Scenario-based Systematic Risk in Earnings

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Abstract

We combine scenario-based analysis with information about aggregate earnings to develop a measure of systematic risk from the variance of expected earnings. Our measure, σ, does not require long time-series and uses variation in firm characteristics in a cross-section. The differential one-year returns of the interquartile range for σ is 2.1% and is incremental to firm characteristics that have been proposed as measures of risk in predicting cross-sectional returns. Our findings support the idea that earnings contain risk information and also provide new evidence that operating profitability may be positively associated with risk.

1 Introduction

Since January 1, 2007, Morgan Stanley has provided state-contingent valuation information in its research reports. Analysts are required to supplement their valuation, or the base-case valuation, with bull and bear case valuations that reflect outcomes under different conditions. Joos et al. (2016) find that the scenario-based valuations implicitly incorporate analysts' assessment of a company's fundamental risk. More directly, scenario-based evaluations are an important component of risk analysis as taught in financial statement analysis classes or used by regulators such as in the Basel III framework for banks. However, these scenario-based valuations do not necessarily relate to priced risk because these valuations may be based on idiosyncratic information (Lui et al., 2007).

A simple application of scenario-analysis to systematic risk only requires that the scenarios considered be macroeconomic states. We apply scenario-analysis to measuring and understanding systematic risk in two ways. First, we develop an empirical approach for estimating possible states of the economy from cross-sectional prediction models and we use these scenarios to create a firm-year measure of systematic risk.[1] Prior research has proposed firm level measures of earnings as a measure of expected returns (Ball et al., 2015; Fama and French, 2006, 2015). Aggregated earnings has been used as the state measure when estimating earnings beta (Beaver et al., 1970). Therefore, our cross-sectional prediction model exploits information about firm level earnings and aggregate earnings to deliver macro information about each cross-section. Second, we show that our scenario-based analysis yields insights about firms' exposure to risk and about future returns. Our measure is positively associated with the cross-section of future returns and is incremental to other firm characteristics that have been used as measures of expected returns. Our risk measure also provides evidence that high profitability firms are more exposed to systematic risk in

[1] We use macro scenarios and states of the economy alternatively throughout the paper, both referring to factor risk premia in the framework of arbitrage pricing theory (Ross, 1976). A factor risk premium is determined by risk aversion and the volatility of consumption that varies with changes in the economy (Cochrane, 2009). We assume that risk aversion is constant and let the economy be the sole determinant of the premium.

earnings.

We start by constructing macro scenarios that mimic the bull and bear states in analyst forecasts. Our approach follows from the evidence that common factors in earnings reflect priced risk and that cross-sectional return regression parameters can be better estimates of factors than time-series factor mimicking portfolios (Ball et al., 2009; Fama and French, 2020). To exploit this idea, for each year t, we regress leading changes in earnings on the components of earnings to deliver a set of coefficients, or historical parameters, that describe the historical state in year t.[2] We focus on the change in rather than the level of earnings because earnings are known to be persistent (Easton and Zmijewski, 1989; Kormendi and Lipe, 1987). The estimated parameters from each historical cross-section capture the common shocks or common variation in earnings at that point-in-time. We use these parameters to represent a potential macroeconomic state.

Next, for each firm-year, we calculate the scenario-based expected change in earnings by combining year t earnings components with the estimated historical parameters. Specifically, we forecast earnings changes using earnings components from year t and estimated scenarios from year $t-11$ to $t-2$ and thereby form ten expected earnings changes for each firm-year. The standard deviation of the ten scenario-based expected earnings changes is our risk measure, σ.

After we measure σ for each firm-year, we carry out three primary analyses. First, we show how σ corresponds with fundamental characteristics and the realized variance of future performance. Consistent with our notion that σ captures systematic risk, in portfolio sorts, we show that high σ firms have higher future returns and operating profitability. After we sort firm-years into two-way ranked quintiles by operating profitability and σ, we show that among the 5×5 groups, the five high σ groups consistently have higher variances in realized future earnings than the five low σ groups, suggesting that σ captures *ex ante* uncertainty and

[2] Depending on the outcome variable we forecast, such as change in net income (NI), change in earnings before extraordinary items (IB), and change in operating profitability (OP), the components are different. For our analysis, we focus on change in OP as the earnings variable. Therefore, our earnings components include revenue, cost of goods sold, SG&A expenses, and R&D expenses.

results in more variant future payoffs. The high operating profitability, high future returns, and high uncertain payoffs corroborate prior conclusions that high operating profitability implies higher risk (Ball et al., 2015; Fama and French, 2006; Novy-Marx, 2013).

Second, we show that σ is positively associated with earnings beta, CAPM beta, earnings volatility, and alternative measures of earnings volatility such as volatility of operating profitability and volatility of change in operating profitability. The association with earnings volatility and its alternatives is consistent with σ capturing a firm's fundamental uncertainty (Dichev and Tang, 2009). The positive association with earnings and CAPM beta is consistent with σ capturing a systematic portion of firm fundamental risks (Ball et al., 2020; Beaver et al., 1970; Ellahie, 2020).

Third, we predict cross-sectional future returns using our scenario-based risk measure. We show that σ significantly predicts future returns up to three years ahead, and the predictive power is incremental to size, book-to-market, investment, and momentum (Fama and French, 2020). In addition, we find that even though σ is constructed from the components of operating profitability, it significantly predicts future returns after controlling for operating profitability, suggesting that σ captures information that is different from and incremental to operating profitability.

We contribute to the literature in three significant ways. First, we provide new insights about earnings model parameters in cross-sectional regressions. Previous studies attribute the determinants of earnings persistence and earnings volatility to economic and accounting factors. Dichev and Tang (2009) posit that earnings volatility captures the effects of economic volatility and show that time-series earnings volatility is negatively associated with earnings persistence. However, time-series earnings volatility does not separate systematic and idiosyncratic volatility, and as Frankel and Litov (2009) show, time-series earnings volatility is not priced. We extract the systematic factors that affect earnings volatility by running earnings prediction models in cross-sections. Because cross-sectional regressions lead to the idiosyncratic factors being canceled out in the error term, the common factors that affect earnings volatility in a cross-section are retained, serving as a measure of the state of the economy that affects accounting returns (Ball et al., 2009).

Second, we develop a firm-year scenario-based risk measure using fundamental information. Our measure contains information regarding a firm's exposures to the economy and the plausible scenarios that affect a firm's performance. In addition, our risk measure has three practical advantages. First, compared to covariance-based risk measures derived from a time-series of earnings such as earnings beta, our measure of firm-year risk does not require long time-series of firm level accounting data. Second, a multi-dimensional state variable is permissible in our cross-sectional approach, whereas the earnings beta literature generally identifies the market-wide aggregate earnings as the single state variable. Our method is consistent with practitioners' view that a firm has multiple key business drivers, and macro factors from multiple sources can affect a firm's performance (Joos et al., 2016). Third, compared to analysts' forecasts that are mostly available for large public firms and that include idiosyncratic estimates of risk, our procedure is applicable to less visible and private firms and are cleanly informative of systematic risk.

The third contribution is our insight into the risk components of earnings, and more specifically, operating profitability. The literature debates whether profitability is a risk exposure or anomaly, as profitability is difficult to reconcile with the evidence that profitable firms are less prone to distress, have longer cash flow durations, and have lower levels of operating leverage (Ball et al., 2015; Bouchaud et al., 2019; Novy-Marx, 2013)). Our study yields insights about how operating profitability is linked to a firm's sensitivity to the systematic change in the economy and hence becomes a risk exposure. Additionally, because σ is constructed from an intuitive framework that features uncertainty, its ability to predict returns seems incompatible with irrational pricing. Since our risk measure σ is derived from the components of operating profitability, we provide evidence to support that at least some components in profitability are correlated with nondiversifiable exposures so that σ is priced.

We recognize two caveats for our study. The first is that we do not explicitly model the time-series covariance structures of earnings components. Built upon papers showing that earnings covaries with state variables, that earnings beta is priced, and that profitability is priced (e.g., Ball et al. (2015); Beaver et al. (1970); Ellahie (2020); Fama and French (2006); Nekrasov and Shroff (2009); Novy-Marx (2013)), we infer that a firm's systematic exposure can be traced to the components of earnings. In addition, since we argue and show that the estimated cross-sectional coefficients represent the market-wide systematic forces that affects systematic earnings volatility, our evidence implies that the input variables represent a company's sensitivities to the change in the economy. We conduct tests to show that our estimated earnings parameters are correlated with other macro variables, consistent with Ball et al. (2009) that find systematic factors in aggregate earnings.

Another caveat is that our measure must be non-negative because we summarize the distributions of expected earnings with the standard deviation. Companies that have negative exposures to systematic risk and thus may reduce the systematic risk of a portfolio would bias against finding results. In the extreme case where every firm positively exposed to a systematic risk has a counter firm that is negatively exposed to the risk with the same magnitude of covariability, each level of σ becomes a hedge of two groups of firms that have the exact opposite exposure, so that σ should not predict returns. We find robust results despite this bias, suggesting that negatively exposed firms may be rare in the economy.

2 Motivation and Literature Review

Our study is related to research on scenario-based risk measurement, firm characteristics as fundamental exposures to risk, accounting measures of risk, and properties of accounting performance and risk.

2.1 Scenario based risk measurement

Joos et al. (2016) argue that analysts can assess a firm's fundamental risks. Analysts identify the key business drivers and the firm-specific and macro factors affecting them, then predict how changes in these factors affect performance and value. The paper shows that the *ex ante* spread of the predicted returns under good and bad states is positively correlated with a firm's fundamental risks, including both idiosyncratic risks and the systematic risk exposure. It also shows that the *ex ante* spread is positively correlated with the *ex post* valuation error, which indicates a higher *ex ante* risk, because the realized return is farther from the expected return.

We view our paper as an adaptation from scenario-based valuation risks and apart from focusing on accounting returns versus stock returns, our approach is distinct in an important way. Analysts do not separately identify systematic and idiosyncratic risk when they forecast returns under different scenarios, and their risk assessments are shown to incorporate both types of risks (Lui et al., 2007). We contribute to this research by providing a scenario-based risk measure that is limited to systematic risk.

2.2 Fundamental exposures to risk

The arbitrage pricing theory posits that required returns are obtained when an asset is influenced by systematic risks and that no extra return can be earned by needlessly bearing diversifiable risk (Ross, 1976). Extensive studies focusing on the market factor. Extended factor models have employed time-series covariance structures to obtain the factor loadings of a risky asset (Fama and French, 1993, 2015; Lintner, 1965; Sharpe, 1964). An implicit assumption in these studies is that risk exposure is time-invariant.

However, many papers argue that factor loadings are likely to vary through time (e.g., Avramov and Chordia (2006), Ferson and Harvey (1991), Ferson and Schadt (1996), Jagannathan and Wang (1996), and Shanken (1990)). Other research has instead investigated time-varying fundamental characteristics and considerable evidence has documented that the cross-sectional pattern of stock returns can be explained by time-varying firm characteristics (Daniel and Titman, 1997).[3] Although it is debatable whether these firm characteristics are true time-varying exposures to risk or are anomalous to risk models, some characteristics persistently explain returns. 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). The firm's aggregated systematic risk is time-varying because it is an average of each project undertaken overtime. Therefore, in this framework, time-varying fundamental characteristics can represent time-varying risk exposures. We exploit the possibility that firm characteristics reflect time-varying exposures to systematic risk in our extraction of this risk from accounting fundamentals.

2.2.1 Accounting variables as exposures to risk

Accounting reports are a primary source of information for investors to learn about *ex ante* risk expectations (Farrelly et al., 1985). The recognition that accounting reports should convey 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).[4]

Beaver et al. (1970) first introduce a CAPM-motivated accounting beta, which measures the systematic risk as the covariance of a firm's time-series of earnings and the aggregated market's time-series of earnings. They show that accounting beta is correlated with market-based beta, and that total variability of earnings has a greater correlation with market-based beta than accounting beta does. A few recent studies use a similar motivation but alternative measurement approaches such as Ball et al. (2020), Ellahie (2020), and Nekrasov and Shroff

[3]Examples include Banz (1981) and Keim (1983) the size anomaly, Rosenberg et al. (1984) the book-to-market effect, Jegadeesh and Titman (1993) the momentum effect, and Titman et al. (2004) the capital investment effect.

[4]However, the benefit of measuring risk from accounting fundamentals is not settled (Elgers, 1980).

(2009). They all suggest that earnings covary with state variables, and the covariability or the exposure to risk is associated with market-based risk measures such as CAPM beta. 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.

Related research has also argued that accounting performance is a measure of a firm's time-varying risk exposure. Fama and French (2006) argue that firms with higher returns on equity are riskier in the sense that they have higher realized returns. Novy-Marx (2013) and Ball et al. (2015) posit and show that a cleaner measure of economic profitability, such as gross profitability and operating profitability, enhances the predictability of future returns. These papers infer that profitable firms are riskier, even though this conjecture is difficult to reconcile with the evidence that profitable firms are less prone to distress, have longer cash flow durations, and have lower levels of operating leverage (Novy-Marx, 2013). We view our study as using scenario-based analysis to examine the components of operating profitability and to understand why profitable firms could be riskier.

2.3 Properties of earnings and risk

Closely related to our study are papers examining the higher moments of accounting returns. Dichev and Tang (2009) argue that earnings volatility, which they measure as the variance of earnings in the most recent five years, captures the effects of real and unavoidable economic volatility. They posit and show that firms operating in environments subject to large economic shocks have more volatile and less predictable earnings. Konstantinidi and Pope (2016) and Chang et al. (2020) both use quantile regressions to derive 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. These results suggest that uncertainty in earnings, whether as realized volatility or as expected dispersion in earnings, conveys risk information. Although we ask a similar question – whether accounting performance conveys *ex ante* risk information, we contribute to this research by focusing on scenario-based risk measurement and in particular on the systematic risk in accounting earnings.

2.4 Cross-sectional regressions and state variables

In monthly cross-sectional regressions that use firm characteristics to explain future stock returns, Fama and French (2020) view the estimated coefficients as the price of the factors that vary for different states of the economy. By their interpretation, the estimated coefficient represents the expected return borne by one unit of risk exposure, and so the coefficient is a common risk factor to all firms in the cross-section at that point-in-time. At different points-in-time, the estimated coefficient may have different values depending on the state of the economy.

The Fama and French (2020) regressions have a close parallel to earnings forecasting regressions. As Dichev and Tang (2009) note, earnings persistence is determined by economic factors and accounting factors. They posit that earnings volatility captures the effects of economic volatility and show that time-series earnings volatility is negatively associated with earnings persistence. The intuition is that firms operating in environments subject to large economic shocks are likely to have both more volatile earnings and less persistent earnings. However, time-series earnings volatility does not separate systematic and idiosyncratic volatility. Accordingly, Frankel and Litov (2009) show that time-series earnings volatility is not priced. We adopt cross-sectional regressions to extract the systematic factors that affect earnings volatility.

3 The Method

In this section, we first demonstrate our derivation of scenario-based risk and then document our measurement procedures.

3.1 Scenario-based risk

The standard expected return equation can be represented as

$$E[R_{i,t+1}] = R_f + \beta_{it} E[\lambda_t] \tag{1}$$

The expected return is a function of the risk free rate of return R_f, the expected risk premium $E[\lambda_t]$ that rewards investors for bearing market-wide volatility, and the sensitivity of the stock to the market-wide volatility, β_{it}. The risk premium λ_t has been treated as a parameter with a single point value in many applications that emphasize measuring β_{it}. However, in our scenario-based analysis, we take β_{it} as fixed, given by observed firm characteristics, and determine λ_t. Additionally, rather than focusing on the expected point value estimate of λ_t, we use the expected distribution of λ_t.

In analysts' scenario-based forecasts, analysts implicitly or explicitly identify a firm's key business drivers and then forecast its returns under a bull scenario and a bear scenario, which we term as H (high) and L (low). In the good state, the risk factor has an outcome $\hat{\lambda}_t^H$ and in the bad state, $\hat{\lambda}_t^L$. As analysts may estimate a firm's fundamental operating risks without separating systematic from idiosyncratic risk, their inputs may include the idiosyncratic risk of a firm in their risk measurement and therefore generate scenario-based return forecasts of the following form,

$$\hat{R}_{i,t+1}^H = \hat{R}_f^H + \beta_{it} \hat{\lambda}_t^H + \hat{e}_{it}^H, \tag{2}$$

$$\hat{R}_{i,t+1}^L = \hat{R}_f^L + \beta_{it} \hat{\lambda}_t^L + \hat{e}_{it}^L. \tag{3}$$

In these two equations, $\hat{e}^H$ and $\hat{e}^L$ represent an analyst's estimate of a firm's idiosyncratic outcomes under the good and bad states, and $\hat{R}_f^H$ and $\hat{R}_f^L$ represent the estimated risk-free rate under the good and bad states. The equation (2) and (3) demonstrate how analysts derive their state-contingent valuation forecasts. Because analysts summarize and report state-contingent valuation forecasts $\hat{R}_i^L$ and $\hat{R}_i^H$, information users and researchers only observe these numbers but not the exact composition of them. In Joos et al. (2016), the spread of the scenario-based return forecast is calculated by subtracting (3) from (2), represented by

$$Spread_{it} = (\hat{R}_f^H - \hat{R}_f^L) + \beta_{it}(\hat{\lambda}_t^H - \hat{\lambda}_t^L) + (\hat{e}_{it}^H - \hat{e}_{it}^L). \tag{4}$$

In this estimation method, analysts implicitly view a firm's fundamental systematic exposure β_{it} as constant under both good and bad states, but the risk-free rate, the risk premium, and the idiosyncratic risk vary across different states. As equation (4) shows, $Spread_{it}$ is a function of the systematic exposure β_{it}, the difference between the risk-free rates forecasted in two states $(\hat{R}_f^H - \hat{R}_f^L)$, the difference between the macro factor outcomes in the two states $(\hat{\lambda}_t^H - \hat{\lambda}_t^L)$, and the difference between the idiosyncratic risk forecasts in two states $(\hat{e}_{it}^H - \hat{e}_{it}^L)$.

In cross-sectional regressions where all firms encounter the same macro scenarios, $(\hat{R}_f^H - \hat{R}_f^L)$ and $(\hat{\lambda}_t^H - \hat{\lambda}_t^L)$ become constant. The variation in $Spread_{it}$ comes from the systematic exposure to the macro factors, β_{it}, as well as the state-contingent idiosyncratic risk $(\hat{e}_{it}^H - \hat{e}_{it}^L)$. As Joos et al. (2016) show in an empirical test, the determinants of $Spread_{it}$ include a firm's β_{it} and its idiosyncratic risk. Since analysts estimate both systematic and idiosyncratic risks (Lui et al., 2007), the *Spread* measure from their scenario-based forecasts does not cleanly separate priced systematic risk from potentially unpriced idiosyncratic risk.

Our method is an adaptation of the analyst scenario-based valuation forecasts. For accounting information, expected earnings are the parallel to market based expected returns (Beaver et al., 1970). We therefore begin with earnings as our primary outcome of interest. We forecast earnings changes rather than the levels of earnings because earnings are autocorrelated (Easton and Zmijewski, 1989; Kormendi and Lipe, 1987). Regressing earnings levels on its components when they are both nonstationary may lead to correlations between the variables even if they are independent (Finger, 1994). Our focus on changes therefore allows us to measure more accurately systematic variation in earnings.

We now demonstrate our construction of macro scenarios and then show how this approach captures only systematic risk. To simplify the derivation for demonstration purposes, we use two cross-sections and assume that one of them is a high state and the other a low state. We use $Sales_{it}$ and $\Delta Sales_{it}$ as two components of earnings that forecast future earnings changes,

$$\Delta Earnings_{i,t+1} = \gamma_0 + \gamma_1 Sales_{it} + \gamma_2 \Delta Sales_{it} + e_{i,t+1}. \tag{5}$$

γ_0, γ_1, and γ_2 are the paramaters that describe the economic state of a cross-section. $e_{i,t+1}$ is the idiosyncratic shock.[5] Note that the earnings components at time t must have a systematic relation with future earnings changes to have an impact on the estimated model. For example, if $\Delta Sales_{it}$ represents idiosyncratic shocks to sales, then the estimated $\hat{\gamma}_2$ is zero.

Suppose between the two cross-sections, in one of them sales and the change in sales are positive predictors of future earnings changes (i.e., the high state). The estimated scenario parameters for that cross-section are represented by ($\hat{\gamma}_0^H$, $\hat{\gamma}_1^H$, $\hat{\gamma}_2^H$). In the other cross-section, sales are a less persistent component of earnings (i.e., a low state) and the estimated parameters are ($\hat{\gamma}_0^L$, $\hat{\gamma}_1^L$, $\hat{\gamma}_2^L$). From these two cross-sectional regressions, we have formed two macro scenarios that mimic the bull and bear case of analyst forecasts.

Next, we forecast state-contingent outcomes. The earnings change forecasts under these two states are

$$\Delta \hat{E}arnings_{i,t+1} = \hat{\gamma}_0 + \hat{\gamma}_1 Sales_{it} + \hat{\gamma}_2 \Delta Sales_{it} \tag{6}$$

$$\Delta \hat{E}arnings^L_{i,t+1} = \hat{\gamma}^L_0 + \hat{\gamma}^L_1 Sales_{it} + \hat{\gamma}^L_2 \Delta Sales_{it} \tag{7}$$

[5] We follow the literature and assume that idiosyncratic shocks are serially independent (e.g., Berk et al. (1999)).

The spread between the forecasts for the two states is the scenario-based risk represented by

$$Spread_{it} = (\hat{\gamma}_0^H - \hat{\gamma}_0^L) + (\hat{\gamma}_1^H - \hat{\gamma}_1^L)Sales_{it} + (\hat{\gamma}_2^H - \hat{\gamma}_2^L)\Delta Sales_{it}. \tag{8}$$

We observe a major distinction between equation (8) and equation (4). In equation (8), there is no state-contingent idiosyncratic risk, e^H and e^L, because the cross-sectional forecasts do not include the idiosyncratic components as analyst forecasts do. This is because the state parameters such as $\hat{\gamma}_0^H$ represent the fitted model expected changes in earnings, or an average change in earnings relevant to that cross-section. Even if $\Delta Sales_{it}$ represents a firm's idiosyncratic shock to sales, it does not affect the measure $Spread_{it}$ because in the example above both $\hat{\gamma}_2^H$ and $\hat{\gamma}_2^L$ will be zero.

In a cross-section, the high and low scenarios are equally applied to all firms so that ($\hat{\gamma}_0$, $\hat{\gamma}_1$, $\hat{\gamma}_2$) are constant across firms. $Spread_{it}$ differs across firms only because $Sales_{it}$ or $\Delta Sales_{it}$, or both of them differ across firms. It therefore becomes apparent that if $Spread_{it}$ varies in a cross-section, it must be that at least one of $Sales_{it}$ and $\Delta Sales_{it}$ is not idiosyncratic, or put differently, at least one of them systematically correlates with cross-sectional leading earnings change (i.e., $\Delta Earnings_{i,t+1}$), so that at least one of ($\hat{\gamma}_1^H$ – $\hat{\gamma}_1^L$) and ($\hat{\gamma}_2^H$ – $\hat{\gamma}_2^L$) is non-zero. Alternatively, if neither $Sales_{it}$ nor $\Delta Sales_{it}$ correlates with cross-sectional leading earnings change, ($\hat{\gamma}_1^H$ – $\hat{\gamma}_1^L$) and ($\hat{\gamma}_2^H$ – $\hat{\gamma}_2^L$) are both equal to zero, and $Spread_{it}$ remains a constant across firms. The intuition is that if none of the earnings components included in equation (5) predicts future earnings change, all estimated parameters will be virtually zero and thus fail to capture the economic force that drives a cross-section of earnings change. State differently, at least one of the earnings components in equation (5) must correlate with leading earnings change, so that at least one of the estimated parameters captures that state of the economy. It further implies that if a cross-section of earnings change, or $\Delta Earnings_{i,t+1}$, is systematic, the estimated macro scenario is also systematic, and so $Spread_{it}$ should be priced.

The same reasoning applies to other components of earnings. As each component may introduce new information about systematic risk, we demonstrate a slightly different scenario-based risk measure by adding a different component of earnings that incorporates a company's investment in intangible capital, selling, general, and administrative (SG&A) expenses to forecast earnings changes (Srivastava, 2014). This leads to the following prediction equation,

$$\Delta Earnings_{i,t+1} = \gamma_0 + \gamma_1 Sales_{it} + \gamma_2 SGA_{it} + e_{i,t+1}. \tag{9}$$

Suppose we have four different states where the γ parameters can take high and low values. These are four hypothetical cross-sections; one where both sales and SG&A predict a positive earnings changes, one where sales predicts a positive earnings change while SG&A predicts a negative, one where sales is negative but SG&A is positive, and one where both are negative. Earnings change forecasts under these four states are

$$\Delta \hat{E}arnings^1_{t+1} = \hat{\gamma}^1_0 + \hat{\gamma}^H_1 Sales_t + \hat{\gamma}^H_2 SGA_t \tag{10}$$

$$\Delta \hat{E}arnings^2_{t+1} = \hat{\gamma}^2_0 + \hat{\gamma}^H_1 Sales_t + \hat{\gamma}^L_2 SGA_t \tag{11}$$

$$\Delta \hat{E}arnings^3_{t+1} = \hat{\gamma}^3_0 + \hat{\gamma}^L_1 Sales_t + \hat{\gamma}^H_2 SGA_t \tag{12}$$

$$\Delta \hat{E}arnings^4_{t+1} = \hat{\gamma}^4_0 + \hat{\gamma}^L_1 Sales_t + \hat{\gamma}^L_2 SGA_t. \tag{13}$$

We cannot summarize across the four states by labelling which is a good or bad state to create the spread measure, so we use the variance of the four forecasts. If the γs are independent, the variance is represented by the following equation,[6]

$$\sigma^2_{it} = Var[\Delta \hat{E}arnings_{i,t+1}] = Var(\hat{\gamma}_0) + Var(\hat{\gamma}_1)Sales^2_{it} + Var(\hat{\gamma}_2)SGA^2_{it}. \tag{14}$$

[6] The variance equation is only shown for the purpose of explaining our method. The methodology remains the same even if the γs are not independent.

Here, the standard deviation σ_{it} is our scenario-based risk measure. Because the same four scenarios are applied to one cross-section, $Var(\hat{\gamma}_0)$, $Var(\hat{\gamma}_2)$, and $Var(\hat{\gamma}_3)$ become constant. Therefore, in the cross-section, the variation in σ_{it} is determined by $Sales$ and SGA. The relative weighting of the terms in σ are given by the relative magnitudes of the variances of $\hat{\gamma}_1$ and $\hat{\gamma}_2$. To give an intuitive example, perhaps there are years in which the investment in intangibles has a larger economy-wide effect than sales. This means that when the economy experiences a negative shock, companies with high investment in intangible capital (e.g., Firm A with high SG&A expenses) suffer more than companies with high levels of sales (e.g., Firm B with high sales). Perhaps when the economy is hit by a positive shock, companies with high intangible capital benefit more than companies with high sales. It would further imply that across different macro environments, the macro factor associated with SG&A is more variable than that of sales, or that $Var(\hat{\gamma}_2)$ is greater than $Var(\hat{\gamma}_1)$. Because the payoff into future earnings of intangible investment varies much more than that of sales, in a cross-section, Firm A that incurs more SG&A expenses will have a higher variance of predicted earnings across the four hypothetical scenarios than Firm B that generates more sales, *ceteris paribus*. Firm A is perceived as riskier because its scenario-based risk is higher. Put differently, Firm A's current investment in intangibles may or may not generate future earnings, depending on the state of the economy, but Firm B's current sales is highly likely to be mapped into future earnings regardless of the state. Therefore, the intangible-intensive Firm A in this example has a higher scenario-based risk.

Whether σ_{it} is priced is determined the same way as we determine $Spread_{it}$ in equation (8). If and only if at least one of the earnings components we include in equation (9) correlates with the cross-section of change in earnings, σ_{it} will reflect the covariability of earnings with macro states and be priced.

3.2 Empirical design

We begin by constructing macro scenarios that are used to create variation in predicted earnings. We do so by estimating cross-sectional earnings prediction models (Fama and French, 2020; Fama and MacBeth, 1973). As we have discussed, we interpret the coefficients as the parameters that represent the state of the economy in the cross-section. The formal regression is equation (15).

$$\Delta OP_{i,t+1} = \gamma_0 + \gamma_1 REVT_{it} + \gamma_2 COGS_{it} + \gamma_3 SGA_{it} + \gamma_4 XRD_{it} \tag{15}$$

As the dependent variable, we use leading change in operating profitability, or ΔOP_{t+1}, scaled by average common equity. Although Easton and Sommers (2003) recommend market capitalization as the proper scale for accounting variables, we scale by common equity rather than market capitalization to limit our model information to accounting-based fundamentals (Ellahie, 2020).[7]

As discussed in Section 3.1, we use change in operating profitability as the dependent variable instead of the level of operating profitability because both earnings and earnings components are persistent (Dechow et al., 2008; Easton and Zmijewski, 1989; Kormendi and Lipe, 1987; Richardson et al., 2005; Sloan, 1996). First-differencing allows us to better capture the common economic forces that affect a cross-section of earnings volatility and to mitigate the spurious statistical significance in the presence of two nonstationary variables (Finger, 1994; Granger et al., 1974).[8]

Operating profitability (OP) is calculated as revenue ($REVT$) less cost of goods sold ($COGS$) and selling, general, and administrative expenses reported by Compustat ($XSGA$).[9]

[7] In robustness tests, we scale by market capitalization and our inferences remain unchanged, tabulated in Table A3.

[8] Another justification for choosing the change in operating profitability as the outcome variable is that Ellahie (2020) shows that earnings betas constructed from changes in expected earnings are more strongly associated with stock returns. This is presumably because earnings is persistent and less sensitive to changes in the economy.

[9] Following Ball et al. (2015), we subtract XRD from $XSGA$ reported by Compustat to obtain each company's self-reported SG&A expenses (SGA). We impute zero for missing XRD. Operating profitability

For the independent variables, we include $REVT$, $COGS$, SGA, and XRD, because they are the primary components of operating profitability.[10] Detailed variable definitions are provided in the appendix.

We require observations to have positive common equity, total assets, and revenue to enter the sample. We also require non-missing values for the five variables we use in the regression equation (15). All variables are trimmed at the top and bottom 1% within each fiscal year. These steps leave us with 215,951 observations for the years 1963 to 2018. The number of observations by year, descriptive statistics, and the correlations as well as autocorrelation among the variables for constructing macro states are tabulated in Table 1. From Panel B, we notice that change variables are generally right skewed with a mean and median slightly greater than zero and means greater than medians, suggesting that companies scale up over time and that scale increases are larger than scale decreases. Panel C shows the Pearson correlation among variables and autocorrelation of each variable, with autocorrelation displayed on the diagonal. From Panel C, we see that level variables generally have higher autocorrelations, while ΔOP_{t+1} has low correlations with all other variables. ΔOP_{t+1} also has low and insignificant autocorrelation. The high correlations and autocorrelation of level variables are consistent with prior literature that the level variable may be persistent and nonstationary and that the first-differenced change variable may mitigate the bias (Finger, 1994; Granger et al., 1974).

The first step for calculating σ is to construct the macro scenarios that represent the states of the economy. By running annual regressions from 1963 to 2018, we obtain the earnings prediction coefficients from equation (15) for each cross-section, the $\hat{\gamma}$s, tabulated in Table 2, Panel A. From this table, we notice several empirical observations. First, each

constructed in Ball et al. (2015) does not account for R&D expenses. Our measure of OP accounts for R&D expenses because many companies such as Apple and Facebook report operating profitability as the line item after subtracting R&D expenses, and because R&D expenses decrease operating profitability in Fama and French (2020).

[10] To account for different information about future earnings changes (i.e. permanent versus transitory earnings components (Ali and Zarowin, 1992)), we use a model that incorporates both change and level components as independent variables to capture the common variation in earnings as one robustness test. The results are largely the same (untabulated).

component can positively or negatively predict ΔOP_{t+1}. For example, in 1963, one unit of $REVT$ predicts 0.132 unit of ΔOP_{t+1}, whereas in 1981, one unit predicts -0.101 unit of ΔOP_{t+1}. This implies that relative to $REVT$, 1963 is a good state because higher $REVT$ is associated with an increase in operating profitability in 1964, whereas 1982 is a bad state because higher $REVT$ from 1981 is associated with a reverse of operating profitability in 1982.

Second, the parameters of $REVT$ and $COGS$ appear to be largely correlated in both magnitude and significance. We conjecture that these two components of earnings largely respond to the same state variable. SGA and XRD behave more differently from these two components, suggesting that they may respond to a different state variable. In Panel B of Table 2, we show the time-series correlations between the five estimated parameters and 13 macro variables, including five state variables from Fama and French (2015) five factors, GDP and change in GDP, and six bond market risk factors. Specifically, the parameters of $REVT$, $COGS$, and SGA are significantly correlated with multiple state variables. The correlations between XRD and these 13 macro factors appear to be less strong, but is still significant for three bond market risk measures. In Panel C of Table 2, we regress the time series of each estimated model coefficient on 13 macro factors and present the model statistics of each coefficient. γ_1, γ_2, and γ_3, which correspond to $REVT$, $COGS$, and SGA all have adjusted R squared of about 70%, while γ_4 that corresponds to XRD has adjusted R squared of about 16%, suggesting that these estimated coefficients from cross-sectional earnings prediction model well incorporate macro state information represented by 13 state variables. Empirical results on these components are consistent with our conjecture that cross-sectional prediction models yield information about the undiversifiable and common volatility, implying that the input variables (i.e., the earnings components) are sensitive to the common volatility.

Third, the variance of the eight parameters differ. For example, $REVT$, $COGS$ and SGA have similar variance in the model parameter, ranging from 0.0054 to 0.0066, tabulated in the last row of Panel A, Table 2. It suggests that the uncertainty associated with these three components are similar. Contrarily, the parameter of XRD has a higher variance at 0.0280. The high variance of the coefficients of R&D is consistent with the notion that R&D expenditures result in risky payoffs (Coles et al., 2006; Gormley et al., 2013). The higher variance of the XRD parameter means that R&D will receive a higher weight in σ than the other components.

After we construct the parameters that constitute our historical macro scenarios, the next step is to forecast ΔOP under the set of macro scenarios and calculate the distribution of $\Delta\hat{O}P$ for each firm-year. The prediction is calculated using equation (16).

$$\Delta\hat{O}P_{i,t+1} = \hat{\gamma}_0 + \hat{\gamma}_1 REVT_{it} + \hat{\gamma}_2 COGS_{it} + \hat{\gamma}_3 SGA_{it} + \hat{\gamma}_4 XRD_{it} \tag{16}$$

To prevent bias created by using information that is not known at each time t, we forecast ten $\Delta OP_{i,t+1}$ for each firm-year by combining earnings components from year t with the ten sets of parameters from $t-11$ to $t-2$. For example, the earliest year for which we predict the different scenarios for ΔOP is 1974 because our earliest macro scenario starts in 1963. We use firm-year earnings components from 1974 and macro scenarios from 1963 to 1972 to predict the outcomes, resulting in ten $\Delta\hat{O}P$ scenario-based outcomes.

After applying the ten macro scenarios for each firm-year and obtaining the ten forecasts, we calculate the standard deviation of the ten forecasts, which is our firm-year systematic risk measure,

$$\sigma_{it} = \sqrt{Var(\Delta\hat{O}P_{i,t+1})}. \tag{17}$$

4 Empirical Tests and Results

We conduct three sets of tests. First, we show the association of our measure of systematic risk, σ, with firm characteristics and σ's ability to capture *ex ante* uncertainty. Second, we show the association of σ with other risk measures: earnings beta, earnings volatility and its alternatives, and CAPM beta. We also test whether σ, incremental to these other measures, significantly predicts future returns (Beaver et al., 1970; Dichev and Tang, 2009; Ellahie, 2020; Frankel and Litov, 2009). Lastly, we compare σ with proposed time-varying priced risk measures in the asset pricing literature: market capitalization, book-to-market, investment, momentum, and operating profitability (Ball et al., 2015; Fama and French, 1993, 2006, 2020).

Descriptive statistics for σ, annual returns, and other variables relevant to our tests are tabulated in Table 3. We assume that annual report information is publicly available at the end of the third month (Ou and Penman, 1989). The annual return ($ANNRET$) is calculated as the 12 month buy-and-hold return, beginning the fourth month after the last fiscal year end and ending three months after the fiscal year end. We lead the variable $ANNRET$ to derive annual returns for future years. The definitions of other variables are tabulated in the appendix and in the table captions. Our observations for the main tests are capped at 130,501, less than in Table 1, because we use data prior to 1974 to calculate σ.

4.1 Fundamental characteristics and realized variances

In order to better understand the generation process of σ and to inspect whether σ captures the uncertainty aspect of a firm's fundamental activities, we examine firm characteristics partitioned by σ. We rank firms within each fiscal year into quintiles based on σ, and we test how characteristics differ across the top and bottom quintiles. Statistics are provided in Table 4. We make several observations. First, if on average a high σ is expected to represent high risk, we expect higher future returns to be realized for companies with high σ. Consistent with this expectation, we see that high σ firms have higher contemporaneous and future annual returns. The differences in annual returns between the highest quintile of σ and the lowest quintile are significant for year t, $t+1$, $t+2$, and $t+3$, although the magnitude of the difference in returns declines moving further from the ranking year.

Second, high σ firms have higher amounts of the four components of OP (i.e., $REVT$,

$COGS$, SGA, and XRD). This observation is partially by construction as we demonstrate in Section 3.1 equation (14), in a cross-section where all firms are imposed with the same set of macro scenarios, higher magnitudes in earnings components result in a higher σ value.[11] To illustrate our inferences on the connection between earnings components and systematic risk exposure, we take revenue as an example that represents a firm's exposure or sensitivity to the economy. When a macro scenario varies, or revenue's γ coefficient varies across several historical cross-sections, a high revenue will cause the expected future earnings of a firm to be more variant compared to a low revenue firm in the same cross-section. This is because we assume a common persistence parameter for revenue for both firms, and the outcome is the multiplication of the parameter and the magnitude of revenue. The intuition is that a high revenue firm in a bad state has more to lose than a low revenue firm and therefore, a higher magnitude of revenue results in more uncertain outcomes as well as a higher σ value.

Our inferences and assumptions that high revenue firms might be more risky could seem unintuitive if a high revenue firm is expected to have more stable earnings across different macro scenarios. However, the persistence of earnings in this claim must refer to idiosyncratic persistence, which should not affect a firm's systematic risk profile. Put differently, a high revenue firm may have higher idiosyncratic persistence of revenue as well as lower idiosyncratic volatility, but as long as a firm's revenue responds to the shocks in the economy, a high revenue as a measure of systematic exposure must result in higher systematic risk. The same reasoning can be applied to other earnings components.

Third, high σ firms have higher OP as well as higher ΔOP. We anticipate the relation between high σ and high OP because σ is constructed from the components of OP. If σ captures a firm's systematic risk, the high OP for a high σ is also consistent with research that posits a positive association between operating profitability and risk (Ball et al., 2015).

Fourth, several firm characteristics differ between the high and the low σ quintiles. High

[11] We recognize that firms with small operational scale can be risky too, but σ does not pick up this size related risk exposure. In additional analysis, we change the scenario-construction model to include an inverse measure of common equity. σ with this model allows small equity firms to have high σ value, and the conclusions from the main analysis remain unchanged, tabulated in Table A3.

σ firms have higher common equity (CEQ), leverage (LEV), market capitalization ($SIZE$), and higher past year returns (MOM). High σ firms also have lower book-to-market (BTM). However, we speculate that this inconsistency is due to the denominator and we further discuss this concern in robustness test.[12]

Next, we are interested in whether σ represents greater *ex ante* uncertainty by examining its *ex post* variance. We rank firm-years based on σ and OP into independent quintiles and form 5 × 5 buckets of firms. We control for OP to address the concern that OP and σ may be measuring the same underlying factor. We use three outcomes of interest: the mean of the realized absolute change in operating profits ($|\Delta OP_{t+1}|$), the within-group variance of the realized leading operating profitability (OP_{t+1}), and the within-group variance of the realized leading accounting earnings (ROE_{t+1}). If σ captures *ex ante* uncertainty, we expect that high σ firms have higher realized absolute change in operating profits, as future operating profitability deviates from the current performance to a greater extent. We also expect high σ firms to have greater realized variance of future financial performance, because conditional on the current OP, the variance of future financial performance reflects the uncertainty of future payoffs. Results are tabulated in Table 5.

Panel A, Table 5 shows the results for realized $|\Delta OP_{t+1}|$ for each bucket. Consistent with our expectation, lower ranked σ groups generally have smaller absolute changes in OP, higher ranked σ groups generally have greater absolute changes in OP, and the differences across groups are significant for each quintile of OP. This shows that σ captures information beyond what is captured by OP. Panel B shows the results for the standard deviation of

[12]If σ is a risk measure, the relation between σ and $SIZE$ and BTM seems inconsistent with the risk relation posited by prior research and the cross-section of returns (Ball et al., 2020; Campbell and Vuolteenaho, 2004; Fama and French, 1995). We speculate that this inconsistency could be due to a scale effect when σ is constructed scaling by common equity instead of market capitalization as recommended by Easton and Sommers (2003). We repeat the macro-scenario construction process using market capitalization as the denominator to derive σ and reexamine the relation between σ and BTM and $SIZE$. Results are tabulated in the Appendix Table A2. We find that when scaling accounting variables by market capitalization, high σ firms have higher BTM and lower $SIZE$, consistent with prior research that documents the relation between these measures and returns. In addition, our inferences on future returns, earnings components, and profitability largely stay the same with the different deflator. Therefore, we present our main tests with common equity as the deflator in order to limit our model information to accounting-based fundamentals (Ellahie, 2020).

realized leading operating profitability (OP_{t+1}). The standard deviation of realized future OP in the low σ groups is generally low, and the standard deviation of realized future OP in the high σ groups is generally high. Importantly, every comparison is conditional on a similar level of current operating performance. Finally, Panel C shows the results for the standard deviation of realized leading accounting earnings (ROE_{t+1}). Again, conditional on operating profitability, low σ groups generally realize low standard deviation of future ROE while high σ groups generally realize high standard deviation of future ROE, and the differences across all quintiles of OP are significant. This set of tests validates our argument that σ captures *ex ante* risk, which results in more variant *ex post* outcomes.

4.2 Earnings volatility, earnings beta, and CAPM beta

In this section, we study the association between σ and several competing risk or uncertainty measures as well as their ability to predict future returns. Following prior research, we use earnings volatility and its alternatives, earnings beta, and CAPM beta (Beaver et al., 1970; Dichev and Tang, 2009; Ellahie, 2020). Earnings volatility ($EVOL$) is calculated as the variance of five years of income before extraordinary items from the statement of cash flows on a rolling basis, following Dichev and Tang (2009). In addition to earnings volatility, we also measure historical volatility of operating profitability and change in operating profitability, calculated as five-year rolling variance of OP and ΔOP ($OPVOL$ and $\Delta OPVOL$). Earnings beta ($EBeta$) is calculated as the covariance of the past five years (20 quarters) of realized return on equity and the aggregate realized return on equity on the same fiscal quarter end date, where return on equity is the core earnings scaled by average common equity. CAPM beta ($Beta$) is the covariance of the past 60-month risk-free rate adjusted return and the market premium. The above mentioned procedures for $EBeta$ and $Beta$ follow the calculation in Ellahie (2020).

Summary statistics for these three competiting variables and their correlations with σ are tabulated in Panel A and B of Table 6. From this table, we can see that σ is significantly positively correlated with all five measures of risk and uncertainty, and that it has relatively stronger correlation with $OPVOL$, $\Delta OPVOL$ and $Beta$. The former two relations are to be expected since σ and the two volatility measures of operating profitability overlap conceptually. σ is a measure of the expected volatility of earnings change with variation coming from a set of plausible macro scenarios, whereas $OPVOL$ and $\Delta OPVOL$ are the realized volatility of profitability with variation coming from both the realized economic environment and the idiosyncratic business of a firm (Dichev and Tang, 2009). Moreover, σ being significantly positively correlated with both earnings beta and market beta suggests that σ captures the covariability of a firm's earnings as well as returns. Additionally, $EBeta$ has a correlation of 0.077 with CAPM $Beta$ while earnings volatility $EVOL$ has a correlation of 0.205 with $Beta$, supporting the extant literature that the relation between earnings covariability and CAPM $Beta$ is weaker than that between earnings total variability and $Beta$ (Beaver et al., 1970). Lastly, both $EBeta$ and $Beta$ are significantly correlated with $EVOL$, $OPVOL$ and $\Delta OPVOL$, suggesting that these time-seires volatility measures capture real and unavoidable economic volatility (Dichev and Tang, 2009).

Next, we show the results from regressing leading one-year returns on the measures of risk and tabulate them in Panel C, Table 6. Column (1) of Panel B, Table 6 shows that σ significantly predicts leading one-year returns. In this specification, we control for fiscal-year fixed effects and the standard errors are clustered by firm and year. We sequentially show the association with returns of $EVOL$, $\Delta OPVOL$, $OPVOL$, $EBeta$, and $Beta$ from Column (2) to (6), and none of them significantly predict future returns. These results are consistent with prior literature that earnings volatility is not priced and that earnings beta constructed from historical return on equity and market-based beta lack the ability to predict future returns (Ellahie, 2020; Frankel and Litov, 2009; Jagannathan and Wang, 1996). In Column (7), we show a model with all six variables together. Under this specification, σ is still significant in leading one-year returns, and none of the other measures load.

4.3 Firm characteristics and future returns

We have shown that σ captures a firm's *ex ante* uncertainty by showing its relation with the realized variance in performance and that σ predicts returns by itself and in competition with other risk measures. In this section, we proceed to test σ's ability to predict future returns compared with measures that have most commonly been used as time-varying systematic risk measures. We follow the literature and start by conducting portfolio tests. We examine the pattern of future returns on one-way sorted portfolios constructed separately from σ, book-to-market (BTM), market capitalization ($SIZE$), and operating profitability (OP_AT). Operating profitability in this set of tests is calculated as operating profitability scaled by lagged total assets, and the definition and calculation strictly follow Ball et al. (2015), as they show that operating profitability scaled by total assets demonstrates a stronger relation with future returns than by other deflators. We rank all firms within the same fiscal year into quintiles based on each variable and calculate the mean one-year return ($ANNRET1$), the mean annual return for the second year after the ranking year ($ANNRET2$), and the mean annual return for the third year after the ranking year ($ANNRET3$) for each quintile.

We first tabulate the future returns on one-way sorted portfolios in Table 7. In Panel A, Table 7, portfolios are constructed from σ quintiles. As expected, higher σ firms on average earn higher future returns, and the difference between the highest and lowest quintiles is statistically significant. The additional one-way sorts follow prior research. In Panel B, portfolios are constructed on $SIZE$. Firms with higher market capitalization earn significantly lower returns in the future three years, compared to the small-cap firms. In Panel C, portfolios are sorted by BTM and the high BTM group has significantly higher future returns in the next three years. The results on $SIZE$ and BTM are consistent with the previously documented empirical findings such as Banz (1981), Fama and French (1993), and Rosenberg et al. (1984), among many others. Panel D of Table 7 displays the return results sorted by OP_AT. Supporting Ball et al. (2015), OP_AT also strongly predicts future returns. Finally, in terms of magnitude, portfolios formed by BTM earn the highest spread in returns between the highest and the lowest quintiles, followed by σ, $SIZE$, and OP_AT.

One-way sorts do not address the possibility that other risk exposures create the observed patterns of returns. Therefore, we perform two-way sorts. We condition on $SIZE$, BTM, and OP_AT and then examine the pattern of future returns for varying levels of σ. Table 8 presents mean returns with two-way sorts. For the exposition, we focus on $ANNRET1$. Panel A tabulates the results conditional on $SIZE$. We notice that within all quintiles of $SIZE$, the highest σ quintile always significantly earns higher returns than the low σ quintile. Four out of five size quintiles with the only exception of $SIZE1$, leading one-year returns monotonically increase from lower-ranked σ to higher-ranked σ. The results of two-way sorts by σ and BTM are tabulated in Panel B. From this panel, we observe that again, conditional on each quintile of BTM, the highest σ firms significantly earn higher returns than the lowest σ firms. The monotonically increasing pattern is strong among four out of five quintiles of BTM, with the only exception of $BTM3$. Lastly, Panel C presents the results on two-way sorts by σ and OP_AT. Conditional on OP_AT, high σ groups earn significantly higher returns among all five quintiles of OP_AT. The monotonic pattern is weaker than the previous sorts, as only OP_AT2 exhibits a cleanly monotonic pattern. We are not entirely surprised by the slightly weaker portfolio returns constructed from σ and OP_AT because σ is not independent from OP_AT. Overall, the portfolio tests suggest that high σ firms on average earn higher returns and its ability to predict returns can persist up to three years ahead. Without imposing any model assumptions, these non-parametric tests seem to support that investors require greater compensation for high σ firms.

Next, we run pooled regression models to control for multiple characteristics while testing σ's ability to predict cross-sectional returns. We use the recommended characteristics from Fama and French (2020) as the control variables: $SIZE$, BTM, INV, and MOM, as well as operating profitability. However, different from OP scaled by common equity in Fama and French (2020), we scale operating profitability by lagged total assets (OP_AT) in order to compete σ against the stronger form of operating profitability (Ball et al., 2015)[13]. $SIZE$ and BTM are the same as we detail in the prior sections. INV represents asset growth, which negatively predicts future returns, and MOM represents return performance over the prior year, which positively predicts future returns (Jegadeesh and Titman, 1993; Titman et al., 2004).

We first show a baseline regression using the five characteristics and year fixed effects in predicting returns. In Column (1) of Table 9, all characteristics but $SIZE$ significantly predict future returns, and the directions are mostly consistent with Fama and French (2020) with the one exception being momentum (MOM). The difference could be attributed to our use of annual returns instead of the leading one-month return. In Column (2), we add σ to the baseline regression. As we discuss earlier, σ and OP_AT share some common information but in this case, both are still strongly significant in leading one-year returns, suggesting that they may capture different aspects of priced information. In terms of economic magnitude, moving σ from its 25th percentile to its 75th percentile, σ increases by 0.013 $(0.034 - 0.021)$, which translates to 0.021 (0.013×1.618), or 12 months of returns of 2.1%. This means that a firm that has a σ at the 75th percentile earns a 2.1% higher buy-and-hold return over the year compared to a firm that has a σ at the 25th percentile with $SIZE$, BTM, OP_AT, INV, and MOM held constant. Meanwhile, moving OP_AT from the its 25th percentile to its 75th percentile, OP_AT increases by 0.168 $(0.222 - 0.054)$, which translates to 0.030 (0.168×0.178), or an annualized return of 3.0%. Therefore, the economic magnitude of σ is over 70% of OP_AT in explaining leading one-year returns.

Next, we repeat the analysis with the annual return for the following year and the results are tabulated in Column (3). We notice that INV and MOM lose their ability to predict returns, but BTM, OP_AT and σ continue to explain returns. Moreover, the coefficients of all variables decrease in magnitude compared with when the dependent variable is $ANNRET1$. Finally in column (4), we repeat the analysis moving the annual returns to the third year.

[13]We also control for OP scaled by common equity in one robustness test, tabulated in Table 3A.

BTM persists to strongly predict returns, while OP_AT and σ decrease in significance but still positively predict returns. Overall, the evidence collectively suggests that σ captures well a firm's operational exposure to the economy as it results in more variant *ex post* payoffs and higher returns, evidence that investors appear to price the information in σ.

5 Robustness Tests

We conduct several additional tests to validate the robustness of the scenario-based approach and our measure σ in its ability to capture a firm's operational exposures to systematic risk. First, our use of a pooled regression analysis differs from many cross-sectional regression tests. We use Fama-MacBeth regressions to examine σ's ability to predict future returns in each cross-section. The inferences for leading one-year and two-year returns are unchanged with the Fama-MacBeth methodology (Fama and MacBeth, 1973), tabulated in Table 3A, Panel A.

Second, as mentioned previously, we choose to scale earnings variables by the book value of common equity. Scaling by the market value of equity yields similar inferences about future returns, profitability, and earnings components with regard to the comparison of high and low σ firms. Scaling by the market value of equity also corrects some observations that are unique to the previous scalor, particularly BTM and $SIZE$ being inconsistent with the prior literature, discussed in Section 4.1. When we scale by market value of equity, higher σ firms have smaller market capitalization and higher book-to-market, consistent with the prior literature. Results of comparing high and low σ groups are tabulated in Table A2, and regrssion results are tabulated in Table 3A, Panel B.

Next, we adapt the model by adding the inverse term of average common equity in the process of constructing macro scenarios so that σ can be inversely correlated with the size of the company. With this model, we allow small equity firms to have high σ value. Our inferences are robust to this alternative model, tabulated in Table 3A, Panel C.

We adapt the model by incorporating not only the level variables of earnings components, but also the change of earnings components, and the test results are highly similar to our main results (untabulated). We also add five-year rolling variance of operating profitability and five-year rolling variance of change in operating profitability as the control variable in the model, and our results are robust to the additional controls (untabulated).

We replace OP_AT with cash-based operating profitability constructed in Ball et al. (2016), and σ remains significant for leading one-year and two-year returns, tabulated Table 3A, Panel D. Lastly, we replace OP_AT with operating profitability scaled by common equity (OP), and our main inferences largely sustain. The results are in Table 3A, Panel E.

6 Conclusion

We revisit whether accounting reports capture systematic risk information by developing a scenario-based measure of risk in earnings. We start by forming historical scenarios represented by the regression coefficients of cross-sectional earnings prediction models. We then combine earnings components with the historical scenarios to create a distribution of expected earnings outcome. The standard deviation of this distribution is our firm-year risk measure σ. We demonstrate that σ captures systematic risk in earnings and that it complements firm characteristics that are used as measures of risk in predicting cross-sectional returns. The differential one-year returns of the interquartile range for σ is 2.1%.

We contribute to the literature in three significant aspects. First, we provide new insights about earnings prediction models in cross-sectional regressions. By running cross-sectional regressions, the variation of earnings captured in the regression coefficients is automatically systematic or common variation, since the idiosyncratic variation of earnings is left in the error. Our argument that the estimated regression coefficients represent macro scenarios is validated by that a group of macro state variables largely overlap with our estimated regression coefficients. Second, we develop a priced scenario-based risk measure using only fundamental information. Our measure does not require long time-series of firm level data and is applicable to private firms and firms without analyst coverage. Lastly, we contribute to the debate whether operating profitability is a risk exposure by showing that the common volatility extracted from operating profitability largely correlates with a battery of macro state variables, which implies that the input variables (i.e., the components of operating profitability) of the cross-sectional prediction model are sensitive to the systematic volatility in the economy.

Appendix

Table A1: Variable definitions

Variable	Definition
Macro scenarios	Data source: Compustat
CEQ	Total book equity (Compustat item CEQ)
$CEQA$	Average book equity (i.e., the sum of CEQ and lagged CEQ over 2)
$REVT*$	Total revenue (Compustat item REVT) scaled by CEQA
$COGS*$	Cost of goods sold (Compustat item COGS) scaled by CEQA
$SGA*$	Selling, general and administrative expenses (i.e., Compustat item XSGA minus XRD) scaled by CEQA
$XRD*$	R&D expenses (Compustat item XRD) scaled by CEQA, imputed zero if missing
$OP*$	Operating profits: REVT − COGS − XSGA, scaled by CEQA
$\Delta OP*$	Lagged raw OP subtracted from raw OP, then scaled by lagged CEQA
Main tests	Data source: Compustat, CRSP, World Bank, and Kenneth French's website
AT	Total assets (Compustat item AT)
LEV	Leverage, calculated as Compustat item LT over AT
$SIZE*$	Natural log of market value of equity (MVE)
MVE	The market value of equity, calculated as Compustat items PRCC_F×CSHO
$BTM*$	Natural log of book-to-market, with book-to-market calculated as CEQ over MVE
OP_AT*	Operating profitability scaled by lagged total assets, with operating profitability calculated as (REVT − COGS − (XSGA − XRD)), following Ball et al. (2015)
$INV*$	Asset growth, calculated as $\log(AT_{t-1}/AT_{t-2})$, the natural log of lagged total assets divided by twice-lagged total assets (Fama and French, 2020)
$MOM*$	Momentum, a stock's buy-and-hold return from month $s-12$ to $s-2$, where s is the month of fiscal year end
$ROE*$	Compustat item NI scaled by CEQA
$ANNRET*$	12 months of market-adjusted (vwret) buy-and-hold returns, starting from the 4th month of a fiscal year to the 3rd month after the current fiscal year
$ANNRET1$	One-year leading ANNRET
$ANNRET2$	Two-year leading ANNRET
$ANNRET3$	Three-year leading ANNRET
σ	The standard deviation of ten predicted earnings for each firm-year. The predicted earnings is the sum of the firm's earnings components in year t multiplying the persistence parameters for each component. We have ten predicted earnings because we use persistence parameters estimated from ten previous cross sections, $t-11$ to $t-2$. Earnings persistence parameters for each cross-section are tabulated in Table 2
$EBeta$	Earnings beta. Calculation strictly follows Ellahie (2020), as the covariance of trailing 20-quarter core earnings and the aggregate earnings
$Beta$	CAPM beta. Calculation strictly follows Ellahie (2020) as the covariance of trailing 60-month risk-free adjusted returns and the market risk-free rate adjusted returns. Risk-free rate is obtained from Kenneth French's library.
$EVOL$	Earnings volatility. Calculation strictly follows Dichev and Tang (2009), as the variance of five years of earnings before extraordinary items (Compustat item IBC) on a rolling basis
$OPVOL$	Operating profitability volatility. It is the analogue of $EVOL$, with the variable being OP
$\Delta OPVOL$	Volatility of change in operating profitability. It is the analogue of $EVOL$, with the variable being ΔOP
$CbOP$	Cash-based operating profitability, calculated following Ball et al. (2016) from cash flow statement: REVT − COGS − (XSGA − XRD) + RECCH + INVCH + APALCH
GDP	U.S. GDP by year, from World Bank
ΔGDP	U.S. GDP growth by year, from World Bank
$MktPrem$	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
FFO	The annual federal funds rate
ΔFFO	Annual change in the federal funds rate
$Term$	The difference in the rate of the 7 year minus the 10 year US Treasury Notes
$\Delta Term$	Annual change of the variable $Term$
$Spread$	The difference in the bond yield for BAA - AAA rated corporate bonds
$\Delta Spread$	Annual change of the variable $Spread$
Note	$*$ indicates that the variable is trimmed at top and bottom 1% within each fiscal year

Table A2: Characteristics of low and high σ firms scaled by market value of equity

Variables	σ1(N=24531)	σ5(N=24621)	Difference	Significance
σ	0.013	0.043	0.030	***
$ANNRET$	0.102	-0.080	-0.182	***
$ANNRET1$	-0.018	0.077	0.095	***
$ANNRET2$	-0.005	0.057	0.062	***
$ANNRET3$	0.011	0.046	0.035	***
AT	3505	6349	2844	***
CEQ	978	847	-130	***
LEV	0.442	0.564	0.122	***
$SIZE$	5.956	4.283	-1.673	***
BTM	-0.982	0.004	0.986	***
INV	0.152	0.061	-0.091	***
MOM	1.013	0.992	-0.021	***
ROE	0.114	-0.042	-0.156	***
ROE_{t+1}	0.093	-0.046	-0.139	***
OP	0.101	0.248	0.147	***
OP_{t+1}	0.104	0.239	0.135	***
ΔOP	0.018	0.018	0.000	
$REVT$	0.648	4.737	4.089	***
$COGS$	0.395	3.535	3.140	***
SGA	0.149	0.871	0.722	***
XRD	0.008	0.058	0.050	***

*p<0.1; **p<0.05; ***p<0.01

This table shows the comparison of fundamental characteristics of firms that are ranked at low and high σ. The only difference between this table and Table 4 is that σ in this table is constructed from earnings component variables scaled by market value of equity (MVE) rather than average common equity ($CEQA$). Specifically, we rank firms within each fiscal years into quintiles by its σ value. Column $\sigma1$ represents the variable mean for firms that have the lowest quintile rank σ, and column $\sigma5$ represents the variable mean for firms that have the highest quintile rank σ. Variables are calculated following these definitions.

σ is the standard deviation of 10 predicted earnings for each firm-year. The predicted earnings is the sum of the firm's earnings components in year t multiplying the persistence parameters for each component. We have 10 predicted earnings because we use persistence parameters estimated from 10 previous cross-sections, $t-11$ to $t-2$. Earnings persistence parameters for each cross-section are tabulated in Table 2. $ANNRET$ is the 12 months market-adjusted (vwret) buy-and-hold returns, starting from the 4th month of a fiscal year to the 3rd month after the current fiscal year. $ANNRET1$, $ANNRET2$, and $ANNRET3$ are the one-year, two-year, and three-year leading $ANNRET$. AT is total assets (Compustat item AT). CEQ is total book equity (Compustat item CEQ). $CEQA$ is average book equity (i.e., the sum of CEQ and lagged CEQ over 2). LEV is leverage, calculated as Compustat item LT over AT. $SIZE$ is the natural log of market value of equity (MVE), with MVE calculated as the multiplication of Compustat items PRCC_F*CSHO. BTM is the natural log of book-to-market, with book-to-market calculated as CEQ over MVE. INV is asset growth, calculated as the natural log of lagged total assets divided by twice-lagged total assets (i.e., $log(AT_{t-1}/AT_{t-2})$), following Fama and French (2020). MOM is momentum, calculated as a stock's buy-and-hold return from month $t-12$ to $t-2$ (Fama and French, 2020). ROE is the Compustat item NI scaled by CEQA. ROE_{t+1} is the leading term of ROE. OP is operating profits, calculated as REVT - COGS - XSGA, scaled by MVE. OP_{t+1} is the leading terms of OP. ΔOP is lagged raw OP subtracted from raw OP, then scaled by lagged MVE. $REVT$ is total revenue (Compustat item REVT) scaled by MVE. $COGS$ is cost of goods sold (Compustat item COGS) scaled by MVE. SGA is selling, general and administrative expenses (i.e., Compustat item XSGA minus XRD) scaled by MVE. XRD is R&D expenses (Compustat item XRD) scaled by MVE, imputed zero if missing. $\Delta REVT$ is lagged raw REVT subtracted from raw REVT, then scaled by lagged MVE. $\Delta COGS$ is lagged raw COGS subtracted from raw COGS, then scaled by lagged MVE. ΔSGA is lagged raw SGA subtracted from raw SGA, then scaled by lagged MVE. ΔXRD is lagged raw XRD subtracted from raw XRD, then scaled by lagged MVE.

Table A3: Robustness tests on σ

	Dependent variable:		
	ANNRET1	ANNRET2	ANNRET3
	(1)	(2)	(3)
Panel A: Fama-MacBeth regression			
σ	1.020***	0.799***	0.448
	[2.836]	[2.523]	[1.501]
Control	Y	Y	Y
Average Adjusted R^2	0.043	0.035	0.031
Panel B: σ constructed from variable scaled by MVE			
σ	2.306***	1.058***	0.873***
	(0.608)	(0.380)	(0.320)
Fyear FE	Y	Y	Y
Two-way cluster	Y	Y	Y
Observations	107,740	94,512	83,381
Panel C: Add an inverse term of CEQ			
σ	1.769***	1.165***	0.693*
	(0.476)	(0.373)	(0.361)
Fyear FE	Y	Y	Y
Two-way cluster	Y	Y	Y
Observations	106,626	92,137	80,339
Panel D: Replace OP_AT with $CbOP$			
σ	1.345***	0.934**	0.696
	(0.517)	(0.411)	(0.440)
$CbOP$	0.223***	0.155***	0.101**
	(0.031)	(0.043)	(0.040)
Fyear FE	Y	Y	Y
Two-way cluster	Y	Y	Y
Observations	48,945	42,436	36,962
Panel E: Replace OP_AT with OP			
σ	1.547**	1.065*	0.760
	(0.633)	(0.585)	(0.506)
OP	0.059	0.033	0.023
	(0.045)	(0.041)	(0.037)
Fyear FE	Y	Y	Y
Two-way cluster	Y	Y	Y
Observations	113,046	98,621	86,724

*p<0.1; **p<0.05; ***p<0.01

In this table, we construct σ using different specifications and show its ability to explain future earnings. In all panels, the benchmark return test is specified as $ANNRET1 = \beta_0 + \beta_1\sigma + \beta_2 SIZE + \beta_3 BTM + \beta_4 OP\_AT + \beta_5 INV + \beta_6 MOM$. In Panel A, σ is constructed the same way as the main analysis, but we run Fama-MacBeth regressions instead of pooled regressions with fixed effects to inspect the average σ and its ability to predict returns. In Panel B, σ is constructed the same way as the main analysis, with the difference being earnings component variables are scaled by MVE. In Panel C, σ is constructed with four earnings components and an inverse term of CEQ, with the rest of the analysis being the same as the main analysis. In Panel D, we replace OP_AT with cash-based operating profitability $CbOP$. Its calculation follows the cash flow statement method in Ball et al. (2016). In Panel E, we replace OP_AT with operating profitability deflated by common equity (OP).

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Table 1: Distribution of fiscal years and descriptive statistics of macro scenarios

Panel A: Distribution of fiscal years

Fyear	N	Pct	Cum	CumPct	Fyear	N	Pct	Cum	CumPct
1963	474	0.22	474	0.22	1991	3971	1.84	89923	41.64
1964	829	0.38	1303	0.60	1992	4072	1.89	93995	43.53
1965	1005	0.47	2308	1.07	1993	4268	1.98	98263	45.50
1966	1425	0.66	3733	1.73	1994	5078	2.35	103341	47.85
1967	1780	0.82	5513	2.55	1995	5322	2.46	108663	50.32
1968	1965	0.91	7478	3.46	1996	5373	2.49	114036	52.81
1969	2480	1.15	9958	4.61	1997	5398	2.50	119434	55.31
1970	2680	1.24	12638	5.85	1998	5218	2.42	124652	57.72
1971	2249	1.04	14887	6.89	1999	5135	2.38	129787	60.10
1972	2043	0.95	16930	7.84	2000	5141	2.38	134928	62.48
1973	2776	1.29	19706	9.13	2001	5214	2.41	140142	64.90
1974	3349	1.55	23055	10.68	2002	5148	2.38	145290	67.28
1975	4345	2.01	27400	12.69	2003	5029	2.33	150319	69.61
1976	4287	1.99	31687	14.67	2004	4886	2.26	155205	71.87
1977	4087	1.89	35774	16.57	2005	4802	2.22	160007	74.09
1978	3880	1.80	39654	18.36	2006	4611	2.14	164618	76.23
1979	3780	1.75	43434	20.11	2007	4611	2.14	169229	78.36
1980	3728	1.73	47162	21.84	2008	4573	2.12	173802	80.48
1981	3676	1.70	50838	23.54	2009	4421	2.05	178223	82.53
1982	3774	1.75	54612	25.29	2010	4380	2.03	182603	84.56
1983	3769	1.75	58381	27.03	2011	4395	2.04	186998	86.59
1984	3904	1.81	62285	28.84	2012	4341	2.01	191339	88.60
1985	3849	1.78	66134	30.62	2013	4337	2.01	195676	90.61
1986	3837	1.78	69971	32.40	2014	4217	1.95	199893	92.56
1987	3910	1.81	73881	34.21	2015	4160	1.93	204053	94.49
1988	4034	1.87	77915	36.08	2016	4055	1.88	208108	96.37
1989	4025	1.86	81940	37.94	2017	3959	1.83	212067	98.20
1990	4012	1.86	85952	39.80	2018	3884	1.80	215951	100.00

Panel B: Descriptive statistics (N = 215951)

	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
$REVT$	2.896	2.846	0.006	1.093	2.119	3.618	34.197
$COGS$	2.000	2.361	0.002	0.521	1.296	2.529	27.007
SGA	0.581	0.615	0.007	0.200	0.393	0.738	7.585
XRD	0.045	0.102	0.000	0.000	0.000	0.0438	1.482
OP_{t+1}	0.261	0.327	−2.440	0.129	0.265	0.401	3.068
ΔOP_{t+1}	0.042	0.214	−1.345	−0.035	0.029	0.105	2.135

Panel C: Pearson correlations and autocorrelation

	$REVT$	$COGS$	SGA	XRD	OP_{t+1}	ΔOP_{t+1}
$REVT$	0.895***					
$COGS$	0.974***	0.911***				
SGA	0.664***	0.517***	0.890***			
XRD	-0.040***	-0.093***	0.128***	0.891***		
OP_{t+1}	0.336***	0.268***	0.128***	-0.182***	0.771***	
ΔOP_{t+1}	0.058***	0.056***	0.089***	0.039***	0.384***	-0.002

*p<0.1; **p<0.05; ***p<0.01

This table displays information for the sample that is used to construct macro scenarios. Observations must have positive common equity, total assets and revenue (Compustat item CEQ, AT, and REVT) to enter the sample. $CEQA$ is average book equity (i.e., the sum of CEQ and lagged CEQ over 2). $REVT$ and $COGS$ are total revenue and cost of goods sold (Compustat items REVT and COGS) scaled by CEQA. SGA is selling, general and administrative expenses (i.e., Compustat items XSGA minus XRD) scaled by CEQA. XRD is R&D expenses (Compustat item XRD) scaled by CEQA, imputed zero if missing. OP is operating profits, calculated as Compustat items REVT - COGS - XSGA, scaled by CEQA. ΔOP is lagged raw OP subtracted from raw OP, then scaled by lagged CEQA. These ten variables are trimmed at top and bottom 1% within each fiscal year. OP_{t+1} (ΔOP_{t+1}) is leading OP (ΔOP). Observations in this sample have non-missing values for all these variables. Panel C diagonal displays the autocorrelation.

Table 2: Cross-sectional earnings prediction coefficients from year 1963 to 2018

Panel A: Regression coefficients for each cross-section

Fyear	$\gamma_0(Intercept)$	γ_1(REVT)	γ_2(COGS)	γ_3(SGA)	γ_4(XRD)
1963	0.009	0.132***	-0.129***	-0.112***	-0.668**
1964	0.016*	0.109***	-0.106***	-0.076***	0.126
1965	0.019**	0.101***	-0.098***	-0.072***	0.040
1966	-0.005	0.072***	-0.075***	-0.016	-0.192
1967	-0.008	0.167***	-0.158***	-0.135***	-0.096
1968	-0.002	0.101***	-0.098***	-0.052**	-0.147
1969	-0.020***	0.012	-0.015	0.021	-0.244*
1970	0.044***	-0.086***	0.096***	0.096***	0.099
1971	0.062***	-0.039**	0.045***	0.043**	0.266***
1972	0.074***	-0.002	0.009	-0.030	0.153*
1973	0.042***	0.018	-0.012	-0.040**	-0.011
1974	0.042***	-0.135***	0.138***	0.177***	0.196***
1975	0.060***	-0.079***	0.083***	0.109***	0.384***
1976	0.040***	-0.012	0.013	0.037***	0.269***
1977	0.045***	0.008	-0.001	0.018	0.254***
1978	0.053***	0.033***	-0.028**	-0.046***	0.220***
1979	0.036***	0.008	-0.014	0.001	0.297***
1980	0.043***	-0.059***	0.057***	0.091***	0.126*
1981	-0.007	-0.101***	0.104***	0.127***	0.107*
1982	0.031***	-0.075***	0.081***	0.112***	0.154***
1983	0.051***	-0.073***	0.083***	0.087***	0.241***
1984	0.030***	-0.145***	0.149***	0.180***	0.216***
1985	0.027***	-0.132***	0.142***	0.165***	0.208***
1986	0.076***	-0.124***	0.127***	0.147***	0.183***
1987	0.052***	-0.093***	0.096***	0.125***	0.169***
1988	0.044***	-0.123***	0.128***	0.159***	0.186***
1989	0.011*	-0.062***	0.062***	0.107***	0.129***
1990	0.011*	-0.145***	0.145***	0.199***	0.281***
1991	0.036***	-0.053***	0.056***	0.074***	0.012
1992	0.028***	-0.030***	0.038***	0.045***	0.102***
1993	0.030***	0.001	0.006	0.020*	0.077**
1994	0.042***	-0.038***	0.041***	0.057***	0.233***
1995	0.035***	-0.006	0.011	0.031***	-0.069**
1996	0.030***	0.008	-0.003	0.022**	0.010
1997	0.015***	-0.049***	0.057***	0.090***	0.035
1998	0.048***	-0.067***	0.067***	0.100***	0.066**
1999	0.034***	0.011	-0.013	0.001	-0.127***
2000	0.023***	-0.153***	0.150***	0.206***	0.000
2001	0.034***	-0.149***	0.148***	0.213***	0.183***
2002	0.051***	-0.082***	0.082***	0.109***	0.254***
2003	0.041***	-0.015*	0.027***	0.022**	0.123***
2004	0.046***	-0.005	0.008	0.014	-0.054**
2005	0.027***	-0.010	0.017**	0.022**	-0.024
2006	0.007	0.007	-0.004	0.007	0.100***
2007	0.000	-0.054***	0.057***	0.066***	0.156***
2008	-0.008*	-0.193***	0.198***	0.252***	0.267***
2009	0.062***	-0.080***	0.095***	0.089***	0.256***
2010	0.041***	-0.055***	0.062***	0.067***	0.075***
2011	0.016***	-0.026***	0.031***	0.039***	-0.092***
2012	0.014***	-0.020***	0.021***	0.030***	0.033
2013	0.017***	-0.017**	0.022***	0.026***	0.030
2014	-0.007*	-0.047***	0.054***	0.065***	0.044*
2015	0.025***	-0.081***	0.086***	0.116***	0.055**
2016	0.031***	-0.026***	0.027***	0.048***	0.072***
2017	0.019***	-0.016**	0.022***	0.028***	0.099***
2018	0.009**	-0.037***	0.039***	0.053***	0.026
Var	0.0004	0.0054	0.0054	0.0066	0.0280

Panel B: Pearson correlations of earnings prediction coefficients and 13 macro variables					
	$\gamma_0(Intercept)$	γ_1(REVT)	γ_2(COGS)	γ_3(SGA)	γ_4(XRD)
$MktPrem$	0.215	0.319**	-0.302**	-0.350**	-0.045
SMB	-0.038	0.372***	-0.365***	-0.317**	0.073
HML	0.025	-0.135	0.142	0.149	0.117
RMW	0.004	-0.394***	0.386***	0.426***	0.153
CMA	0.092	-0.320**	0.322**	0.334**	0.176
ΔGDP	-0.045	0.400***	-0.409***	-0.389***	-0.215
GDP	-0.031	-0.430***	0.434***	0.386***	0.014
ΔFFO	-0.252*	0.307**	-0.326**	-0.318**	-0.378***
FFO	0.015	-0.198	0.182	0.218	0.188
$\Delta Term$	0.072	-0.337**	0.349**	0.368***	0.342**
$Term$	0.273**	-0.231*	0.260*	0.172	0.192
$\Delta Spread$	-0.125	-0.205	0.191	0.262*	0.127
$Spread$	0.232*	-0.544***	0.553***	0.502***	0.516***

Panel C: Regressing the time-series earnings prediction coefficients to 13 macro variables					
	$\gamma_0(Intercept)$	γ_1(REVT)	γ_2(COGS)	γ_3(SGA)	γ_4(XRD)
$Adj.R^2$	0.111	0.737	0.737	0.700	0.160
$PVal$	0.161	0.000	0.000	0.000	0.086

*p<0.1; **p<0.05; ***p<0.01

This table shows the estimated coefficients for prediction earnings within each cross-sections, following the regression $\Delta OP_{i,t+1} = \gamma_0 + \gamma_1 REVT_{it} + \gamma_2 COGS_{it} + \gamma_3 SGA_{it} + \gamma_4 XRD_{it} + e_{i,t+1}$. Each γ is the estimated persistence parameter for the earnings component noted in the header. Panel A displays the estimated coefficients from year 1963 to 2018. Var is the variance for each estimated parameters for the 56 cross-sections. Panel B shows the correlation between each of the five series of estimated cross-sections coefficients and 13 macro variables. The definition and calculation of each macro variables are detailed in the appendix. In Panel C, we regress each time-series of the estimated coefficients to 13 time-series of macro variable. $Adj.R^2$ and $PVal$ indicate the adjusted R-squared and the P-value of the model F statistics.

Table 3: Distribution of fiscal years and descriptive statistics of the main tests

Panel A: Distribution of fiscal years for the main tests

Fyear	N	Pct	Cum	CumPct	Fyear	N	Pct	Cum	CumPct
1974	2141	1.64	2141	1.64	1996	3766	2.89	62024	47.53
1975	2389	1.83	4530	3.47	1997	3674	2.82	65698	50.34
1976	2245	1.72	6775	5.19	1998	3691	2.83	69389	53.17
1977	2388	1.83	9163	7.02	1999	3563	2.73	72952	55.90
1978	2445	1.87	11608	8.89	2000	3448	2.64	76400	58.54
1979	2434	1.87	14042	10.76	2001	3521	2.70	79921	61.24
1980	2459	1.88	16501	12.64	2002	3541	2.71	83462	63.96
1981	2472	1.89	18973	14.54	2003	3504	2.69	86966	66.64
1982	2522	1.93	21495	16.47	2004	3398	2.60	90364	69.24
1983	2576	1.97	24071	18.45	2005	3278	2.51	93642	71.76
1984	2576	1.97	26647	20.42	2006	3123	2.39	96765	74.15
1985	2644	2.03	29291	22.45	2007	3060	2.34	99825	76.49
1986	2664	2.04	31955	24.49	2008	3006	2.30	102831	78.80
1987	2572	1.97	34527	26.46	2009	3002	2.30	105833	81.10
1988	2687	2.06	37214	28.52	2010	2895	2.22	108728	83.32
1989	2810	2.15	40024	30.67	2011	2905	2.23	111633	85.54
1990	2815	2.16	42839	32.83	2012	2856	2.19	114489	87.73
1991	2846	2.18	45685	35.01	2013	2842	2.18	117331	89.91
1992	2853	2.19	48538	37.19	2014	2714	2.08	120045	91.99
1993	2947	2.26	51485	39.45	2015	2653	2.03	122698	94.02
1994	3095	2.37	54580	41.82	2016	2630	2.02	125328	96.04
1995	3678	2.82	58258	44.64	2017	2613	2.00	127941	98.04
					2018	2560	1.96	130501	100.00

Panel B: Descriptive statistics (N = 130501)

	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
AT	4,777	51,995	0.505	56	273	1,387	3,065,553
CEQ	894	3,934	0.072	27	106	456	211,704
LEV	0.520	0.231	0.000	0.347	0.514	0.675	0.998
$SIZE$	5.209	2.257	−1.054	3.540	5.108	6.808	11.819
BTM	−0.470	0.771	−3.977	−0.947	−0.441	0.039	2.437
ROE	0.057	0.240	−3.044	0.017	0.099	0.165	1.304
OP_AT	0.148	0.136	−1.016	0.054	0.140	0.222	0.929
ΔOP	0.039	0.180	−1.336	−0.030	0.030	0.098	1.792
INV	0.105	0.224	−1.095	−0.006	0.076	0.181	1.955
MOM	1.004	0.036	0.848	0.983	1.002	1.023	1.248
$ANNRET$	0.026	0.445	−0.915	−0.242	−0.037	0.201	5.778
σ	0.029	0.014	0.007	0.021	0.026	0.034	0.453

This table shows the descriptive statistics for the variables that are used in the main analyses. The sample starts from 1974 and ends at 2018. Sample years from 1963 to 1973 are disposed in order to maintain out-of-sample calculation of σ. Observations must have non-missing values in all variables to enter the sample, which yields the number of observations at 130501. Variables are calculated following these definitions.

AT is total assets (Compustat item AT). CEQ is total book equity (Compustat item CEQ). LEV is leverage, calculated as Compustat item LT over AT. $CEQA$ is average book equity (i.e., the sum of CEQ and lagged CEQ over 2). $SIZE$ is the natural log of market value of equity (MVE), with MVE calculated as the multiplication of Compustat items PRCC_F*CSHO. BTM is the natural log of book-to-market, with book-to-market calculated as CEQ over MVE. ROE is the Compustat item NI scaled by CEQA. OP_AT is operating profitability scaled by lagged total assets, with operating profitability calculated as Compustat items (REVT − COGS − (XSGA − XRD)), following Ball et al. (2015). OP is operating profits scaled by CEQA, where operating profitability is calculated as Compustat items (REVT − COGS − XSGA). ΔOP is lagged raw OP subtracted from raw OP, then scaled by lagged CEQA. INV is asset growth, calculated as the natural log of lagged total assets divided by twice-lagged total assets (i.e., $log(AT_{t-1}/AT_{t-2})$), following Fama and French (2020). MOM is momentum, calculated as a stock's buy-and-hold return from month $s-12$ to $s-2$, where s is the month of fiscal year end (Fama and French, 2020). $ANNRET$ is the 12 months market-adjusted (vwret) buy-and-hold returns, starting from the 4th month of a fiscal year to the 3rd month after the current fiscal year. σ is the standard deviation of ten predicted earnings for each firm-year. The predicted earnings is the sum of the firm's earnings components in year t multiplying the persistence parameters for each component. We have ten predicted earnings because we use persistence parameters estimated from ten previous cross-sections, $t-11$ to $t-2$. All variables except for σ are trimmed at top and bottom 1%.

Table 4: Characteristics of low and high σ firms

Variables	$\sigma 1$(N=26056)	$\sigma 5$(N=26146)	Difference	Significance
σ	0.019	0.049	0.030	***
$ANNRET$	-0.038	0.066	0.104	***
$ANNRET1$	0.004	0.050	0.046	***
$ANNRET2$	0.016	0.039	0.023	***
$ANNRET3$	0.022	0.033	0.011	**
AT	3569	3801	232	
CEQ	534	831	297	***
LEV	0.461	0.605	0.144	***
$SIZE$	4.482	5.375	0.893	***
BTM	-0.143	-0.855	-0.712	***
INV	0.087	0.106	0.019	***
MOM	0.998	1.008	0.010	***
ROE	0.014	0.042	0.028	***
ROE_{t+1}	-0.009	0.038	0.047	***
OP	0.140	0.424	0.284	***
OP_{t+1}	0.143	0.406	0.263	***
ΔOP	-0.006	0.099	0.105	***
$REVT$	1.687	5.218	3.531	***
$COGS$	1.045	3.784	2.739	***
SGA	0.487	0.886	0.399	***
XRD	0.014	0.114	0.100	***

*p<0.1; **p<0.05; ***p<0.01

This table shows the comparison of fundamental characteristics of firms that are ranked at low and high σ. Specifically, we rank firms within each fiscal years into quintiles by its σ value. Column $\sigma 1$ represents the variable mean for firms that have the lowest quintile rank σ, and column $\sigma 5$ represents the variable mean for firms that have the highest quintile rank σ. Variables are calculated following these definitions.

σ is the standard deviation of ten predicted earnings for each firm-year. The predicted earnings is the sum of the firm's earnings components in year t multiplying the persistence parameters for each component. We have ten predicted earnings because we use persistence parameters estimated from 10 previous cross-sections, $t-11$ to $t-2$. Earnings persistence parameters for each cross-section are tabulated in Table 2. $ANNRET$ is the 12 months market-adjusted (vwret) buy-and-hold returns, starting from the 4th month of a fiscal year to the 3rd month after the current fiscal year. $ANNRET1$, $ANNRET2$, and $ANNRET3$ are the one-year, two-year, and three-year leading $ANNRET$. AT is total assets (Compustat item AT). CEQ is total book equity (Compustat item CEQ). $CEQA$ is average book equity (i.e., the sum of CEQ and lagged CEQ over 2). LEV is leverage, calculated as Compustat item LT over AT. $SIZE$ is the natural log of market value of equity (MVE), with MVE calculated as the multiplication of Compustat items PRCC_F*CSHO. BTM is the natural log of book-to-market, with book-to-market calculated as CEQ over MVE. INV is asset growth, calculated as the natural log of lagged total assets divided by twice-lagged total assets (i.e., $log(AT_{t-1}/AT_{t-2})$), following Fama and French (2020). MOM is momentum, a stock's buy-and-hold return from month $s-12$ to $s-2$, where s is the month of fiscal year end (Fama and French, 2020). ROE is the Compustat item NI scaled by CEQA. ROE_{t+1} is the leading term of ROE. OP is operating profits, calculated as REVT - COGS - XSGA, scaled by CEQA. OP_{t+1} is the leading terms of OP. ΔOP is lagged raw OP subtracted from raw OP, then scaled by lagged CEQA. $REVT$ is total revenue (Compustat item REVT) scaled by CEQA. $COGS$ is cost of goods sold (Compustat item COGS) scaled by CEQA. SGA is selling, general and administrative expenses (i.e., Compustat item XSGA minus XRD) scaled by CEQA. XRD is R&D expenses (Compustat item XRD) scaled by CEQA, imputed zero if missing.

Table 5: Realized variability of future performance on two-way sorts by OP and σ

Panel A: $\lvert\Delta OP_{t+1}\rvert$					
	$OP1$	$OP2$	$OP3$	$OP4$	$OP5$
$\sigma1$	0.104	0.081	0.086	0.104	0.139
$\sigma2$	0.119	0.078	0.075	0.090	0.123
$\sigma3$	0.143	0.094	0.083	0.086	0.110
$\sigma4$	0.177	0.115	0.104	0.098	0.124
$\sigma5$	0.277	0.153	0.133	0.133	0.184
H-L	0.174***	0.072***	0.047***	0.028***	0.045***
Panel B: $std.dev(OP_{t+1})$					
	$OP1$	$OP2$	$OP3$	$OP4$	$OP5$
$\sigma1$	0.194	0.144	0.132	0.142	0.186
$\sigma2$	0.214	0.132	0.120	0.136	0.183
$\sigma3$	0.244	0.150	0.126	0.125	0.152
$\sigma4$	0.314	0.178	0.149	0.134	0.176
$\sigma5$	0.478	0.239	0.199	0.183	0.345
H-L	0.283***	0.095***	0.066***	0.041***	0.159***
Panel C: $std.dev(ROE_{t+1})$					
	$OP1$	$OP2$	$OP3$	$OP4$	$OP5$
$\sigma1$	0.282	0.203	0.169	0.191	0.260
$\sigma2$	0.295	0.183	0.152	0.147	0.239
$\sigma3$	0.332	0.201	0.160	0.140	0.174
$\sigma4$	0.390	0.239	0.194	0.157	0.193
$\sigma5$	0.553	0.295	0.254	0.225	0.274
H-L	0.272***	0.092***	0.084***	0.034***	0.014**

*p<0.1; **p<0.05; ***p<0.01

We conduct independent quintile sorts on σ and OP and divide the sample into 5 × 5 buckets, or 25 groups of firms. σ is the standard deviation of ten predicted earnings for each firm-year. The predicted earnings is the sum of the firm's earnings components in year t multiplying the persistence parameters for each component. We have ten predicted earnings because we use persistence parameters estimated from ten previous cross-sections, $t-11$ to $t-2$. OP is operating profits, calculated as Compustat items (REVT − COGS − XSGA), scaled by CEQA. $CEQA$ is the average book equity, calculated as the sum of CEQ and lagged CEQ over 2). This table shows the realized absolute change in operating profitability, the standard deviation of realized future operating profitability, and the standard deviation of realized future ROE for each of the 25 groups of firms. Panel A is the realized absolute change in operating profitability (i.e., $\lvert\Delta OP_{t+1}\rvert$) for 25 groups. ΔOP_{t+1} is the leading term of ΔOP, where ΔOP is calculated as lagged raw OP subtracted from raw OP, then scaled by lagged CEQA. Panel B is the standard deviation of realized leading operating profitability (i.e., $std.dev(OP_{t+1})$) for 25 groups, where OP_{t+1} is the leading term of OP. Panel C is the standard deviation of realized leading accounting earnings (i.e., $std.dev(ROE_{t+1})$) for 25 groups, where ROE_{t+1} is the leading term of ROE, calculated as Compustat item NI scaled by CEQA. H-L indicates the difference between the highest ranked σ and the lowest ranked σ within the same quintile rank of OP.

Table 6: Comparison among σ, earnings volatility, earnings beta, and CAPM beta

Panel A: Descriptive statistics

	N	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
$EBeta$	116,837	0.644	3.632	−41.336	−0.616	0.309	1.618	47.457
$EVOL$	139,570	0.006	0.015	0.000	0.0002	0.001	0.004	0.336
$Beta$	125,841	1.082	0.707	−6.456	0.616	1.019	1.459	10.349
$\Delta OPVOL$	113,199	0.027	0.052	0.000	0.002	0.008	0.026	1.090
$OPVOL$	113,199	0.019	0.043	0.000	0.002	0.006	0.018	1.200

Panel B: Pearson correlations

	σ	$EBeta$	$EVOL$	$Beta$	$\Delta OPVOL$
$EBeta$	0.016***				
$EVOL$	0.061***	0.117***			
$Beta$	0.130***	0.074***	0.205***		
$\Delta OPVOL$	0.129***	0.130***	0.320***	0.139***	
$OPVOL$	0.268***	0.115***	0.324***	0.091***	0.659***

Panel C: Regressions

	Dependent variable:						
	ANNRET1						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
σ	1.027***						1.126***
	(0.250)						(0.397)
$EVOL$		0.291					0.752
		(0.889)					(1.011)
$\Delta OPVOL$			−0.044				−0.100
			(0.109)				(0.080)
$OPVOL$				0.021			0.044
				(0.121)			(0.114)
$EBeta$					−0.000		0.001
					(0.001)		(0.002)
$Beta$						0.009	0.008
						(0.022)	(0.020)
Constant	0.112***	0.088***	0.089***	0.088***	−0.171***	0.142***	0.068**
	(0.009)	(0.001)	(0.001)	(0.001)	(0.001)	(0.027)	(0.034)
Fyear FE	Y	Y	Y	Y	Y	Y	Y
SE Cluster by firm	Y	Y	Y	Y	Y	Y	Y
SE Cluster by Fyear	Y	Y	Y	Y	Y	Y	Y
Observations	113,144	71,376	71,376	71,376	68,935	63,403	40,219
Adjusted R^2	0.069	0.063	0.063	0.063	0.071	0.067	0.069
F Statistic	186.304***	109.687***	109.627***	109.589***	117.766***	101.973***	67.353***

*p<0.1; **p<0.05; ***p<0.01

This table shows the comparison among σ, earnings volatility, earnings beta, CAPM beta, volatility of operating profitability, and volatility of change in operating profitability. Variables are defined and calculated as the following. σ is the standard deviation of ten predicted earnings for each firm-year. The predicted earnings is the sum of the firm's earnings components in year t multiplying the persistence parameters for each component. We have ten predicted earnings because we use persistence parameters estimated from ten previous cross-sections, $t-11$ to $t-2$. Earnings persistence parameters for each cross-section are tabulated in Table 2. $EVOL$ is earnings volatility. Its calculation strictly follows Dichev and Tang (2009), as the variance of five years of earnings before extraordinary items (Compustat item IBC) on a rolling basis. $OPVOL$ is the analogue of $EVOL$ with the variable being OP. $\Delta OPVOL$ is the analogue of $EVOL$ with the variable being ΔOP. $EBeta$ is earnings beta. Its calculation strictly follows Ellahie (2020), as the covariance of trailing 20-quarter core earnings and the aggregate earnings. $Beta$ is CAPM beta. Its calculation strictly follows Ellahie (2020) as the covariance of trailing 60-month risk-free adjusted returns and the market risk-free rate adjusted returns. Risk-free rate is obtained from Kenneth French's library. Panel A displays their descriptive statistics, Panel B shows the Pearson correlation among σ and the five risk or uncertainty measures, and Panel C demonstrates their ability in explaining future returns. Fiscal year fixed effects are included in all models. Standard errors are double-clustered by both firm and fiscal year in all models.

Table 7: Future returns on one-way sorts

Panel A: σ				
Rank	σ	$ANNRET1$	$ANNRET2$	$ANNRET3$
1	0.019	0.004	0.016	0.022
2	0.022	0.023	0.017	0.021
3	0.026	0.027	0.028	0.023
4	0.031	0.039	0.033	0.032
5	0.049	0.050	0.039	0.033
H-L	0.030***	0.046***	0.022***	0.011**
Panel B: $SIZE$				
Rank	$SIZE$	$ANNRET1$	$ANNRET2$	$ANNRET3$
1	2.513	0.049	0.041	0.032
2	4.039	0.032	0.023	0.028
3	5.140	0.030	0.031	0.031
4	6.274	0.025	0.029	0.030
5	8.069	0.010	0.013	0.013
H-L	5.555***	−0.039***	−0.028***	−0.019***
Panel C: BTM				
Rank	BTM	$ANNRET1$	$ANNRET2$	$ANNRET3$
1	−1.508	−0.001	0.007	0.011
2	−0.795	0.012	0.019	0.024
3	−0.419	0.026	0.025	0.024
4	−0.083	0.039	0.030	0.031
5	0.451	0.067	0.054	0.044
H-L	1.959***	0.068***	0.047***	0.033***
Panel D: OP_AT				
Rank	OP_AT	$ANNRET1$	$ANNRET2$	$ANNRET3$
1	−0.016	0.016	0.017	0.014
2	0.076	0.030	0.023	0.026
3	0.140	0.030	0.034	0.029
4	0.202	0.036	0.025	0.027
5	0.338	0.030	0.031	0.033
H-L	0.354***	0.015***	0.014***	0.018***

*p<0.1; **p<0.05; ***p<0.01

We conduct one-way quintile sorts on σ, $SIZE$, BTM, and OP_AT within each fiscal year. We tabulate the mean value for each variable, as well as the mean future returns for each quintile of that variable in Panel A, B, C, and D. H-L indicates the difference between the highest and the lowest rank. $ANNRET$ is the 12 months market-adjusted (vwret) buy-and-hold returns, starting from the 4th month of a fiscal year to the 3rd month after the current fiscal year. $ANNRET1$, $ANNRET2$, and $ANNRET3$ are the one-year, two-year, and three-year leading $ANNRET$. $SIZE$ is the natural log of market value of equity (MVE), with MVE calculated as the multiplication of Compustat items PRCC_F*CSHO. BTM is the natural log of book-to-market, with book-to-market calculated as CEQ over MVE. OP_AT is operating profitability scaled by lagged total assets, with operating profitability calculated as Compustat items (REVT − COGS − (XSGA − XRD)), following Ball et al. (2015). σ is the standard deviation of ten predicted earnings for each firm-year. The predicted earnings is the sum of the firm's earnings components in year t multiplying the persistence parameters for each component. We have ten predicted earnings because we use persistence parameters estimated from ten previous cross-sections, $t-11$ to $t-2$. Earnings prediction coefficients for each cross-section are tabulated in Table 2.

Table 8: Future returns of two-way sorts

Panel A: $SIZE$ **and** σ

$ANNRET1$	$SIZE1$	$SIZE2$	$SIZE3$	$SIZE4$	$SIZE5$
$\sigma1$	0.014	−0.004	0.012	0.002	−0.017
$\sigma2$	0.056	0.024	0.015	0.021	−0.001
$\sigma3$	0.054	0.042	0.031	0.021	0.004
$\sigma4$	0.049	0.064	0.045	0.037	0.018
$\sigma5$	0.096	0.054	0.055	0.041	0.024
H-L	0.081***	0.058***	0.043***	0.038***	0.041***

Panel B: BTM **and** σ

$ANNRET1$	$BTM1$	$BTM2$	$BTM3$	$BTM4$	$BTM5$
$\sigma1$	−0.067	−0.034	−0.014	0.014	0.039
$\sigma2$	−0.031	−0.0005	0.018	0.030	0.062
$\sigma3$	−0.014	0.008	0.033	0.046	0.065
$\sigma4$	0.010	0.028	0.048	0.054	0.090
$\sigma5$	0.022	0.037	0.047	0.081	0.166
H-L	0.090***	0.072***	0.061***	0.067***	0.127***

Panel C: OP_AT **and** σ

$ANNRET1$	OP_AT1	OP_AT2	OP_AT3	OP_AT4	OP_AT5
$\sigma1$	−0.012	0.004	0.026	0.025	−0.007
$\sigma2$	0.017	0.014	0.020	0.045	0.025
$\sigma3$	0.044	0.037	0.017	0.022	0.024
$\sigma4$	0.043	0.064	0.035	0.033	0.033
$\sigma5$	0.039	0.087	0.058	0.053	0.038
H-L	0.051***	0.083***	0.031***	0.028**	0.045***

*p<0.1; **p<0.05; ***p<0.01

We conduct two-way independent quintile sorts on σ and $SIZE$, BTM, and OP_AT. σ is the standard deviation of ten predicted earnings for each firm-year. The predicted earnings is the sum of the firm's earnings components in year t multiplying the persistence parameters for each component. We have ten predicted earnings because we use persistence parameters estimated from ten previous cross-sections, $t-11$ to $t-2$. Earnings persistence parameters for each cross-section are tabulated in Table 2. H-L indicates the difference between the highest and the lowest rank. $SIZE$ is the natural log of market value of equity (MVE), with MVE calculated as the multiplication of Compustat items PRCC_F*CSHO. BTM is the natural log of book-to-market, with book-to-market calculated as CEQ over MVE. OP_AT is operating profitability scaled by lagged total assets, with operating profitability calculated as Compustat items (REVT − COGS − (XSGA − XRD)), following Ball et al. (2015). In Panel A, we divide the sample into 5 × 5 buckets, or 25 groups of firms, based on $SIZE$ and σ. $ANNRET$ is the 12 months market-adjusted (vwret) buy-and-hold returns, starting from the 4th month of a fiscal year to the 3rd month after the current fiscal year. This panel shows the realized leading one-year returns ($ANNRET1$) for each of the 25 groups of firms. H-L indicates the difference between the highest ranked σ and the lowest ranked σ within the same quintile rank of $SIZE$. In Panel B, we divide the sample into 5 × 5 buckets, or 25 groups of firms, based on BTM and σ. This panel shows the realized leading one-year returns ($ANNRET1$) for each of the 25 groups of firms. H-L indicates the difference between the highest ranked σ and the lowest ranked σ within the same quintile rank of BTM. In Panel C, we divide the sample into 5 × 5 buckets, or 25 groups of firms, based on OP and σ. This panel shows the realized leading one-year returns ($ANNRET1$) for each of the 25 groups of firms. H-L indicates the difference between the highest ranked σ and the lowest ranked σ within the same quintile rank of OP_AT.

Table 9: Return regression test controlling for time-varying characteristics

	Dependent variable:			
	$ANNRET1$		$ANNRET2$	$ANNRET3$
	(1)	(2)	(3)	(4)
σ		1.618***	1.105***	0.741**
		(0.402)	(0.308)	(0.298)
$SIZE$	−0.003	−0.003	−0.002	−0.002
	(0.004)	(0.004)	(0.004)	(0.004)
BTM	0.038***	0.047***	0.039***	0.033***
	(0.012)	(0.013)	(0.009)	(0.010)
OP_AT	0.198***	0.178***	0.119**	0.120**
	(0.030)	(0.029)	(0.052)	(0.049)
INV	−0.073***	−0.068***	−0.007	−0.012
	(0.017)	(0.017)	(0.016)	(0.015)
MOM	−0.448**	−0.427*	−0.130	0.046
	(0.228)	(0.220)	(0.142)	(0.145)
Constant	0.551**	0.499**	0.283*	−0.045
	(0.240)	(0.226)	(0.158)	(0.145)
FYear FE	Y	Y	Y	Y
SE Clustered by firms	Y	Y	Y	Y
SE Clustered by Fyear	Y	Y	Y	Y
Observations	113,144	113,144	98,692	86,780
Adjusted R^2	0.075	0.077	0.072	0.070
F Statistic	189.089***	190.369***	156.587***	136.955***

*p<0.1; **p<0.05; ***p<0.01

In this table, we show the ability of time-varying firm characteristics to explain future earnings. $ANNRET1$, $ANNRET2$, and $ANNRET3$ are the one-year, two-year, and three-year leading $ANNRET$, which is the 12 months market-adjusted (vwret) buy-and-hold returns, starting from the 4th month of a fiscal year to the 3rd month after the current fiscal year. σ is the standard deviation of ten predicted earnings for each firm-year. The predicted earnings is the sum of the firm's earnings components in year t multiplying the persistence parameters for each component. We have ten predicted earnings because we use persistence parameters estimated from ten previous cross-sections, $t-11$ to $t-2$. Earnings persistence parameters for each cross-section are tabulated in Table 2. $SIZE$ is the natural log of market value of equity (MVE), with MVE calculated as the multiplication of Compustat items PRCC_F*CSHO. BTM is the natural log of book-to-market, with book-to-market calculated as CEQ over MVE. OP_AT is operating profitability scaled by lagged total assets, with operating profitability calculated as Compustat items (REVT − COGS − (XSGA − XRD)), following Ball et al. (2015). INV is asset growth, calculated as the natural log of lagged total assets divided by twice-lagged total assets (i.e., $log(AT_{t-1}/AT_{t-2})$), following Fama and French (2020). MOM is momentum, calculated as a stock's buy-and-hold return from month $s-12$ to $s-2$ (Fama and French, 2020), with s being the month of fiscal year end. Fiscal year fixed effects are included in all models, and standard errors are double-clustered by both firm and fiscal year.