Measuring Expected Volatility Using Earnings Line Items as Risk Exposures

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Abstract

We exploit the cross-section of earnings to create a measure, σ, of a firm's expected earnings volatility driven by systematic risk. σ captures firm-year risk by treating income statement line items as exposures to systematic risk and combining them with the variance-covariance matrix of line-item-related systematic risk factors. σ is positively associated with measures of total earnings volatility and time series measures of systematic risk; but, it incrementally explains the cross-section of expected returns, with an annualized hedge portfolio four-factor equal(value)-weighted alpha of 6.3%(12.1%). σ explains returns when analysts' forecasts are not available, when firms do not have historical information, and performs better during recessionary periods and for low operating profitability firms for which time varying, multi-factor risk is likely to be important. Our findings support the view that accounting income statement line items contain important information about systematic risk.

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1 Introduction

We create a measure of a firm's expected earnings volatility that is driven by systematic risk. Our approach is motivated by research that uses cross-sectional and panel data to measure firm-year earnings uncertainty (Chang et al., 2020; Donelson and Resutek, 2015; Konstantinidi and Pope, 2016). The innovation that allows us to measure the expected earnings volatility driven by systematic risk is that the cross-section of income statement line items can be viewed as exposures to systematic risk. This view is supported by prior research that argues that a company's decisions and circumstances determine future risk exposures and that earnings contain information about risk (Ball et al., 2021; Beyer and Smith, 2021; Chang et al., 2020; Ellahie, 2020; Penman and Zhang, 2019).

We develop our measure based on a simple model of earnings. Our model points to the estimation method for extracting risk factors from cross-sectional regressions when income statement line items are treated as exposures to risk. Our method follows Fama and French (2020) that finds that cross-sectional regressions successfully extract risk factors for returns. In our empirical design, we use income statement line items as observable characteristics that capture companies' exposures to systematic risk and we estimate line item related factors from cross-sectional regressions. We capture the variances and covariances of these risk factors with the historical variation in the coefficients. Combining the variance-covariance matrix of the time-series of the coefficients with the income statement line items in a calculation for the standard deviation of expected changes in earnings gives our firm-year estimate of systematic risk, σ.[1] σ is the ex ante standard deviation of expected earnings changes based on observable income statement line items and the historical volatility and co-movement of factors related to the income statement line items.

We highlight the main empirical results here. First, the coefficients from our cross-sectional estimations, i.e. the risk factors that are related to income statement line items, are correlated with other systematic factors. Second, the top line items of the income

[1]We provide the details of the calculation in sections 2 and 4.

statement have the largest impact on σ because the factors related to the top line items of the income statement have the largest variances and covariances in the variance-covariance matrix, consistent with the intuition in Ball et al. (2015) and Novy-Marx (2013) that top line items better capture “true economic profitability”. Third, σ is positively correlated with other measures of total and systematic risk: earnings volatility, earnings uncertainty, CAPM beta, and earnings beta. Fourth, σ is positively associated with the cross-section of future returns in magnitudes comparable to other firm characteristics used to explain the cross-section of returns, and σ captures variation in returns not explained by a four-factor model with an annualized decile hedge portfolio alpha of approximately 6.3%(12.1%) equal(value)-weighted.[2] Fifth, we show that σ provides information about returns that is incremental to other measures of earnings uncertainty or risk which we attribute to the multi-factor, time-varying nature of our measure. Sixth, σ is associated with returns when limiting the sample to stocks that have no analyst coverage and when limiting the sample to firms that have no prior year information. This is important because some measures of risk from the time series of earnings require analyst forecasts or historical earnings (e.g. Ellahie, 2020). Lastly, we find that σ better explains the cross-section of returns where time varying, multi-factor risk exposure is likely to be most important, for low profitability companies and during recessions.

Our study is important because it exploits the rich information available in cross-sections to estimate an ex-ante firm-year measure of multi-factor systematic risk. Compared to measures of total earnings volatility or earnings uncertainty, our measure extracts ex-ante volatility driven by systematic risk from the cross-section of income statements. Our paper is related to and contrasts with other research that creates and studies measures of earnings volatility or earnings uncertainty (Chang et al., 2020; Dichev and Tang, 2009; Donelson and Resutek, 2015; Konstantinidi and Pope, 2016). Donelson and Resutek (2015) find that uncertainty is associated with optimistic forecasts by analysts, suggesting that the correction

[2] See table 6.

of optimistic forecasts may lead to lower future returns. Chang et al. (2020) find that higher variance, skewness, and kurtosis are associated with higher stock prices, suggesting that investors value the upside potential for positive payoffs. In contrast, we find that the expected volatility of earnings driven by systematic risk is positively associated with expected returns. Our findings suggest that investors require higher returns to earnings volatility that is driven by systematic risk.

Our paper is also related to research that finds that measures of systematic risk derived from firm level time series of earnings are associated with expected returns (Ellahie, 2020). Ellahie (2020) finds that an earnings beta estimated using analysts' earnings forecasts is associated with returns. Our measure contributes to this research by providing a risk measure that is associated with expected returns even when analysts' forecasts or long time series are not available. Additionally, our measure captures exposure to multiple risk factors, which is difficult to achieve with low frequency, short time series earnings data.

Finally, while prior research finds that the summary number from the income statement provides information about total and systematic risk, our paper provides new evidence that income statement line items contain important information about systematic risk. Accordingly, our paper adds to the evidence that earnings are informative about risk (Chang et al., 2020). Our findings are important because the line items that report on the drivers of cash flows also report on a company's time varying multi-factor risk exposures. In addition, the line items may interact in ways that increase exposures to risk factors and in ways that provide hedges against risk factors. We develop a method for combining the complex effects of these risk exposures and risk factors on expected volatility in earnings.

2 An earnings model and the variance of expected changes in earnings

We use a simple model of earnings that helps develop the concepts and empirical methods for extracting systematic risk from the income statement in cross-sectional data. Our ending point is an equation for the variance of expected changes in net income driven by systematic risk for company i in year t+1 given information known in year t (equation 8). We develop this final equation from a simple model and describe insights that come from this derivation. Our model, shown in equation 1 below, begins with accounting earnings and book values of equity because accounting reporting is closely tied to risk through conservative accounting (Penman, 2016; Penman and Zhu, 2014) and because accounting earnings capture systematic risk (Ball et al., 2009, 2021; Beaver et al., 1970). Additionally, accounting balance sheets are a summary of a company's historical business decisions and circumstances because they provide the end-of-period (conservative) assets and liabilities of the company (Sunder et al., 2018; Watts, 2003), and thus should reveal a firm's current and future exposures to systematic risks (Beyer and Smith, 2021).

$$NI_{i,t+1} = \alpha_i + \alpha_t + \sum_{1}^{C} \gamma_{c,t} BV_{c,i,t} + \epsilon_{i,t+1} \tag{1}$$

Here BV is accounting book value of equity that is made up of components c. Each component (BV_c) is the net cost of an investment that generates a firm's exposure to systematic risk. The payoffs to systematic risk for each component BV_c is given by γ_c that varies over time and represents a systematic risk factor to which a company is exposed. For example, a company that invests in oil extraction equipment will record an asset on their balance sheet, BV_c, and the return to that investment, $\gamma_{c,t}$, will depend on the aggregate supply and demand of oil that affects their production and the price for which the oil may be sold. The idea that expected earnings are determined by a company's cost of capital and the book value of equity in place at the beginning of the period has a long history in accounting valuation (Ohlson, 1995; Penman, 2010).

Company earnings may be determined by persistent idiosyncratic performance that is unrelated to systematic risk. The persistent component is represented by α_i. α_t captures time varying market wide average earnings that affect all firms equally. Independent shocks to earnings are represented by $\epsilon_{i,t+1}$.

Prior research using earnings to estimate a company's exposure to systematic risk uses a time series model.

$$NI_{i,t+1} = \alpha_i + \gamma_t \beta_i + \epsilon_{i,t+1} \tag{2}$$

With the time series estimation approach, γ_t is taken as given and is a systematic macro factor, e.g. aggregate earnings. Exposure to the factor is estimated and is assumed to be static over the regression window. However, the true γ_t is unknown and risk exposure β is dynamic (Berk et al., 1999; Beyer and Smith, 2021). Additionally, for practical purposes, earnings may be exposed to multiple risk factors, making a short time series impractical for estimating exposure to the risk factors. In this regression, α captures the persistent performance of company i and the idiosyncratic performance is captured by ϵ while β is the static exposure to systematic risk.

An important assumption with the time-series estimation is the role that NI plays. NI_{t+1} is the outcome of risky investments and therefore only captures risk to the extent that higher systematic risk, as a product of β and γ, leads to higher payoffs. This logic is common in prior research discussing why earnings forecasts the cross-section of stock returns (Fama and French, 2006). More specifically, earnings forecast returns because earnings at time t is a proxy for expected earnings, i.e. NI_{t+1}, and holding price constant, higher expected earnings imply higher expected returns.

In the time series model, the only other way that earnings can reflect risk is if it is correlated with β, the systematic risk exposure. This type of logic is implied by prior empirical research that finds evidence that measures of earnings, such as operating profitability, are positively associated with the cross-section of future returns, in which the implication would be that companies with higher earnings must have, by assumption, higher exposure to systematic risk, i.e., higher β (Ball et al., 2015; Novy-Marx, 2013). Consistent with earnings reflecting exposure to risk, Kogan et al. (2021) present analytical and empirical evidence that higher operating profitability companies are less operationally hedged against risk.[3]

In our paper, we focus on the more direct implication described below that earnings reflects systematic risk *exposure*. To do so, in contrast to prior research, we consider a cross-sectional version of the NI model.

The first thing we note is that when estimating equation (1) in a cross-section, α_i is not estimable. We circumvent this problem with a changes model where we use the first difference of the equation and by doing so, α_i is dropped from the equation. The model is presented as equation 3 below.[4]

$$\Delta NI_{i,t+1} = \alpha_t + \sum_{1}^{C} \gamma_{c,t} NI_{c,i,t} + \epsilon_{i,t+1} \tag{3}$$

For simplicity, we redefine α_t and ϵ as the parameters that represent the changes from the first difference of the equation.

The change in earnings as the dependent variable, in addition to being conceptually consistent with this changes model of earnings, is also desirable because earnings components are persistent (Dechow et al., 2008; Easton and Zmijewski, 1989; Kormendi and Lipe, 1987). First-differencing allows us to better capture the common economic forces that affect a cross-section of earnings and to mitigate the spurious statistical significance in the presence of two non-stationary variables (Finger, 1994; Granger et al., 1974). Additionally, the change in earnings as the outcome variable is consistent with Ellahie (2020) that shows that earnings betas constructed from changes in expected earnings are more strongly associated

[3]However, the risk explanation is unsettled. Ahmed et al. (2021) find evidence that the returns to operating profitability are more consistent with a mispricing explanation for operating profitability than with a risk explanation.

[4]To avoid complications, we ignore dividends. In other words, to be precisely correct, the NI components would have to include dividends.

with stock returns, presumably because earnings is persistent and less sensitive to changes in the economy. This model also echoes the premise in Beyer and Smith (2021) that each firm's earnings is determined by three sets of components: an idiosyncratic component ($\epsilon_{i,t+1}$), a set of market-wide factors (α_t and $\gamma_{c,t}$), and the firm's exposures to factors ($NI_{c,i,t}$).

In this equation, a NI_c component is in the most straightforward manner a measure of a company's sensitivity to a related risk factor. Given equation 3, it may be helpful to consider the way that earnings line items reflect a company's exposure to systematic risk. First, it is important to note that the risk factor that is represented by γ is the average expected association between the NI component and subsequent changes in NI. Therefore, γ does not represent an individual company's observed association, but rather the association that is expected based on all companies in the cross-section.[5] Second, NI components reflect changes to the decisions and circumstances that expose a company to risk. For example, cash inflows change the risk composition of a company's assets. Revenues and expenses reflect a company's supply and demand positions in the market. Research and development reflects changes to a company's risky investment mix.

Another way to think about our cross-sectional approach is that we have latent risk exposure βs for which NI components are instrumental variables. To make this more explicit, assume the true model of earnings is the following, with Γs representing the mutually orthogonal underlying systematic factors and each β representing the latent exposure to each factor.

$$\Delta NI_{i,t+1} = A_t + \sum_{1}^{C} \Gamma_{c,t}\beta_{c,i,t} + \nu_{i,t+1} \tag{4}$$

Rather than estimating equation 4, we estimate equation 3 that is based on observable components of earnings. To simplify the exposition, we assume that the net income components $NI_{c,i,t}$ are uncorrelated or in the case that they are correlated have been made

[5] In the appendix, we show how the γs can be alternatively interpreted as market-wide summary measures that are similar to accounting aggregate factors used in prior research (e.g. Ball et al., 2009; Ellahie, 2020).

orthogonal to each other prior to estimating the regression (Wooldridge, 2015).[6] For presentation purposes, we also assume that the number of net income components included in the regression, C, is the same as the number of true factors and βs.

Estimating the equation with the net income components in a cross section at time t (equation 3), we obtain the estimated γs:

$$\hat{\gamma}_{c,t} = \frac{Cov(\Delta NI_{i,t+1}, NI_{c,i,t})}{Var(NI_{c,i,t})} \tag{5}$$

Plugging in the underlying process of ΔNI using equation 4, we obtain the following:

$$\hat{\gamma}_{c,t} = \frac{Cov(A_t + \sum_1^C \Gamma_{k,t}\beta_{k,i,t} + \nu_{i,t+1}, NI_{c,i,t})}{Var(NI_{c,i,t})} \tag{6}$$

Because the true A and Γs are common in the cross section, they do not affect the cross-sectional estimation. Consequently, A is dropped because it is a constant in the cross section; Γs is retained in the estimates if and only if an observable earnings component NI_c has a non-zero correlation with the latent exposure β_k. Put differently, if NI_c is a reasonable proxy for β_k, information regarding the true latent factor Γ_k is extracted and retained in the estimates. Assuming ν is an independent error term, it should not affect the γ estimate either so long as it is independent from NI_c. Thus the equation above simplifies into the following:

$$\hat{\gamma}_{c,t} = \sum_1^C \Gamma_{k,t} \cdot \frac{Cov(\beta_{k,i,t}, NI_{c,i,t})}{Var(NI_{c,i,t})} \tag{7}$$

The estimated factor $\hat{\gamma}$ is a combination of the true systematic factors to which earnings are exposed and the correlation between the true βs and the observed net income components. In the extreme, including a component of net income that has no correlation with any βs will

[6] We acknowledge that line items from the income statement are or can be highly correlated. We use our discussion that relies on this assumption to develop the intuition about some of the important drivers of the estimated coefficients. While the same intuition applies when the line items are correlated, the drivers and the explanation are more complicated.

result in an estimated $\gamma_{c,t}$ of zero. If a component NI_c can only partially proxy for one risk exposure β_k, then its estimated $\gamma_{c,t}$ will be non-zero and will result in an under-weighted $\Gamma_{k,t}$. If each component of net income perfectly correlates with each true β_c, then each estimated $\gamma_{c,t}$ will exactly equal the true risk factor $\Gamma_{c,t}$.

In our final step, we use the variance of expected changes in earnings, with expected change in earnings calculated following equation 3, to form an ex-ante expectation about the systematic variation in changes in earnings for a company i at time t+1 based on information available at time t. Such information includes the historical volatility and co-movement of $\hat{\gamma}$s available at time t.

$$
\begin{aligned}
VAR(\Delta \widehat{NI_{i,t+1}}) = VAR(\hat{\alpha}) + \sum_{c=1}^{C} VAR(\hat{\gamma}_c) NI_{c,i,t}^2 + \\
2\sum_{c=1}^{C} COV(\hat{\alpha}, \hat{\gamma}_c) NI_{c,i,t} + 2\sum_{c=1}^{C}\sum_{j>c}^{C} COV(\hat{\gamma}_c, \hat{\gamma}_j) NI_{c,i,t} NI_{j,i,t} \quad (8)
\end{aligned}
$$

The focus on the variance of expected changes in earnings is related to other research that forecasts the higher moments of earnings, forecasts of earnings uncertainty (Donelson and Resutek, 2015), and studies analysts' scenario-based forecasts (Chang et al., 2020; Joos et al., 2016; Konstantinidi and Pope, 2016).

Equation 8 demonstrates some important properties of the variance of changes in earnings. The variance and covariance terms such as $VAR(\gamma_c)$ and $COV(\gamma_c, \gamma_j)$ determine how income statement line items are combined to calculate the variance of expected changes in net income. These terms weight squared line items or the product of line items with the variance-covariance matrix of the estimated γs. The historical variation of each γ is determined by two sources based on equation 7: the association between the earnings line item (NI_c) and the firm's underlying factor sensitivity (β_k), and the historical volatility of the underlying risk factor Γ_k. This means that for a particular γ_c that has a strong association between NI_c and β_k and a more volatile Γ_k, the variance of γ_c and the earnings component

c become a larger part of the variance calculation in equation 8. On the other hand, as the historical volatility effect decreases or the line item's association with the underlying factor sensitivity decreases, $VAR(\hat{\gamma}_c) \rightarrow 0$.[7] This means that the variance calculation in equation 8 will be most affected by the largest variance risk factors and the line items with the strongest association between the line item and the underlying factor sensitivity.

2.1 Calculating σ

In this section, we describe how we use equation 8 to create an empirical measure of the systematic risk information contained in accounting earnings. For the earnings variable, we use income before extraordinary items, IB. Following the accounting identity equation (equation 9), we choose these 10 items because IB is defined by these 10 items (Ball et al., 2015).

$$\begin{aligned} IB \equiv\, & REVT - COGS - SGA - XRD - DP \\ & - XINT - TXT + NOPI + SPI - MII. \end{aligned} \tag{9}$$

The IB line items are the primary standardized components of income as reported in Compustat; total revenues, $REVT$, cost of goods sold, $COGS$, sales, general, and administrative expenses, SGA, research and development expense, XRD, depreciation expense, DP, interest expense, $XINT$, non-operating income, $NOPI$, income tax expense, TXT, special items, SPI, and minority interest, MII.[8]

Using major line items from the income statement for our implementation of equation 3,

[7] We also note that because latent risk factors are mutually orthogonal, the covariance output such as $COV(\hat{\gamma}_c, \hat{\gamma}_j)$ is inherently a function of the *variance* of one or more common latent factors to which the exposure NI_c and NI_j both proxy for.

[8] Ideally, we would be able to separate investment specific income components of the income statement that could be applied to the cross-section of companies. However, because general purpose financial reporting summarizes reporting into aggregate numbers, we use the disaggregated version that applies to the largest set of companies.

we use the following empirical model.

$$\Delta IB_{i,t+1} = \alpha_t + \gamma_1 REVT_{i,t} + \gamma_2 COGS_{i,t} + \gamma_3 SGA_{i,t} + \gamma_4 XRD_{i,t} + \gamma_5 DP_{i,t} + \gamma_6 XINT_{i,t} + \gamma_7 NOPI_{i,t} + \gamma_8 TXT_{i,t} + \gamma_9 SPI_{i,t} + \gamma_{10} MII_{i,t} + \epsilon_{i,t+1} \quad (10)$$

We impute zero for missing earnings component variables except for $REVT$ to allow for a maximized sample size when estimating the γs from equation 3.[9]

We begin by estimating yearly cross-sectional models given by equation 10. These cross-sectional models give yearly estimates of the γs. From the historical γs we create a rolling window variance-covariance matrix.[10] Following equation 8, we combine year t earnings components with the variance-covariance matrix of past cross sections of estimated γs to deliver the measure $VAR(\widehat{\Delta NI_{i,t+1}})$, and we use the square root of this firm-year estimate as our measure of systematic risk, σ. Note that for each yearly variance-covariance matrix, we only utilize cross sections before year t to avoid a look-ahead bias.[11]

2.2 What is the risk that σ represents?

Developing σ above, we show *how* our measure captures systematic risk. An important question is *what* is the risk that σ captures. We begin the discussion of *what* σ measures by describing how σ captures multi-factor risk. We then develop some intuition about σ and later turn to empirical descriptions of what σ captures.

An important point is that only under some specific conditions can we take the summary number from the income statement to calculate the same systematic risk as captured by σ.

[9] We recognize that imputation may introduce noise into the data especially when companies intentionally avoid reporting information such as R&D expenses (Koh and Reeb, 2015). To remedy this, we perform a robustness test in which we require the absolute difference between reported IB and calculated IB using imputation (both unscaled) to be no greater than 0.01% (i.e., $\leq$ \$100) to ensure that imputation does not cause material bias. Our inferences remain unchanged, tabulated in column (4), Table A5.

[10] To ensure that the historical variance-covariance matrix captures meaningful variation, we require historical variance-covariance matrices to contain at least 10 years of γs.

[11] For example, with a firm's earnings components in 1998, we use and only use the γs from 1997 and before when forming the variance-covariance matrix of γs.

In other words, the following inequality holds true in all other conditions, in which γ_{NI} is obtained by regressing $\Delta NI_{i,t+1}$ on $NI_{i,t}$ as a summary measure in each cross section.

$$\sigma^2 = VAR(\widehat{\Delta NI_{i,t+1}}) \neq [VAR(\gamma_{NI})NI^2] \tag{11}$$

To expand the last term, NI^2 could be restated in a familiar format, for example $(REV - EXP)^2 = REV^2 + EXP^2 - 2REV \times EXP$, so that $VAR(\gamma_{NI})NI^2$ can be rewritten as:

$$VAR(\gamma_{NI})NI^2 = VAR(\gamma_{NI})REV^2 + VAR(\gamma_{NI})EXP^2 - 2VAR(\gamma_{NI})REV \times EXP \tag{12}$$

Comparing equation 12 and 8, we notice two major distinctions that result in the inequality in equation 11. First, the variances of the different risk factors $\hat{\gamma}_c$s of equation 8 can be different $(VAR(\hat{\gamma}_c))$ while the variances of equation 12 are the same $(VAR(\gamma_{NI}))$. This implies that a feature of σ is that it potentially captures multiple risk factors with different levels of historical volatility.

Second, the last part of equation 12 contains a negative component , $-2VAR(\gamma_{NI})REV \times EXP$. This term seemingly resembles the covariance terms in equation 8, which can be written as $2COV(\gamma_{REV}, \gamma_{EXP})REV \times EXP$. To make these two terms equal, $COV(\gamma_{REV}, \gamma_{EXP}) = -VAR(\gamma_{NI})$ must hold as a necessary but insufficient condition for the two sides of equation 11 to be equal. This illustrates that using the summary net income number to calculate variance imposes the assumption that the covariance between the γs of REV and EXP must be negative and that the negative covariance must have a specific magnitude. Because we do not impose such assumptions in calculating an ex ante standard deviation of earnings changes using multiple earnings components (as opposed to using one summary measure of earnings), another feature of σ is that it allows different state variables represented by $\hat{\gamma}_c$s to have an empirically determined covariance, which can help uncover risk information from component interactions (e.g., hedging).

The primary intuition we gain from this discussion is that σ captures the effects of a firm's exposure to multiple risk factors in a way that cannot be easily summarized by a single factor measure except under a specific set of circumstances. We can use the intuition from this discussion to ask when might our cross-sectional measurement approach capture information that is not captured by a single factor or time-series risk-exposure estimation. First, because accounting time series models typically must rely on short time series, the number of factors that can be considered simultaneously is limited and is typically a single factor. This means that if risk is multi-factored, our measure will capture systematic risk exposure not captured by time series models. Second, aggregated income assumes an equal importance of different line item related risk factors and will not capture instances where companies are exposed in varying degrees to different risk factors. Third, time series models assume that risk exposure is constant over the estimation window while our approach measures exposure at a point-in-time. If risk exposure is time varying, our measure will capture risk exposure information incremental to other measures.

The complex nature of multi-factor risks in equation 8 makes developing intuition about what the risks are that σ captures difficult. As discussed above, earnings volatility depends on individual risk factors as well as the covariance structure of those risk factors. In addition, the aggregate nature of financial reports also presents challenges. If in equation 1 the assets were separable and independent, then we would expect γ to be an estimate of the required return for each separate asset. However, the assets are not independent and the regressors do not directly map onto individual assets. For example, revenues from low risk projects are mingled with revenues from high risk projects and different line items can contain different product mixes. Because of these challenges, we believe that the best that we can do is to form some interpretations about the marginal effect on a firm's required return conditional on the other regressors and factors in the model.

Given the caveats above, we describe some expectations about the γs based on the marginal changes in risk exposure line items represent. Even though aggregate general purpose financial reporting does not typically provide project or investment specific balance sheet and income statement numbers, income records the exchange of high risk for low risk assets (Penman and Zhang, 2019). This means that higher levels of revenues represent a greater addition of low risk assets in exchange for high risk assets and therefore also represent a marginal reduction in risk. This is equivalent to a lower expected return. On the other hand, expenses represent the use of low risk assets in exchange for relatively higher risk future cash flows. Therefore, we expect a negative γ on revenue items and a positive γ on expense items.[12] Despite the expected effect of collecting or using low risk assets, the total effect on a company's expected earnings volatility depends on the resulting mix of assets and the degree to which the assets add risk and/or result in hedges against other risk factors. We return to this discussion when we later describe empirically some of the features of these risks and in particular the empirical variance-covariance matrix of the γs.

3 Literature Review

Most related to our study, prior research develops approaches to measuring uncertainty or total risk in earnings. Donelson and Resutek (2015) use a non-parametric matching design to extract an earnings uncertainty measure that is distinct from a firm's historical earnings volatility. They find that uncertainty rather than volatility is associated with analysts' optimism and lower future stock returns. Konstantinidi and Pope (2016) and Chang et al. (2020) use quantile regressions to extract the higher moments of the distribution of future earnings (e.g., dispersion, skewness, and kurtosis) and show that these moments are associated with equity and credit risk measures. Other research finds that analysts can assess a firm's fundamental risks as reflected in the dispersion of their target price scenarios (Joos et al., 2016). We contribute to this literature by developing a measure of the expected systematic variation in earnings and show that the systematic variation in earnings is positively associated with expected returns. The positive association with returns suggests that investors require a

[12]The negative expectation for revenue items comes from the multiple regression interpretation where holding constant the effects of the expense items, revenue items have a lower required return.

higher return for earnings volatility driven by systematic risk.

Some research argues that accounting should be a primary source of information about a company's risk (Chang et al., 2020; Farrelly et al., 1985). For example, Beyer and Smith (2021) show that conditional on the market state, investors can learn indirectly about a company's risk exposure from reported earnings. The recognition that accounting reports should convey systematic risk information to investors has a long history and has generated a handful of approaches to extracting risk information from reported accounting numbers (Beaver et al., 1970; Beaver and Manegold, 1975; Bowman, 1979; Ellahie, 2020; Nekrasov and Shroff, 2009; Ryan, 1997). A few recent studies use a similar motivation but alternative measurement approaches such as Ball et al. (2021), Ellahie (2020), and Nekrasov and Shroff (2009). For instance, Ellahie (2020) shows that earnings betas constructed from analyst earnings forecasts predict future returns better than those constructed from historical earnings, presumably because analyst forecasts include analysts' forward-looking information.

Other research proposes that accounting information or other firm characteristics can reflect a firms' exposure to risk. Berk et al. (1999) design a dynamic model, in which a firm updates its risk exposure by taking on new projects, with each project having varying risk exposure (i.e., they bear cash flow shocks that covary with the interest rate shocks differently). Kogan et al. (2021) proposes that higher profitability companies are more exposed to systematic risk because they have lower operational hedging. Most related to our empirical approach, Fama and French (2020) estimate risk factors from cross-sectional regressions by treating firm characteristics as exposures to risk factors and find that these estimated risk factors better capture variation in returns than time series factors. We contribute to this research by showing that earnings are a natural measure of risk exposure and create a measure of systematic variation in earnings using cross-sectional regressions that treat earnings line items as exposures to systematic risk.

4 Data and descriptive statistics

Our data begins with annual financial information from Compustat. We require observations to have positive total assets, total equity, and revenue.[13]. All firm-year variables are trimmed at the top and bottom 1% within each yearly cross section (Ball et al., 2015; Ellahie, 2020). After trimming the variables, we standardize income statement items to have zero means and unit standard deviation to make the estimated factors comparable. We merge Compustat data with monthly stock returns and prices from CRSP for stocks listed on major U.S. exchanges (NYSE, AMEX, NASDAQ). Monthly returns are from June to May beginning the year after the fiscal year end and include delisting returns (Donelson and Resutek, 2015). We also calculate other measures of earnings uncertainty, earnings beta, and macro-economic variables. The variables are defined in table A1 in the appendix.

The steps to prepare for the changes in earnings regressions (equation 10) leave us with 327,957 firm-year observations for the years 1950 through 2019. Table 1 presents a summary of the firm-year data and financial variables. Panel A shows the number of companies by fiscal year. The number of companies increases from 449 in 1950 to approximately 5000 in 2019 with the largest number of companies in the mid to late 1990s. Panel B provides descriptive statistics before standardization for the income statement variables that are used to calculate σ.

Panel C presents a Pearson correlation matrix for the income statement variables. Some of the correlations among the line item variables are large. The correlation between REVT and COGS is 94.9% and the correlation between REVT and SGA is 58.7%. While the high correlations should not introduce bias to our estimates of γ, they may introduce instability to the estimates, which may affect our estimates of σ (Wooldridge, 2015). In robustness tests, we repeat our main tests calculating σ after removing the most correlated line items, COGS and SGA, and find similar results, tabulated in column (2) and (3) of table A5.

[13]We require positive total equity because we follow Ball et al. (2015) by using a natural log of book-to-market ratio (BEME), in which the ratio has to be positive.

The first step for creating σ is to estimate yearly cross-sectional regressions of equation 10. Summary information about the coefficients from these yearly regressions are displayed in table 2, while the comprehensive table of all coefficients across all sample years is in table A2 in the appendix. Panel A shows the summary statistics for the estimated γs. The mean of the yearly coefficients are similar to the coefficients that would be estimated for the pooled sample. As expected and discussed in section 2.2, the mean sign of the coefficients are mostly negative for revenue items and positive for expense items. This is consistent with line items' effects on cash balances and therefore their marginal effect on the riskiness of a company's asset mix.[14]

The absolute magnitudes of the coefficients are generally larger for items higher on the income statement, i.e. REVT, COGS, SGA. Similarly, the standard deviations of the coefficients are larger for line items higher on the income statement. The importance of these higher line items in determining future changes in earnings may reflect the idea that higher line items are more economically informative than lower line items (Ball et al., 2015; Novy-Marx, 2013). However, the larger magnitudes and stronger significance of higher line items should not imply that lower line items will not contribute to the risk measure, because the Fama-MacBeth t-statistic has an absolute magnitude over 3 for each line item, including the lower line items. This suggests that over the entire sample period, every line item, on average, has a statistically significant systematic relation with changes in earnings, further implying that every line item can be a reasonable proxy for underlying risk exposures.

Panel B gives the variance-covariance matrix for the full panel of γ estimates that represent the matrix used when calculating σ. γ_{REVT} is negatively correlated with γ_{COGS} and the γs for the other major expense line items (SGA, XRD, DP, XINT, TXT). To understand

[14] One explanation is that our cross-sectional regression coefficients capture mean reversion in earnings where higher levels of revenues are more likely to have earnings declines in the future and higher levels of expenses are more likely to have earnings increases in the future. We would argue that mean reversion represents one source of risk that extreme earnings represent. If the risk of mean reversion is related to systematic risk factors, then some firms should have varying exposures to these factors and the risk should be priced. However, if mean reversion without systematic risk were the primary driver of these regression results, we would expect the coefficients on line items with the strongest mean reversion (e.g. SPI) to have the largest coefficients.

the connection between the mean γ_{REVT} and the mean of expense related coefficients, e.g. γ_{COGS}, we discuss the variances and covariances of these terms. The variance of γ_{COGS} is among the largest of the γs (58.3) but is smaller than the variance of γ_{REVT} (83.8). Thus the main effect of the the γs on $REVT$ and $COGS$ are to significantly increase the variance of changes in earnings with γ_{COGS} being less than γ_{REVT}. As discussed earlier, expenses exchange low-risk assets, cash, for higher risk expected future cash flows. This intuition is most obvious when considering expenses such as advertising or research and development. Expenses (e.g. COGS) increase the exposure to a high risk factor (γ_{COGS}). However, the covariance between γ_{COGS} and γ_{REVT} is negative and the largest of all of the covariances (-69.8). In risk factor terms, γ_{REVT} partially hedges the risk in γ_{COGS}, or equivalently, γ_{COGS} partially hedges the risk in γ_{REVT}. γ_{REVT} also hedges the risk in the other expense γs, but the effectiveness of the hedging is lower (i.e. weaker negative covariances). The total effect on a firm's expected variance depends on the mix of its exposures and the variance-covariance matrix. The benefit of σ is that it is designed to capture these complicated combinations of effects.

As a whole, panel B demonstrates that many covariances of γs are far from zero. We note the largest magnitude γs reported in panel A are also the γs with the largest variances and covariances in the variance-covariance matrix presented in panel B. This means that the γs captured from the cross-sectional regressions are not independent, the magnitudes depend on the correlation structure of the coefficients, and therefore the covariance terms in equation 8 are important in determining the variance of expected changes in earnings.

We provide an example of how the variances and covariances are combined with line items as well as how they impact the output σ values in the appendix table A3. In this table, for simplicity, we focus on the intercept, γ_{REVT}, and γ_{COGS}. Equation 8 is a matrix operation that produces the output measure σ, which is the matrix product of a vector of net income line items, the variance-covariance matrix of γs, and the transposed vector of net income line items. In case 1 of table A3 (panel C), when firm A has one unit of $REVT$

and 0.5 units of $COGS$, the output σ equals 26.972; In case 2 (panel D), when firm B has one unit of $REVT$ and 0.9 unit of $COGS$, the output σ equals 5.327. Contrasting these two cases, we note that more closely matched $COGS$ and $REVT$ decreases firm B's risk. The importance of $COGS$ is consistent with the view that sales and variable production costs hedge against each other when a systematic shock occurs (Kogan et al., 2021). Empirically, this is supported by the large magnitude of the negative covariance between the γs for $REVT$ and $COGS$. Thus, while the marginal effect of $COGS$ is to increase risk by exchanging low risk for high risk assets, $COGS$ and $REVT$ also interact to decreases risk, implying that the covariances of the factors are essential for understanding how individual line items work together to contribute to expected volatility.

In panels C and D of Table 2, we describe the correlations between the estimated γs and 13 macro variables used in prior research to capture systematic factors. These factors include growth in industrial production (ΔIP), growth in durable goods (ΔDG), non-durable goods (ΔNGD), and service (ΔSG) (Baker and Wurgler, 2007); growth in GDP (ΔGDP); five factors including the market premium (Mkt_rf), SMB, HML, RMW, and CMA (Fama and French, 2015); and the change in the federal funds rate (ΔFFO), the spread between long and short interest rate ($\Delta Term$), and the spread between low-grade bonds and long-term government bonds rate ($\Delta Sprd$) (Chen et al., 1986).

The Pearson correlations between the realized γs and the macro factors are presented in panel C. We do not develop ex ante expectations for the signs of the correlations between γs and the macro variables.[15] Creating predictions about the correlations between the discount rates for line item related factors and macro factors is challenging. However, the γs can also be interpreted as market aggregates that more closely resemble accounting aggregate ratios from prior research (e.g. Ball et al., 2021). We explain this interpretation in the appendix. With this interpretation, we expect the γs to be associated with macro variables built on measures of earnings growth. The correlations in panel C reasonably reflect these

[15] Prior research notes the challenge of developing ex-ante expectations for macro variable premia (Chen et al., 1986).

expectations. γ_{REVT}, γ_{COGS}, and some of the other γs are correlated with ΔSG, Mkt_rf, RMW, and less significantly, but also with ΔIP and ΔNDG.

Panel D provides the R-squared values from regressing the time series of the γs on the 13 macro factors. The macro factors explain over 50% of the variation in γ_{REVT}, γ_{COGS}, γ_{SGA}, and γ_{SPI}. While not conclusive, panels C and D provide some evidence that the line item related factors we are capturing with the γs are measuring variation that is shared, at least in part, with macro factors used in prior research, suggesting that at least some of the estimated γs recover factors that are used in prior research. These panels also provide evidence that the risk composition captured by σ is complex and could be incremental to the risk factors from prior research.

We use the income statement line items and the historical variance-covariance matrix of γs available before the year of the income statement line items to calculate the standard deviation of expected changes in earnings for each firm-year. For instance, for income statement line items in 1998, we use the variance-covariance matrix of γs calculated from 1950 to 1997 to form σ.

We then combine our annual financial information including σ with monthly returns and other variables that have been used to explain the cross-section of returns. For the main analyses, we require an observation to have non-missing characteristics used for control variables: SIZE, BEME, ret_1 (short-term momentum), and $\text{ret}_{12,2}$ (long-term momentum). We also require at least 10-years of historical γ coefficients to calculate the expected variance, so that we have a total of 214,904 firm-years and 2,478,383 firm-months for the main analyses, starting from 1960. In some of our analyses, the sample size changes with the availability of other control variable.

Table 3 provides the summary statistics for the firm-month data set. Panel A presents the variables we use in the main analyses and other comparable measures of earnings uncertainty, volatility, and risk. The summary statistics of return variables are similar to those in prior papers such as Ball et al. (2015). σ has a mean value of 0.016 and standard deviation of 0.015. While moving from the first quartile to the third quartile, σ increases by 0.007, moving from the third quartile to 99th percentile, σ increases by 0.065, suggesting that σ is right skewed. OP has a mean value of 0.117 and IB has a mean value of 0.016, and their distributions are similar to Ball et al. (2015) and Ball et al. (2016). β_{CAPM} has a mean value close to one. Other variables, including EU, IQR, β_{Wealth}, β_{TFP}, and $\beta_{Analyst}$, are similar to the variables calculated in Donelson and Resutek (2015), Konstantinidi and Pope (2016), Ball et al. (2021), and Ellahie (2020).

Panel B gives the correlation matrix for σ and firm characteristics that have been used to explain the cross-section of returns and other measures of total risk and systematic risk exposure. These firm characteristics include SIZE, BEME, short-term momentum (ret_1), and long-term momentum ($\text{ret}_{12,2}$) (Ball et al., 2015; Ellahie, 2020; Novy-Marx, 2013). σ is negatively associated with SIZE, suggesting that companies with lower market capitalization are more risky as measured by σ. σ is also positively correlated with measures of historical earnings volatility ($\sigma(\Delta IB)$ 0.250), earnings uncertainty (EU 0.113), earnings dispersion (IQR 0.692), CAPM (β_{CAPM} 0.159) and earnings beta ($\beta_{Analyst}$ 0.009). These correlations are consistent with σ capturing certain aspects of risk, earnings volatility or earnings uncertainty.

σ is negatively correlated with BEME (-0.211), OP (-0.242), β_{Wealth} (-0.036) and β_{TFP} (-0.005). These correlations are opposite to the sign that prior research has found between these characteristics and returns (Ball et al., 2021; Fama and French, 2015). They suggest that σ may in part capture something different, potentially about risk, from these firm characteristics. We also include IB, which is the summary number from which we extract income components when calculating σ. σ is also negatively correlated with this income measure.

Panel C presents summary information about the firm-level autocorrelation in σ. In the first row, we restrict the sample to firms that have at least 10 years of observations (7,707 unique firms). The median auto-correlation of σ is 0.295. When we sequentially examine firms that have at least 20, 30, and 40 years of observations, the number of unique firms drops while the median auto-correlation increases, suggesting that a firm's time-varying σ measure is moderately persistent, and that persistence of σ increases with firm age. This observation suggests that a mature firm's risk composition, measure by σ, is less variable over time, while a young firm may change its risk composition more frequently and have more time-varying risk exposures.

Panel D complements the descriptive information of individual γs and macro variables in Table 2 by describing the association between average σ by year and the same macro variables. Average σ is negatively associated with growth related macro variables: ΔDG, ΔNGD, ΔSG, and ΔGDP. An interpretation for these correlations is that during an economic downturn, e.g. a decline in GDP, average risk is higher than during expansionary periods. In the last cell, we show the R-squared of regressing annual average σ on 13 time-series of macro variables, and the R-squared is 0.713, suggesting that annual average σ is explained by macroeconomic variables to a great extent.

Panel E provides the frequency with which companies in the Fama-French 12 industries are ranked into quintiles of σ. Companies in some industries are more frequently ranked into the top or the bottom quintiles. For example, 57.07% of utility company-years are ranked in the lowest quintile of σ and more than 80% are in the lowest two quintiles; similarly, companies in the finance sector also have over 70% of observations ranked in the lowest two quintiles. Utilities and finance companies are more likely to have line items that hedge risk. For example, utilities may earn revenues as a margin over costs and finance companies may have hedging instruments and closely hedged costs and revenues. Companies in the Business Equipment, Healthcare, and Other are more frequently in the top two quintiles. These higher risk industries are arguably a set of industries with high exposures to new innovations, changing demand, and other systematic risks.(Donelson and Resutek, 2015).

5 Results

To test whether σ captures meaningful information about systematic risk that is reflected in asset prices, we follow empirical methods that are common in prior research (Ball et al., 2015; Chang et al., 2020; Donelson and Resutek, 2015; Ellahie, 2020; Fama and French, 1993, 2006, 2015). We describe the tests and the results in this section.

5.1 σ and future fundamental risk

Before turning to systematic risk, we test whether σ provides an ex-ante signal of total fundamental risk as measured by future absolute changes in earnings and the standard deviation of future changes in earnings. Prior research finds that higher moments of forecasted earnings provide an ex-ante signal about fundamental risk (Chang et al., 2020; Konstantinidi and Pope, 2016). Table 4 panel A sorts companies each year into quintiles by σ. While the association is not monotonic, the high σ portfolios have significantly higher absolute changes in IB and higher standard deviations in changes in IB.[16]

One possible explanation for the higher future fundamental risk for high σ portfolios is that this result is driven by the association between σ and prior fundamental risk. Panels B and C address this explanation by sorting companies independently on σ and historical earnings volatility, $\sigma(\Delta IB)$. Panel B provides the mean absolute value of changes in IB for the two-way sorted portfolios and panel C provides the future standard deviation of changes in IB for these portfolios. The results show that for higher quintiles of $\sigma(\Delta IB)$, increasing down the column from the lowest to highest quintile of σ, fundamental risk increases monotonically. For panels B and C, across all quintiles of $\sigma(\Delta IB)$, the portfolio with the highest

[16] Similar to the interpretations in Bali et al. (2011), we attribute the non-monotonicity to the skewness of σ. Shown in the first column of Table 4, in higher quintiles of σ, the variation in σ is larger, while in the lower quintiles, variation in σ is more limited. Specifically, mean σ increases from 0.017 to 0.034 from the fourth quintile to the fifth quintile; however, mean σ increases from 0.008 to 0.010 and from 0.010 to 0.013 from the first quintile to the second and from the second to the third. When we sort σ each year into the following five buckets of percentiles in order to achieve comparable differences in average σ across sorts: [P0, P60], [P60, P70], [P70, P80], [P80, P90], and [P90, P100], the increases in the response variables of panel A, B, and C of table 4 are monotonic, except for column 2 of panel C.

quintile of σ has a fundamental risk measure that is significantly greater than the lowest quintile.

In Panel D, we formally test if σ is a reasonable proxy of a firm's expected variance of earnings change. We regress the realized absolute value of unexpected changes in earnings, which is the absolute difference between realized changes in earnings and the predicted change in earnings following equation 9, on σ. If σ is a reasonable proxy for volatility in earnings changes, we expect σ to have a positive regression coefficient. In column (1) of Panel D, we use a pooled regression specification and in column (2), we use a panel linear regression that controls for firm and year fixed effects. In both specifications, σ is positively associated with the realized absolute unexpected change in earnings. The coefficient is near one with fixed effects, suggesting that σ captures volatility in earnings changes.

5.2 σ and future systematic risk exposure

Table 4 provides evidence that σ and total fundamental risk are positively associated. Next, we turn to σ as a leading indicator of future systematic risk. As shown previously, σ is positively associated with contemporaneous measures of exposure to systematic risk, β_{CAPM}.

If σ captures time varying exposure to systematic risk, we expect σ to anticipate future risk exposures. In Table 5, we sort stocks each year into quintiles by year t β_{CAPM} and then within each β_{CAPM} quintile, we sort stocks into quintiles by σ. Table 5 presents the mean β_{CAPM} one year (panel A), two years (panel B), and three years (panel C) after the ranking year.

Because the results in each panel are similar, for exposition we focus on panel A. Moving from left to right for each row shows that sorting on β_{CAPM} in year t also sorts stocks into portfolios that have increasing β_{CAPM} in year t+1, t+2, and t+3. In the middle quintile, the mean β_{CAPM} is approximately equal to 1. In the lowest quintile, β_{CAPM} is between 0.371 and 0.684 depending on the σ quintile and horizon. This means that on average, β_{CAPM} tends to be positive. β_{CAPM} in the highest quintile is closer to 2 than to 1. Moving from top to bottom for each column shows that the highest quintile of σ has a significantly higher future β_{CAPM} than the lowest σ quintile. However, similar to what we observe in Table 4, the association between σ and β_{CAPM} is not monotonic for any but the highest quintile of β_{CAPM}, which we attribute to the highest quintile of β_{CAPM} capturing the right skewness of σ, and the limited variation of low quintile σ among the lower quintiles of β_{CAPM}.[17] In general, this table is consistent with σ providing a leading indicator of future β_{CAPM} that is incremental to the contemporaneous β_{CAPM}.

5.3 σ and the cross-section of returns

In this section, we follow prior research that tests the pricing of earnings volatility and systematic risk measured from earnings (Ball et al., 2021; Chang et al., 2020; Donelson and Resutek, 2015; Ellahie, 2020). σ may be associated with expected returns for two reasons. First, if σ captures a higher positive exposure to systematic risk as suggested by the results in the previous section, then σ should be positively associated with the risk that investors price (Ball et al., 2021; Ellahie, 2020). Second, investors may also directly price earnings uncertainty that is driven by systematic risk and this may differ from idiosyncratic or total uncertainty (Chan et al., 2001; Donelson and Resutek, 2015).

5.3.1 Portfolio sorts

We first sort stocks into five portfolios by ranking σ within each fiscal year and then calculate the equal weighted and value weighted portfolio monthly returns for the 12-month period, starting from June after the current fiscal year end to May the next year, for each of these portfolios. Table 6 presents these results.

Panel A provides the raw equal and value weighted portfolio returns for sorts into quintiles

[17] Again, we sort σ in each year into the following five buckets of percentiles in order to reach to comparable differences of average σ across sorts: [P0, P60], [P60, P70], [P70, P80], [P80, P90], and [P90, P100]. In untabulated analyses, the increases in the response variables of panel A, B, and C of Table 5 are monotonic, except for column 2 and column 3 of panel A, column 3 of panel B, and column 3 of panel C. The differences between the high and low groups are all statistically significant at 0.01 level.

based on σ. For the equal and value weighted portfolios, the mean portfolio return increases from the lowest to the highest quintile portfolio. The increase in returns is monotonic.[18] The hedge portfolio return is significantly greater than zero and economically significant with a monthly (annualized) return for the equal weighted portfolio of 0.300% (3.6%) and for the value weighted portfolio 0.673% (8.4%).

To test whether σ contains information incremental to other systematic risk factors, we then regress the portfolio returns on a four factor model (Carhart, 1997; Fama and French, 1993).[19] Panel B presents the results when sorting by σ into quintiles. Following other papers (e.g., Bali et al., 2011; Ball et al., 2015), we repeat the analysis by sorting into deciles, and the results are in panel C.

α is the intercept for the time series portfolio return regressions. In each specification (equal weighted and value weighted, quintiles and deciles), α generally increases from the portfolios with the lowest σs to the portfolios with the highest σs. The increase is generally monotonic, and the αs from the hedge portfolios are significantly positive, ranging from 0.422% monthly to 0.953%. These monthly return magnitudes translate to annualized returns ranging from 5.2% to 12.1%, which are similar to those in prior research studying different factors (Fama and French, 1995).

The significant hedge portfolio αs show that σ captures risk information that is incremental to the risk factors included in the model. However, coefficients on the included risk factors also show that ranking on σ ranks on sensitivity to other risk factors.

In table 7, we examine the potential non-linear effects of σ and other risk factor variables by first sorting on the other firm characteristics and then on σ. Sorting on σ within each quintile of SIZE, BEME, and $ret_{12,2}$ creates a significant hedge portfolio return. However, the magnitude of the hedge portfolio return varies across some of the characteristic portfolios. For example, the hedge return is the largest for firms in the mid quintile of SIZE. The

[18] At the same time, we also notice that the increase of future returns from the first quintile to the second is much less than the increase in future returns from the fourth quintile to the fifth quintile of σ, again, consistent with lower variation in lower quintiles of σ.

[19] We repeat the same test with alternative factor models in the appendix, tabulated in Table A4.

hedge portfolio return is the largest for the lowest quintile of $ret_{12,2}$. There appears to be an interaction with $ret_{12,2}$ in that the hedge portfolio return from sorting on $ret_{12,2}$ is the largest for firms in the lowest quintile of σ.

5.3.2 Fama-MacBeth regressions

Following prior research, we estimate monthly cross-sectional regressions and summarize the monthly coefficient estimates (Fama and MacBeth, 1973). To demonstrate σ's ability to incrementally explain returns, we add variables that capture other aspects of earnings volatility, earnings uncertainty, earnings dispersion, and earnings sensitivity in different specifications (e.g. Ball et al., 2021; Dichev and Tang, 2009; Donelson and Resutek, 2015; Konstantinidi and Pope, 2016).

In panel A, we contrast σ with other measures that capture the second moment of earnings. In column (1), panel A of table 8, we present the baseline results from the model including σ and control variables from prior research: SIZE, BEME, short momentum (ret_1) and long momentum ($\mathrm{ret}_{12,2}$) (e.g. Ball et al., 2015; Ellahie, 2020; Novy-Marx, 2013). Similar to the portfolio tests, σ is strongly positively associated with the cross-section of returns after controlling for other firm characteristics. The coefficient has a magnitude of 0.221, which translates to a 0.43 basis point monthly return when σ moves from the first decile value (0.0079) to the tenth decile value (0.0272). This is equivalent to an annualized return of 5.3%, close in magnitude to the equal-weighted quintile sort in excess returns (table 6). As a benchmark, the same calculation for BEME yields a 0.63 basis point monthly return (7.9% annualized).

Columns (2) through (5) of panel A present models that include other related measures of volatility or uncertainty.[20] Column (2) presents the results from including a measure of σ

[20]The number of observations differs across the columns because the alternative variables have different data requirements. Specifically, column (2) requires non-missing IB; column (3) requires at least 2 years of observations of a firm to calculate its historical volatility of earnings changes; column (4) requires at least 2 years of observations of a firm to calculate earnings changes, and each firm must have peer firms that match with its past earnings attributes following the criteria set in Donelson and Resutek (2015); column (5) requires cash-flow data, which are unavailable before 1988.

using only the summary income number, income before extraordinary items, rather than the individual line items when calculating σ. While the coefficient on σ_{IB} is significant before adding σ (untabulated coefficient of 0.294 and t-statistics of 4.58), the coefficient on σ_{IB} is not significant after adding σ, as shown in column (2). This is consistent with our discussion in section 2.2 that the multi-factor information captured by σ is important. Specifically, it suggests that factor volatilities are not equal, that the covariances are not the same as what is imposed by using the summary income number, and that these two features of σ are important for capturing systematic risk.

Column (3) includes the historical volatility of earnings. The coefficient is insignificant. Other papers, such as Frankel and Litov (2009), have shown that historical volatility of earnings ($\sigma(\Delta IB)$) is not priced. Column (4) includes the earnings uncertainty measure, EU, from Donelson and Resutek (2015). Consistent with the findings in Donelson and Resutek (2015), the coefficient is significantly negative. However, σ remains significantly positive, suggesting that these measures capture different aspects of investors' learning about future earnings. Column (5) includes the earnings dispersion measure from Konstantinidi and Pope (2016), IQR. The earnings dispersion measure is negatively associated with future returns, supporting the positive price premium associated with higher total expected earnings variance in Chang et al. (2020). σ again remains significantly positive.

Panel B repeats the regressions in panel A with measures of the level of earnings and systematic risk sensitivity measures (e.g. Ball et al., 2015, 2021; Ellahie, 2020). Column (1) is repeated from panel A for reference. Again, in all columns, σ is strongly positively associated with the cross-section of returns after controlling for other firm characteristics. Columns (2) through (6) of panel B present the models that include each of the measures of earnings or risk in earnings.[21]

Column (2) presents the results from including the mean forecast that parallels our

[21] The number of observations differs across the columns because the alternative variables have different data requirements. Specifically, column (3) requires non-missing IB; column (4) requires non-missing OP; column (5) requires analyst forecasts from IBES; column (6) requires Compustat variables OIADP and PDVC.

calculation of σ. $\widehat{\Delta IB}$ is the mean forecasted changed in income using equation 10. The coefficient is significant without σ (untabulated coefficient of 0.211 and t-statistics of 3.29), but becomes insignificant after adding σ to the model. This suggests that the variance-covariance matrix of γs contains richer information than the mean γs for capturing the risk in σ that is associated with expected returns, and σ subsumes the predicting power of the first-moment estimates. Columns (3) and (4) include measures of the level of income because prior research finds that measures of earnings are associated with the cross-section of returns (Ball et al., 2015; Novy-Marx, 2013). The coefficients on the income measures are positive. However, the coefficient on σ remains significant.

Columns (5) and (6) include risk sensitivity measures derived from earnings time series regressions (Ball et al., 2021; Ellahie, 2020). In column (5), $\beta_{Analyst}$ is positively associated with returns and in column (6), β_{Wealth} is positively associated with returns.[22] In both columns σ remains significant. Notice that in column (5), the number of observations is significantly lower because the tests require analyst forecasts.

Together in panels A and B, our results show that σ captures meaningful and incrementally important information about systematic risk that helps explain the cross-section of expected returns incremental to other measures of expected returns, earnings risk, and uncertainty.

5.4 Additional tests

In this section, we evaluate the robustness of the main results and conduct additional tests that provide insights into the risk that σ captures.

5.4.1 σ and returns without analyst coverage

One benefit of σ is that it can be calculated for stocks without a long time-series of data, without stock returns, or without the analyst data required for forecast-based measures of

[22] In untabulated analysis, without σ in the model, both β_{Wealth} and β_{TFP} positively predict future returns.

risk (Ellahie, 2020). To test whether the usefulness of σ is limited to the sample with analyst coverage, we split the sample into observations with and without analyst coverage. Table 9 panel A presents these results. σ is statistically significant and of similar magnitudes for both subsamples, and the differences across the two groups are insignificant.

5.4.2 σ and firm age

Since we argue one benefit of σ is that it can be calculated without a long firm specific time series, we examine if σ can predict returns on a sample of firms that have a short time series. Column (1), Table 9 panel B presents the results. σ is statistically significant and of particularly high magnitude for firms that show up in Compustat for the first time. We then split the original sample into young firms that are less than 5 years old and firms that are greater than 5 years old, with age being calculated as the number of years that a firm has data available in Compustat. Column (2) and (3) of Table 9 panel B present these results. σ is statistically significant for both subsamples, and σ has a significantly higher magnitude among younger firms particularly for firms that enter Compustat for the first time, which implies that future returns of a young firm are more sensitive to σ.

5.4.3 Transaction costs

Many firm characteristics are no longer associated with the cross-section of returns after controlling for transaction costs, raising the possibility that the characteristics result from mispricing and only exist when arbitrage is limited (Hou et al., 2015). If σ captures risk that is unrelated to arbitrage costs, we would expect it to be associated with returns even outside of costly-to-arbitrage stocks. Table 9 panel C presents the resutls from subsamples of stocks that represent higher or lower transaction costs. Column (1) is for micro cap stocks that should have the highest transaction costs. Columns (2) and (3) remove microcap stocks or stocks with prices lower that \$5. σ is statistically significant in all three subsamples. Perhaps surprisingly, σ performs better among the subsamples that have lower transaction costs, as the coefficients between the micro-cap firms and the all-but-micro-cap firms (non-penny stock firms) are statistically different. These results suggest that the ability of σ to predict returns is not driven by limits to arbitrage.

5.4.4 Level of operating profitability

As we discuss in section 2.2, σ is different from the variance of net income. An important reason that σ captures incremental information about risk is that σ captures time varying and multi-factor risk. We therefore turn to testing the information contained in σ by creating subsamples of companies that are likely to vary by their exposure to time varying, multi-factor risks. To first capture variation in companies' exposure to time varying, multi-factor risk, we use operating profitability and split the sample into companies with high versus low operating profitability. In the next section, we consider the effect of recessionary periods.

Operating profitability may be associated with time varying, multi-factor risk exposure for several reasons. First, when expenses represent a larger portion of income (subtracting from revenues), these companies with poor performance are more likely to change course and invest in different ways and in riskier projects (Hemmer and Labro, 2019; Miller and Friesen, 1983). Second, early stage companies with low profitability often have expenses that require high risk investments such as advertising and marking expenses or research and development expenses. Together, we expect that low profitability companies are exposed to a wider variety of risk factors than high profitability companies and therefore that σ contains relatively more incremental information about risk for low than high profitability companies.

Table 9 panel D presents the results from this test. Columns (1) through (4) present the results for subsamples of companies ranked by the level of operating profitability. The coefficients on σ are significant in all columns, and the coefficients and the magnitudes are particularly higher in column (1). This column is for subsamples of companies with low levels of operating profitability where we expect time varying, multi-factor risks to be the most important. The coefficient decreases in magnitude and in significance moving from column

(1) to column (4). In addition, comparing column (1) to column (3) or column (4), the differences in the coefficients are statistically significant, further suggesting that σ captures risk particularly well when firms have poor operating performance.

5.4.5 Recession

In panel E, we also consider time periods for which multi-factor risks and/or time varying risk exposure are likely to be important by separating sample periods based on whether they occurred during a recession. We focus on recessionary and non-recessionary periods because companies are likely to restructure and recreate business practices and investments and therefore change risk exposures during recessions (Caballero and Hammour, 1996; Francois and Lloyd-Ellis, 2003; Perelman, 1995). We estimate the association between σ and returns for subsamples of company-months when σ is measured during a recession. A company's fiscal year is defined as being in recession if NBER has flagged any month of its fiscal year as being in a recession. The results are consistent with multi-factor, time varying risk being captured by σ, since its ability to predict returns is significantly higher during recessions than non-recessions.

5.5 Robustness tests

We conduct a number of robustness tests and include important robustness tests in the appendix. We briefly highlight those tests here. Some of these tests were referenced earlier.

In our main tests, we find that σ is incrementally significant when explaining the cross-section of returns where the factors included in the models are based on common factors. In table A4 we repeat the portfolio sorts with the Fama-French five factors (Fama and French, 2015). We find that σ continues to be incrementally significant in all specifications.

Table A5 column (1) presents the Fama-MacBeth regressions including the firm characteristics that parallel the Fama-French five factors (Fama and French, 2015). The coefficient on σ remains significant after controlling for these variables. In column (2), we remove

COGS in estimating the γs for the σ calculation to decrease the effects of multicollinearity. In column (3), we remove COGS and SGA. σ continues to predict future returns. Since we calculate IB using imputed earnings components following the identity equation of IB, imputation may have caused bias. We take the absolute difference between the calculated IB (with imputation) and reported IB from Compustat, and we restrict the sample to the observations that have an absolute difference of less than 10^{-4} (i.e., dollar difference below \$100) to minimize potential biases introduced by imputation. In column (4), the coefficient on σ remains significant.

Table A6 presents the Fama-MacBeth regressions including different profitability measures. The results show that the coefficients on profitability measures decline slightly in magnitude and in significance when σ is included in the regressions, leading to the conclusion that σ and profitability share some overlapping information about returns, but that this shared information cannot completely explain the relation between profitability and returns.

6 Conclusion

We develop a measure of the expected volatility of earnings that is driven by systematic risk. Our measure contributes to prior research that finds that accounting earnings contain macro-economic information (Ball et al., 2009) and that earnings contain important information about total and systematic risk (Ball et al., 2021; Chang et al., 2020; Ellahie, 2020; Konstantinidi and Pope, 2016)

We show that income statement items convey information about a firm's sensitivity to systematic factors and that cross-sectional changes in earnings regressions reveal systematic risk factors. We find that our measure of ex-ante systematic risk, σ, is associated with other total and systematic risk measures, is a leading indicator of risk exposure, and is a statistically and economically important predictor of the cross-section of expected returns.

Our measure performs well when analyst' coverage is not available, for equal and value weighted portfolios, and for low and high transaction cost stocks. One of the primary advantages of σ is that it captures time varying, multi-factor risk exposures in earnings that is particularly important in some circumstances, which we measure as young companies, companies with low profitability, and during recessions.

Appendix

The relation between estimated macro-economic states and aggregated earnings ratios

Prior accounting research has loosely interpreted cross-sectional earnings regression coefficients as relating to the average idiosyncratic properties of earnings. Because of this typical type of interpretation, our interpretation of the regression coefficients as reflecting properties of a macro-state is somewhat new, but our approach is an application of the recent use of cross sectional regressions to extract risk factor premia in finance (Fama and French, 2020). In this appendix, we demonstrate the tight correspondence between aggregated earnings information and cross-sectional regression coefficients. For simplicity, we use the example of aggregate return-on-assets (ROA).

Consider the example where a researcher would like to use aggregated ROA as a macro-economic factor (e.g., Beaver et al. (1970); Ellahie (2020)). One common approach is to use the equal or value-weighted average of firm level ROA to represent the state variable.

$$AggROA_t = \sum_i^N w_i \cdot \frac{Earnings_{i,t}}{Assets_{i,t-1}} = \sum_i^N w_i \cdot ROA_i$$

In this representation, we have $\sum_i^N w_i = 1$. When each firm in year t is weighted equally, we have $w_i = 1/N$ or when each firm is weighted by size, $w_i = Assets_i / \sum Assets_i$. $AggROA$ can be used as a macro factor to which companies may have different levels of exposure - i.e. risk sensitivity. An alternative approach to capturing aggregated ROA would be to use a cross-sectional regression estimate such as follows.

$$Earnings_{i,t} = \beta_0 + \beta_1 Assets_{i,t-1} + \epsilon_{i,t}$$

Note that in this regression, the estimated β_1 can be interpreted as the weighted average ROA. This is because the estimated β_1 can be represented as the following (subscripts omitted).

$$\hat{\beta}_1 = \frac{\sum Assets \cdot Earnings - \frac{1}{N} \cdot \sum Assets \cdot \sum Earnings}{\sum Assets^2 - \frac{1}{N} \cdot (\sum Assets)^2}$$

After some manipulation, $\hat{\beta}_1$ can be further represented as

$$\hat{\beta}_1 = \frac{Assets_1^2 \cdot \frac{Earnings_1}{Assets_1} + ... + Assets_N^2 \cdot \frac{Earnings_N}{Assets_N} - \frac{1}{N} \cdot (\sum Assets)^2 \cdot \frac{\sum Earnings}{\sum Assets}}{\sum Assets^2 - \frac{1}{N} \cdot (\sum Assets)^2}$$

$$= \frac{Assets_1^2 \cdot ROA_1 + ... + Assets_N^2 \cdot ROA_N - \frac{1}{N} \cdot (\sum Assets)^2 \cdot \overline{ROA}}{\sum Assets^2 - \frac{1}{N} \cdot (\sum Assets)^2}$$

$$= w_1 \cdot ROA_1 + ... + w_N \cdot ROA_N + w_{N+1} \cdot \overline{ROA}.$$

In this representation, when $i = 1, ..., N$, we have

$$w_i = \frac{Assets_i^2}{\sum Assets^2 - \frac{1}{N} \cdot (\sum Assets)^2}$$

When $i = N + 1$, we have

$$w_i = \frac{-\frac{1}{N} \cdot (\sum Assets)^2}{\sum Assets^2 - \frac{1}{N} \cdot (\sum Assets)^2}$$

Therefore, $\sum_i^{N+1} w_i = 1$, and $\hat{\beta}_1$ can be interpreted as the weighted average ROA in the cross section. The weight of each firm's ROA in the representation is proportional to the square of assets, suggesting that a large company's earnings contributes more to the aggregated earnings than a small company. The representation bears resemblance to taking value weighted returns as the systematic factor in empirical CAPM practices.

Table A1: Variable definitions

Main Variables	Data sources: Compustat, CRSP, IBES
ΔIB	Income before extraordinary items (Compustat item IB) substracting lagged IB, scaled by lagged total assets (AT)
IB	Income before extraordinary items (Compustat item IB) scaled by total assets (AT)
$REVT$	Total revenue (Compustat item REVT) scaled by AT
$COGS$	Cost of goods sold (Compustat item COGS) scaled by AT, imputed zero if missing
SGA	Selling, general and administrative expenses (i.e., Compustat item XSGA − XRD) scaled by AT, imputed zero if missing
XRD	R&D expenses (Compustat item XRD) scaled by AT, imputed zero if missing
DP	Depreciation and amortization (Compustat item DP) scaled by AT, imputed zero if missing
$XINT$	Interest expenses (Compustat item XINT) scaled by AT, imputed zero if missing
TXT	Income tax expenses (Compustat item TXT) scaled by AT, imputed zero if missing
$NOPI$	Non-operating expense (Compustat item NOPI) scaled by AT, imputed zero if missing
SPI	Special items (Compustat item SPI) scaled by AT, imputed zero if missing
MII	Minority interest (Compustat item MII) scaled by AT, imputed zero if missing
ret	Monthly return, obtained from CRSP
ret_1	Prior one month return, obtained from CRSP
$ret_{12,2}$	The prior year's return skipping the last month, obtained from CRSP
σ	Standard deviation of the predicted $\Delta IB_{i,t+1}$ using income statement line items and estimated historical γs available until the year before income statement year, following equation $\Delta IB_{i,t+1} = \alpha_t + \gamma_1 REVT_{i,t} + \gamma_2 COGS_{i,t} + \gamma_3 SGA_{i,t} + \gamma_4 XRD_{i,t} + \gamma_5 DP_{i,t} + \gamma_6 XINT_{i,t} + \gamma_7 NOPI_{i,t} + \gamma_8 TXT_{i,t} + \gamma_9 SPI_{i,t} + \gamma_{10} MII_{i,t} + \epsilon_{i,t+1}$
σ_{IB}	Standard deviation of the predicted $\Delta IB_{i,t+1}$ using the level of earnings and estimated historical γs available until the year before income statement year, following equation $\Delta IB_{i,t+1} = \alpha_t + \gamma IB_{i,t} + \epsilon_{i,t+1}$
$SIZE$	The natural log of market cap, which is the fiscal-year-end SHROUT times the absolute value of PRC scaled by 1000, from CRSP
$BEME$	The natural log of equity scaled by market cap, in which equity is calculated as Shareholder book value (SH) plus deferred taxes and investment tax credit (TXDITC) subtracting preferred stock (PS), following Freyberger et al. (2020). SH, TXDITC, and PS are obtained from Compustat. SH is set to SEQ (shareholder equity); if missing, it is set at CEQ (common equity) plus PS (preferred stock, detailed below); if CEQ+PS is missing, it's set at AT−LT. PS is set at PSTKRV (preferred stock redemption value); if missing, it is set at PSTKL (preferred stock liquidating value); if PSTKL is missing, it is set at PSTK (preferred stock, total); if missing, set at zero
INV	Asset growth, AT over lagged AT and then take the natural log
OP	Operating profitability scaled by total assets, in which operating profitability is calculated as (REVT − COGS − (XSGA − XRD)), following Ball et al. (2015)
$\sigma(\Delta IB)$	The historical volatility of ΔIB, calculated as the standard deviation of a firm's ΔIB trailing over five years, with at least two-year observations
EU	Non-parametric earnings uncertainty of earnings, calculated as the standard deviation of forward earnings change of a focal firm's matched peer firms, with matching criteria following Donelson and Resutek (2015)
IQR	Following Konstantinidi and Pope (2016), we use quantile regression to forecast earnings at the first quartile and the third quartile, and we take the interquartile range (IQR) as a measure of earnings uncertainty
$\widehat{\Delta IB}$	Mean predicted $\Delta IB_{i,t+1}$ using income statement line items and estimated historical γs available until the year before income statement year, following equation $\Delta IB_{i,t+1} = \alpha_t + \gamma_1 REVT_{i,t} + \gamma_2 COGS_{i,t} + \gamma_3 SGA_{i,t} + \gamma_4 XRD_{i,t} + \gamma_5 DP_{i,t} + \gamma_6 XINT_{i,t} + \gamma_7 NOPI_{i,t} + \gamma_8 TXT_{i,t} + \gamma_9 SPI_{i,t} + \gamma_{10} MII_{i,t} + \epsilon_{i,t+1}$
$\beta_{Analyst}$	It is an earnings beta based on price-scaled expectations shocks, following Ellahie (2020). Change in earnings is the monthly revision in the 1-year ahead analyst forecast of earnings per share, multiplying outstanding shares and adjusted for the split factors, then scaled by market value of equity. Earnings beta is the coefficient of five-year trailing change in earnings and aggregated change in earnings. Data are from IBES and CRSP
β_{CAPM}	CAPM beta, the coefficient of regressing trailing 60-month firm returns to market returns
β_{Wealth}	Earnings sensitivity to aggregate demand shock, following Ball et al. (2021)
β_{TFP}	Earnings sensitivity to aggregate supply shock, following Ball et al. (2021)

Macro Variables	Data sources: BEA, Federal Reserve Bank Reports, and Kenneth French's website (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html)
ΔIP	Annual growth in the industrial production index (Federal Reserve Statistical Release G.17)
ΔDG, ΔNDG, &ΔSG	Growth in consumer durables goods, nondurables goods, and services, from BEA National Income and Product Accounts Table 1.1.5
ΔGDP	U.S. GDP growth by year, from BEA National Income and Product Accounts Table 1.1.5
Mkt_RF	Annual market premium, obtained from Kenneth French's library
SMB	Annual SMB factor, obtained from Kenneth French's library
HML	Annual HML factor, obtained from Kenneth French's library
RMW	Annual RMW factor, obtained from Kenneth French's library
CMA	Annual CMA factor, obtained from Kenneth French's library
ΔFFO	Annual change in the federal funds rate, from Federal Reserve H15 Reports
$\Delta Term$	Annual change of the variable $Term$, i.e., the difference in the rate of the 10 year minus the 1 year US Treasury Notes , from Federal Reserve H15 Reports
$\Delta Sprd$	Annual change of the variable $Sprd$, i.e., the difference in the bond yield for BAA and the rate of the 10 year US Treasury Notes, from Federal Reserve H15 Reports

Table A2: Comprehensive historial γs

Panel A: Comprehensive historial γs and cross-sectional $R^2 \times 100$

Fyear	Intercept	REVT	COGS	SGA	XRD	DP	XINT	TXT	NOPI	SPI	MII	R^2
1950	−0.960	−0.495	0.118	−0.066	−0.004	0.445	−0.276	−1.457	−0.139	0.055	−0.084	30.957
1951	−0.452	0.125	−0.161	−0.006	−0.058	0.105	−0.046	−0.324	0.004	0.031	−0.031	3.223
1952	0.493	0.038	0.050	0.077	−0.044	0.071	0.043	−0.029	0.013	0.056	−0.023	1.426
1953	0.869	0.242	−0.654	0.416	0.249	−0.017	0.226	0.580	0.054	−0.356	−0.170	8.265
1954	2.184	−0.396	0.228	−0.104	0.373	0.172	−0.316	−0.035	0.379	−0.004	−0.109	7.201
1955	1.073	−0.220	−0.034	0.186	−0.275	0.068	0.217	0.388	0.073	0.041	−0.002	3.451
1956	−0.086	0.262	−0.034	0.204	0.054	−0.095	0.231	−0.236	−0.025	0.131	0.058	5.916
1957	−0.605	0.382	−0.336	0.453	0.045	−0.007	0.401	−0.451	0.029	−0.161	0.043	11.263
1958	1.848	−0.157	0.080	0.023	0.132	0.243	−0.202	0.137	0.021	−0.021	−0.160	2.938
1959	−0.218	−0.040	−0.101	0.331	−0.080	−0.116	0.189	0.143	0.010	0.205	0.117	4.147
1960	0.370	0.036	−0.100	0.186	−0.061	0.147	0.240	0.100	−0.023	0.061	−0.032	1.217
1961	0.981	−0.306	0.317	0.104	0.017	0.227	−0.097	0.163	−0.163	−0.098	−0.098	1.926
1962	0.630	−0.638	0.724	0.186	0.098	0.193	0.044	0.140	0.051	−0.122	0.017	1.766
1963	1.371	−0.121	0.242	0.296	0.047	0.249	0.032	0.203	0.041	−0.019	−0.015	3.882
1964	1.457	−8.092	7.241	1.974	0.153	0.328	0.162	0.926	−0.142	−0.030	−0.109	6.032
1965	1.428	1.969	−1.596	−0.350	−0.001	0.095	0.026	0.516	−0.089	−0.111	−0.091	6.551
1966	0.448	−5.518	4.725	1.384	0.005	0.095	0.105	0.659	−0.033	−0.079	−0.049	1.114
1967	1.070	−11.644	10.141	2.677	0.266	0.307	0.309	1.233	−0.085	−0.062	0.069	2.853
1968	0.614	5.267	−4.525	−1.088	−0.108	−0.262	0.055	−0.136	0.058	−0.049	−0.075	1.275
1969	−0.470	−4.160	3.313	0.984	−0.186	−0.108	0.218	0.854	−0.128	−0.006	0.136	2.529
1970	0.924	−30.650	26.448	6.809	0.556	0.898	0.535	2.921	−0.477	−0.083	0.138	8.379
1971	1.545	−24.916	21.077	5.511	0.832	0.747	0.420	2.452	−0.184	−0.164	−0.110	7.334
1972	1.520	−12.776	10.795	2.682	0.707	0.736	0.078	1.331	0.032	−0.039	0.010	5.520
1973	0.463	−7.787	6.548	1.553	0.174	0.960	−0.284	0.711	−0.178	0.067	0.115	3.518
1974	0.298	−16.953	14.370	4.426	0.340	0.611	0.020	0.929	−0.426	−0.425	0.030	6.702
1975	1.462	−14.184	11.967	3.591	0.753	0.812	0.242	0.919	−0.223	−0.636	−0.091	8.374
1976	0.966	−26.168	21.957	6.178	0.909	0.788	0.581	2.596	−0.415	−0.528	0.085	7.336
1977	1.474	−22.289	18.981	5.374	0.921	0.810	0.459	2.301	−0.305	−0.313	−0.045	5.686
1978	1.173	−9.954	8.114	2.261	0.661	0.596	0.052	1.231	−0.072	−0.468	0.142	4.496
1979	0.514	−23.720	19.505	5.781	0.712	1.126	0.486	2.308	−0.551	−0.615	0.018	6.638
1980	0.406	−19.349	16.321	4.537	0.788	0.818	0.465	2.094	−0.727	−0.713	−0.067	4.157
1981	−1.232	−10.021	8.507	2.695	0.125	0.060	0.770	1.252	−1.117	−0.625	−0.011	3.712
1982	0.881	−13.916	12.212	3.621	0.618	0.515	1.167	1.727	−0.993	−0.628	−0.005	4.661
1983	0.547	−11.309	9.621	2.745	0.809	0.655	0.926	1.920	−0.849	−1.155	−0.031	5.135
1984	−0.341	−19.314	16.364	4.995	0.698	0.262	1.068	2.397	−0.847	−1.304	−0.104	8.173
1985	−0.062	−21.755	18.856	5.880	1.117	0.071	1.213	3.034	−0.918	−2.507	0.134	11.472
1986	1.153	−20.970	16.830	6.080	0.873	1.989	0.888	2.865	−0.984	−2.539	0.274	13.778
1987	1.124	−19.547	16.566	5.735	1.093	0.898	0.840	2.446	−0.773	−1.998	0.148	11.636
1988	0.413	−25.658	21.048	7.663	1.465	1.467	0.776	2.644	−0.562	−1.568	0.031	13.036
1989	0.069	−16.941	13.801	4.917	0.843	1.166	0.729	1.875	−1.058	−2.363	0.077	11.553
1990	0.001	−17.813	14.683	5.524	1.280	0.131	1.106	1.932	−0.823	−2.522	0.174	12.264
1991	0.560	−7.159	6.019	2.154	0.079	0.851	0.795	0.961	−0.576	−2.936	0.077	9.198
1992	0.380	−5.334	4.634	1.468	−0.286	0.306	0.915	1.211	−0.476	−3.083	0.255	8.373
1993	0.940	−10.117	8.711	2.566	0.762	0.710	0.747	1.543	−0.769	−2.989	0.077	10.166
1994	0.537	−8.832	7.389	1.886	1.304	0.497	0.403	1.237	−0.666	−2.420	0.289	7.278
1995	−0.025	−3.285	2.965	0.727	−0.567	0.381	0.549	0.942	−0.651	−2.644	0.126	4.990
1996	−0.106	−2.756	3.073	0.418	−0.354	0.059	0.216	1.199	−0.749	−2.839	0.151	5.746
1997	−0.782	−7.882	6.799	2.736	−0.445	0.130	0.761	1.554	−0.754	−3.354	0.172	7.469
1998	−0.171	0.109	0.304	−0.721	−0.634	0.868	0.311	0.479	−0.532	−3.203	0.104	4.163
1999	−2.678	12.134	−9.268	−5.441	−1.922	0.682	1.066	0.055	−0.850	−1.557	0.224	5.516
2000	−0.811	−23.380	19.057	8.385	0.097	0.246	2.245	2.561	−1.534	−4.022	0.185	17.420
2001	3.251	−27.122	22.326	9.664	1.772	2.293	1.667	2.899	−1.479	−8.388	0.066	45.950
2002	3.101	−17.901	14.202	6.238	2.344	1.698	0.361	1.978	−0.930	−6.088	0.314	34.656
2003	1.849	−0.091	0.784	−0.025	0.561	0.623	−0.042	0.161	0.081	−2.700	0.018	7.479
2004	0.846	−4.383	3.473	1.329	−0.374	0.915	0.101	0.775	−0.277	−2.023	0.064	5.235
2005	0.816	−4.065	3.519	1.189	0.018	0.424	0.064	1.055	−0.366	−2.214	0.363	5.232
2006	−0.280	−1.508	1.189	0.558	0.218	0.188	0.133	0.801	−0.673	−2.001	0.094	3.943
2007	−2.025	−8.611	6.697	2.544	0.511	0.643	0.529	1.564	−1.164	−2.599	0.142	6.318
2008	1.911	−23.576	19.657	7.525	1.752	0.378	1.232	2.095	−2.889	−7.484	0.026	43.210
2009	2.607	−9.527	8.003	2.967	1.479	0.803	0.132	1.107	−0.883	−3.140	−0.014	17.002
2010	0.422	−7.752	6.019	2.406	0.200	0.704	0.471	1.459	−0.904	−1.950	0.174	7.943
2011	−0.242	−8.349	6.858	2.415	−0.361	0.063	0.419	1.037	−0.521	−1.825	0.203	6.362
2012	−0.011	−6.798	5.841	1.611	−0.129	−0.148	0.456	1.255	−0.206	−2.379	−0.023	7.750
2013	−0.139	−5.094	4.124	1.174	−0.028	0.086	0.325	1.214	−0.565	−1.887	0.005	5.062
2014	−1.027	−6.213	5.401	2.758	−0.040	−0.805	0.706	0.988	−1.218	−2.063	0.067	8.567
2015	0.510	−9.560	7.307	3.151	−0.494	1.058	0.270	1.142	−1.348	−2.267	0.027	10.587
2016	0.723	−8.086	6.044	2.751	−0.760	1.293	0.455	1.253	−0.863	−1.867	−0.049	8.928
2017	0.123	−4.975	3.740	2.038	−0.190	0.527	0.305	2.017	−0.951	−2.000	0.211	8.066
2018	−0.805	−4.872	3.291	2.054	−0.460	−0.368	0.131	1.001	−0.961	−2.338	0.050	7.540
2019	−1.149	−5.426	4.791	2.241	0.112	−0.563	0.122	0.926	−1.117	−1.886	−0.080	5.417

Panel B: Regressing varying time-series of γs to macro variables											
Economic production set of macro variables: ΔIP, ΔDG, ΔNGD, ΔSG, and ΔGDP											
	γ_{Int}	γ_{REVT}	γ_{COGS}	γ_{SGA}	γ_{XRD}	γ_{DP}	γ_{XINT}	γ_{TXT}	γ_{NOPI}	γ_{SPI}	γ_{MII}
1950–1984											
R^2	0.292	0.468	0.460	0.481	0.596	0.426	0.375	0.522	0.383	0.426	0.127
Pval	0.062	0.002	0.002	0.001	0.000	0.005	0.014	0.000	0.012	0.005	0.532
1985–2019											
R^2	0.379	0.415	0.436	0.359	0.327	0.287	0.480	0.367	0.257	0.318	0.289
Pval	0.013	0.006	0.004	0.019	0.034	0.068	0.001	0.016	0.107	0.040	0.065
Equity market set of macro variables: Mkt_rf, SMB, HML, RMW, and CMA											
1950–1984											
R^2	0.242	0.192	0.197	0.228	0.222	0.021	0.434	0.246	0.381	0.396	0.193
Pval	0.134	0.261	0.246	0.163	0.177	0.986	0.004	0.126	0.012	0.009	0.258
1985–2019											
R^2	0.365	0.575	0.563	0.641	0.451	0.153	0.307	0.433	0.405	0.548	0.103
Pval	0.017	0.000	0.000	0.000	0.003	0.410	0.048	0.004	0.007	0.000	0.650
Bond market set of macro variables: ΔFFO, $\Delta Sprd$, and $\Delta Term$											
1950–1984											
R^2	0.224	0.068	0.073	0.067	0.172	0.071	0.149	0.126	0.044	0.149	0.252
Pval	0.046	0.529	0.494	0.536	0.114	0.512	0.165	0.236	0.699	0.166	0.028
1985–2019											
R^2	0.281	0.103	0.113	0.095	0.174	0.167	0.109	0.073	0.378	0.400	0.105
Pval	0.016	0.329	0.287	0.371	0.112	0.124	0.302	0.495	0.002	0.001	0.324

This table displays the comprehensive list of estimated γs across all fiscal years available in Compustat, as well as the relation between estimated γs and macro variables across different time periods. We require REVT to be non-missing and greater than zero, and impute zero for all other variables to retain a maximized sample. Variable definitions are in Table A1. In Panel A, The cross-sectional regression model follows $\Delta IB_{i,t+1} = \alpha_t + \gamma_1 REVT_{i,t} + \gamma_2 COGS_{i,t} + \gamma_3 SGA_{i,t} + \gamma_4 XRD_{i,t} + \gamma_5 DP_{i,t} + \gamma_6 XINT_{i,t} + \gamma_7 NOPI_{i,t} + \gamma_8 TXT_{i,t} + \gamma_9 SPI_{i,t} + \gamma_{10} MII_{i,t} + \epsilon_{i,t+1}$, in which each variable is standardized to have a zero mean and a unit standard deviation within each cross section. Intercept refers to α_t, which is a constant in a cross section. Each column in the table represents the γ estimate for that variable, and the column named R^2 indicates the R-squared of the regression in each cross section. In Panel B, we break each time-series of γ into two pieces (1950–1985, 1986–2019), and regress each piece of time-series on three sets of macro variables, the economic production set that includes ΔIP, ΔDG, ΔNGD, ΔSG, and ΔGDP; the equity market set that includes Mkt_rf, SMB, HML, RMW, and CMA; and the bond market set that includes ΔFFO, $\Delta Sprd$, and $\Delta Term$. R^2 and $PVal$ indicate the R-squared and the P-value of the model F statistics.

Table A3: A demonstration of how two components affect the output σ

Panel A: Variance-covariance matrix of two earnings components (REVT and COGS)

	γ_{Int}	γ_{REVT}	γ_{COGS}
γ_{Int}	1.069	−2.252	1.864
γ_{REVT}	−2.252	83.486	−69.401
γ_{COGS}	1.864	−69.401	57.830

Panel B: Combine the vector of earnings components with the variance-covariance matrix

$$\sigma^2 = Var[\widehat{\Delta NI_{t+1}}] = Var[1 \times \hat{\gamma}_{Int} + REVT \times \hat{\gamma}_{REVT} + COGS \times \hat{\gamma}_{COGS}]$$

$$= \begin{bmatrix} 1 \\ REVT \\ COGS \end{bmatrix}^T \times \begin{bmatrix} Var(\gamma_{Int}) & Cov(\gamma_{Int}, \gamma_{REVT}) & Cov(\gamma_{Int}, \gamma_{COGS}) \\ Cov(\gamma_{Int}, \gamma_{REVT}) & Var(\gamma_{REVT}) & Cov(\gamma_{REVT}, \gamma_{COGS}) \\ Cov(\gamma_{Int}, \gamma_{COGS}) & Cov(\gamma_{REVT}, \gamma_{COGS}) & Var(\gamma_{COGS}) \end{bmatrix} \times \begin{bmatrix} 1 \\ REVT \\ COGS \end{bmatrix}$$

Panel C: Case 1, firm A with 1 unit of REVT and 0.5 unit of COGS

$$\sigma_A^2 = \begin{bmatrix} 1 \\ 1 \\ 0.5 \end{bmatrix}^T \times \begin{bmatrix} 1.069 & -2.252 & 1.864 \\ -2.252 & 83.486 & -69.401 \\ 1.864 & -69.401 & 57.830 \end{bmatrix} \times \begin{bmatrix} 1 \\ 1 \\ 0.5 \end{bmatrix} = 26.972$$

Panel D: Case 2, firm B with 1 unit of REVT and 0.9 unit of COGS

$$\sigma_B^2 = \begin{bmatrix} 1 \\ 1 \\ 0.9 \end{bmatrix}^T \times \begin{bmatrix} 1.069 & -2.252 & 1.864 \\ -2.252 & 83.486 & -69.401 \\ 1.864 & -69.401 & 57.830 \end{bmatrix} \times \begin{bmatrix} 1 \\ 1 \\ 0.9 \end{bmatrix} = 5.327$$

This table demonstrates how the variance-covariance matrix of the estimated γs of two components, REVT and COST, along with these two components, affects the output measure σ. Detailed in Section 4, the first step is to estimate γs from available prior cross sections; the second step is to use estimated γ from each prior cross section to form each point estimate of ΔIB for that cross section, and the third step is to take the second moment of all point estimates of ΔIB from all prior cross sections. The second and the third step combined is equivalent to form the historical variance-covariance matrix of γs and conduct a matrix multiplication, which is a row vector of a firm's earnings components, multiplied by the variance-covariance matrix of γs, multiplied by a column vector of the firm's earnings components. The variance-covariance matrix of REVT and COGS (and the intercept) of all historical cross sections is shown in Panel A, and the matrix operation is shown in Panel B. Panel C and D demonstrate how different firm characteristics, or varying line items, affect the output σ. Shown in Panel C, firm A has 1 unit of REVT and 0.5 unit of COGS, and the output σ is 26.972; in Panel D, firm B has 1 unit of REVT and 0.9 unit of COGS, and the output σ is 5.327. The contrast of firm A and B indicates that holding REVT constant, a higher COGS results lower risk, consistent with the operating hedging theory in Kogan et al. (2021).

Table A4: Fama-French five factors: portfolio sorting tests

Panel A: Quintile sort						
	EW portfolio return					
Portfolio	α	β_{mkt}	β_{smb}	β_{hml}	β_{rmw}	β_{cma}
Low	−0.123	0.960	0.712	0.463	0.131	−0.066
2	−0.061	0.932	0.680	0.388	0.232	0.028
3	0.016	0.986	0.774	0.271	0.106	−0.079
4	0.189	0.992	0.800	0.081	−0.179	−0.054
High	0.414	1.010	0.906	−0.173	−0.593	−0.061
H−L	0.536***	0.050**	0.194***	−0.636***	−0.724***	0.004
	[5.69]	[2.14]	[5.92]	[−14.59]	[−15.76]	[0.06]
	VW portfolio return					
Portfolio	α	β_{mkt}	β_{smb}	β_{hml}	β_{rmw}	β_{cma}
Low	0.370	0.980	0.085	0.294	0.101	0.101
2	0.382	1.030	0.049	0.268	0.148	0.119
3	0.536	1.061	0.147	0.109	0.114	0.090
4	0.874	1.055	0.200	−0.199	−0.096	0.075
5	1.281	1.033	0.303	−0.404	−0.340	0.096
H−L	0.911***	0.053**	0.219***	−0.698***	−0.440***	−0.005
	[9.44]	[2.20]	[6.52]	[−15.63]	[−9.35]	[−0.07]
Panel B: Decile sort						
	EW portfolio return					
Portfolio	α	β_{mkt}	β_{smb}	β_{hml}	β_{rmw}	β_{cma}
Low	−0.191	0.971	0.802	0.484	0.157	−0.088
2	−0.055	0.949	0.622	0.441	0.105	−0.042
3	−0.063	0.934	0.646	0.410	0.201	0.020
4	−0.059	0.929	0.716	0.366	0.263	0.037
5	−0.012	0.981	0.766	0.311	0.191	−0.057
6	0.043	0.992	0.781	0.231	0.021	−0.103
7	0.111	0.990	0.792	0.162	−0.089	−0.079
8	0.267	0.993	0.808	0.001	−0.269	−0.03
9	0.373	1.020	0.857	−0.093	−0.441	−0.064
High	0.458	1.000	0.956	−0.255	−0.751	−0.057
H−L	0.649***	0.029	0.154***	−0.739***	−0.909***	0.031
	[5.14]	[0.93]	[3.51]	[−12.65]	[−14.74]	[0.35]
	VW portfolio return					
Portfolio	α	β_{mkt}	β_{smb}	β_{hml}	β_{rmw}	β_{cma}
Low	0.404	0.997	0.146	0.269	0.091	0.111
2	0.324	0.969	0.044	0.312	0.120	0.103
3	0.329	1.027	0.039	0.323	0.168	0.072
4	0.428	1.034	0.067	0.228	0.129	0.152
5	0.436	1.071	0.126	0.191	0.194	0.119
6	0.633	1.051	0.175	0.015	0.027	0.060
7	0.737	1.062	0.169	−0.101	0.033	0.073
8	0.994	1.058	0.229	−0.288	−0.209	0.088
9	1.122	1.044	0.289	−0.328	−0.297	0.062
High	1.517	1.023	0.331	−0.520	−0.449	0.190
H−L	1.113***	0.026	0.186***	−0.789***	−0.540***	0.079
	[9.39]	[0.88]	[4.51]	[−14.38]	[−9.33]	[0.94]

This table shows monthly equal-weighted and value-weighted average excess returns to portfolios sorted on σ, defined in Table A1, and the results of time series regressions of these portfolios' returns on the Fama and French five factors (Fama and French, 2015) (i.e., the market factor (MKT), the size factor small-minus-large (SMB), the value factor high-minus-low (HML), the profitability factor robust-minus-weak (RMW), and the investment factor conservative-minus-aggressive (CMA)). Portfolio returns are scaled up by 10^2. Panel A reports these results based on a quintile-sorted σ, and Panel B reports these results based on a decile-sorted σ. The sample covers June 1960 to May 2020, and return data cover June 1961 to May 2021. T-statistics are reported in the brackets. *,**, and *** indicate two-tailed p<0.1, p<0.05, and p<0.01, respectively.

Table A5: Returns: Fama-MacBeth regression tests, robustness checks

	(1)	(2)	(3)	(4)
σ	0.159***	0.383***	0.397***	0.242***
	[3.41]	[7.59]	[7.86]	[5.48]
SIZE	−0.001***	−0.001**	−0.001**	−0.001**
	[−3.24]	[−2.47]	[−2.50]	[−2.54]
BEME	0.002***	0.003***	0.003***	0.003***
	[5.36]	[6.57]	[6.59]	[6.36]
ret_1	−0.051***	−0.050***	−0.049***	−0.050***
	[−14.54]	[−14.08]	[−14.08]	[−14.16]
$\text{ret}_{12,2}$	0.005***	0.006***	0.006***	0.006***
	[3.37]	[3.77]	[3.79]	[3.70]
OP	0.018***			
	[6.20]			
INV	−0.011***			
	[−10.33]			
Intercept	0.013***	0.011***	0.011***	0.012***
	[5.25]	[4.22]	[4.20]	[4.72]
N	2,284,131	2,492,237	2,515,265	2,431,412
R^2	4.84%	4.28%	4.25%	4.32%

This table shows σ's ability to predict cross-sectional future returns, using Fama-Macbeth regression method (Fama and MacBeth, 1973). Variables are defined in Table A1. Future returns start from June after a firm's fiscal-year-end to May of the following year. The sample covers June 1960 to May 2020, and return data cover June 1961 to May 2021. In column (1), we show the baseline regression model with two additional firm characteristics as control variables, INV and OP (Ball et al., 2015; Titman et al., 2004). In column (2), we remove COGS in estimating cross-sectional models to decrease the effect of multicollinearity on the estimated γs. In other words, we use this model: $\Delta IB_{i,t+1} = \alpha_t + \gamma_1 REVT_{i,t} + \gamma_3 SGA_{i,t} + \gamma_4 XRD_{i,t} + \gamma_5 DP_{i,t} + \gamma_6 XINT_{i,t} + \gamma_7 NOPI_{i,t} + \gamma_8 TXT_{i,t} + \gamma_9 SPI_{i,t} + \gamma_{10} MII_{i,t} + \epsilon_{i,t+1}$. In column (3), we remove SGA in estimating cross-sectional models to further decrease the effect of multicollinearity on the estimated γs. We use this model: $\Delta IB_{i,t+1} = \alpha_t + \gamma_1 REVT_{i,t} + \gamma_4 XRD_{i,t} + \gamma_5 DP_{i,t} + \gamma_6 XINT_{i,t} + \gamma_7 NOPI_{i,t} + \gamma_8 TXT_{i,t} + \gamma_9 SPI_{i,t} + \gamma_{10} MII_{i,t} + \epsilon_{i,t+1}$. All other procedures in column (2) and (3) follow exactly the same as the main analyses. In column (4), we calculate IB using imputed earnings components following the identity equation of IB: $IB \equiv REVT - COGS - SGA - XRD - DP - XINT - TXT + NOPI + SPI - MII$. We calculate the absolute difference between the calculated IB and reported IB from Compustat, and we restrict the sample to the observations that have an absolute difference of less than 10^{-4} to minimize potential biases introduced by imputation. T-statistics are reported in the brackets. *,**, and *** indicate two-tailed p<0.1, p<0.05, and p<0.01, respectively.

Table A6: Returns: Fama-MacBeth regression tests, σ and profitability measures

	GP		OP_{BGLN}		IB	
	(1)	(2)	(3)	(4)	(5)	(6)
Profits	0.008***	0.007***	0.019***	0.017***	0.014***	0.011**
	[7.34]	[6.39]	[6.87]	[5.71]	[3.04]	[2.10]
σ		0.222***		0.253***		0.307***
		[5.26]		[5.53]		[6.81]
SIZE	−0.001**	−0.001**	−0.001***	−0.001***	−0.001***	−0.001***
	[−2.36]	[−2.18]	[−3.57]	[−3.25]	[−3.28]	[−3.05]
BEME	0.003***	0.004***	0.003***	0.004***	0.003***	0.003***
	[6.24]	[7.49]	[5.78]	[7.17]	[5.24]	[6.43]
ret_1	−0.050***	−0.051***	−0.050***	−0.050***	−0.050***	−0.050***
	[−14.01]	[−14.41]	[−14.10]	[−14.43]	[−14.46]	[−14.58]
$ret_{12,2}$	0.006***	0.005***	0.005***	0.005***	0.005***	0.005***
	[3.68]	[3.61]	[3.51]	[3.51]	[3.60]	[3.55]
Intercept	0.013***	0.010***	0.014***	0.011***	0.015***	0.012***
	[4.61]	[4.02]	[5.16]	[4.42]	[5.74]	[4.68]
N	2,470,006	2,470,006	2,469,331	2,469,331	2,472,577	2,472,577
R^2	4.32%	4.60%	4.31%	4.57%	4.46%	4.62%

This table shows σ's ability to absorb some predicting power of profitability measures. Variables are defined in Table A1. Future returns start from June after a firm's fiscal-year-end to May of the following year. The sample covers June 1960 to May 2020, and return data cover June 1961 to May 2021. In column (1) and (2), GP represents gross profits, which is revenue subtracting cost of goods sold, scaled by total assets (Novy-Marx, 2013). In column (3) and (4), OP_{BGLN} represents operating profitability calculated following Ball et al. (2015), which is revenue subtracting cost of goods sold and self-reported selling, general and administrative expenses, scaled by total assets. In column (5) and (6), IB represents income before extraordinary items, which is IB scaled by total assets. T-statistics are reported in the brackets. *,**, and *** indicate two-tailed p<0.1, p<0.05, and p<0.01, respectively.

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Table 1: Distribution of fiscal years and annual financial data

Panel A: Distribution of fiscal years

Fyear	N	Pct	Cum	CumPct	Fyear	N	Pct	Cum	CumPct
1950	449	0.14	449	0.14	1985	5895	1.80	107308	32.72
1951	458	0.14	907	0.28	1986	5946	1.81	113254	34.53
1952	465	0.14	1372	0.42	1987	6002	1.83	119256	36.36
1953	469	0.14	1841	0.56	1988	5813	1.77	125069	38.14
1954	445	0.14	2286	0.70	1989	5668	1.73	130737	39.86
1955	465	0.14	2751	0.84	1990	5619	1.71	136356	41.58
1956	486	0.15	3237	0.99	1991	5727	1.75	142083	43.32
1957	504	0.15	3741	1.14	1992	6055	1.85	148138	45.17
1958	522	0.16	4263	1.30	1993	7187	2.19	155325	47.36
1959	539	0.16	4802	1.46	1994	7478	2.28	162803	49.64
1960	1057	0.32	5859	1.79	1995	7910	2.41	170713	52.05
1961	1388	0.42	7247	2.21	1996	8184	2.50	178897	54.55
1962	1751	0.53	8998	2.74	1997	7981	2.43	186878	56.98
1963	1941	0.59	10939	3.34	1998	7940	2.42	194818	59.40
1964	2136	0.65	13075	3.99	1999	8134	2.48	202952	61.88
1965	2283	0.70	15358	4.68	2000	7817	2.38	210769	64.27
1966	2479	0.76	17837	5.44	2001	7279	2.22	218048	66.49
1967	2672	0.81	20509	6.25	2002	7055	2.15	225103	68.64
1968	3220	0.98	23729	7.24	2003	6991	2.13	232094	70.77
1969	3423	1.04	27152	8.28	2004	6979	2.13	239073	72.90
1970	3506	1.07	30658	9.35	2005	6815	2.08	245888	74.98
1971	3632	1.11	34290	10.46	2006	6727	2.05	252615	77.03
1972	3761	1.15	38051	11.60	2007	6527	1.99	259142	79.02
1973	4098	1.25	42149	12.85	2008	6229	1.90	265371	80.92
1974	5311	1.62	47460	14.47	2009	6050	1.84	271421	82.76
1975	5317	1.62	52777	16.09	2010	6030	1.84	277451	84.60
1976	5311	1.62	58088	17.71	2011	5927	1.81	283378	86.41
1977	5299	1.62	63387	19.33	2012	6024	1.84	289402	88.24
1978	5243	1.60	68630	20.93	2013	6010	1.83	295412	90.08
1979	5158	1.57	73788	22.50	2014	5933	1.81	301345	91.89
1980	5222	1.59	79010	24.09	2015	5596	1.71	306941	93.59
1981	5256	1.60	84266	25.69	2016	5384	1.64	312325	95.23
1982	5556	1.69	89822	27.39	2017	5319	1.62	317644	96.86
1983	5785	1.76	95607	29.15	2018	5193	1.58	322837	98.44
1984	5806	1.77	101413	30.92	2019	5120	1.56	327957	100.00

Panel B: Descriptive statistics

	N	Mean	St. Dev.	Pctl(1)	Pctl(25)	Median	Pctl(75)	Pctl(99)
ΔIB	304,511	0.003	0.101	−0.340	−0.014	0.004	0.025	0.326
REVT	327,957	0.984	0.809	0.035	0.325	0.842	1.437	3.608
COGS	327,957	0.688	0.666	0.005	0.169	0.514	1.008	3.052
SGA	327,957	0.180	0.214	−0.070	0.016	0.115	0.277	0.914
XRD	327,957	0.021	0.054	0.000	0.000	0000	0.010	0.276
DP	327,957	0.036	0.030	0.000	0.016	0.032	0.050	0.139
XINT	327,957	0.018	0.019	0.000	0.002	0.014	0.028	0.081
TXT	327,957	0.024	0.035	−0.041	0.001	0.014	0.040	0.139
NOPI	327,957	0.008	0.017	−0.028	0.000	0.004	0.013	0.073
SPI	327,957	−0.006	0.031	−0.148	0.000	0.000	0.000	0.036
MII	327,957	0.0004	0.002	−0.001	0.000	0.000	0.000	0.010

Panel C: Pearson correlations

	ΔIB$_{t+1}$	REVT	COGS	SGA	XRD	DP	XINT	TXT	NOPI	SPI
REVT	**0.038**									
COGS	**0.040**	**0.949**								
SGA	**0.060**	**0.587**	**0.393**							
XRD	**0.025**	**−0.024**	**−0.091**	**0.176**						
DP	**0.072**	**0.196**	**0.149**	**0.166**	**0.089**					
XINT	**0.039**	**0.076**	**0.099**	*0.003*	**−0.144**	**0.161**				
TXT	**0.008**	**0.372**	**0.270**	**0.160**	**−0.078**	**0.032**	**−0.164**			
NOPI	**−0.043**	**0.046**	**0.043**	**0.066**	**0.098**	**0.055**	**0.061**	**0.102**		
SPI	**−0.265**	**−0.007**	0.000	**−0.082**	**−0.152**	**−0.122**	**−0.008**	**0.144**	**0.006**	
MII	**−0.006**	**−0.013**	**−0.009**	**−0.049**	**−0.047**	−0.001	**0.022**	**0.009**	**0.033**	**0.022**

This table displays information for the sample that is used to construct the income-statement-related systematic factors (i.e., γs), using cross-sectional regression model $\Delta IB_{i,t+1} = \alpha_t + \gamma_1 REVT_{i,t} + \gamma_2 COGS_{i,t} + \gamma_3 SGA_{i,t} + \gamma_4 XRD_{i,t} + \gamma_5 DP_{i,t} + \gamma_6 XINT_{i,t} + \gamma_7 NOPI_{i,t} + \gamma_8 TXT_{i,t} + \gamma_9 SPI_{i,t} + \gamma_{10} MII_{i,t} + \epsilon_{i,t+1}$. The sample covers 70 fiscal years, spanning from 1950 to 2019. Observations must have positive total assets (Compustat item AT), positive revenue (Compustat item REVT), non-missing earnings (Compustat item IB), and positive equity to enter the sample. Equity is calculated as Shareholder book value (SH) plus deferred taxes and investment tax credit (TXDITC) subtracting preferred stock (PS), following Freyberger et al. (2020). ΔIB_{t+1} is IB subtracted from leading year IB then scaled by AT. Detailed variable definition and calculation are in Table A1. We impute zero for all other earnings components, including COGS, SGA, XRD, DP, XINT, TXT, NOPI, SPI, and MII. All variables displayed are trimmed at the top and bottom 1% within each fiscal year. Panel B displays the summary statistics of earnings-related variables after scaling by AT but before standardization. Panel C displays Pearson correlation among these variables. Italics, underline, and boldness indicate two-tailed p<0.1, p<0.05, and p<0.01, respectively.

Table 2: Cross-sectional γ coefficients from year 1950 to 2019

Panel A: Regression coefficients ($\times 10^2$) for each cross-section (N=70)

	Mean	St. Dev.	T-stats	Pctl(1)	Pctl(25)	Median	Pctl(75)	Pctl(99)
γ_{INT}	0.481	1.059	3.801	−2.227	−0.131	0.502	1.072	3.148
γ_{REVT}	−8.998	9.154	−8.224	−28.215	−16.252	−7.770	−0.531	7.396
γ_{COGS}	7.531	7.633	8.255	−5.995	0.739	6.031	13.403	23.604
γ_{SGA}	2.503	2.639	7.934	−2.437	0.417	2.197	4.225	8.781
γ_{XRD}	0.301	0.680	3.704	−1.120	−0.060	0.128	0.743	1.949
γ_{DP}	0.469	0.544	7.206	−0.638	0.095	0.379	0.799	2.084
γ_{XINT}	0.428	0.461	7.762	−0.294	0.109	0.318	0.723	1.846
γ_{TXT}	1.168	0.944	10.343	−0.763	0.532	1.125	1.909	2.956
γ_{NOPI}	−0.533	0.531	−8.405	−1.954	−0.860	−0.526	−0.086	0.174
γ_{SPI}	−1.540	1.711	−7.532	−7.764	−2.410	−1.430	−0.087	0.154
γ_{MII}	0.052	0.117	3.697	−0.163	−0.031	0.037	0.135	0.329

Panel B: 70-year historical variance-covariance matrix ($\times 10^4$) of γs

	γ_{Int}	γ_{REVT}	γ_{COGS}	γ_{SGA}	γ_{XRD}	γ_{DP}	γ_{XINT}	γ_{TXT}	γ_{NOPI}	γ_{SPI}	γ_{MII}
γ_{INT}	1.121	−2.966	2.451	0.907	0.423	0.271	−0.066	0.201	0.073	−0.323	−0.023
γ_{REVT}	−2.966	83.793	−69.789	−23.336	−4.399	−2.672	−2.360	−7.682	2.294	5.264	−0.143
γ_{COGS}	2.451	−69.789	58.261	19.292	3.643	2.181	1.974	6.403	−1.881	−4.269	0.116
γ_{SGA}	0.907	−23.336	19.292	6.965	1.312	0.733	0.742	2.152	−0.776	−2.087	0.047
γ_{XRD}	0.423	−4.399	3.643	1.312	0.462	0.166	0.084	0.363	−0.102	−0.417	0.003
γ_{DP}	0.271	−2.672	2.181	0.733	0.166	0.296	0.064	0.254	−0.071	−0.360	0.015
γ_{XINT}	−0.066	−2.360	1.974	0.742	0.084	0.064	0.213	0.292	−0.168	−0.457	0.018
γ_{TXT}	0.201	−7.682	6.403	2.152	0.363	0.254	0.292	0.892	−0.287	−0.725	0.034
γ_{NOPI}	0.073	2.294	−1.881	−0.776	−0.102	−0.071	−0.168	−0.287	0.282	0.690	−0.020
γ_{SPI}	−0.323	5.264	−4.269	−2.087	−0.417	−0.360	−0.457	−0.725	0.690	2.927	−0.089
γ_{MII}	−0.023	−0.143	0.116	0.047	0.003	0.015	0.018	0.034	−0.020	−0.089	0.014

Panel C: Pearson correlations of γs and 13 macro variables

	γ_{Int}	γ_{REVT}	γ_{COGS}	γ_{SGA}	γ_{XRD}	γ_{DP}	γ_{XINT}	γ_{TXT}	γ_{NOPI}	γ_{SPI}	γ_{MII}
ΔIP	**−0.467**	*0.222*	*−0.220*	$\underline{-0.257}$	**−0.383**	$\underline{-0.247}$	−0.049	−0.057	*0.223*	0.186	$\underline{0.302}$
ΔDG	−0.122	−0.012	0.013	−0.058	−0.075	0.014	0.003	0.032	$\underline{0.246}$	$\underline{0.284}$	−0.022
ΔNDG	*−0.216*	*−0.200*	*0.208*	0.099	−0.009	−0.005	−0.031	0.097	0.169	**0.336**	0.028
ΔSG	−0.012	**−0.340**	**0.351**	*0.218*	0.191	0.094	0.064	*0.200*	$\underline{0.244}$	**0.450**	−0.180
ΔGDP	*−0.228*	−0.126	0.131	0.024	−0.015	−0.034	−0.088	0.015	$\underline{0.293}$	**0.454**	−0.100
Mkt_rf	0.014	**0.318**	**−0.310**	**−0.368**	$\underline{-0.258}$	−0.094	$\underline{-0.270}$	*−0.232*	**0.312**	*0.223*	$\underline{-0.259}$
SMB	**0.309**	−0.042	0.046	0.014	0.134	0.128	0.028	0.024	0.093	0.020	*−0.209*
HML	*0.229*	*−0.204*	*0.204*	$\underline{0.242}$	0.130	0.089	0.150	0.100	0.039	−0.032	−0.082
RMW	0.172	**−0.413**	**0.399**	**0.516**	**0.368**	0.129	**0.348**	**0.389**	**−0.327**	**−0.405**	0.187
CMA	0.155	$\underline{-0.292}$	$\underline{0.292}$	**0.335**	$\underline{0.255}$	0.160	**0.310**	*0.209*	−0.131	−0.157	0.064
ΔFFO	**−0.373**	$\underline{0.261}$	$\underline{-0.272}$	$\underline{-0.266}$	**−0.318**	$\underline{-0.235}$	**−0.352**	$\underline{-0.279}$	$\underline{0.287}$	**0.380**	0.010
ΔSprd	−0.064	0.011	−0.016	0.032	−0.004	−0.127	−0.025	−0.107	*−0.212*	−0.118	$\underline{-0.271}$
ΔTerm	$\underline{0.261}$	−0.104	0.111	0.114	$\underline{0.276}$	0.035	0.154	0.001	−0.092	−0.144	$\underline{-0.297}$

Panel D: Regressing the γs to 13 macro variables

	γ_{Int}	γ_{REVT}	γ_{COGS}	γ_{SGA}	γ_{XRD}	γ_{DP}	γ_{XINT}	γ_{TXT}	γ_{NOPI}	γ_{SPI}	γ_{MII}
Rsq	0.417	0.529	0.530	0.581	0.473	0.226	0.404	0.443	0.391	0.553	0.401
Pval	0.002	0.000	0.000	0.000	0.000	0.266	0.003	0.001	0.004	0.000	0.003

This table displays information on the estimated γs from the cross-sectional regression model $\Delta IB_{i,t+1} = \alpha_t + \gamma_1 REVT_{i,t} + \gamma_2 COGS_{i,t} + \gamma_3 SGA_{i,t} + \gamma_4 XRD_{i,t} + \gamma_5 DP_{i,t} + \gamma_6 XINT_{i,t} + \gamma_7 NOPI_{i,t} + \gamma_8 TXT_{i,t} + \gamma_9 SPI_{i,t} + \gamma_{10} MII_{i,t} + \epsilon_{i,t+1}$. α_t indicates the γ_{Int} that is constant for each cross section. The sample covers 70 fiscal years, spanning from 1950 to 2019. Panel A displays the distribution and summary information of 70 γs, and each γ corresponds to each earnings component. Panel B shows the 70-year historical variance-covariance matrix of ten γs. Panel C shows the Pearson correlation between the time-series of each γ and 13 time-series macro variables. The definition and calculation of each macro variable is detailed in Table A1. Italics, underline, and boldness indicate two-tailed p<0.1, p<0.05, and p<0.01, respectively. In Panel D, we regress each time-series of γ on 13 macro variables. R^2 and $PVal$ indicate the R-squared and the P-value of the model F statistics.

Table 3: Descriptive statistics of the main tests

Panel A: Descriptive statistics for the main tests

	Mean	St. Dev.	Pctl(1)	Pctl(25)	Median	Pctl(75)	Pctl(99)
				Variables for the main analyses			
σ	0.016	0.015	0.006	0.010	0.012	0.017	0.082
SIZE	5.008	2.165	0.653	3.392	4.913	6.545	10.104
BEME	−0.373	0.909	−2.635	−0.907	−0.355	0.144	2.382
ret	0.012	0.163	−0.364	−0.059	0.002	0.070	0.509
ret_1	0.013	0.162	−0.359	−0.059	0.001	0.070	0.507
$\text{ret}_{12,2}$	0.139	0.725	−0.790	−0.179	0.063	0.323	2.280
				Other control variables			
σ_{IB}	0.012	0.010	0.006	0.008	0.010	0.012	0.061
$\sigma(\Delta IB)$	0.109	0.407	0.001	0.014	0.034	0.087	1.183
EU	0.070	0.262	0.010	0.026	0.042	0.074	0.368
IQR	0.093	0.117	0.022	0.039	0.052	0.091	0.618
$\widehat{\Delta IB}$	0.006	0.016	−0.028	−0.000	0.005	0.008	0.071
IB	0.016	0.121	−0.518	0.005	0.034	0.069	0.189
OP	0.117	0.119	−0.279	0.047	0.118	0.184	0.394
β_{Wealth}	0.285	0.943	−2.024	−0.144	0.158	0.630	2.822
β_{TFP}	1.277	4.018	−3.710	−0.263	0.520	2.058	16.996
β_{CAPM}	1.082	0.652	−0.153	0.629	1.023	1.457	2.960
$\beta_{Analyst}$	0.665	1.672	−3.193	−0.002	0.350	1.005	7.182

Panel B: Pearson correlations

Variables for the main analyses

	σ	SIZE	BEME	ret_1
SIZE	**−0.008**			
BEME	**−0.211**	**−0.289**		
ret_1	**0.003**	**−0.020**	**0.026**	
$\text{ret}_{12,2}$	**−0.002**	**−0.033**	**0.013**	**0.002**

σ and other control variables

	σ_{IB}	$\sigma(\Delta IB)$	EU	IQR	$\widehat{\Delta IB}$	IB	OP	β_{Wealth}	β_{TFP}	β_{CAPM}	$\beta_{Analyst}$
σ	**0.773**	**0.250**	**0.113**	**0.692**	**0.588**	**−0.635**	**−0.242**	**−0.036**	−0.005	**0.159**	**0.009**

Panel C: Auto-correlation of firm-level σ (lag = 1)

	N	Mean	St. Dev.	Pctl(1)	Pctl(25)	Median	Pctl(75)	Pctl(99)
$t \geq 10$	7,707	0.293	0.301	−0.370	0.057	0.295	0.528	0.878
$t \geq 20$	3,301	0.375	0.285	−0.185	0.141	0.376	0.605	0.904
$t \geq 30$	1,278	0.414	0.275	−0.112	0.183	0.403	0.633	0.915
$t \geq 40$	581	0.424	0.272	−0.057	0.194	0.415	0.631	0.921

Panel D: Pearson correlation of annual average σ and macro variables

	ΔIP	ΔDG	ΔNGD	ΔSG	ΔGDP	Mkt_rf	SMB
σ_t	−0.049	**−0.452**	**−0.541**	**−0.810**	**−0.710**	0.111	−0.142
	HML	RMW	CMA	ΔFFO	ΔSprd	ΔTerm	R^2
σ_t	−0.181	0.109	−0.083	−0.117	0.212	−0.037	**0.706**

Panel E: Distribution of Fama–French 12-industry classification across σ quintiles

	Percentage of total firm-year observations of σ quintiles					
Industry Classification	1	2	3	4	5	N
Business Equipment	6.30	7.35	16.09	30.58	39.69	28,333
Chemicals	16.21	15.78	22.56	23.45	22.00	5,014
Durables	18.42	15.78	24.34	22.73	18.74	6,266
Nondurables	20.44	16.52	23.14	22.05	17.85	14,137
Finance	29.72	41.81	18.04	6.31	4.12	36,758
Healthcare	9.29	8.15	15.52	25.82	41.22	11,944
Manufacturing	21.12	18.35	24.22	20.51	15.81	27,337
Energy	12.89	13.36	25.60	26.72	21.43	8,982
Other	13.51	13.26	18.12	22.61	32.50	7,329
Telecom	22.27	15.39	21.50	21.30	19.54	3,925
Utilities	57.07	27.36	9.64	3.78	2.14	8,778
Retail	15.98	15.02	24.37	25.88	18.75	19,469

This table shows the sample distribution overtime and descriptive statistics for the variables that are used in the main analyses. The sample covers 60 fiscal years, spanning from 1960 to 2019. Sample years before 1959 are disposed to ensure that γ captures at least 10-year time-series variation. Variable definitions are in Table A1. Observations must have non-missing values for σ, SIZE, and BEME for firm-year variables and ret, ret_1, and $ret_{12,2}$ for firm-month variables to be in the sample for the main analyses, resulting 214,904 firm-year observations or 2,478,383 firm-month observations. Other control variables are calculated based on data availability. Summary statistics are in Panel A. In Panel B, we show the Pearson correlation table of variables that participate the main analyses, as well as the relation between σ and other comparable uncertainty, volatility or risk measures. In Panel C, we show the distribution of auto-correlation of firm-level $\sigma_{i,t}$, with the lag equal to one. $t \geq T$ indicates that the firm has at least T observations in its own time-series. In Panel D, we take the average $\sigma_{i,t}$ of each cross section as the annual σ_t, and we show the Pearson correlation between σ_t and each of the 13 macro variables that represent systematic risk factors. In the last cell of the second row, the R^2 is the R-squared of regressing σ_t on 13 time-series of macro variables. In Panel E, we show the quintile distribution of σ of each year across Fama-French 12-industry classification. Industry specification is the variable SICCD obtained from CRSP, and we exclude observations that have missing SICCD information. Italics, underline, and boldness in Panel C and Panel E indicate two-tailed p<0.1, p<0.05, and p<0.01, respectively.

Table 4: Realized variability of change in performance and future performance

Panel A: Mean of $|\Delta IB_{t+1}|$ and and standard variation of ΔIB_{t+1}, sorted by σ

		Mean σ	Mean$\|\Delta IB_{t+1}\|$	SD(ΔIB_{t+1})
	Low	0.008	0.021	0.045
	2	0.010	0.020	0.044
σ	3	0.013	0.032	0.063
	4	0.017	0.047	0.084
	High	0.034	0.099	0.168
	H−L	0.026***	0.078***	3.733***
		[213.52]	[105.12]	[14.19]

Panel B: Mean $|\Delta IB_{t+1}|$, sorted by $\sigma(\Delta IB)$ and σ

		$\sigma(\Delta IB)$						
		Low	2	3	4	High	H−L	
	Low	0.009	0.020	0.029	0.040	0.029	0.020***	[28.79]
	2	0.007	0.020	0.031	0.048	0.051	0.044***	[45.46]
σ	3	0.007	0.022	0.034	0.054	0.076	0.069***	[53.98]
	4	0.009	0.025	0.038	0.065	0.100	0.091***	[61.29]
	High	0.017	0.033	0.058	0.113	0.180	0.163***	[64.03]
	H−L	0.008***	0.013***	0.029***	0.073***	0.151***		
		[19.16]	[19.49]	[29.79]	[42.76]	[57.94]		

Panel C: Standard variation ΔIB_{t+1}, sorted by $\sigma(\Delta IB)$ and σ

		$\sigma(\Delta IB)$						
		Low	2	3	4	High	H/L	
	Low	0.019	0.037	0.050	0.074	0.066	3.489***	[12.18]
	2	0.015	0.036	0.054	0.083	0.096	6.442***	[41.50]
σ	3	0.016	0.041	0.056	0.088	0.132	8.517***	[72.54]
	4	0.021	0.042	0.065	0.105	0.158	7.656***	[58.62]
	High	0.039	0.056	0.094	0.168	0.260	6.662***	[44.38]
	H/L	2.061***	1.523***	1.901***	2.253***	3.934***		
		[4.25]	[2.32]	[3.61]	[5.08]	[15.48]		

Panel D: Regressing realized absolute unexpected change in earnings on σ

	Dependent variable: $\|\Delta IB_{i,t+1} - E_t[\Delta IB_{i,t+1}]\|$	
	(1)	(2)
σ	2.453***	1.271***
	[202.21]	[86.70]
Constant	0.009***	
	[34.04]	
N	203,120	203,120
R^2	0.168	0.481
Fixed Effects	NA	Firm, Year

This table shows the relation between σ and realized variability of change in performance or future performance. Variables are defined in Table A1. In Panel A, we show the realized absolute change in earnings ($|\Delta IB_{t+1}|$) of each quintile for each quintile-sorted σ, as well as realized standard deviation of change in earnings (ΔIB_{t+1}) of each quintile for each quintile-sorted σ. In Panel B and C, we first sort on historical earnings volatility, $\sigma(\Delta IB)$, into quintiles within each year, and then sort σ within each quintile-year of $\sigma(\Delta IB)$. Panel B (C) show the realized absolute change in earnings, $|\Delta IB_{t+1}|$ (realized standard deviation of change in earnings, $|\Delta IB_{t+1}|$), of double-quintile sorts. In Panel D, we take the absolute difference of each firm-year's realized change in earnings ($\Delta IB_{i,t+1}$) and the mean predicted change in earnings $E_t[\Delta IB_{i,t+1}]$ from cross-sectionally estimated γs. Observations must have non-missing leading year change in earnings ($\Delta IB_{i,t+1}$) to enter the regression. Column (1) shows the specification of an ordinary least square model, regressing the realized absolute difference on $\sigma_{i,t}$. Column (2) shows the same model as column (1), augmented with firm and year fixed effects. T-statistics of mean tests and F-statistics of variance tests are reported in the brackets. *,**, and *** indicate two-tailed p<0.1, p<0.05, and p<0.01, respectively.

Table 5: Two-way sorts: future systematic risk sensitivity (β_{CAPM})

Panel A: β_{CAPM} in year $t+1$

		β_{CAPM}						
		Low	2	3	4	High	H−L	
	Low	0.382	0.731	1.012	1.321	1.878	1.496***	[201.46]
	2	0.371	0.727	1.001	1.307	1.889	1.518***	[201.02]
σ	3	0.375	0.728	0.998	1.309	1.926	1.550***	[197.56]
	4	0.397	0.740	1.012	1.326	1.937	1.539***	[183.30]
	High	0.422	0.774	1.034	1.347	1.973	1.552***	[164.78]
	H−L	0.039***	0.044***	0.021***	0.026***	0.095***		
		[6.19]	[7.65]	[3.79]	[4.28]	[9.39]		

Panel B: β_{CAPM} in year $t+2$

		β_{CAPM}						
		Low	2	3	4	High	H−L	
	Low	0.451	0.762	1.020	1.291	1.746	1.295***	[145.43]
	2	0.440	0.750	0.995	1.275	1.752	1.312***	[148.64]
σ	3	0.448	0.756	1.001	1.268	1.785	1.336***	[145.10]
	4	0.501	0.783	1.016	1.296	1.795	1.295***	[129.27]
	High	0.563	0.830	1.052	1.323	1.835	1.272***	[112.39]
	H−L	0.112***	0.068***	0.032***	0.032***	0.089***		
		[13.92]	[8.81]	[4.15]	[3.86]	[7.47]		

Panel C: β_{CAPM} in year $t+3$

		β_{CAPM}						
		Low	2	3	4	High	H−L	
	Low	0.515	0.790	1.028	1.264	1.613	1.098***	[108.45]
	2	0.502	0.774	1.001	1.238	1.628	1.126***	[115.17]
σ	3	0.518	0.789	1.003	1.224	1.660	1.142***	[109.38]
	4	0.597	0.831	1.021	1.261	1.659	1.063***	[93.93]
	High	0.684	0.881	1.064	1.299	1.709	1.025***	[79.62]
	H−L	0.169***	0.092***	0.036***	0.035***	0.095***		
		[17.92]	[9.74]	[3.83]	[3.48]	[7.10]		

This table shows the realized future systematic sensitivity, or β_{CAPM} in year $t+1$, $t+2$, and $t+3$, double sorted on σ and and current β_{CAPM}. Variables are defined in Table A1. In this table, we aggregate firm-month β_{CAPM} to firm-year β_{CAPM} by a firm's fiscal year. We first sort annual β_{CAPM} into quintiles within each year, and then sort σ within each quintile-year of β_{CAPM}. Panel A shows the realized leading one-year systematic sensitivity (i.e., β_{CAPM} in year $t+1$) of double-quintile sorts; Panel B shows the realized leading two-year systematic sensitivity (i.e., β_{CAPM} in year $t+2$) of double-quintile sorts; and Panel C shows the realized leading three-year systematic sensitivity (i.e., β_{CAPM} in year $t+3$) of double-quintile sorts. T-statistics are reported in the brackets. *,**, and *** indicate two-tailed p<0.1, p<0.05, and p<0.01, respectively.

Table 6: Fama-French-Carhart four factors: portfolio sorting tests

Panel A: Realized future raw returns, sorted into σ quintiles

		EW portfolio return	*VW portfolio return*
	Low	0.720	1.073
	2	0.796	1.113
σ	3	0.844	1.233
	4	0.917	1.442
	High	1.020	1.746
	H−L	0.300**	0.673***
		[2.20]	[5.14]

Panel B: Realized future excess returns, sorted into σ quintiles

	EW portfolio return					*VW portfolio return*				
	α	β_{mkt}	β_{smb}	β_{hml}	β_{mom}	α	β_{mkt}	β_{smb}	β_{hml}	β_{mom}
Low	0.024	0.939	0.66	0.472	−0.152	0.466	0.954	0.05	0.318	−0.059
2	0.092	0.905	0.609	0.47	−0.094	0.463	1.004	0.007	0.322	−0.025
3	0.161	0.973	0.734	0.301	−0.144	0.594	1.041	0.115	0.162	−0.032
4	0.295	0.982	0.831	0.112	−0.189	0.865	1.043	0.23	−0.138	−0.025
High	0.446	1.012	1.06	−0.139	−0.239	1.187	1.032	0.408	−0.301	−0.017
H−L	0.422***	0.073***	0.399***	−0.611***	−0.087***	0.721***	0.079***	0.358***	−0.619***	0.042*
	[3.91]	[2.88]	[11.03]	[−15.75]	[−3.32]	[7.17]	[3.33]	[10.61]	[−17.15]	[1.72]

Panel C: Realized future excess returns, sorted into σ deciles

	EW portfolio return					*VW portfolio return*				
	α	β_{mkt}	β_{smb}	β_{hml}	β_{mom}	α	β_{mkt}	β_{smb}	β_{hml}	β_{mom}
Low	−0.033	0.956	0.737	0.488	−0.166	0.484	0.969	0.111	0.312	−0.058
2	0.079	0.922	0.585	0.457	−0.139	0.434	0.944	0.007	0.329	−0.058
3	0.091	0.903	0.58	0.478	−0.108	0.419	1.001	−0.009	0.346	−0.047
4	0.093	0.907	0.637	0.463	−0.079	0.499	1.01	0.029	0.306	−0.006
5	0.146	0.967	0.706	0.356	−0.125	0.518	1.044	0.074	0.254	−0.042
6	0.176	0.98	0.762	0.246	−0.164	0.661	1.038	0.166	0.059	−0.025
7	0.251	0.98	0.802	0.176	−0.193	0.769	1.048	0.164	−0.05	−0.026
8	0.341	0.984	0.86	0.048	−0.186	0.956	1.045	0.29	−0.215	−0.031
9	0.410	1.016	0.958	−0.064	−0.208	1.037	1.04	0.363	−0.261	−0.026
High	0.485	1.007	1.165	−0.214	−0.271	1.436	1.024	0.507	−0.34	−0.017
H−L	0.518***	0.051	0.428***	−0.702***	−0.106***	0.953***	0.056*	0.397***	−0.652***	0.041
	[3.58]	[1.52]	[8.83]	[−13.53]	[−3.02]	[6.89]	[1.71]	[8.56]	[−13.14]	[1.24]

This table shows monthly equal-weighted and value-weighted average excess returns to portfolios sorted on σ, defined in Table A1, and the excess returns from time series regressions of these portfolios' returns on the Fama-French-Carhart four factors (Carhart, 1997; Fama and French, 2015) (i.e., the market factor (MKT), the size factor small-minus-large (SMB), the value factor high-minus-low (HML), and the momentum factor (MOM)). Portfolio returns are scaled up by 10^2. Panel A reports the raw returns based on a quintile-sorted σ. Panel B reports the excess returns based on a quintile-sorted σ, and Panel C reports the excess returns based on a decile-sorted σ. The sample covers June 1960 to May 2020, and return data cover June 1961 to May 2021, a total of 720 months. T-statistics are reported in the brackets. *,**, and *** indicate two-tailed p<0.1, p<0.05, and p<0.01, respectively.

Table 7: Two-way sorts: future returns

Panel A: ***SIZE*** **and** σ

		SIZE						
		Low	2	3	4	High	H−L	
	Low	0.014	0.011	0.010	0.011	0.010	-0.004^{***}	[−5.76]
	2	0.015	0.012	0.011	0.011	0.010	-0.005^{***}	[−7.40]
σ	3	0.017	0.012	0.012	0.011	0.011	-0.006^{***}	[−7.87]
	4	0.019	0.013	0.013	0.011	0.011	-0.008^{***}	[−10.27]
	High	0.016	0.013	0.014	0.012	0.012	-0.004^{***}	[−4.22]
	H−L	0.002^{*}	0.003^{***}	0.004^{***}	0.001^{*}	0.002^{***}		
		[1.84]	[3.13]	[5.32]	[1.83]	[3.19]		

Panel B: ***BEME*** **and** σ

		BEME						
		Low	2	3	4	High	H−L	
	Low	0.006	0.009	0.010	0.011	0.014	0.009^{***}	[11.77]
	2	0.008	0.010	0.012	0.013	0.015	0.007^{***}	[9.60]
σ	3	0.010	0.010	0.012	0.014	0.015	0.005^{***}	[6.66]
	4	0.011	0.013	0.014	0.014	0.016	0.005^{***}	[5.63]
	High	0.009	0.016	0.017	0.017	0.018	0.009^{***}	[8.53]
	H−L	0.003^{***}	0.007^{***}	0.007^{***}	0.005^{***}	0.003^{***}		
		[3.13]	[9.09]	[9.34]	[7.18]	[3.97]		

Panel C: $ret_{12,2}$ **and** σ

		$ret_{12,2}$						
		Low	2	3	4	High	H−L	
	Low	0.004	0.010	0.011	0.013	0.016	0.012^{***}	[15.33]
	2	0.006	0.010	0.011	0.014	0.017	0.010^{***}	[12.68]
σ	3	0.008	0.011	0.012	0.014	0.018	0.010^{***}	[11.29]
	4	0.011	0.011	0.012	0.014	0.018	0.007^{***}	[7.24]
	High	0.012	0.012	0.013	0.015	0.019	0.007^{***}	[6.33]
	H−L	0.008^{***}	0.002^{***}	0.002^{***}	0.003^{***}	0.003^{***}		
		[6.82]	[3.05]	[3.04]	[4.42]	[3.85]		

This table shows the equal-weighted average excess returns to portfolios, double quintile-sorted on firm characteristics and σ. Variable definitions are in Table A1. Panel A reports the double sorts on σ and SIZE (Fama and French, 1992). Panel B reports the double sorts on σ and BEME (Fama and French, 1992). Panel C reports the double sorts on σ and $ret_{12,2}$, or momentum (Carhart, 1997). For Panel A and B, We sort on the firm characteristic variable first within each year, and then sort σ within each quintile-year of the firm characteristic variable. For Panel C, We sort on the $ret_{12,2}$ first within each month, and then sort σ within each quintile-month. The sample covers June 1960 to May 2020, and return data cover June 1961 to May 2021, a total of 720 months. T-statistics are reported in the brackets. *,**, and *** indicate two-tailed p<0.1, p<0.05, and p<0.01, respectively.

Table 8: Fama-MacBeth regressions: σ and other measures of uncertainty, volatility or risk

Panel A: σ and other measures of earnings uncertainty or earnings volatility

	(1)	(2)	(3)	(4)	(5)
σ	0.221***	0.226***	0.211***	0.401***	0.169***
	[5.40]	[3.76]	[5.30]	[8.04]	[5.10]
SIZE	−0.001**	−0.001***	−0.001***	−0.001**	−0.001***
	[−2.51]	[−2.67]	[−2.63]	[−1.98]	[−2.63]
BEME	0.003***	0.003***	0.003***	0.003***	0.001**
	[6.36]	[6.08]	[6.50]	[5.62]	[2.36]
ret_1	−0.050***	−0.050***	−0.050***	−0.049***	−0.034***
	[−14.18]	[−14.40]	[−14.27]	[−12.93]	[−7.53]
$\text{ret}_{12,2}$	0.006***	0.006***	0.006***	0.005***	0.002
	[3.75]	[3.65]	[3.90]	[3.02]	[0.84]
σ_{IB}		0.083			
		[0.84]			
$\sigma(\Delta IB)$			−0.000		
			[−0.03]		
EU				−0.015**	
				[−2.21]	
IQR					−0.016***
					[−2.68]
Intercept	0.013***	0.012***	0.013***	0.010***	0.015***
	[4.95]	[4.50]	[5.18]	[3.98]	[4.25]
N	2,478,383	2,472,577	2,336,409	1,939,404	1,192,306
R^2	4.33%	4.53%	4.55%	4.21%	3.53%

Panel B: σ and other measures of risk in earnings

	(1)	(2)	(3)	(4)	(5)	(6)
σ	0.221^{***}	0.250^{***}	0.307^{***}	0.253^{***}	0.140^{**}	0.213^{***}
	[5.40]	[5.85]	[6.81]	[5.53]	[2.37]	[5.12]
SIZE	-0.001^{**}	-0.001^{**}	-0.001^{***}	-0.001^{***}	-0.001^{***}	-0.001^{***}
	[−2.51]	[−2.51]	[−3.05]	[−3.25]	[−2.71]	[−2.63]
BEME	0.003^{***}	0.003^{***}	0.003^{***}	0.004^{***}	0.000	0.003^{***}
	[6.36]	[6.47]	[6.43]	[7.17]	[0.91]	[5.52]
ret_1	-0.050^{***}	-0.050^{***}	-0.050^{***}	-0.050^{***}	-0.034^{***}	-0.050^{***}
	[−14.18]	[−14.38]	[−14.58]	[−14.43]	[−7.79]	[−14.14]
$\text{ret}_{12,2}$	0.006^{***}	0.006^{***}	0.005^{***}	0.005^{***}	0.004^{**}	0.006^{***}
	[3.75]	[3.68]	[3.55]	[3.51]	[2.21]	[3.70]
$\widehat{\Delta IB}$		0.092				
		[1.34]				
IB			0.011^{**}			
			[2.10]			
OP				0.017^{***}		
				[5.71]		
$\beta_{Analyst}$					0.001^{***}	
					[2.63]	
β_{Wealth}						0.000^{**}
						[2.38]
β_{TFP}						−0.000
						[−0.05]
Intercept	0.013^{***}	0.011^{***}	0.012^{***}	0.011^{***}	0.015^{***}	0.013^{***}
	[4.95]	[4.55]	[4.68]	[4.42]	[4.73]	[5.04]
N	2,478,383	2,478,383	2,472,577	2,469,331	801,378	2,291,135
R^2	4.33%	4.51%	4.62%	4.57%	4.81%	4.51%

Panel A shows the comparison of σ and other measures of second moment of earnings. In column (1), we show the baseline regression model. In column (2), σ_{IB} refers to the sigma measure constructed using the level of IB only. In column (3), we add historical volatility of change in earnings, $\sigma(\Delta IB)$ (Dichev and Tang, 2009). In column (4), we add non-parametric earnings uncertainty EU (Donelson and Resutek, 2015). In column (5), we add IQR, an inter-quartile uncertainty measure using quantile regression (Konstantinidi and Pope, 2016). Panel B shows the comparison of σ and other measures of earnings risk, including first moment of earnings and covariance of earnings. In column (1), we show the baseline regression model. In column (2), we add the mean predicted change in net income. In column (3), we add current year earnings IB. In column (4), we add current year operating profitability OP. In column (5), we add earnings beta constructed using analyst forecasts (Ellahie, 2020). In Column (6), we add earnings beta constructed using aggregated shocks, wealth and TFP (Ball et al., 2021). The main sample covers June 1960 to May 2020. Return data cover June 1961 to May 2021, a total of 720 months. Other variables are subject to their data availability discussed in the original papers. T-statistics are reported in the brackets. *,**, and *** indicate two-tailed p<0.1, p<0.05, and p<0.01, respectively.

Table 9: Returns: FM regression tests by groups

Panel A: Analyst coverage

	(1) No coverage	(2) With coverage
σ	0.193^{***}	0.141^{***}
	[4.69]	[2.64]
SIZE	-0.001^{***}	-0.001^{*}
	[−3.77]	[−1.75]
BEME	0.004^{***}	0.002^{***}
	[7.49]	[3.02]
ret_1	-0.053^{***}	-0.036^{***}
	[−14.47]	[−8.87]
$\text{ret}_{12,2}$	0.005^{***}	0.007^{***}
	[3.29]	[3.84]
Intercept	0.015^{***}	0.013^{***}
	[5.80]	[4.38]
Differences		(1)−(2)
		0.052
		[0.77]
N	1,284,487	1,193,896
R^2	4.43%	4.07%

Panel B: Firm age

	(1) Age = 1	(2) Age ≤ 5	(3) Age > 5
σ	1.160^{***}	0.248^{***}	0.187^{***}
	[2.70]	[3.76]	[4.32]
SIZE	−0.003	-0.001^{**}	-0.001^{**}
	[−1.33]	[−2.36]	[−2.57]
BEME	0.005	0.003^{***}	0.003^{***}
	[1.36]	[4.25]	[5.94]
ret_1	-0.083^{***}	-0.052^{***}	-0.050^{***}
	[−3.59]	[−11.67]	[−14.09]
$\text{ret}_{12,2}$	0.009	0.007^{***}	0.006^{***}
	[0.76]	[3.91]	[3.72]
Intercept	0.008	0.011^{***}	0.013^{***}
	[0.54]	[3.86]	[5.14]
Differences		(1)−(2)	(1)−(3)
		0.912^{**}	0.972^{**}
		[2.10]	[2.25]
N	32,760	498,564	1,979,819
R^2	36.08%	6.07%	4.45%

Panel C: Transaction costs			
	(1) Micro caps	(2) All-but-micro caps	(3) Price>$5
σ	0.136**	0.314***	0.376***
	[2.51]	[5.58]	[8.10]
SIZE	−0.002***	−0.000	−0.004***
	[−4.36]	[−0.81]	[−12.72]
BEME	0.003***	0.003***	0.002***
	[5.92]	[5.02]	[4.02]
ret_1	−0.054***	−0.038***	−0.043***
	[−14.27]	[−9.25]	[−11.99]
$\text{ret}_{12,2}$	0.005***	0.007***	−0.000
	[3.54]	[3.74]	[−0.07]
Intercept	0.019***	0.008**	0.030***
	[6.46]	[2.52]	[12.12]
Differences		(2)−(1)	(3)−(1)
		0.177**	0.240***
		[2.27]	[3.35]
N	1,350,538	1,127,845	1,966,839
R^2	3.80%	6.25%	4.80%

Panel D: High and low operating profitability				
	(1) Q1	(2) Q2	(3) Q3	(4) Q4
σ	0.339***	0.301***	0.145**	0.104**
	[4.18]	[3.43]	[2.03]	[2.13]
SIZE	−0.001***	−0.001***	−0.001***	−0.001**
	[−3.08]	[−2.76]	[−3.41]	[−2.24]
BEME	0.005***	0.004***	0.003***	0.003***
	[7.84]	[6.18]	[5.32]	[4.49]
ret_1	−0.06***	−0.048***	−0.047***	−0.048***
	[−13.53]	[−11.69]	[−11.64]	[−12.29]
$\text{ret}_{12,2}$	0.005**	0.006***	0.006***	0.006***
	[2.55]	[3.26]	[3.34]	[4.19]
Intercept	0.012***	0.012***	0.015***	0.015***
	[4.59]	[4.58]	[5.78]	[5.33]
Differences		(1)−(2)	(1)−(3)	(1)−(4)
		0.038	0.194*	0.235**
		[0.32]	[1.80]	[2.49]
N	619,536	619,595	619,596	619,656
R^2	5.74%	5.59%	5.17%	5.33%

Panel E: Recession		
	(1) Recession = 1	(2) Recession = 0
σ	0.432^{***}	0.139^{***}
	[4.60]	[2.63]
SIZE	-0.001^{*}	-0.001^{***}
	[−1.86]	[−2.59]
BEME	0.005^{***}	0.002^{***}
	[4.74]	[3.54]
ret_1	-0.068^{***}	-0.052^{***}
	[−10.94]	[−11.97]
$\text{ret}_{12,2}$	0.002	0.006^{***}
	[0.49]	[3.53]
Intercept	0.015^{***}	0.015^{***}
	[3.21]	[5.34]
Difference		(1)−(2)
		0.293^{***}
		[2.72]
N	586,726	1,891,657
R^2	5.43%	4.92%

This table shows σ's ability to predict cross-sectional future returns across different groups of firms, using Fama-Macbeth regression method (Fama and MacBeth, 1973). Variables are defined in Table A1. Future returns start from June after a firm's fiscal-year-end to May of the following year. In Panel A, we partition firms into those that have information and those that do not have information in IBES. In Panel B, we partition firms into first entering Compustat, firms younger than 5-year-old, and firms older than 5-year-old. Age is calculated based on a firm's existance in Compustat. In column (1) and (2) of Panel C, we partition firms into micro caps and all-but-micro-caps (i.e., SIZE below or above the NYSE 20 percentile breakpoint). In column (3) or Panel C, we exclude penny stocks (price equal to or less than \$5). In Panel D, we partition firm-years into quartiles of operating profitability, sorting by OP within each yearly cross section. In Panel E, we partition firm-years into being in recession or not. A firm-year is in recession if any month of its fiscal year is flagged by NBER as being in recession. The sample covers June 1960 to May 2020, and return data cover June 1961 to May 2021, a total of 720 months. Differences of coefficients across samples are tested using two-sample T tests. T-statistics are reported in the brackets. *,**, and *** indicate two-tailed p<0.1, p<0.05, and p<0.01, respectively.