Risk Management for Tangible and Intangible Investments: The Relationship between R&D and Capital Expenditures and Risk Components

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We examine the differential relationship across R&D and capital expenditures, and competition risk, operations risk, disruptive technology risk and tax risk. We measure competition risk as the future volatility of sales; operations risk as the future volatility of cost of goods sold and selling, general and administrative expenses purged of sales volatility; disruptive technology risk as the future volatility of special items; and tax risk as the future volatility of income tax expense. We find that compared to capital expenditures, R&D expenditures are less strongly associated with competition risk and operations risk measured by cost of goods sold volatility; and more strongly associated with disruptive technology risk, operations risk measured by selling, general and administrative cost volatility and income tax risk. The results for competition and disruptive technology risks are driven by industries that are more prone to disruptive technology risk. Drilling down on the categories of special items, we find that R&D expenditures are more strongly associated with future restructuring expenses, goodwill impairment, mergers and acquisition, gain/loss and others volatilities than capital expenditures; and these results are driven by industries that are exposed to disruptive technology. Collectively, the results indicate that R&D does not uniformly lead to more risk; it helps mitigate competition risk but exacerbates disruptive technology risk. This insight should be useful for assessing the risk appetite and resource allocation decisions.

1.Introduction

Corporate research and development (R&D) activities are widely considered to be riskier than most other investments, such as in fixed assets and business acquisitions. That's the major reason for U.S. GAAP mandating that R&D should be expensed (except for software development costs—SFAS 86), despite the obvious expectation of future benefits from this activity. Managers too consider innovation investments, and R&D in particular, to significantly enhance the firm's risk: A 2012 Conference Board CEO survey reports that executives consider innovation management as one of the top-5 aspects of corporate risk management (Mitchell et al., 2012).[1]

But, is it a fact that all R&D activities – research development, modification of existing technologies, are equally risky, and what exactly are the main risk-drivers of R&D? is it the expected competition to the products emerging from the R&D activities, that is, "product-market risk"? or, perhaps, it's "process-cost risk," since much of R&D, particularly in certain industries, like chemicals, cars, and Oil& Gas, is aimed at reducing manufacturing costs and streamlining operations. The risk here is that the R&D actually fails to substantially reduce operating costs. And then there is a third major R&D risk driver—"disruptive risk," introduced by___ Christensen (_. This is the often catastrophic risk of competitors developing new technologies that void altogether existing R&D efforts and technologies (telephone – telegraph, word processors – typewriters, index investing – individual stock picks). So, what are the major R&D risk-drivers?

We don't really know. Hardly any accounting or finance research is aimed at identifying the specific factors that determine R&D risk. Obviously, understanding these factors is critical to corporate risk management, as well as for accounting policymakers shaping accounting rules for

[1] Some studies consider R&D expenditures as risky investments compared to capital expenditures; for example, Coles et al. (2006) examine whether risk induced by executive compensation is associated with more R&D expenditures. Also, Kothari, et. Al, 2002, reporting that R&D is substantially riskier than capital expenditures.

R&D. the objective of this study is to further our understanding regarding the specific R&D risk drivers. We use investments in tangible assets, i.e., capital expenditures as a benchmark and compare the differential relationship between the risk components and R&D and capital expenditures.

We measure R&D product-market risk by the future volatility of sales/revenue. Process-cost risk is measured by the future volatility of operating costs, i.e., cost of goods sold and selling general and administrative expenses before R&D expenditures. Disruptive technology risk is measured by the future volatility of special items, since technological disruption is generally manifested in accounting by asset writeoffs and restructuring charges. We also consider the future volatility of income taxes to provide insights into uncontrollable risk, since the tax rules for R&D tax credits are nebulous and changing. We expect the differential relationships of R&D and capital expenditures and risk drivers to be more pronounced in industries that are particularly exposed to disruptive technologies.[2]

We examine a sample of U.S. firms from 1972-2008. To test our hypotheses, we regress the measures of product-market, process risk and disruptive technology risk on R&D expenditure and capital expenditure; and control for factors that have been shown in prior research to be related to business risk – advertising expenditure, financial leverage and firm-size. We find, surprisingly, that compared to capital expenditures, R&D expenditures are less strongly associated with product-market risk and process risk, measured by sales and cost of goods sold volatility; and more strongly associated with disruptive technology risk and income tax risk.

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[2] We argue that the differential relationships of R&D and capital expenditures on future COGS and SGA volatilities are empirical questions. On the one hand, both R&D and capital expenditures have high adjustment costs and thus are likely to be associated with more future volatility. On the other hand, both R&D and capital expenditures could improve productivity, leading to less operating cost volatility.

We then examine whether the differential relationships of R&D and capital expenditures are driven by industries that are more exposed to disruptive technologies. For each four-digit industry SIC, we compute a disruptive technology score using six variables: the incidence of large special items, the relative number of patents, the relative number of patent citations, the aggregate R&D expenditure, the number of initial public offerings and the number of mergers and acquisitions. We find that in high disruptive risk industries, compared to capital expenditures, R&D expenditures are less strongly associated with product-market risk and process risk, and more strongly associated with disruptive technology risk. Taken together, the results show that for high disruptive industries compared to capital expenditures, R&D expenditures mitigate competition risk and exacerbate disruptive technology risk.

Given that the future special items volatility is higher for R&D expenditures than capital expenditures, we examine the future volatility of the *components* of special items to provide further insights. Specifically, we consider the following components of special items: restructuring expenses, asset write-downs, goodwill impairment, mergers and acquisition, large gains/losses, litigation/insurance settlement and others. We compute the future volatility of these special item components and obtain the residuals of each of the component by regressing the components' future volatility on the future sales volatility, residual cost of goods sold volatility and residual selling, general and administrative cost volatility. We find that R&D expenditures are more strongly associated with future restructuring expenses, goodwill impairment, mergers and acquisition, gain/loss and others volatilities than capital expenditures – these results are driven by industries that are exposed to disruptive technology.

To summarize, the results show that compared to a one dollar of spending on capital expenditure, a dollar spending on R&D expenditure is associated with lower product-market and process-cost risks and higher disruptive technology risk, and especially so for firms in industries exposed to disruptive technologies. This provides a new perspective on R&D risk, particularly from an accounting perspective: compared to tangible investment outlays, R&D outlays mitigate, rather than enhance, product-market and process-costs risk, but increase the risk of disruptive technologies as measured by restructuring activities. Stated differently, R&D poses a pronounced risk when it is exposed to disruptive technologies. These findings have important implications for enterprise risk management as well as disclosures on risk management practices of firms. Enterprise risk management should explicitly consider the future prospects of technological disruptions and strategically plan for it (Rittenberg and Martens, 2012). In addition, risk management practices should embody disclosures of how these one-time items are managed and provide investors with information on plans of action to manage the risk of technology disruption through voluntary disclosures is likely to reduce the cost of capital (see for example, Lev 2012). Regarding accounting policy, our findings indicate that different R&D activities should not be treated equally in terms of capitalization-expensing. Only a heightened risk of technological disruption should, in our opinion, support R&D expensing.

2. Motivation and Empirical Expectations

2.1 Background and Motivation

The Conference Board's CEO challenge 2012 survey of 776 CEOs reports that managing innovation is one of the top-five aspects for risk management (Mitchell et al., 2012). Rittenberg and Martens (2012) discuss the importance of measuring the risk appetite of business by incorporating innovation and technological risk. They provide examples of the telecommunications and defense industries and claim that the risk appetite of the companies are high because of disruptive technology risk. "As an example of high risk appetite, a defense contractor dealing in trucks decided that the risk of being behind in technology was so large that it essentially "bet the company" on developing a vehicle appropriate for the types of wars occurring around the world. If the contractor had been unsuccessful in procuring a new government order, it would have been out of business. The risk appetite was high, but it was understood by all involved in the process." The question then is: what are the major drivers of innovation (R&D) risk?

Prior academic research has examined the relationship between overall business risk as measured by the future earnings volatility and R&D expenditures. The underlying premise in most studies is that R&D activities are more risky than tangible capital expenditures. In line with this notion, Kothari et al. (2002) show that a one dollar R&D expenditure leads to roughly four times more future earnings volatility than capital expenditures. Ciftci et al. (2011) show that among firms who engage in R&D, those with high R&D intensity exhibit lower future earnings volatility than firms with low R&D intensity. Similarly, Pandit et al. (2011) show that compared to firms with a low number of patents, firms with a high number of patents exhibit lower future earnings volatility.[3] These results suggest that firms that are innovation leaders have lower business risk than firms that are followers.

Even though enterprise risk management frameworks incorporate innovation and technological risk and prior research in accounting and finance show that R&D affects risk; little is known about whether R&D helps to mitigate or exacerbate specific risk components? In other words, what is the source of R&D risk? The objective of this study is to provide insights into these questions by examining how R&D expenditures are related to the following risks: product-market, process, and disruptive technologies.

[3] Shi (2003) finds a positive association between R&D expenditures and bond default risk and bond risk premium, suggesting that R&D investments are risky. However, Eberhart et al. (2007) show that Shi's (2003) results are sensitive to the way R&D intensity is measured. Specifically, they find that R&D investments are negatively associated with bond risk premium.

2.2 Empirical Expectations

2.2.1 R&D Expenditures, Capital Expenditures and Competitive Risk

Early theoretical literature on R&D race predicts that compared to new entrants, incumbents have less incentive to engage in innovative activity (Arrow 1962).[4] However, empirical research indicates otherwise. Blundell et al. (1999) shows a positive relationship between market share and R&D activity, suggesting that incumbent/monopolists engage in considerable innovative activity. Blundell et al. (1999) state: 'It is often asserted that the superior performance of large firms in innovating is because they have a higher cash flow from which to finance investment in R&D. Our findings suggest that this is not the whole story – dominant firms innovate because they have a relatively greater incentive to do so. Firms with high market shares who innovate get a higher valuation on the stock market than those who do not.' Etro (2004) shows that incumbents pre-commit to high R&D levels to deter new entrants.[5] Consistent with this notion, Aghion et al. (2009) empirically find that in technologically advanced industries incumbents innovate more successfully and such innovation staves-off new entrants. From this strategic perspective, R&D expenditures enable firms to capture market share for new technologies, and thus firms engaging in R&D are likely to face less volatile sales.

Capital expenditures can also be used for such preemptive and strategic reasons to deter new entrants (see Woolridge and Snow 1990; Porter 1980, 1985). However, another role of capital expenditure is to provide a buffer for managing uncertainty of demand in the product market (Anupindi and Jiang 2008; Van Mieghem 2003). Uncertainty of demand is likely to manifest as

[4] This is referred to as the Arrow effect. The intuition behind this prediction is that for the incumbent the expected gain is the difference between the expected profits of the new technology and the current one, while for the entrant the expected gain is the expected profit of the new technology. This is called the Arrow effect (see Arrow, 1962).
[5] Etro (2008) shows that the aggressive behavior of incumbents is as follows: under quantity competition the incumbent will produce more, while under price competition the incumbent will lower prices.

competition risk. As such, firms that face a higher competition risk due to uncertainty of demand are likely to have higher capital expenditures.

Putting these arguments together, we predict that R&D expenditures will be associated with less product-market risk than capital expenditures. Furthermore, we expect that the strategic use of R&D is likely to be more beneficial for firms in mitigating competition risk in industries that are more prone to disruptive technologies.

2.2.2 R&D Expenditures, Capital Expenditures and Disruptive Technology Risk

Many innovative firms operate in an environment characterized by radical technological changes, i.e., disruptive technologies (see Christensen 2003). Christensen (2003) finds that compared to entrants, incumbents often falter in adopting disruptive technologies. Similarly, Henderson and Clark (1990) and Utterback (1994) find that innovations that transform an industry on average do not come from incumbent firms. Disruptive technologies require companies to refocus their processes and ways of doing business. Firms faced with disruptive technologies are more likely to end up with corporate restructuring because these firms generally find it difficult to adapt to such radical changes (Rothaermel 2001). That is, firms operating in innovative environments are more likely to face a need for fundamental transformation periodically due to disruptive technologies, which in turn is likely to lead to restructuring. On the other hand, firms that have more capital expenditures are likely to have a natural barrier to entry in the sense that new entrants or competitors will not be able to set up new plants instantaneously. As such, capital expenditures are likely to be less associated with restructuring than R&D expenditures.

Putting the above arguments together, we predict that compared to capital expenditures, R&D expenditures will be associated with more disruptive technology risk. Furthermore, we expect this predicted relationship to be more pronounced in industries that are prone to disruptive technologies, because by definition more disruptive industries will be subject to more restructuring. This is stated in the following hypothesis.

H2: *R&D expenditures are more strongly associated with disruptive technology risk than capital expenditures; and this relationship is stronger for high disruptive industries ceteris paribus.*

2.2.3 R&D Expenditures, Capital Expenditures and Operations Risk

R&D investments have a number of characteristics that differentiate them from tangible investments. Roughly fifty percent or more of R&D expenditures are due to compensation for human capital such as scientists and engineers (Hall and Lerner 2009). Innovation created by the scientists and engineers is tacit knowledge that is likely to be lost when they leave the firm. This leads to R&D expenditures being sticky over time (see Hall et al. 1986). In other words, R&D expenditures are not likely to be adjusted downwards or upwards as firms tend to smooth these expenditures over time in order to avoid laying-off such knowledge workers: R&D expenditures behave as if adjustment costs are high.

Similar to R&D expenditures, the adjustment cost for capital expenditures is also high because of two inherent characteristics of capacity costs. First, capacity cannot be ramped-up or down instantaneously, i.e., adjustment of capacity to demand takes time. Second, capacity costs are typically lumpy in the sense that physical capacity can only be increased in a step-fashion of ‘n’ units at a time. The capacity costs are embedded in cost of goods sold and/or selling, general and administrative expenses. As such, both R&D and capital expenditures have high adjustment costs, leading to both R&D and capital expenditures inducing operations risk.

On the other hand, R&D expenditures can help improve product quality by decreasing cost of rework with programs such as six-sigma quality control programs. Similarly, capital expenditures can be substitutes for other factors of production such as labor by automating assembly lines. These effects can result in both R&D and capital expenditures inducing less operations volatility. As such, whether R&D expenditures are more or less strongly associated with operations risk is an empirical question.

2.2.4 R&D Expenditures, Capital Expenditures and Income Tax Risk

We examine income tax risk to provide insights into controllable and uncontrollable risks. The R&D tax credit rules are based on defining qualified research expenditures incurred in the U.S. In general, it is difficult if not impossible to define R&D expenditures precisely because innovation is about known and unknown, unknowns.[6] The definition of qualified expenses has been changing to accommodate new types of research as well as provide adequate incentives to U.S. firms to maintain their innovative edge (see Mansfield 1986).[7] The R&D tax credit is a temporary provision; this tax credit has been resurrected 13 times by Congress but has not been made permanent. Even until mid-January 2010, the R&D credit is among a number of “extender” provisions still awaiting congressional authorization (Karnis 2010). The temporary nature of this credit from year to year is likely to induce more uncertainty in R&D firms’ income taxes. Furthermore, the rules for application of the R&D tax credit in terms of the tax credit rates, the qualified base amount and the foreign income allocation rules have been modified repeatedly (see

[6] The Internal Revenue Code in the U.S. contains two broad provisions: (1) the expensing rules for R&D in general (IRC Section 174); (2) R&D tax credit (IRC Section 44).

[7] R&D tax credit as initially embodied in 1964 defines qualified research broadly in Section 174 as, “research and development costs in the experimental or laboratory sense.” In 1986, the Tax Reform Act created a four-part definition of qualified research. This definition requires the research (1) meet the requirements under Section 174; (2) be undertaken for the purpose of discovering information which is technological in nature; (3) be intended to be useful in the development of a new or improved business component; and (4) that substantially all of its activities constitute a process of experimentation. However, no guidance was available until 1998 on how to apply this four-part definition of qualified research. Mansfield (1986) argues that due to the vagueness of the definition, firms that invested in R&D projects may not have obtained the tax credit.

Hemphill 2009).[8] As a result of the vagueness of the tax codes, R&D expenditures are likely to be associated with more future income tax volatility.

Compared to the R&D tax credit, the tax credit related to capital investment started in the 1900s and is more mature in terms of precedents. While there have been changes in the rules related to depreciation and investment tax credit, and the definition of what is capitalizable is vague, the degree of vagueness as well as the investment tax credits has not been subject to as many revisions and the R&D credit provisions. Consequently the capital investment related tax credits are less vague than the R&D tax credits. As such, we expect R&D expenditures to be associated with more income tax volatility than capital expenditure.

Putting the above arguments together, we predict that compared to capital expenditures, R&D expenditures will be associated with more future income tax expense volatility controlling for sales and operating cost volatilities. For high disruptive industries this relationship can be stronger if the definitions for R&D under tax rules are more nebulous for such industries. However, if it is the case that the definitions are not clear for the low disruptive industries, then the relationship will be stronger for the low disruptive industries. As such, we do not have a prediction for whether this relationship is stronger or weaker for high disruptive industries. This is stated in the following hypothesis.

[8] We discuss each of these briefly. First, the R&D tax credit rate was initially set (from July 1981 to December 1985) at 25% of qualified research expenses above a base amount. Since January 1986, the rate was reduced to 20%. Second, the base amount, when the credit was introduced in 1981 was the maximum of previous three-year average or 50% of the current year. However, beginning in June 1990 (The Omnibus Budget Reconciliation Act of 1989), the base amount is the 1984-1988 R&D to sales ratio times current sales with a maximum ratio of 0.16, and a ratio of 0.03 for start-ups. In its 2005 Congressional extension, two other methods were introduced to compute the base amount. Third, the foreign source income allocation rules for R&D allowed for a 100% deduction of R&D expenditures against domestic income during July 1981 to December 1986. In 1987, this was reduced to 50% for domestic and 50% was allocated to foreign income. The rules then changed to 64%-36% allocations to domestic-foreign incomes; and then onto 30%-70% allocations to domestic-foreign incomes. In addition in 1996 an “Alternative R&D Tax Credit Program” was introduced to benefit established companies that have smaller annual increases relative to their base period (Hemphill 2009).

H3: *R&D expenditures are more strongly associated with tax risk than capital expenditures, ceteris paribus.*

3.Research Design and Empirical Analysis

3.1Variable Definition

Product-market risk is measured using the future volatility of sales/revenue. The top-line sales/revenues provides a measure of the realized demand for the firm. As such, it embodies elements of competition risk. We follow the procedure that Kothari et al. (2002) use for measuring bottom-line/earnings risk. For each firm-year, SALES is defined as the sales/revenues divided by the beginning of the year market value of equity. The future volatility of sales in year t is the standard deviation of SALES, SD(SALES) computed using SALES from years t+1 to t+5 scaled by end of year t-1 market value of equity.

We use two measures for process risk: cost of goods sold and selling, general and administrative expenses. We use these measures for process risk because, the fixed costs of capital expenditures and certain types of R&D (process R&D) are aimed at reducing manufacturing costs and streamlining operations. The resources required for sustaining the tacit knowledge of R&D generally forms part of selling, general and administrative expenses (Lev and Radhakrishnan 2005; Lev et al. 2009). We measure operations risk following a similar procedure to competition risk. For each firm-year, COGS is defined as cost of goods sold divided by the beginning of the year market value of equity; and SGA is the selling, general and administrative expenses plus R&D expenditures divided by the beginning of the year market value of equity. Selling, general and administrative expenses contain R&D expenditures and thus adding-back R&D expenditures potentially mitigates mechanical relationship between R&D and SGA. SD(COGS) and SD(SGA) are the standard deviation of COGS and SGA, respectively from years t+1 to t+5 scaled by beginning of the year market value of equity.

Disruptive technology risk is prefaced on restructuring charges which are embedded as a non-recurring charge in special items. Bens et al. (2009) find that restructuring charges are one of the more prevalent special items, and Dechow, Huson, and Sloan (1994) find that restructuring charges constitute roughly 80 percent of the net income before the charge. Lopez (2002) finds that restructuring charges on average are 9.80% of the market value of equity. In short, restructuring charges are substantial and are likely to occur when a firm is faced with disruptive technologies (in addition to other reasons). As such, we measure disruptive technology risk using the future volatility of special items. Special items are one-time charges in the income statement that represent costs of fundamental changes in the operations such as restructuring. For each firm-year, SPI is defined as special item times minus one divided by the beginning of the year market value of equity. We multiply SPI by minus one, because Compustat defines charges as a negative number. SD(SPI) is the standard deviation of SPI from years t+1 to t+5 scaled by beginning of the year market value of equity.

Tax risk is measured using income tax expense. For each firm-year, TAX is defined as income tax expense divided by the beginning of the year market value of equity. SD(TAX) is the standard deviation of TAX from years t+1 to t+5 scaled by beginning of the year market value of equity. For each of the future volatility measures if a firm does not survive for any part of the next five years, the future volatility of firms in the same Altman Z-Score decile portfolio is substituted to mitigate survivorship induced biases in the estimations (see Kothari et al. 2002).

To provide a benchmark with earlier work we also compute the future volatility of earnings. For this purpose, we define earnings as income before extraordinary items, discontinued operations, depreciation and R&D (IBEDRD). We add-back depreciation and R&D expenditures to earnings because we do not want the depreciation method to influence the volatility of earnings and potentially lead to spurious correlations. For each firm-year, IBEDRD is defined as earnings divided by the beginning of the year market value of equity. SD(IBEDRD) is the standard deviation of IBEDRD from years t+1 to t+5 scaled by beginning of the year market value of equity. We use to IBEDRD to provide a benchmark with earlier studies. We also define OTHERS as the difference between IBEDRD and SALE, COGS, SGA, SPI and TAX; and compute SD(OTHERS) in a similar fashion.[9] We use OTHERS to fully decompose the component of earnings, even though it is not pertinent to our research question.

Anderson et al. (2003) argue and show that sales revenue is the activity driver for SGA and COGS. Given that sales revenue is the activity driver for costs, we consider the volatility of COGS that is not attributable to the volatility of sales.[10] We measure R_SD(COGS) as the residuals obtained from regressing SD(COGS) on SD(SALES) separately for each year. Similarly, we measure R_SD(SGA) as the residual obtained from regressing SD(SGA) on SD(SALES) and R_SD(COGS); and R_SD(SPI), R_SD(TAX) and R_SD(OTHERS) are the residuals obtained by regressing SD(SPI), SD(TAX) and SD(OTHERS) on SD(SALES), R_SD(COGS) and R_SD(SGA), respectively.

All the variables are defined in Appendix I.

3.2Research Design

[9] Specifically, “OTHERS” include Interest Income (Expense), Nonoperating Income (Expense), Minority Interest, Dividends-Preferred, and Common Stock Equivalents.

[10] Considering sales as the activity driver, COGS is modeled as: COGS = a + b SALES. Thus, Variance(COGS) = b^2 Variance(SALES).

To test the hypotheses, we regress future volatility of earnings and its components on current years R&D (RD) and capital expenditures (CAPEX) and control for advertising expenditures (ADV), leverage (LEV), firm-size (MV) and industry fixed effect. Specifically, we estimate the following equation.

$$\text{FUTURE VOLATILITY}_{i,t} = \text{Industry-fixed effects} + \beta_{1t}\,RD_{it} + \beta_{2t}\,CAPEX_{it} + \beta_{3t}\,ADV_{it} + \beta_{4t}\,LEV_{it} + \beta_{5t}\,MV_{it} + \text{error} \quad (1)$$

where future volatility variables are SD(SALES), R_SD(COGS), R_SD(SGA), R_SD(SPI), R_SD(Tax) and R_SD(OTHERS); and all variables are defined in Appendix I. We use Fama Macbeth procedure and correct the standard errors for serial correlations for up to five lags using the Newey-West procedure.[11] Specifically, we estimate the equations separately for each year and present the mean coefficient estimates. The t-statistics are based on the standard errors obtained from the annual estimates, corrected for serial correlation up to five lags using the Newey-West procedure. We test the difference of the annual coefficient estimates on RD and CAPEX, i.e., β_{1t} and β_{2t} using the two-sample t-test.

3.3 Sample and Descriptive Statistics

We obtain financial data from the *Compustat* Annual files for the period 1972 to 2011. We delete observations with missing values of sales, total assets, book value of equity or market value of equity, debt and negative book value of equity.[12] Similar to Ciftci et al. (2011) to ensure that our results are not driven by small firms, we delete observations if any of the following conditions are met: (1) firms for which book value of assets is less than \$10 million; (2) data for year t is missing; and (3) firms with stock price less than \$1. The final sample contains 49,483 firm-year observations.

[11] Since the error terms across the estimations are likely to be correlated, we also use the seemingly unrelated regression procedure and obtain similar results.
[12] We get price data from CRSP if they are missing in *Compustat*.

Table 1, Panel A presents the descriptive statistics for investment and firm characteristics, earnings and its components and future volatility of earnings and its components which form our measures of risk in the top, middle and bottom panels, respectively. The mean investment outlays on research and development (RD) and tangible assets (CAPEX) are 3% and 12% of market value of equity, respectively. This indicates that tangible asset investments outlays are on average 3 times higher than R&D outlays.

The middle panel provides the descriptive statistics for earnings and its components that are used to measure bottomline risk and components of risk. The mean (median) IBEDRD are 16% (13%); the average earnings-to-price is higher than those in prior studies primarily because we consider earnings before charges related to investment outlays. The mean (median) values of scaled SALES, COGS, SGA, SPI, TAX and OTHERS are 2.92, 2.04, 0.60, 0.01, 0.05 and 0.05 (1.46, 0.88, 0.29, 0.00, 0.04 and 0.02), respectively. This suggests that on average the operating cost structure has the following pecking order: COGS, SGA, TAX, OTHERS and SPI.[13] Overall, this shows that regular operations as measured by COGS and SGA account for more resource consumption than special items and income taxes.

The bottom panel provides the descriptive statistics of our measures of competition, operations and disruptive technology risks. The mean (median) standard deviation of earnings, SD(IBEDRD) is 9% (8%), which are roughly similar to those in earlier studies. The mean (median) standard deviations of SALES, COGS and SGA are 94%, 68% and 18% (72%, 52% and 12%), respectively; considerably higher than that of earnings, suggesting that the covariance among earnings components are negative. The mean (median) standard deviations of SPI, TAX and

[13]Even though depreciation and amortization charges are contained in COGS and SGA, we take them out of OTHERS because how much depreciation is contained in COGS and SGA is not available separately. OTHERS is likely to be biased downwards because we remove depreciation and amortization from other costs.

OTHERS are 3%, 4% and 4% (2% 3% and 2%), respectively; which are considerably lower than those of operations related earnings components' volatility.

Table 1, Panel B provides the correlations between the future volatility of earnings and its components. The correlations are computed for each year, and the distribution of the annual correlation coefficients are used to compute the t-statistics. The Spearman correlations between SD(Sales) and SD(COGS), SD(SGA), SD(SPI), SD(TAX) and SD(OTHERS) are 97%, 81%, 40%, 69% and 61%, respectively. This shows that sales volatility is more strongly correlated with operations related volatility (SD(COGS) and SD(SGA)) than non-operations related volatility (SD(SPI) and SD(OTHERS)).

Table 2, Panel A provides the results of the regressions of operations and disruptive technology risks on competition risk. We use the Fama-McBeth procedure and correct for serial correlation in the standard errors up to five years using the Newey-West procedure. The first column presents the results of regressing SD(COGS) on SD(SALES). The coefficient on SD(SALES) is 0.76 (t-stat = 193.09) and the adjusted R-square is 0.96 indicating that the volatility of COGS is strongly related to the volatility of SALES. The second column presents the results of regressing SD(SGA) on SD(SALES) and R_SD(COGS). The coefficients on SD(SALES) and R_SD(COGS) are 0.15 (t-stat = 63.61) and -0.61 (t-stat = -35.56), respectively, and the adjusted R^2 is 0.81. The result is consistent with adjustment costs for SGA being higher than those of COGS and consequently, the relationship between the volatility of the activity driver and volatility of SGA is less strong (see Anderson et al. 2003). The results of regressing SD(SPI) on SD(SALES), R_SD(COGS) and R_SD(SGA) are shown in the third column. The coefficient on SD(SALES) is 0.01 (t-stat = 10.72), indicating that the volatility of special items is also positively associated with the volatility of sales. The coefficient on R_SD(COGS) is insignificant while that on R_SD(SGA) is 0.05 (t-stat=5.62). The results suggest that after filtering out the volatility of the activity driver, the volatility of SGA is positively associated with the volatility of special items. However, the adjusted R^2 of the model is 0.14, much lower than that in the first two columns. The fourth column provides the result with future income tax volatility as the dependent variable. The coefficient on SD(SALES), R_SD(COGS) and R_SD(SGA) are 0.02 (t-stat=33.06), -0.02 (t-stat=-3.74) and -0.01 (t-stat=-1.47), respectively; and the adjusted R^2 is 0.35. The result suggests that the SALES volatility, COGS volatility and SGA volatility explain more future income tax volatility than about future special items volatility. We multiply all the residuals-based measures by 100. While there is no theoretical reason for considering the pecking order in terms of operating and non-operating components, we use the future sales volatility and all other earnings components' future volatility as control variables and obtain similar results.

3.4 Differential effects of R&D and capital expenditure on Components of Risk

Panel B of Table 2 presents the results of estimating equation (1). When the dependent variable is SD(SALES), the coefficient on RD is 0.50 (t-stat=4.65) while that on CAPEX is 0.81 (t-stat=13.39). The coefficient on CAPEX is 1.62 (=0.81/0.50) times that RD and the difference in the coefficients is statistically significant (t-stat=-2.56). The results suggest that a one dollar additional spending on capital expenditure is associated with about 62% (=(0.81-0.50)/0.50) times more competitive risk as measured by the future sales volatility than a one dollar additional expenditure in R&D. The result supports hypothesis H1.

The second column presents the results where the dependent variable is R_SD(COGS) instead of SD(SALES). The coefficient estimates on RD and CAPEX are -0.17 (t-stat=-5.07) and 0.04 (t-stat=6.04), respectively; and the difference between the coefficients is -0.21 and statistically significant (t-stat=-6.21). In the third column, when the dependent variable is

R_SD(SGA) the coefficient estimates on RD and CAPEX are -0.02 (t-stat=-1.94) and -0.04 (t-stat=-8.47), respectively; and the difference between these coefficients is statistically significant (t-stat=2.05). This shows that R&D expenditures are associated with less (more) operations risk as measured by future COGS (SGA) volatility than capital expenditures. This suggests that for COGS the efficiency improvement effect of RD is greater than that of CAPEX; and for SGA the adjustment cost effect of RD is greater than that of CAPEX.

The fourth and fifth columns present the results for R_SD(SPI) and R_SD(TAX) as the dependent variables. When R_SD(SPI) is the dependent variable, the coefficient estimates on RD and CAPEX are 2.40 (t-stat=5.55) and 0.16 (t-stat=0.99), respectively; and the difference is statistically significant (t-stat=4.86). This shows that compared to capital expenditures, R&D expenditures are associated with more disruptive technology risk as measured by future special items volatility. This finding supports hypothesis H2.

When R_SD(TAX) is the dependent variable, the coefficient estimates on RD and CAPEX are 0.40 (t-stat=1.72) and -0.21 (t-stat=-2.64), respectively; and the difference is statistically significant (t-stat=2.48). Consistent with hypothesis H3 this shows that R&D expenditures are associated with more future income tax volatility than capital expenditures.

To round-off all the earnings components, we also report the results with R_SD(OTHERS) as the dependent variable. When R_SD(OTHERS) is the dependent variable, the coefficient estimates on RD and CAPEX are 0.64 (t-stat=1.30) and 1.56 (t-stat=7.21), respectively; and the difference is statistically insignificant (t-stat=-1.71).[14]

3.5 Do Industries Prone to Technological Change Drive the Hypothesis?

[14] When we use the raw measures of future volatility instead of the residual based measures as dependent variables, the results are similar.

In this section, we examine whether industries that are more prone to technological change, i.e., disruptive technologies drive the relationship between investment outlays and future earnings component volatility. We describe the industry-based measure of disruptive technologies, and then provide the results.

3.5.1 Measure of High and Low disruptive industries

We use six measures that are related to industry's exposure to disruptive technologies. Specifically, for all years, for each four digit industry we compute the aggregate value of large special items (BIGSPI), the number of patents (PATENTS), number of patent citations (CITATIONS), industry research and development expenditure (INDRD), the number of initial public offerings (IPO) and the number of mergers and acquisitions (MA).[15]

BIGSPI is one if the special item scaled by market value of equity for a firm-year is greater than 5%, and zero otherwise. We aggregate the BIGSPI for each industry across all years, and code HIGH_BIGSPI as one if the aggregate BIGSPI is greater than one, otherwise HIGH_BIGSPI is zero. In essence, HIGH_BIGSPI is one if there is at least one firm in the industry that has undergone a major restructuring during the sample period. We consider BIGSPI because it measures the ex post disruption of an industry.

We obtain patent and citation data from NBER's dataset "pat76_06_assg".[16] Specifically, the number of patents (PATENTS) and number of patent citations (CITATIONS) are data items "*Patent*" and "*Allcites*", respectively. We aggregate PATENTS and CITATIONS for each four-digit industry across all years and compute the median number of aggregate patents and citations. HIGH_PATENTS (HIGH_CITATIONS) is one if the aggregate number of patents

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[15] Our results remain qualitatively unchanged if we use 2-digit-SIC code in classifying disruptive technologies industry.
[16] https://sites.google.com/site/patentdataproject/Home/downloads.

(citations) for an industry is greater than the median value, otherwise zero.[17] Industry R&D (INDRD) is computed as the sum of R&D expenditures for each four digit industry divided by the sum of the market value of equity for each four digit industry across all the years. HIGH_INDRD is one for industries with INDRD greater than the median industry R&D, and zero otherwise. We use PATENTS, CITATIONS and INDRD as measures of the ex ante potential for disruptive technologies.

IPO takes on value of one if a firm goes public in that year. For this purpose, we use the "*ipodate*" and "*datadate*" items in *Compustat* to determine whether a firm goes public in a given year. Specifically, if the difference between "*ipodate*" and "*datadate*" is less than 365 days, we code IPO as one, otherwise IPO is zero. We then sum IPO across all years for each four digit industry. HIGH_IPO is one if the sum of IPO is greater than the median, otherwise HIGH_IPO is zero. We use IPO because these companies are the ones who are likely to disrupt the incumbents with innovative ways of doing business. IPO also measures the ease of entry into the industry; the easier it is to enter the industry the more likely it is that the industry is prone to disruptive technology.

MA takes on value of one if a firm has a merger event in that year. Specifically, if "sale_fn" is 'AA' or 'AB' in *funda_fncd* dataset in *Compustat*, then MA is one. We then sum MA across all years for each four digit industry. HIGH_MA is one if the sum of MA is greater than the median, otherwise HIGH_MA is zero. We use MA because incumbent firms are likely to engage in mergers and acquisitions to respond to disruptive and new technologies.

[17] The patent and citations data are available from 1976 to 2006. In the sensitivity analysis, when we use a rolling window to classify industries as high and low disruptive industries, we use the value of 1976 for the prior years and the values of 2006 for the years after 2007.

We construct an aggregate score (DISRUP) by summing up the six scores so that DISRUP ranges from 0 to 6. We then categorize the industries whose DISRUP is greater (lesser) than the median as high (low) disruptive industries. Specifically, HIGH_DISRUP is one if the DISRUP score is greater than the median and zero otherwise. Appendix II lists the four-digit SIC codes that are classified as high disruptive industries.

As a veracity check, prior research classifies the following four industries as science-based: chemicals and allied products (2-digit SIC code=28); industrial machinery and equipment (2-digit SIC code=35); electronic and other electric equipment (2-digit SIC code=36); and instruments and related products (2-digit SIC code=38) (see Griliches and Mairesse 1984; Bernstein and Nadiri 1988). Comparing the science-based classification with the high disruptive industry classification we find a considerable overlap. For example, the "chemicals and allied products" industry consists of 16 four-digit SIC codes, of which 15 are classified as high disruptive under our measure; the "industrial machinery and equipment" industry consists of thirty four-digit SIC codes and 26 of them are classified as high disruptive; "electronic and other electric equipment" industry consists of 21 four--digit SIC codes and 19 of them are classified as high disruptive; "instruments and related products" industry consists of 17 four-digit SIC codes, among which 14 are classified as high disruptive. When we use the two-digit industries to compute DISRUP, all the four industries are classified as high disruptive.

3.5.2 Empirical results

Table 3, Panel A provides the descriptive statistics across high and low disruptive industries. The mean SD(SALES), SD(COGS) and SD(TAX) for high (low) disruptive industries are 0.93, 0.68 and 0.04 (0.98, 0.72 and 0.04), respectively; the future volatilities of these items are significantly lower for the high disruptive industries than those for the low disruptive industries.

The mean SD(SGA) for high disruptive industries is 0.18 and that of low disruptive industries is 0.17; the future volatility of SGA is significantly higher for the high disruptive industries than those for the low disruptive industries. The mean values of R_SD(SPI) and R_SD(OTHERS) in high disruptive industries are not significantly different from those in low disruptive industries.

The mean RD for firms in the high disruptive industries is spend 3% of their market value of equity on R&D, which is significantly higher than the mean RD of 1% for firms in the low disruptive industries. Note that this is attributable to the way in which we classify industries, using the research spending and research outputs, i.e., patents and citations. The mean ADV for firms in the high disruptive industries is 7% of their market value, which is significantly higher than the mean of 6% for firms in the low disruptive industries. CAPEX is however similar for firms in both industry groups. The mean leverage, LEV and firm size, MV for high (low) disruptive industries are 0.34 (0.47) and 5.01 (4.41), respectively; indicating that high disruptive industries are less leveraged and are larger in size.

We augment equation (1) as follows to examine the differential effects of RD and CAPEX across the industries. Specifically, we estimate equation (2).

$$\begin{aligned} \text{FUTURE VOLATILITY}_{i,t} = {} & \text{Industry-fixed effects} + \alpha_{1t}\,\text{RD}_{it} + \alpha_{2t}\,\text{CAPEX}_{it} \\ & + \alpha_{3t}\,\text{HIGH\_DISRUP}_{it} + \alpha_{4t}\,\text{RD}_{it} \times \text{HIGH\_DISRUP}_{it} + \alpha_{5t}\,\text{CAPEX}_{it} \times \text{HIGH\_DISRUP}_{it} \\ & + \alpha_{6t}\,\text{ADV}_{it} + \alpha_{7t}\,\text{LEV}_{it} + \alpha_{8t}\,\text{MV}_{it} + \text{error} \end{aligned} \tag{2}$$

where FUTURE VOLATILITY variables are SD(Sales), R_SD(COGS), R_SD(SGA), R_SD(SPI), R_SD(Tax) and R_SD(OTHERS); and all variables are defined in Appendix I. As with equation (1) we use Fama Macbeth procedure and correct the standard errors for serial correlations for up to five lags using the Newey-West procedure. We test the difference of the annual coefficient estimates on RD and CAPEX, i.e., α_{1t} minus α_{2t} for the low disruptive industries; and $(\alpha_{1t} + \alpha_{4t})$ minus $(\alpha_{2t} + \alpha_{5t})$ for the high disruptive industries using the two-sample t-test.

Table 3, Panel B presents the results of estimating equation (3). When the dependent variable is SD(SALES) the coefficient on RD is 2.23 (t-stat=2.75) and that on CAPEX is 0.80 (t-stat=6.89), and the difference in the coefficients 1.43 is insignificant (t-stat=1.75). For the high disruptive industries the coefficient on RD is 0.37 [=2.23-1.86] and that on CAPEX is 0.83 [=0.80+0.03], and the difference -0.47 in the coefficients is statistically significant. This shows that compared to capital expenditures, R&D expenditures help to mitigate competitive risk mainly for the high disruptive industries; that is, hypothesis H1 is driven by high disruptive industries.

For operations risk measured by COGS, the difference in coefficient on RD minus the coefficient on CAPEX for the high (low) disruptive industry is -0.22 (-0.21) and statistically significant. For operations risk measured by SGA, the difference in coefficient on RD minus the coefficient on CAPEX for the high (low) disruptive industry is 0.01 (0.18) and only the difference for low disruptive industries is statistically significant. Collectively, these results suggest that for operations risk measured by COGS R&D helps to mitigate such risk compared to capital expenditures for both high and low disruptive industries, while for operations risk measured by SGA R&D imposes more risk than capital expenditures for low disruptive industries.

For disruptive technology risk measured by SPI, the difference in coefficient on RD minus the coefficient on CAPEX for the high (low) disruptive industry is 2.47 (1.19) and only the difference for the high disruptive industries is statistically significant. This result shows that hypothesis H2 is driven by industries that are more prone to disruptive technologies.

For the uncontrollable, tax risk measured by TAX, the difference in coefficient on RD minus the coefficient on CAPEX for the high (low) disruptive industry is 0.24 (2.62) and only the difference for the low disruptive industries is statistically significant. This result shows that hypothesis H3 is driven by industries that are not prone to disruptive technologies, i.e., the low disruptive technology industries.

3.6 Drilling-down the Disruptive Technology Risk

To further investigate the volatility of special items, we examine the components of special items to provide additional insights into the differential impact of R&D and capital expenditure on the future volatility of the special item components. Particularly, *Compustat* provides the following break-down of special items. Special items consist of mainly one-time charges such as restructuring expenses (RSTR), asset write-downs (WD), goodwill impairment (GWILL), mergers and acquisition (MA), gain/loss (GL), litigation/insurance settlement (SET) and others (OTH).[18]

Table 4, Panel A presents the descriptive statistics of the categories of special items and their volatilities across high and low disruptive industries. Most of the components of special items are zero. As such, we multiply the volatility measures by 100. The descriptive statistics show that firms in high disruptive industries have lower mean values of volatilities of RSTR and OTH than those in low disruptive industries.

In Panel B of Table 4 we report the results of estimating equation (2) when the dependent variables are the residual volatilities of special item components. For the low disruptive industry the difference across the RD and CAPEX coefficient is statistically significant only for asset write-downs; when the dependent variable is R_SD(WD) the coefficient on RD minus the

[18] Restructuring charges (RSTR) includes reorganization costs, closing costs, early retirement, exit costs, rationalizations, realignment, reductions in workforce, relocation charges, repositioning and severance when included in a restructuring amount by the company or when broken out as a separate line item on the income statement. Write-downs (WD) include impairment of assets other than goodwill and the write-down/write-off of assets other than goodwill. Goodwill (GWILL) includes (1) impairment of goodwill and other intangibles when combined; (2) impairment of unamortized intangibles; (3) positive impairments of goodwill and/or unamortized intangibles that indicate company is reversing part of a previous charge; (4) write-off of goodwill. Mergers and acquisitions (MA) includes the costs of failed acquisitions and the write-off of capitalized acquisition/merger costs. Gains and losses (GL) includes all gains and losses not included in restructuring and write-downs. Litigation settlement (SET) includes (1) insurance recovery/proceeds, (2) provisions to boost reserves for litigation and settlements, and (3) reversal of reserve for litigation/settlements. *Compustat* reports income/gains as positive and expenses/losses as negative numbers. Thus, we multiply the reported special item components by minus one so that it is consistent with the costs.

coefficient on CAPEX is -0.85 (t-stat= -3.12). For the high disruptive industry the difference across RD and CAPEX coefficients are positive and statistically significant for R_SD(RSTR), R_SD(GWILL), R_SD(MA), R_SD(GL), R_SD(SET) and R_SD(OTH). This indicates that for all categories of special items other than asset write-downs hypothesis H2 is driven by high disruptive industries.[19]

3.7 Robustness Tests

3.7.1Classifying Disruptive Industries Using Large special items

Instead of using measures that are based on R&D expenditures and outcomes of industries, we use only the BIGPI to classify industries. Specifically, if HIGH_BIGSPI is one for the industry we classify the industry as high disruptive industry, and low otherwise. As such, industries where at least one firm has had a large special item during the sample period is classified as high disruptive industries. As discussed earlier, this is an ex post measure of the potential for disruption. The results are qualitatively similar to those discussed in Tables 3 and 4.

3.7.2Rolling method

We classify industries using all the available data from all the years. There are two potential issues with this. First there could be a look ahead bias; that is, industries where there have been a lot of restructuring and special items will get classified as high disruptive industries and thus, the results especially of special items hence could be due to this look ahead bias. Second, we implicitly assume that industry dynamics are similar from 1976 through to 2006. To address these potential concerns we compute the DISRUP score on a rolling three year basis using data from years t-1 to t-5. For the patent and citation data we use the first and last year's available data to fill the earlier and later years respectively. We find that the results are qualitatively similar to those

[19] We obtain similar results when we use the future volatilities instead of the residual based measures.

discussed with Table 3 except that that the average coefficient on RD is not significantly different from that on CAPEX in future COGS volatility regression and SGA volatility regression. Also, for future SPI volatility regression, the difference in coefficient on RD minus the coefficient on CAPEX is significant for both high and low disruptive industries (t-stat=2.21 and 5.25, respectively).

3.7.3Seemingly unrelated regression

We estimate equation (2) using the seemingly unrelated regression procedure, because it is likely that the error terms across the different risk components are likely to be correlated. The results are similar to those reported in Table 3 except that the average coefficient on RD is not significantly different from that on CAPEX (t-stat=1.05) in future tax volatility regression.

3.7.4 Using future volatility instead of residual volatility as dependent variables

We also substitute the residual variables with the volatility variables as the dependent variables and reexamine the main test. Since sales is the activity driver for costs, we augment each regression (except future sales volatility regression) with SD(SALES) as a control variable. The results are similar to those reported in Table 3 except the future SGA volatility and future TAX volatility. When the dependent variable is SD(SGA), the average coefficients on RD, CAPEX, RD×HIGH_DISRUP and CAPEX×HIGH_DISRUP are 0.15 (t-stat=1.92), -0.09 (t-stat=-5.65), -0.13 (t-stat=-1.68) and -0.01 (t-stat=-0.80). A t-test of the difference in means of RD and CAPEX indicates a significant result in both low and high disruptive industries (t-stat=2.96 and 6.18, respectively). When the dependent variable is SD(TAX), the difference in coefficient on RD minus the coefficient on CAPEX is significant for both high and low disruptive industries. Generally speaking, the results are consistent with our hypotheses.

4.Concluding Remarks

We examined the differential relationship across R&D and capital expenditures, and competition risk, operations risk, disruptive technology risk and tax risk. We measure competition risk as the future volatility of sales; operations risk as the future volatility of cost of goods sold and selling, general and administrative expenses purged of sales volatility; disruptive technology risk as the future volatility of special items; and tax risk as the future volatility of income tax expense. We find that compared to capital expenditures, R&D expenditures are less strongly associated with competition risk and operations risk measured by cost of goods sold volatility; and more strongly associated with disruptive technology risk, operations risk measured by selling, general and administrative cost volatility and income tax risk. The results for competition and disruptive technology risks are driven by industries that are more prone to disruptive technology risk. The results also show that tax risk which is largely uncontrollable by manager should be used to assess the efficacy of risk management; in other words, bottomline risk measures should be used with caution when evaluating managers/firms with respect to their risk management practices. Drilling down on the categories of special items, we find that R&D expenditures are more strongly associated with future restructuring expenses, goodwill impairment, mergers and acquisition, gain/loss and others volatilities than capital expenditures; and these results are driven by industries that are exposed to disruptive technology. Collectively, the results indicate that R&D does not uniformly lead to more risk; it helps mitigate competition risk but exacerbates disruptive technology risk. This insight should be useful for assessing the risk appetite and resource allocation decisions. This being the first step in examining the relationship between innovation and risk components provides many opportunities for future research. Future research can examine whether the relationship between components of risk and innovation at the firm level translates to components of risk at the industry level. Furthermore exploring whether the relationship between innovations and components of risk arise due to industry characteristics or firm characteristics will provide insights that are useful for risk management. Future research can also examine the current practices relating to disclosures of risk.

Appendix A: Variable definitions

Investment and Firm Characteristics Variables

$MCAP_t$ is the market capitalization computed as the fiscal year closing price (#PRCC_F) times common shares outstanding (#CSHO).

RD_t is research and development (#XRD) deflated by $MCAP_{t-1}$.

$CAPEX_t$ is the capital expenditure (#CAPX) deflated by $MCAP_{t-1}$.

ADV_t is advertising expenditure (#XAD) deflated by $MCAP_{t-1}$.

LEV_t is the sum of long-term debt (#DLTT) and debt in current liabilities (#DLC) divided by the sum of long-term debt and $MCAP_t$.

MV_t is the natural logarithm of $MCAP_t$.

Earnings and its Components

IBEDRD is income before extraordinary items, discontinued operations, depreciation and R&D ({#EPSPX×#CSHO}+#DP+#XRD), deflated by $MCAP_{t-1}$.

SALES is sales revenue (#SALES), deflated by $MCAP_{t-1}$.

COGS is cost of goods sold (#COGS), deflated by $MCAP_{t-1}$.

SGA is selling, general and administration expenses minus RD (#XSGA-#XRD), deflated by $MCAP_{t-1}$.

SPI is special items (#SPI) multiplied by negative one, deflated by $MCAP_{t-1}$.

TAX is income taxes (#TXT), deflated by $MCAP_{t-1}$.

OTHERS is other costs, computed as (SALES-IBEDRD)-(COGS+SGA+SPI+TAX), deflated by $MCAP_{t-1}$.

Future Volatility Variables of Earnings and its Components

$SD(X_{t+1,t+5})$ is the standard deviation of X, deflated by $MCAP_{t-1}$, where X ={IBEDRD, SALES, COGS, SGA, SPI, TAX, OTHERS}. The standard deviations are calculated using five annual observations for years t + 1 through t + 5 and are set to equal to the mean standard deviations of the firms in the same Altman Z-Score decile portfolio if the data is missing for any part of years t+1 through t+5. Deflated values are winsorized to at 1 and 99 percentiles of the empirical distribution.

Residuals for Future Volatility of Earnings Components

R_SD(X) is the residual estimated annually for the earning component X, where X = {COGS, SGA, SPI, TAX, OTHERS}. Specifically, R_SD(COGS) is the residual from regressing: $SD(COGS_{t+1,t+5})_{it} = a_{0t} + a_{1t}\, SD(SALES_{t+1,t+5})_{it} + error_{it}$. R_SD(SGA) is the residual from regressing: $SD(SGA_{t+1,t+5})_{it} = a_{0t} + a_{1t}\, SD(SALES_{t+1,t+5})_{it} + a_{2t}\, R\_SD(COGS) + error_{it}$. R_SD(Y) is the residual of regressing: $SD(Y_{t+1,t+5})_{it} = a_{0t} + a_{1t}\, SD(SALES_{t+1,t+5})_{it} + a_{2t}\, R\_SD(COGS) + a_{3t}\, R\_SD(SGA) + error_{it}$ for Y = {SPI, TAX, OTHERS}.

Components of Special Items

RSTR is Restructuring Pretax (#RCP) multiplied by negative one, deflated by $MCAP_{t-1}$.

WD is Asset Write-Downs Pretax (#WDP) multiplied by negative one, deflated by $MCAP_{t-1}$.

GWILL is Goodwill Impairment Pretax (#GDWLIP) multiplied by negative one, deflated by $MCAP_{t-1}$.

MA is Acquisition/Mergers Pretax (#AQP) multiplied by negative one, deflated by $MCAP_{t-1}$.

GL is Gain/Loss Pretax (#GLP) multiplied by negative one, deflated by $MCAP_{t-1}$.

SET is Litigation/Insurance Settlement Pretax (#SETP) multiplied by negative one, deflated by $MCAP_{t-1}$.

OTH is Other-Special Items Pretax (#SPIOP) multiplied by negative one, deflated by $MCAP_{t-1}$.

Future Volatility of Special Item Components

$SD(X_{t+1,t+5})$ is the standard deviation of special item component X deflated by $MCAP_{t-1}$ for X = {RSTR, WD, GWILL, MA, GL, SET, OTH}. The standard deviation is computed similar to that of earnings components.

Residuals of Special Item Components

R_SD(X), the residual of the regression estimated annually: $SD(Xr_{t+1,t+5})_{it} = a_{0t} + a_{1t}\ SD(SALES_{t+1,t+5})_{it} + a_{2t}\ R\_SD(COGS) + a_{3t}\ R\_SD(SGA) + error_{it}$ for X = {RSTR, WD, GWILL, MA, GL, SET, OTH}.

Variables measuring high and low disruptive industries

BIGSPI is one if the special items (#SPI) of a firm-year are higher than 5% of $MCAP_{t-1}$ and zero otherwise.

HIGH_BIGSPI is one if the aggregate value of BIGSPI of a four-digit industry is higher than one and zero otherwise.

PATENTS is the number of patents (dataitem "*Patent*") for each firm year obtained from https://sites.google.com/site/patentdataproject/Home/downloads/pat76_06_assg.

HIGH_PATENTS is one if the aggregate PATENTS of a four-digit industry is higher than the median and zero otherwise.

CITATIONS is the total number of patent citations (dataitem "*allcites*") for each firm year obtained from https://sites.google.com/site/patentdataproject/Home/downloads.

HIGH_CITATIONS is one if the aggregate value of CITATIONS of a four-digit industry is higher than the median and zero otherwise.

INDRD is the sum of R&D expenditure divided by the sum of $MCAP_{t-1}$, where the sum is over four-digit industry.

HIGH_INDRD is one if INDRD of a four-digit industry is higher than the median and zero otherwise.

IPO is one if a firm goes public in year *t*; IPO is coded as 1 if the difference between "*ipodate*" and "*datadate*" (both items are from *Compustat*) is less than 365 days and zero otherwise.

HIGH_IPO is one if the sum of IPO of a four-digit industry is higher than the median and zero otherwise.

MA is one if a firm experiences mergers and acquisitions in a year. M&A data are from *funda_fncd* dataset in *Compustat*. If the item "*sale_fn*" is coded as AA or AB then the observation experiences M&A in that year.

HIGH_MA is one if the sum of mergers and acquisitions of a four-digit industry is higher than the median and 0 otherwise.

DISRUP is the sum of HIGH_BIGSPI, HIGH_PATENTS, HIGH_CITATIONS, HIGH_INDRD, HIGH_IPO and HIGH_MA.

HIGH_DISRUP is 1 if a firm-year observation is from a high-disruptive industry. An industry is classified as high-disruptive if its DISRUP score is higher than the median.

Appendix II: High disruptive industries based on aggregate score (223 out of 414 industries are classified as high disruptive)

0100	2086	2621	2860	3440	3564	3630	3728	3861	5141	5990	7812
1221	2090	2670	2870	3443	3567	3634	3730	3910	5160	6020	7830
1311	2111	2711	2890	3448	3569	3640	3743	3942	5200	6141	7900
1381	2200	2721	2891	3452	3570	3651	3751	3944	5211	6211	7948
1389	2211	2731	2911	3460	3571	3652	3760	3949	5311	6324	7990
1531	2221	2750	3011	3470	3572	3661	3790	3990	5331	6331	8051
1600	2273	2761	3021	3490	3575	3663	3812	4512	5399	6552	8071
2000	2300	2771	3060	3510	3576	3669	3821	4812	5411	6794	8200
2011	2320	2800	3080	3523	3577	3670	3823	4813	5600	6798	8700
2013	2330	2810	3081	3524	3578	3674	3825	4833	5621	7011	8711
2020	2390	2820	3089	3531	3579	3678	3826	4841	5661	7200	8731
2030	2400	2821	3140	3532	3580	3679	3827	4899	5700	7311	8742
2033	2430	2834	3270	3533	3585	3690	3829	5040	5731	7320	9995
2040	2510	2835	3290	3537	3590	3695	3841	5065	5812	7370	9997
2050	2511	2836	3312	3540	3600	3711	3842	5070	5900	7372	
2052	2520	2840	3350	3555	3612	3714	3843	5090	5912	7373	
2060	2522	2842	3357	3559	3613	3716	3844	5110	5940	7374	
2080	2540	2844	3420	3560	3620	3721	3845	5122	5944	7389	
2082	2590	2851	3430	3561	3621	3724	3851	5140	5961	7510	

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Table 1. Descriptive statistics

Panel A: Investment and Firm Characteristics

Variables	Mean	Std	Min	Q1	Median	Q3	Max
Investment and firm characteristics							
RD	0.03	0.05	0.00	0.00	0.00	0.03	0.43
CAPEX	0.12	0.19	0.00	0.02	0.06	0.14	2.20
ADV	0.07	0.13	0.00	0.01	0.03	0.07	1.59
LEV	0.36	0.40	0.00	0.07	0.26	0.54	4.25
MV	4.91	2.12	0.33	3.33	4.67	6.28	11.46
Earnings and its components							
IBEDRD	0.16	0.19	-1.16	0.07	0.13	0.23	1.64
SALES	2.92	4.29	0.01	0.63	1.46	3.44	53.03
COGS	2.04	3.37	0.00	0.31	0.88	2.37	43.11
SGA	0.60	0.88	-0.20	0.12	0.29	0.69	9.51
SPI	0.01	0.05	-0.21	0.00	0.00	0.00	0.67
TAX	0.05	0.08	-0.39	0.01	0.04	0.07	0.84
OTHERS	0.05	0.12	-0.28	0.00	0.02	0.06	1.65
Measures of Risk Components							
SD(IBEDRD)	0.09	0.08	0.00	0.04	0.08	0.11	0.99
SD(SALES)	0.94	1.18	0.00	0.27	0.72	1.15	21.84
SD(COGS)	0.68	0.93	0.00	0.16	0.52	0.87	17.87
SD(SGA)	0.18	0.24	0.00	0.06	0.12	0.19	3.86
SD(SPI)	0.03	0.04	0.00	0.00	0.02	0.03	0.43
SD(TAX)	0.04	0.03	0.00	0.02	0.03	0.04	0.46
SD(OTHERS)	0.04	0.05	0.00	0.01	0.02	0.05	0.65

Panel B: Correlations (Pearson above and Spearman below the diagonal)

Variable	SD(IBEDRD)	SD(SALES)	SD(COGS)	SD(SGA)	SD(SPI)	SD(TAX)	SD(OTHERS)
SD(IBEDRD)	-	0.60*	0.57*	0.51*	0.57*	0.65*	0.56*
SD(SALES)	0.71*	-	0.98*	0.82*	0.31*	0.56*	0.53*
SD(COGS)	0.67*	0.97*	-	0.73*	0.30*	0.54*	0.51*
SD(SGA)	0.56*	0.81*	0.74*	-	0.28*	0.47*	0.41*
SD(SPI)	0.57*	0.40*	0.40*	0.33*	-	0.40*	0.30*
SD(TAX)	0.72*	0.69*	0.68*	0.55*	0.44*	-	0.47*
SD(OTHERS)	0.65*	0.61*	0.60*	0.42*	0.42*	0.57*	-

Table 2. R&D, capital expenditure and risk components

Panel A: Sales as the driver of future cost components' volatility

	(1) Dep. Var. = SD(COGS)		(2) Dep. Var. = SD(SGA)		(3) Dep. Var. = SD(SPI)		(4) Dep. Var. = SD(TAX)		(5) Dep. Var. = SD(OTHERS)	
	Coef.	**t-stat**	**Coef.**	**t-stat**	**Coef.**	**t-stat**	**Coef.**	**t-stat**	**Coef.**	**t-stat**
SD(SALES)	0.76*	193.09	0.15*	63.61	0.01*	10.72	0.02*	33.06	0.03*	27.05
R_SD(COGS)			-0.61*	-35.56	-0.01	-1.48	-0.02*	-3.74	-0.03*	-6.24
R_SD(SGA)					0.05*	5.62	-0.01	-1.47	-0.06*	-4.70
Industry fixed	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-
Adj. R2	0.96	-	0.81	-	0.14	-	0.35	-	0.38	-

Panel B: R&D, Capital expenditure and Risk Components

	(1) Dep. Var. = SD(SALES)		(2) Dep. Var. = R_SD(COGS)		(3) Dep. Var. = R_SD(SGA)		(4) Dep. Var. = R_SD(SPI)		(5) Dep. Var. = R_SD(TAX)		(6) Dep. Var. = R_SD(OTHERS)	
	Coef.	**t-stat**	**Coef.**	**t-stat**	**Coef.**	**t-stat**	**Coef.**	**t-stat**	**Coef.**	**t-stat**	**Coef.**	**t-stat**
RD	0.50*	4.65	-0.17*	-5.07	-0.02	-1.94	2.40*	5.55	0.40	1.72	0.64	1.30
CAPEX	0.81*	13.39	0.04*	6.04	-0.04*	-8.47	0.16	0.99	-0.21*	-2.64	1.56*	7.21
ADV	1.37*	9.27	-0.16*	-9.91	0.14*	7.21	-0.38	-1.75	0.28	1.38	-1.82*	-6.31
LEV	-0.0*9	-12.56	0.01*	9.91	0.00*	-7.60	-0.04*	-5.25	-0.22*	-9.31	-0.02	-0.73
MV	0.46*	15.10	0.00	-0.41	-0.02*	-10.66	0.91*	11.89	0.61*	8.69	3.08*	16.47
Industry fixed	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-
Difference= RD minus CAPEX	-0.31*	-2.56	-0.21*	-6.21	0.02*	2.05	2.24*	4.86	0.62*	2.48	-0.92	-1.71
Adj. R2	0.24	-	0.05	-	0.08	-	0.03	-	0.08	-	0.19	-

Notes:

1. Equation (1): FUTURE VOLATILITY$_{i,t}$ = Industry-fixed effects + β_{1t} RD$_{it}$ + β_{2t} CAPEX$_{it}$ + β_{3t} ADV$_{it}$ + β_{4t} LEV$_{it}$ + β_{5t} MV$_{it}$ + error, where future volatility variables are SD(Sales), R_SD(COGS), R_SD(SGA), R_SD(SPI), R_SD(Tax) and R_SD(OTHERS). Variable definitions are in Appendix I.
2. The sample consists of 43,654 firm-year observations from 1972-2008.
3. Equation (1) is estimated annually and the mean coefficients are reported. The t-statistics are based on the annual coefficient estimates, i,e, the Fama-MacBeth procedure; and corrected for serial correlation using the Newesy-West procedure for five lags.
4. * denotes two-tailed significance at 5% level.

Table 3. R&D, capital expenditure and risk components across high and low disruptive industries

Panel A: Descriptive statistics across high and low disruptive industries

	HIGH DISRUPTIVE		**LOW DISRUPTIVE**		**DIFFERENCE = HIGH minus LOW**			
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Variable	**Mean**	**Median**	**Mean**	**Median**	**(1)-(3)**	**t-stat**	**(2)-(4)**	**z-stat**
Investments & firm characteristics								
RD	0.03	0.00	0.01	0.00	0.02*	38.72	0.00*	50.92
CAPEX	0.12	0.06	0.12	0.05	0.00	-0.76	0.01*	6.78
ADV	0.07	0.03	0.06	0.02	0.01*	8.00	0.01*	11.66
LEV	0.34	0.24	0.47	0.36	-0.13*	-26.14	-0.12*	-18.45
MV	5.01	4.78	4.41	4.18	0.60*	23.21	0.60*	19.04
Earnings and its components								
IBEDRD	0.16	0.13	0.15	0.12	0.01*	5.18	0.01*	9.22
SALES	2.90	1.44	3.04	1.54	-0.15*	-2.78	-0.10*	-3.70
COGS	2.02	0.86	2.19	0.98	-0.17*	-4.15	-0.12*	-5.53
SGA	0.60	0.30	0.57	0.27	0.03*	2.88	0.03*	4.38
SPI	0.01	0.00	0.01	0.00	0.00*	2.21	0.00*	8.96
TAX	0.05	0.03	0.06	0.04	0.00*	-3.42	-0.01*	-9.37
OTHERS	0.05	0.02	0.06	0.03	-0.01*	-9.27	-0.01*	-14.28
Measures of Risk Components								
SD(IBEDRD)	0.09	0.08	0.09	0.07	0.00	1.21	0.00	1.60
SD(SALES)	0.93	0.72	0.98	0.72	-0.04*	-2.99	0.00	1.67
SD(COGS)	0.68	0.52	0.72	0.52	-0.04*	-3.96	0.00	1.11
SD(SGA)	0.18	0.13	0.17	0.10	0.01*	2.34	0.02*	6.19
SD(SPI)	0.03	0.02	0.02	0.02	0.00*	4.20	0.00*	7.72
SD(TAX)	0.04	0.03	0.04	0.03	0.00*	-3.98	0.00	-1.13
SD(OTHERS)	0.04	0.02	0.04	0.03	0.00*	-8.12	0.00*	-7.39

Panel B: R&D, Capital expenditure and future volatility of earnings and its components across high and low disruptive industries

	(1) Dep. Var. = SD(SALES)		(2) Dep. Var. = R_SD(COGS)		(3) Dep. Var. = R_SD(SGA)		(4) Dep. Var. = R_SD(SPI)		(5) Dep. Var. = R_SD(TAX)		(6) Dep. Var. = R_SD(OTHERS)	
	Coef.	**t-stat**	**Coef.**	**t-stat**	**Coef.**	**t-stat**	**Coef.**	**t-stat**	**Coef.**	**t-stat**	**Coef.**	**t-stat**
RD	2.23*	2.75	-0.22*	-2.66	0.13	1.72	2.27	0.98	1.62	1.26	2.52	0.98
CAPEX	0.80*	6.89	-0.02	-1.68	-0.05*	-6.70	1.08*	3.22	-1.00*	-4.87	0.86	1.62
HIGH_DISRUP.	-0.02	-1.50	-0.02*	-5.37	0.00	1.89	0.21*	3.67	-0.08*	-2.29	0.21*	2.72
RD×HIGH_DISRUP	-1.86*	-2.19	0.06	0.76	-0.16*	-2.05	0.16	0.07	-1.36	-1.11	-2.07	-0.88
CAPEX×HIGH_DISRUP	0.03	0.24	0.08*	5.41	0.00	0.47	-1.12*	-3.49	1.01*	5.03	0.83	1.71
ADV	1.38*	9.59	-0.16*	-10.16	0.14*	7.35	-0.38	-1.72	0.23	1.12	-1.92*	-6.66
LEV	0.46*	15.14	0.00	-0.61	-0.02*	-10.49	0.92*	12.35	0.60*	8.60	3.10*	16.45
MV	-0.09*	-12.32	0.01*	9.56	0.00*	-7.39	-0.04*	-5.23	-0.22*	-9.39	-0.02	-0.98
Low Disruptive Industries												
Difference = RD minus CAPEX	1.43	1.75	-0.21*	-2.43	0.18*	2.32	1.19	0.51	2.62	2.01*	1.66	0.63
High Disruptive Industries												
Difference = [RD + (RD × HIGH_DISRUP.)] minus (CAPEX + CAPEX × HIGH_DISRUP.)]	-0.47*	-3.15	-0.22*	-6.55	0.01	0.90	2.47*	5.60	0.24	0.94	-1.25*	-2.71
Adj. R2	0.25	-	0.05	-	0.08	-	0.03	-	0.08	-	0.20	-

Notes:

1. Equation (2): FUTURE VOLATILITY$_{i,t}$ = Industry-fixed effects + α_{1t} RD$_{it}$ + α_{2t} CAPEX$_{it}$ + α_{3t} HIGH_DISRUP$_{it}$ + α_{4t} RD$_{it}$ × HIGH_DISRUP$_{it}$ + α_{5t} CAPEX$_{it}$× HIGH_DISRUP$_{it}$ + α_{6t} ADV$_{it}$ + α_{7t} LEV$_{it}$ + α_{8t} MV$_{it}$ + error, where future volatility variables are SD(Sales), R_SD(COGS), R_SD(SGA), R_SD(SPI), R_SD(Tax) and R_SD(OTHERS). Variable definitions are in Appendix I.
2. The sample consists of 43,654 firm-year observations from 1972-2008.
3. Equation (2) is estimated annually and the mean coefficients are reported. The t-statistics are based on the annual coefficient estimates, i,e, the Fama-MacBeth procedure; and corrected for serial correlation using the Newesy-West procedure for five lags.
4. * denotes two-tailed significance at 5% level.

Table 4. R&D, capital expenditure and future volatility of special item components across high and low disruptive industries
Panel A: Descriptive statistics across high and low disruptive industries

	HIGH DISRUPTIVE		LOW DISRUPTIVE		DIFFERENCE = HIGH minus LOW			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variable	**Mean**	**Median**	**Mean**	**Median**	**(1)-(3)**	**t-stat**	**(2)-(4)**	**z-stat**
SPI components								
RSTR	-0.25	0.00	-0.25	0.00	0.00	0.25	0.00*	-3.13
WD	-0.18	0.00	-0.20	0.00	0.03	1.65	0.00	0.56
GWILL	-0.26	0.00	-0.42	0.00	0.16*	3.57	0.00	1.83
MA	-0.02	0.00	-0.01	0.00	-0.01*	-3.25	0.00*	-4.86
GL	0.07	0.00	0.07	0.00	-0.01	-0.83	0.00*	2.44
SET	-0.01	0.00	0.00	0.00	-0.01	-1.05	0.00*	-2.61
OTH	-0.05	0.00	-0.08	0.00	0.02*	3.11	0.00	-0.19
Volatility of SPI components								
SD(RSTR)	0.39	0.29	0.48	0.41	-0.08*	-7.41	-0.12*	-7.43
SD(WD)	0.36	0.25	0.44	0.31	-0.08*	-7.00	-0.06*	-9.43
SD(GWILL)	1.03	0.43	1.17	0.75	-0.14*	-3.43	-0.32*	-5.83
SD(MA)	0.05	0.04	0.04	0.04	0.01*	3.94	0.00	-0.41
SD(GL)	0.19	0.10	0.19	0.13	0.01	1.51	-0.03*	-3.31
SD(SET)	0.17	0.14	0.17	0.16	-0.01	-1.41	-0.02*	-4.93
SD(OTH)	0.18	0.15	0.22	0.17	-0.05*	-9.05	-0.02*	-9.67
Residual Volatility of SPI components								
R_SD(RSTR)	-0.01	-0.07	0.03	-0.04	-0.04*	-4.02	-0.03	-1.88
R_SD(WD)	0.00	-0.05	0.00	-0.07	0.00	-0.20	0.02*	2.20
R_SD(GWILL)	0.00	-0.30	-0.01	-0.32	0.01	0.27	0.02	0.91
R_SD(MA)	0.00	-0.02	0.00	-0.02	0.00*	2.24	0.00*	-2.52
R_SD(GL)	0.00	-0.08	-0.01	-0.06	0.02*	2.45	-0.02*	-3.53
R_SD(SET)	0.00	-0.04	0.00	-0.02	0.00	1.19	-0.02*	-6.36

R_SD(OTH)	-0.01	-0.04	0.02	-0.02	-0.03*	-5.39	-0.03*	-8.48

Panel B: Estimating equation (2)

	(1) Dep. Var. =R_SD(RSTR)		(2) Dep. Var. = R_SD(WD)		(3) Dep. Var. = R_SD(GWILL)		(4) Dep. Var. = R_SD(MA)		(5) Dep. Var. = R_SD(GL)		(6) Dep. Var. = R_SD(SET)		(7) Dep. Var. = R_SD(OTH)	
	Coef.	**t-stat**	**Coef.**	**t-stat**	**Coef.**	**t-stat**	**Coef.**	**t-stat**	**Coef.**	**t-stat**	**Coef.**	**t-stat**	**Coef.**	**t-stat**
RD	1.26	1.11	-0.81*	-3.28	0.64	0.76	0.08*	2.77	0.33	1.41	0.34	1.27	0.04	0.26
CAPEX	0.18	1.17	0.04	0.37	-0.77*	-2.42	0.04*	2.59	0.00	0.04	-0.02	-0.88	0.14*	4.01
HIGH_DISRUP.	-0.05*	-3.22	0.00	-0.28	0.02	0.45	0.01*	5.77	0.02*	3.72	0.00	1.04	-0.02*	-2.68
RD×HIGH_DISRUP.	-0.34	-0.32	0.80*	2.78	-0.46	-0.55	-0.04	-1.34	0.06	0.25	-0.23	-0.82	0.11	0.60
CAPEX×HIGH_DISRUP.	-0.26	-1.74	0.16	1.03	-0.48	-2.05	-0.09*	-5.72	-0.02	-0.29	0.02	0.74	-0.18*	-5.36
ADV	0.25*	3.32	0.07	1.27	0.03	0.15	0.02	1.35	0.06	1.71	0.09*	5.75	0.04	1.11
LEV	0.09*	6.69	0.11*	6.46	0.25*	3.65	0.01*	2.41	0.11*	12.65	0.02*	6.01	0.05*	8.42
MV	0.03*	8.09	0.00	-1.62	0.01	0.98	0.00*	3.13	0.00	1.73	0.00*	-4.37	0.00*	2.84
Low Disruptive Industries Difference = RD minus CAPEX	1.08	0.95	-0.85*	-3.12	1.41	1.57	0.04	1.27	0.33	1.37	0.37	1.36	-0.10	-0.58
High Disruptive Industries Difference = [RD + (RD × HIGH_DISRUP.)] minus (CAPEX + CAPEX × HIGH_DISRUP.)]	1.00*	6.39	-0.21	-1.39	1.43*	6.37	0.09*	6.71	0.41*	6.41	0.12*	3.07	0.18*	2.93
Adj. R2	0.02	-	0.01	-	0.002	-	0.001	-	0.02	-	0.001	-	0.004	-