^2	0.51	0.47	0.54	0.24

This table reports the results of tests investigating how the risk-relevance of accruals and cash flows has developed over the 35-year period from 1989 to 2023. The sample includes all firm-years with available data in the Compustat-CRSP universe after eliminating firms with a missing Fama-French 48 Industry code, firms in Fama-French industries 44-48, firms with total assets less than or equal to zero, and firms with a missing standard deviation of returns. Depending on data availability of the other variables, the sample size for individual tests can vary. The standard deviation of returns (*STDRET*) is measured as the standard deviation of daily returns over a three-year period that ends three months after the fiscal year-end. We regress the standard deviation of returns annually on the standard deviation of accruals or cash flows and use the annual R-squared of this regression as the measure of risk-relevance (Risk-Relevance - R^2). We use quarterly data (i.e., 12 quarters) from the same three fiscal years over which we estimate the standard deviation of returns. *CFO* is quarterly operating cash flow scaled by lagged total assets. We transform Compustat's year-to-date operating cash flow variable (OANCFY) into quarterly cash flows. *ACC – NI* is net income-based accruals calculated as net income less cash flow from operating activities, scaled by lagged total assets ((NIQ – qOANCF) / lag ATQ). *ACC- IB* is accruals based on income before extraordinary items, calculated as income before extraordinary items less cash flow from operating activities, scaled by lagged total assets ((IBQ – qOANCF) / lag ATQ). *ACC - OPER* is accruals based on operating profits, calculated as operating income after depreciation less cash flow from operating activities, scaled by lagged total assets ((OIADPQ – qOANCF) / lag ATQ). *TIME* is a time trend that is equal to 0 in 1989 and 34 in 2023. To investigate the development in risk-relevance, we regress the annual risk-relevance on *TIME*. T-statistics are reported in parentheses under the coefficients. *, **, *** indicate statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively (two-tailed).

TABLE 9

Risk-Relevance of Earnings over Time – Machine Learning

	Risk-Relevance – R^2			
Model	***OLS***	***XGBoost***	***Random Forests OOS***	***Random Forests OOB***
Intercept	0.1433***	0.2014***	0.1931***	0.1939***
	(10.57)	(11.62)	(11.87)	(11.94)
TIME	0.0043***	0.0057***	0.0048***	0.0048***
	(8.58)	(8.98)	(8.07)	(8.05)
N	48	48	48	48
R^2	0.61	0.64	0.59	0.58

This table reports the results of tests investigating how the risk-relevance of earnings components has developed over the 48-year period from 1976 to 2023. The sample includes all 199,032 firm-years with available data in the Compustat-CRSP universe after eliminating firms with a missing Fama-French 48 Industry code, firms in Fama-French industries 44-48, firms with total assets less than or equal to zero, and firms with a missing standard deviation of returns. The standard deviation of returns (*STDRET*) is measured as the standard deviation of daily returns over a three-year period that ends three months after the fiscal year-end. We regress the standard deviation of returns annually on the standard deviation of earnings components and Fama-French 12 industry indicators and use the annual R-squared of this regression as the measure of risk-relevance (Risk-Relevance - R^2). We use quarterly data (i.e., 12 quarters) from the same three fiscal years over which we estimate the standard deviation of returns. We use three models to estimate the Risk-Relevance - R^2: Ordinary Least Squares (OLS), Gradient Boosting (XGBoost), and Random Forests. For each model, we model the standard deviation of returns annually on the standard deviation of earnings components and the Fama-French industry indicators. We use the resulting annual R-squared as the measure of risk-relevance (Risk-Relevance - R2). For OLS and XGBoost, we derive the out-of-sample (OOS) R-squared obtained through 10-fold cross-validation. For Random Forests, we use both the out-of-sample R-squared from 10-fold cross-validation and the out-of-bag (OOB) R-squared. *TIME* is a time trend that is equal to 0 in 1976 and 47 in 2023. To investigate the development in risk-relevance, we regress the annual risk-relevance on *TIME*. T-statistics are reported in parentheses under the coefficients. *, **, *** indicate statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively (two-tailed).