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Essays on Asset Pricing Anomalies

By

Quan Wen
Doctor of Philosophy

Business

Narasimhan Jegadeesh, Ph.D.
Advisor

Tarun Chordia, Ph.D.
Committee Member

T. Clifton Green, Ph.D.
Committee Member

Jay Shanken, Ph.D.
Committee Member

Tao Zha, Ph.D.
Committee Member

Accepted:

Lisa A. Tedesco, Ph.D.
Dean of the James T. Laney School of Graduate Studies

Date

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Quan Wen
B.A., Southwestern University of Finance and Economics, 2005

Advisor: Narasimhan Jegadeesh, Ph.D., Columbia University, 1987

An abstract of
A dissertation submitted to the Faculty of the
James T. Laney School of Graduate Studies of Emory University
in partial fulfillment of the requirements for the degree of
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Abstract

Essays on Asset Pricing Anomalies

By Quan Wen

This dissertation investigates the pervasiveness of two asset pricing anomalies: asset growth and financial distress. In the first essay ("Asset growth and stock market returns: a time-series analysis"), I examine whether the firm-level asset growth effects extend to the aggregate stock market. I find that aggregate asset growth is a robust negative predictor of future stock market returns. The return predictability is short-term but economically large, and holds both in and out-of-sample. I find that high aggregate asset growth is also associated with more optimistic analyst forecasts and subsequent downward revisions, as well as greater earnings disappointments. These results are consistent with investor over-extrapolation hypothesis, but inconsistent with the rational explanation. The time-series framework sheds new light on the source of the anomaly. In the second essay ("A new measure of investor sentiment"), I investigate the implications of aggregate asset growth in a broad set of anomalies in cross-sectional stock returns. I find that asset growth has significant predictive power for the anomaly returns, consistent with asset growth capturing investor sentiment. Most importantly, unlike the commonly used sentiment index, the predictive power of asset growth for cross-sectional stock returns is not driven by economic fundamentals or business-cycle variables. In the third essay ("Financial distress innovations and the distress-return relation", joint work with Mark Rachwalski), we examine the puzzling evidence that financial distress risk is negatively related to subsequent returns. We find that this negative relation lasts only for a year but after that financial distress risk is positively related to returns. We find that the negative relation in the first year is driven by innovations in financial risk during the prior year and not by the level of risk. The evidence indicates that distress risk commands a positive risk premium although investors initially underreact to distress risk innovations. We also find that the positive distress risk premium explains the size effect.

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First Essay: Asset Growth and Stock Market Returns: a Time-Series Analysis

Quan Wen *

Abstract

We examine whether the firm-level asset growth effects documented in Cooper, Gulen, and Schill (2008) extend to the aggregate stock market. We find that aggregate asset growth is a robust negative predictor of future stock market returns. The return predictability is short-term but economically large, and holds both in and out-of-sample. Consistent with the extended q-theory, the return predictability is stronger when investment frictions are higher. However, high aggregate asset growth is also associated with more optimistic analyst forecasts and subsequent downward revisions, as well as greater earnings disappointments. These findings suggest that the behavioral explanation for the asset growth anomaly at the firm-level extends to the market and a high level of aggregate asset growth induces an overvaluation of the stock market.

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1 Introduction

We examine whether the firm-level asset growth effects extend to the aggregate stock market. The use of asset growth is motivated by the findings of Cooper, Gulen, and Schill (2008) who show that asset growth at the firm-level is a strong and robust negative predictor of cross-sectional variation in stock returns.[1] In this paper, we construct an aggregate measure of asset growth and examine its time-series implications for the stock market returns, as well as its relation to the cross-sectional stock returns. We also study the source of the asset growth effects. We examine whether the behavioral explanation for the firm-level effects can explain our aggregate evidence.

It has been well documented that firms experiencing rapid growth by equity or debt offering subsequently have low stock returns, whereas firms experiencing contraction via spinoffs, share repurchases, and debt prepayments enjoy high future returns.[2] Cooper, Gulen, and Schill (2008) create a simple but comprehensive measure of firm growth, the total asset growth, and find that it is a strong predictor of future abnormal returns. By decomposing the total asset growth into its major components from both the investment side and financing side of the balance sheet, they find that asset growth synergistically benefits from the predictability of all subcomponents of growth, allowing asset growth to better predict the cross-section of returns relative to any single component of growth. Recent studies show that the asset growth anomaly applies to stocks of all sizes (Lipson, Mortal, and Schill (2011)), and is robust in international equity markets (e.g., Watanabe, Xu, Yao, and Yu (2013); Titman, Wei, and Xie (2012)).

There are two prominent explanations for the asset growth anomaly: one is behavioral and the other is based on risk. The rational explanation argues that the returns reflect compensation for risk, in that firms make large investments when discount rates (i.e., costs

[1]Cooper, Gulen, and Schill (2008) show that during the period from 1968 to 2003, a value-weighted portfolio of stocks in the highest growth decile underperforms the portfolio of stocks in the lowest decile by 13% per year, and such cross-sectional return difference cannot be explained by standard asset pricing models.

[2]See Cooper, Gulen, and Schill (2008) for a survey of literature.

of capital) are lower, inducing a negative relation between investment and subsequent stock returns.[3] The rational explanation implies that the investment-return relation should be stronger among firms facing higher investment and financing frictions. The behavioral explanation (Titman, Wei, and Xie (2004); Cooper, Gulen, and Schill (2008)) argues that investors excessively extrapolate on past growth when they value firms and are surprised by the subsequent performance reversal. The behavioral explanation suggests that the anomaly should be more pronounced for stocks that are difficult to arbitrage than for stocks that are easy to arbitrage. Using large proxies for investment frictions and limits-to-arbitrage, Lam and Wei (2011) provide evidence that both the investment friction effect and the limits to arbitrage effect are supported by a similar amount of evidence.[4]

The motivation for our study is twofold. First, we test whether the asset growth effects show up in aggregate data, and whether the firm-level effects extend to the aggregate level. Empirically, some firm-level effects do extend to the aggregate level, whereas others become much weaker. For example, Kothari and Shanken (1997), and Pontiff and Schall (1998) provide evidence that the aggregate book-to-market ratio positively predicts stock market returns, consistent with the firm-level evidence. Baker and Wurgler (2000) find that the poor return performance following equity issuance extends to the market level. Hirshleifer, Hou, and Teoh (2009) examine whether the firm-level accrual effects extend to the aggregate stock market and find that, in sharp contrast to firm-level findings, aggregate accruals is a significant positive predictor of stock market returns.[5] Therefore, it is an empirical question whether the asset growth effects hold in the time series at the aggregate level.

Second, we provide out-of-sample evidence about the extent to which the behavioral theory used to explain the firm-level findings extends to the aggregate level. The behavioral

[3]See Cochrane (1991, 1996), Berk, Green, and Naik (1999, 2004), Carlson, Fisher, and Giammarino (2004), Cooper (2006), Li, Livdan, and Zhang (2009), Liu, Whited, and Zhang (2009), Li and Zhang (2010), and Cooper and Priestley (2011).

[4]Lam and Wei (2011) also note that it is very difficult, if not possible, to distinguish between the rational and behavioral explanation as proxies for limits to arbitrage and proxies for investment frictions are highly correlated.

[5]Sloan (1996) document that accruals (the non-cash component of earnings) negatively predicts individual stock returns at the firm-level, and provides an earnings fixation hypothesis for the accrual effects.

explanation attributes the asset growth effects to investor over-extrapolation, so that firms with high asset growth become overvalued. As a result, a natural question to ask is, do investor's behavioral biases also affect aggregate returns? Does a high level of asset growth also induce an overvaluation of the entire stock market?

Several other studies also test whether behavioral biases at the individual level show up in aggregate data. For example, Kothari, Lewellen, and Warner (2006) test whether the post-earnings announcement drift (PEAD) documented in Bernard and Thomas (1990) extends to the aggregate level. Behavior theories often attribute the drift to investors' underreaction to earnings surprise. However, Kothari, Lewellen, and Warner (2006) find that returns are unrelated to past earning surprises at the aggregate level, suggesting that prices neither underreact nor overreact to aggregate earnings news. The findings in Kothari, Lewellen, and Warner (2006) suggest that the behavioral models on PEAD are incomplete since they provide little guidance for understanding why firm and aggregate price behavior should differ.

We find that for the 1972Q1-2011Q4 period, the level of aggregate asset growth is a strong and robust negative predictor of aggregate stock returns.[6] The magnitude of predictability is statistically significant and economically large. In the univariate regression, a one standard deviation increase in quarterly aggregate asset growth is associated with about 2.30% decline in one-quarter-ahead market returns. Small sample bias does not affect the predictive coefficient since aggregate asset growth is not a price-scaled variable and is not highly autocorrelated. The first-order autocorrelation of aggregate asset growth is 0.56, lower than the first-order autocorrelation of the dividend-to-price ratio (0.98) or the book-to-market ratio (0.98). In the multivariate regressions, we control for several other predictive variables surveyed in Goyal and Welch (2008) and find that the asset growth effect remains strong.[7] To further examine whether the conclusions are affected by

[6]Results are similar when we use yearly data from 1951-2011 as a robustness check.

[7]These predictive variables include the earnings-to-price ratio (EP), the dividend-to-price ratio (DP), the book-to-market ratio (BM), the treasury bill rate (TBL), the term spread (TMS), the default spread (DFY), the equity issuance (NTIS), the equity variance (SVAR), the investment-to-capital ratio (IK), and

small-sample bias, we follow Nelson and Kim (1993) to use a randomization procedure to generate empirical p-values for the coefficients on aggregate asset growth. Our results in the univariate and multivariate regressions confirm that aggregate asset growth is a robust negative predictor of stock market returns.

Goyal and Welch (2008) show that most models seem unstable or even spurious in predicting the equity premium: some predictors may perform well in sample but fail to beat the unconditional historical mean benchmark out of sample. We study the out-of-sample predictive power of aggregate asset growth relative to the historical mean model. For the quarterly measure of aggregate asset growth, our results suggest that it delivers significantly positive out-of-sample R^2 than the benchmark model. The out-of-sample R^2 ranges from 2.67% to 13.67% depending on the forecast period and the measure of market returns. We obtain qualitatively similar results using yearly data as additional robustness check.

To better understand the drivers of market return predictability, we follow Cooper, Gulen, and Schill (2008) and decompose total asset growth from both the investment side and financing side of the balance sheet. The decomposition is conducted at the firm-level and we construct an aggregate measure of each subcomponent of total asset growth. Our findings suggest that many of the subcomponents contribute to the asset growth effect. From an investment decomposition, growth in cash and other assets are significantly and negatively associated with future stock market returns. From an financing decomposition, growth in operating liability, equity financing, and retained earnings are associated with the strongest effects. Our decomposition results suggest that as a comprehensive measure of firm growth, asset growth synergistically benefits from the predictability of all subcomponents of growth. These findings complement the cross-sectional analysis in Cooper, Gulen, and Schill (2008) and provide additional insight as to why aggregate asset growth is a strong negative predictor of stock market returns.

consumption-wealth ratio (CAY).

We also explore the source of market return predictability and the aggregate asset growth effect. There are two prominent competing hypotheses concerning time series predictability: market inefficiency and time-variation in equilibrium expected returns. The behavioral explanation (Titman, Wei, and Xie (2004); Cooper, Gulen, and Schill (2008)) argues that investors excessively extrapolate on past growth when they value firms and are surprised by the subsequent performance reversal. We test this hypothesis and the source of return predictability in two steps. In the first step, we construct measures of aggregate earnings news based on analyst forecast revisions (Chan, Jegadeesh, and Lakonishok (1996); Chen and Zhao (2009); Da and Warachka (2009)) and examine their relation to aggregate asset growth. Changes in analyst forecasts offer an attractive way to measure earnings news because they represent changes in the market's earnings expectations. We find that high asset growth is associated with future downward revisions in the earnings forecasts, as well as negative forecast errors. These results suggest that investors' ex-ante expectation of future profits is too optimistic, compared with the realized earnings. In the second step, we examine stock returns around earnings announcements to infer expectation errors implied by the market's response to earnings news. We find that high aggregate asset growth is associated with lower earnings announcement returns, and greater earnings disappointments. To the extent that analyst forecast errors and revisions convey earnings news to the market, these findings suggest that failing to recognize the predictable component of forecast errors and revisions may result in return predictability.

Our work contributes to the literature on asset growth anomaly and time series predictability along several different dimensions: (a) to the best of our knowledge, this is the first paper to consider an aggregate measure of asset growth and study its relation to stock market returns. The evidence that aggregate asset growth negatively predicts stock market returns complements the cross-sectional analysis in Cooper, Gulen, and Schill (2008). (b) we provide new evidence that aggregate asset growth is the strongest predictor of stock market returns than the investment or financing subcomponents of growth. As a comprehensive measure of firm growth, asset growth benefits from the predictability of all subcomponents, allowing it to better predict stock market returns relative to any single component of growth. (c) we provide out-of-sample test of the behavioral explanation for the asset growth anomaly. We find that the behavioral theory used to explain the firm-level findings extends to the aggregate level. By constructing novel measures of earnings news based on analyst forecast revisions, we show that on aggregate level, asset growth negatively predicts analyst forecast errors and revisions, as well as earnings announcement returns. These results are consistent with investor over-extrapolation and hard to reconcile with the rational explanation.

The paper is organized as follows. Section 2 introduces the data and the construction of aggregate asset growth. Section 3 describes the empirical methods using predictive regression. Section 4 presents the univariate and multivariate regression results, and out-of-sample evidence of return predictability. Section 5 presents results on asset growth decomposition. Section 6 examines the source of the market return predictability and introduces the measures of aggregate earnings news. Section 7 concludes.

2 Data and Variable Construction

2.1 Data

We compile the data from several sources. We obtain quarterly market returns (including distributions) and returns on S&P500 from CRSP by compounding monthly returns in each quarter. Three measures of stock market returns are used: the value-weighted excess return (VWRET), the equal-weighted excess return (EWRET), and the S&P500 excess return (SPRET).

Our sample of firm-level accounting information and the book value of total assets are obtained from COMPUSTAT quarterly files over 1972Q1 to 2011Q4. The starting quarter is restricted by the availability of COMPUSTAT quarterly data. Following Cooper, Gulen, and Schill (2008), we define the firm-level asset growth as the the percentage change in the book value of total assets

$$AG_{j,t} = \frac{AT_{j,t} - AT_{j,t-1}}{AT_{j,t-1}}$$

We restrict our sample to firms with March, June, September, or December fiscal year ends, to ensure that fiscal quarters are aligned (Kothari, Lewellen, and Warner (2006)).[8] We exclude financial firms (SIC codes 6000 through 6999) from the sample. To avoid influential observation problems, we follow Cooper, Gulen, and Schill (2008) and winsorize the firm-level asset growth if it is outside the 1% or 99% percentile distribution.[9] We then value-weight the firm-level asset growth by market capitalization as of the end of the fiscal quarter to obtain an aggregate measure. This methodology is similar to Hirshleifer, Hou, and Teoh (2009) who construct an aggregate measure of accruals and examine its relation to stock market returns. To ensure that the accounting information is known to investors at the beginning of the return quarter, we match returns in quarter t to accounting information in quarter $t-1$.[10] Other predictive variables are obtained from Goyal and Welch (2008). These variables have been shown in the literature to have predictive power on stock market returns: the earnings-to-price ratio (EP), the dividend-to-price ratio (DP), the book-to-market ratio (BM), the treasury bill rate (TBL),the term spread (TMS), the default yield (DFY), the net equity issuance (NTIS), the equity variance (SVAR), the investment-to-capital ratio (IK), and the consumption-wealth ratio (CAY).

2.2 Descriptive Statistics

Table 1 reports the summary statistics for the market returns, aggregate asset growth, and other return predictors from 1972Q1 to 2011Q4. Panel A shows that the quarterly average

[8]The sample represents about 90% of total market value of the CRSP universe.

[9]We obtain qualitatively similar results without winsorization.

[10]For example, if quarterly asset growth is computed at the end of 1972Q1, we assume a three-month gap for this number to become public, that is, at the end of 1972Q2. The market returns of 1972Q3 will be the one-quarter-ahead aggregate returns used in the predictive regression.

of the value-weighted log excess return (VWRET) is 1.0% and the quarterly average of the equal-weighted excess return (EWRET) is 1.6%, with standard deviations of 9.1% and 12.1%. The quarterly average log excess return on S&P500 (SPRET) is 0.3%. Aggregate asset growth (AG) has an average of 3.4% and a standard deviation of 1.7%. Unlike scaled-price variables such as the earnings-to-price ratio or the book-to-market ratio which is highly persistent, aggregate asset growth shows a first-order autocorrelation of 0.56. The augmented Dickey-Fuller test rejects the null that aggregate asset growth has a unit root.

Panel B presents the correlations between one-quarter-ahead market returns and aggregate asset growth. Regardless of the measures of market returns, all simple correlations of one-quarter-ahead aggregate returns with aggregate asset growth are negative and large in magnitude, around -25%. This relation is consistent with the negative cross-sectional correlations between future stock returns and firm-level asset growth (Cooper, Gulen, and Schill (2008)). Since aggregate asset growth is also correlated with most of the other predictive variables, it is important to control for these variables in the regression when examining the predictive power of aggregate asset growth on stock market returns.

3 Empirical Methods

3.1 Predictive Regression

We run predictive regression of multi-quarter-ahead market returns R_t on variables such as aggregate asset growth or other predictors, denoted by X_{t-1},

$$R_t = \alpha + \beta X_{t-1} + u_t \quad u_t \sim i.i.d.(0, \sigma_u^2) \tag{1}$$

$$X_t = \phi + \rho X_{t-1} + v_t \quad v_t \sim i.i.d.(0, \sigma_v^2) \tag{2}$$

Stambaugh (1986), Mankiw and Shapiro (1986) show that the predictive regression coefficient is subject to an upward small-sample bias if innovations in the independent variables are negatively correlated with contemporaneous returns. For the scaled-price variables such as the dividend yield or the book-to-market ratio, the residuals of equation (1) covary negatively with the residuals of equation (2), since a large increase in return is usually associated with a decrease in the level of these variables. Stambaugh (2000) shows that in a general autoregressive framework, the bias in the OLS estimate of β in the predictive regression is proportional to the bias in the OLS estimate of ρ in the first-order autoregression for the predictive variable,

$$E(\hat{\beta} - \beta) = (\sigma_{uv}/\sigma_v^2)E(\hat{\rho} - \rho) \tag{3}$$

The downward bias in the autoregression coefficient introduces an upward bias in the predictive regression coefficient, if the residuals from two equations are negatively correlated. This bias is more pronounced when the sample size is small, or when the independent variable is highly persistent.

Aggregate asset growth is not a scaled-price variable and is not highly persistent, with a first-order autocorrelation of 0.56. Empirically we do not find that innovations in aggregate asset growth are negatively correlated with contemporaneous stock returns.[11] As a result, there is not as strong a reason to suspect that the regression coefficients in equation (1) should be affected by small sample bias. To ensure the robustness of our results, we follow Nelson and Kim (1993) to use a randomization procedure to generate empirical p-values for the coefficients on aggregate asset growth (see, e.g., Kothari and Shanken (1997); Pontiff and Schall (1998); Baker, Taliaferro, and Wurgler (2006); Hirshleifer, Hou, and Teoh (2009).) Specifically, we simulate pseudo-returns and independent variables under the null of no predictability by randomly drawing with replacement of the residual pairs from

[11] Although the lagged market return and future asset growth are positively correlated, we don't reject the hypothesis that market return and future asset growth is unrelated.

the predictive regression and the autoregression of the independent variables. We follow Kothari and Shanken (1997) and use bias-adjusted estimates and residuals. The starting value of the simulation is the initial historical value of the independent variable. This process creates a series of pseudo-independent variables and returns that have similar time-series properties as the actual series used to test return predictability, but are generated under the null of no predictability. This randomization procedure is conducted for 5,000 iterations, and an empirical distribution of the slope estimates is obtained. Randomization or bootstrap p-value is then the fraction of the 5,000 simulated slopes that are further away from zero than the actual slope estimate.

4 Regression Results

4.1 Univariate Regression

Table 2 presents the time series regression of multi-quarter-ahead stock market returns on aggregate asset growth. In each panel, we employ three measures of stock market returns: the value-weighted excess return, the equal-weighted excess return, and the S&P500 excess return. The independent variable is standardized to have zero mean and unit variance, in order to interpret the economic significance of the predictability. Newey-West t-statistics are reported. We also report the bootstrap p-values following Nelson and Kim (1993).

Over the period 1972Q1-2011Q4, aggregate asset growth is a strong negative predictor of the market returns, with a slope estimate of -2.27% ($t = -3.69$) for the value-weighted excess market return and -2.61 ($t = -3.04$) for the equal-weighted excess market return. This magnitude is economically large: a one standard deviation increase in aggregate asset growth is associated with about 2.61% decline in one-quarter-ahead value-weighted market returns. For returns on S&P500, the slope estimates are smaller but still economically large: -2.05 ($t = -3.53$). The adjusted R^2 varies from 4.10% to 5.75% for all specifications. Randomization p-values confirm that aggregate asset growth remains a negative and significant predictor of the market returns. This finding is not surprising since aggregate asset growth is not a scaled-price variable and not highly autocorrelated. The return predictability is relatively short-term and becomes weaker for two-quarter-ahead stock market returns. For three and four-quarter ahead returns, the results are generally not significant.

In sum, Table 2 indicates that the time series relation between aggregate asset growth and stock market returns is consistent with the strong negative cross-sectional relationship in Cooper, Gulen, and Schill (2008). To provide further robustness check on whether the predictive coefficients are affected by small sample bias, Figure 1 presents the density plots of the predictive coefficients from regressing simulated market returns on aggregate asset growth under the null of no predictability. The randomization procedure is conducted for 5,000 iterations. Randomization p-value is computed based on the empirical distribution of estimated slopes. When we compare the average estimated coefficients from simulation and the actual predictive coefficients, the results confirm that the significance of the bootstrap p-values: small-sample bias only accounts for, at most 1% of the actual slope coefficient estimate.

4.2 Multivariate Regression

To examine whether aggregate asset growth has incremental power to predict market returns, we include in the regression other predictors surveyed in Goyal and Welch (2008). EP is the log earnings-to-price ratio. DP is the log dividend-to-price ratio. BM is the book-to-market ratio. TBL is the 30-day T-bill rate. TMS is the difference between long term yield on government bonds and the Treasury-bill. DFY is the difference between BAA and AAA-rated corporate bonds. NTIS is the net equity issuance. SVAR is the equity variance. IK is the investment to capital ratio. CAY is the consumption-wealth ratio.

Table 3 presents the multivariate regression results of multi-quarter-ahead market return on aggregate asset growth and other control variables. Panel A reports the results for one-quarter-ahead stock market returns and Panel B reports the results for the two-quarter-ahead returns. In each panel we report the Newey-West t-statistics. The coefficients are multiplied by 100 and expressed in percentage. All independent variables are standardized with zero mean and unit variance. We find that the coefficients on aggregate asset growth remain negative and significant. Interestingly, the magnitude of the coefficients on aggregate asset growth are almost the same or even larger than those in the univariate regression: a one standard deviation increase in aggregate asset growth is associated with about 2.81% decrease in one-quarter-ahead market returns. These results suggest that adding other control variables has little effect on the ability of aggregate asset growth to predict returns. On the other hand, the adjusted R^2s in the multivariate regression range from 8.63% to 11.50%, higher than those in the univariate regression, suggesting that the inclusion of other control variables does add incremental power to the regression. In Panel B, results are qualitatively similar: aggregate asset growth remains a negative and significant predictor of aggregate market returns.

4.3 Out-of-sample Results

In this section we examine the out-of-sample performance of aggregate asset growth in predicting one-year-ahead market returns. Goyal and Welch (2008) show that most models seem unstable or even spurious in predicting the equity premium: some predictors may perform well in sample but fail to beat the unconditional historical mean model out-of-sample. We study the out-of-sample predictive power of aggregate asset growth relative to the historical average benchmark. The baseline model contains only an intercept and generates stock return forecasts equal to the historical mean. We use the OOS R^2 statistic, following Campbell and Thompson (2008), as our out-of-sample forecast evaluation,

$$R^2_{OS} = 1 - \frac{\sum_{t=1}^{T}(\hat{r}_t - r_t)^2}{\sum_{t=1}^{T}(\overline{r}_t - r_t)^2} \tag{4}$$

where T is the out-of-sample window, $\sum_{t=1}^{T}(\overline{r}_t - r_t)^2$ is the mean square forecast error of the historical average benchmark model, and $\sum_{t=1}^{T}(\hat{r}_t - r_t)^2$ is the mean square forecast error of the predictive variables. If $R^2_{OS} > 0$, the model with our predictive variables outperform the historical average forecast. To evaluate the statistical significance of R^2_{OS}, we use Clark and West (2007) out-of-sample MSPE-adjusted statistic, which corresponds to a one-sided test of the null hypothesis $R^2_{OS} = 0$ against the alternative hypothesis $R^2_{OS} > 0$. The MSPE-adjusted statistic for one-step ahead forecast is defined as,

$$MSPE_{adj} = \hat{f}_{t+1} = (r_{t+1} - \overline{r}_{t+1})^2 - [(r_{t+1} - \hat{r}_{t+1})^2 - (\overline{r}_{t+1} - \hat{r}_{t+1})^2] \tag{5}$$

where r_{t+1} is the actual return, $\overline{r}_{t+1}$ is the historical average and $\hat{r}_{t+1}$ is the forecast made by predictive variables. By regressing $\hat{f}_{t+1}$ on a constant and using the resulting t-statistic for a zero coefficient, we are able to test for equal MSPE across the model with predictive variables and the historical average benchmark model. Similar to Goyal and Welch (2008), we generate out-of-sample forecasts using a recursive (expanding) estimation window. This out-of-sample forecasting exercise simulates the situation of an investor in real time.

Table 4 reports the out-of-sample performance of predictive variables across different forecasting periods. We have a long out-of-sample forecasting period 1985Q1-2011Q4, the recent forecast period 1990Q1-2011Q4, the very recent period 1995Q1-20114, and the most recent period 2000Q1-2011Q4. In Panel A where the forecast period is 1985Q1-2011Q4, the model using aggregate asset growth as a predictor has better out-of-sample performance than the historical average benchmark, regardless of how market returns are measured. In comparison, all other predictive variables underperform the historical average benchmark except for CAY. For the subperiod 1990Q1 to 2011Q4, all the out-of-sample R^2s associated with aggregate asset growth are positive and significant at 5% using Clark and West (2007) MSPE-adjusted statistic. The magnitude of out-of-sample R^2s ranges from 2.31% to 6.00%, higher than those in Panel A. The improvement in the out-of-sample R^2 could be due to a longer estimation window we use for subperiod 1990Q1 to 2011Q4 to allow more stable point estimates as our out-of-sample forecasts. For the very recent subperiod 1995Q1 to 2011Q4, aggregate asset growth still delivers better out-of-sample performance than the historical average. In sum, Table 4 confirms that aggregate asset growth is a robust negative predictor of stock market returns.

To further investigate the out-of-sample performance, Figure 2 decomposes the mean squared forecast error into the sum of forecast variance and the squared forecast bias, and presents the scatterplots for each predictive variable. The dotted (horizontal) and dashed (vertical) line for each out-of-sample period corresponds to the forecast variance and squared forecast bias of the historical average benchmark, respectively. The forecast variance is scaled by 100. The area to the left of the dashed line indicates the region in which the forecast bias is less than the historical average. The area above the dotted line indicates the region in which the forecast bias is larger than the historical average. Figure 2 shows that the historical average benchmark has the lowest forecast variance among all the predictors. Consistent with Goyal and Welch (2008), many of the existing predictors fail to deliver significant out-of-sample performance, since they have larger forecast variance as well as forecast bias. However, asset growth has the smallest squared forecast bias among all the predictive variables, which contributes to the positive and significant out-of-sample performance.

5 Decomposing Asset Growth

Total asset growth is a comprehensive measure of firm growth. To better understand the drivers of return predictability, we follow Cooper, Gulen, and Schill (2008) and decompose firm-level asset growth from both the investment side and financing side of the balance sheet. The asset investment decomposition is as follows:

$$\text{Total asset growth (AG)} = \Delta\text{Cash} + \Delta\text{CurAsst} + \Delta\text{PPE} + \Delta\text{OthAssets} \tag{6}$$

where ΔCash is the cash growth, ΔCurAsst is the growth in noncash current assets, ΔPPE is the growth in property, plant, and equipment, and ΔOthAssets is the growth in other assets. Similarly, we construct an asset financing identity as follows:

$$\text{Total asset growth (AG)}=\Delta\text{OpLiab} + \Delta\text{RE} + \Delta\text{Stock} + \Delta\text{Debt} \tag{7}$$

where ΔOpLiab is the growth in operating liabilities, ΔRE is the growth in retained earnings, ΔStock is the growth in equity financing, ΔDebt is the growth in debt financing. We scale each subcomponent on the right-hand side of both decomposition equations by the previous quarter's total asset value, in order to maintain the total asset growth identity. To obtain an aggregate measure of each subcomponent of asset growth, we take value-weighted average, using market capitalization at the end of quarter $t-1$ as weights.

Table 5 reports the coefficients and t-statistics from time series regressions of one-quarter-ahead market returns on the subcomponents of asset growth, from an investment and a financing decomposition. From an asset investment decomposition, growth in cash and other assets are associated with significant negative coefficients. In Panel A where the dependent variable is the value-weighted market excess return, the coefficient on ΔCash is -1.91 ($t=-2.41$) and the coefficient on ΔOthAssets is -1.37 ($t=-2.01$). Since all of the independent variables are standardized to have zero mean and unit variance, these coefficients are economically large as well. A coefficient of -1.91 on ΔCash implies that a one standard deviation increase in growth in cash is associated with about 1.91% decrease in one-quarter-ahead value-weighted market excess returns.

From an asset financing decomposition, growth in operating liability and equity financing are associated with significant negative coefficients. In Panel A, the coefficient on ΔOpLiab is -1.85 ($t=-2.09$) and the coefficient on ΔStock is -1.47 ($t=-2.51$). These results are consistent with the findings of Baker and Wurgler (2000) who find that equity issuance is a strong negative predictor of stock market returns. We obtain qualitatively similar results in other panels. As a final test, we regress one-quarter-ahead market returns on aggregate asset growth and each of the subcomponents to identify whether the effect of any of the components subsumes the asset growth effect. In untabulated results, we find that the coefficient on asset growth is the strongest across all investment and financing components, and provides a partial explanation for the equity issuance effect.

Overall, the decomposition results in Table 5 suggest that as a comprehensive measure of firm growth, asset growth synergistically benefits from the predictability of all subcomponents of growth, allowing aggregate asset growth to better predict stock market returns relative to any single component of growth. These findings complement the cross-sectional analysis in Cooper, Gulen, and Schill (2008) and provide additional insight as to why aggregate asset growth is a strong negative predictor of stock market returns.

6 The Source of the Asset Growth Effect

This section examines the source of market return predictability by aggregate asset growth. There are two prominent competing hypotheses concerning time series predictability: market inefficiency and time-variation in equilibrium expected returns. The behavioral explanation (Titman, Wei, and Xie (2004); Cooper, Gulen, and Schill (2008)) argues that investors excessively extrapolate on past growth when they value firms and are surprised by the subsequent performance reversal. Following this logic, if investors overreact to past firm performance, then we should expect a negative relation between earnings news and aggregate asset growth.[12] As a result, we study whether the behavioral explanation for asset growth anomaly at the firm level extends to the market in two steps. In the first step, we show that aggregate asset growth is a robust negative predictor of aggregate analyst forecast errors and forecast revisions. In the second step, we examine stock returns around earnings announcements to infer expectation errors implied by the market's response to earnings news. We show that aggregate asset growth negatively predicts announcement returns.

[12]Earnings news is defined as the unexpected changes in earnings, or earnings surprises.

6.1 Tests of Q-theory with Investment Frictions

The extended q-theory by Li and Zhang (2010) suggests that investment frictions should steepen the investment-return relation. With frictions, investment entails deadweight costs, which cause investment to be less elastic to changes in the discount rate than when frictions are absent. The empirical implication is that a given change in investment corresponds to a larger change in the discount rate, meaning that the expected investment-return relation is steeper when there are higher investment frictions. Given that investment frictions vary with the business cycle, the extended q-theory predicts that the return predictability should be stronger in recessions than in expansions, since recessions create financial constraints that limit real investment.

Table 6 reports the results when aggregate asset growth is interacted with business cycles. We use recessions and expansions as a proxy for aggregate investment frictions, consistent with time-varying external finance costs. Recession is a dummy variable which equals one if in recession and zero otherwise. The results suggest that the return predictability is almost three times as large in business recessions as in expansions. In Panel A, for one-quarter-ahead stock market returns, the coefficient on the interaction term is -5.85% for the value-weighted excess return, almost twice larger than the coefficient in expansions (-1.82%). However, proxies for investment frictions and proxies for limits-to-arbitrage are highly correlated (Lam and Wei (2011)). These tests may lack power to distinguish between the rational and mispricing explanations. As a result, we directly test the behavioral explanations of the asset growth effect using analyst earnings forecasts.

6.2 Tests of Investor Over-extrapolation: Asset Growth and Earnings News

6.2.1 Measuring Earnings News

We construct measures of aggregate earnings news (surprises) based on analyst forecast revisions (e.g., Chan, Jegadeesh, and Lakonishok (1996); Chen and Zhao (2009); Da and Warachka (2009)). Changes in analyst forecasts offer an attractive way to measure earnings news because they represent changes in the market's earnings expectations. To empirically measure earnings news, we utilize revisions in analysts' consensus earnings forecasts. Security analysts play an important role as information intermediaries between firms and investors and their forecasts are an important set of expectations regarding future cash flows. Consistent with this view, serval studies document a strong relationship between analyst forecast revisions and recommendation changes and stock returns (e.g., Givoly and Lakonishok (1979); Lin and McNichols (1998); Ivkovic and Jegadeesh (2004); Jegadeesh, Kim, Krische, and Lee (2004); Kirk (2011)). As a result, analyst forecast revisions are likely to capture the unexpected change in earnings, or earnings news. For robustness checks, we also use realized forecast errors as an additional measure of earnings news.

Our sample of analyst earnings forecast is obtained from the Institutional Broker's Estimate System (IBES) summary unadjusted file. The IBES sample consists of all firm-quarters for which there exist FY1 (one-quarter-ahead) earnings consensus forecasts. The IBES unadjusted forecasts are not adjusted by share splits thus mitigate the rounding errors as detailed in Diether, Malloy, and Scherbina (2002). To obtain an aggregate measure of analyst forecast revisions or forecast errors, we start by measuring the firm level consensus forecast. Forecast error (FE), is defined as the realized difference between earnings as reported in Compustat and the prevailing consensus forecasts, scaled by price per share.[13]

[13] We use the EPS from Compustat rather than IBES since the its realized EPS tends to suffer from significant data errors (Hong and Kacperczyk (2010)). Our analysis is conducted on an earnings-per-share (EPS) basis.

Following So (2013), throughout the paper we define earnings as income before extraordinary items (IB) after substracting special items (SPI) multiplied by 0.65, where the 0.65 reflects an assumed tax rate of 35% as in Bradshaw and Sloan (2002). This facilitates a comparison between IBES and Compustat definition of earnings. The difference exists because IBES earnings and analyst forecasts often omit nonrecurring items that are included in GAAP earnings (e.g, Philbrick and Ricks (1991); Bradshaw and Sloan (2002)). To avoid influential observation problems, we winsorize the earnings if they are outside the 0.5 or 99.5 percentile each year. Forecast revision (REV), is defined as the change in consensus forecasts quarter-by-quarter. We restrict our sample to firms with March, June, September, or December fiscal year ends and we exclude financial firms (SIC codes 6000 through 6999) from the sample. We then equal- or value-weight the firm-level forecast errors by the market capitalization as of the end of the fiscal quarter to obtain an aggregate measure. Our final sample of quarterly aggregate forecast errors or revisions starts from 1976Q1 to 2011Q4.

6.2.2 Predicting Realized Forecast Errors and Forecast Revisions

Table 7 presents the results from regressing aggregate realized forecast revisions (REV) or forecast errors (FE), on aggregate asset growth with different lags,

$$\begin{aligned} REV_t &= \alpha + \beta AG_{t-\tau} + \gamma REV_{t-1} + u_t \\ FE_t &= \alpha + \beta AG_{t-\tau} + \gamma FE_{t-1} + u_t \end{aligned} \tag{8}$$

where FE is the realized analyst forecast errors and REV is the forecast revisions. AG is the aggregate asset growth. τ represents different time horizons and τ=1, 2, 3, or 4 quarters. It is well documented that analyst forecast errors tend to be persistent (Abarbanell (1991); Lys and Sohn (1990)). Therefore, current earnings forecasts are more likely to be optimistic (pessimistic) if they were optimistic (pessimistic) during the recent past. To address this concern and control for the persistence in analyst forecast errors or revisions, we include past forecast errors or revisions as a control variables.

Panel A of Table 7 contain the regression results where the dependent variable measures aggregate forecast revisions. The coefficients on aggregate asset growth are negative in general and most are significant at 5% level, indicating that analysts tend to revise their earnings forecasts down in the direction of high past aggregate asset growth. Panel B reports the results where the dependent variable is the aggregate forecast errors. In Panel B, the coefficients on aggregate asset growth are all negative and significant for all lags, consistent with asset growth offering explanatory power for the realized analyst forecast errors. For example, focusing on one period lagged asset growth ($\tau = 1$), the coefficient on asset growth is -0.24 ($t = -3.00$) using equal-weighted forecast errors and -0.49 ($t = -2.45$) using value-weighted forecast errors.

Figure 3 plots the quarterly aggregate asset growth (AG), analyst forecast errors (FE) and revisions (REV). The figure shows a counter-cyclical pattern between asset growth, analyst forecast errors and revisions. In periods where we observe high asset growth, analyst subsequently make downward revisions and their forecast errors are more negative. Overall, this pattern is consistent with the regression results.

To summarize the results up to this point, we find that aggregate asset growth negatively predicts analyst forecast errors and forecast revisions. These results suggest that investors may extrapolate high growth into future so that their ex-ante expectation of future profits is too optimistic, and they are subsequently surprised by the earnings reversal. To the extent that analyst forecast errors and revisions convey earnings news to the market, these findings suggest that failing to recognize the predictable component of forecast errors and revisions may result in return predictability.

6.3 Asset Growth and Earnings Announcement Returns

Although aggregate asset growth is a negative predictor of analyst forecast errors and forecast revisions, we cannot be sure that investors are surprised by the subsequent earnings reversal. As a result we examine stock returns around earnings announcements to infer expectation errors implied by the market's response to earnings news (e.g., Bernard and Thomas (1990); La Porta (1996)). The research design is to construct an aggregate measure of abnormal earnings announcement returns and examine its relation with aggregate asset growth. Our time-series analysis complements the cross-sectional study in Cooper, Gulen, and Schill (2008), who find that for high (low) growth firms, the earnings announcement day returns will tend to be lower (higher) than nonearnings announcement day returns as investors are surprised by the subsequent unanticipated bad (good) news.

To construct aggregate earnings announcement returns we obtain the earnings announcement dates from the quarterly COMPUSTAT and daily returns from CRSP. For each S&P 500 firm from 1972Q1 to 2011Q4, we compute the abnormal return as the difference between daily stock return and the expected return using CAPM, Fama-French three factor, or Carhart (1997) four factor model.[14] The estimation window is [-250, -10] and two different event windows are used: [-1, +1] or [-2, +2], where day 0 is the earnings announcement date.[15] We require 10 days gap between estimation window and event window to ensure the estimators for the parameters of the benchmark model are not influenced by the event-related returns. We then accumulate the abnormal returns for each firm over the event window. The aggregate quarterly CARs is computed as the equal- or value-weighted average CARs of firms whose earnings announcements fall into the corresponding quarter. Finally, we have a quarterly time series of CARs around earnings announcements and we examine its relation to aggregate asset growth,

[14] We focus on S&P500 firms since they are larger firms in the economy with higher levels of analyst coverage. In addition, S&P500 firms represent a relatively stable portion of the aggregate economy over time. We obtain qualitatively similar results using the entire IBES firms.

[15] The results are robust if we use estimation window [-360, -10] or use a five day gap between estimation window and the event window.

$$CAR_t = \alpha + \beta AG_{t-\tau} + u_t, \quad \tau = 1, 2, 3, 4 \tag{9}$$

where CAR is the quarterly cumulative abnormal returns and AG is the aggregate asset growth. Table 8 reports the regression results using two event windows. Panel A reports the results for the event window [-1,+1] and Panel B reports the results for the window [-2,+2]. Table 8 suggests that aggregate asset growth is negatively related to future announcement returns, and this effect is particulary strong for announcement-window returns during the second and third quarter. To interpret the economic significance the independent variable is standardized to have zero mean and unit variance, and the coefficients are multiplied by 100 and expressed in percentage. In Panel A.1 using equal-weighted CARs and Carhart four factor model as the benchmark, the coefficient on aggregate asset growth is -0.05, indicating that a one standard deviation increase in aggregate asset growth is associated with 5 basis points decrease in returns during the earnings announcement window on average. Note that the mean of the equal-weighted CARs using Carhart four factor model in Panel A.1 is about 12 basis points, the 5 basis points decrease is approximately 42% lower below the mean.

Table 8 also demonstrates that aggregate asset growth does not significantly predict announcement returns during the third or fourth quarterly earnings announcement. This suggests a substantial portion of expectation errors embedded in prices are gradually corrected during non-announcement periods after the third quarter. Overall, our results are consistent with the interpretation that investors are surprised by subsequent bad (good) earnings news associated with high (low) aggregate asset growth. The results in Table 8, combined with the findings that asset growth predicts analyst forecast errors and revisions, suggest that investors overreact to changes in aggregate earnings implied by asset expansions or contractions, and are subsequently surprised by the earnings reversal.

7 Conclusions

We examine the ability of an aggregate asset growth to forecast stock market returns. We test whether the firm-level asset growth effects documented in Cooper, Gulen, and Schill (2008) extend to the market level, and whether the behavioral explanation for the firm-level effects can explain our aggregate evidence. We find that the level of aggregate asset growth is a strong and robust negative predictor of aggregate stock returns. The magnitude of the predictability is statistically significant and economically large. The results hold in and out-of-sample. Our time series analysis complements the cross-sectional analysis in Cooper, Gulen, and Schill (2008).

We also explore the source of the market return predictability. We find that aggregate asset growth negatively predicts analyst forecast errors and revisions, as well as earnings announcement returns, lending support to the behavioral explanation. These results suggest that investors excessively extrapolate past growth into future and are subsequently surprised by the earnings reversal. Overall, our results suggest that investors overreact to asset growth and a high level of aggregate asset growth induces an overvaluation of the stock market. Our work contributes to the source of asset growth anomaly, the market return predictability, and the role of investor sentiment in the cross-section of stock returns.

Second Essay: A New Measure of Investor Sentiment

Quan Wen*

Abstract

We propose a new measure of investor sentiment using aggregate asset growth. Our measure lines up well with major fluctuations in investor sentiment and better captures investor sentiment relative to any individual components of growth. Aggregate asset growth captures investors' biased belief about expected future cash flows, consistent with the nature of investor sentiment described in Baker and Wurgler (2006). Most importantly, unlike the commonly used sentiment index, the predictive power of our measure for cross-sectional stock returns is not driven by economic fundamentals or business-cycle variables.

*Goizueta Business School, Emory University, 1300 Clifton Rd., Atlanta, GA 30322, USA.

1 Introduction

In recent years an extensive literature has focused on the role of investor sentiment in asset pricing.[1] Investor sentiment, defined broadly, is a belief about future cash flows and investment risks that is not justified by the facts at hand (Baker and Wurgler (2006)). Although sentiment is not observable and difficult to measure, a large body of research relies on the composite sentiment index from Baker and Wurgler (2006) and interprets it as a behavioral variable unrelated to economic fundamentals. However, a large percent of the total variation in this sentiment index is shown to be strongly correlated with contemporaneous and well-known business cycle variables. Sibley, Xing, and Zhang (2012) show that the power of the sentiment index to predict cross-sectional stock returns is mainly driven by the business-cycle component, while the component unrelated to business cycle conditions has little significance. Their results cast doubt on the information content of the widely-used sentiment measure which contains rich information about economic fundamentals or rational risk premia, and might not be a pure behavioral measure of sentiment.[2] As a result, it still remains a challenge to measure investor sentiment.

In this paper, we propose a new measure of investor sentiment that aims to capture investors' behavioral biases rather than economic fundamentals. We construct an aggregate measure of asset growth and examine its relation to investor sentiment.[3] There are several reasons why aggregate asset growth might be influenced, and mirrors investor sentiment. First of all, two major components of asset growth include equity financing and corporate

[1] For example, Baker and Wurgler (2006) examine the role of market-wide sentiment in the cross-section of stock returns. Lemmon and Portniaquina (2006) explore the relation between consumer confidence and the small-stock premium. Stambaugh, Yu, and Yu (2012) examine the role of sentiment in a broad set of anomalies in cross-sectional stock returns. Da, Engelberg, and Gao (2013) use daily internet search volume from millions of households to reveal market-level sentiment.

[2] As noted in Sibley, Xing, and Zhang (2012), it is still likely that sentiment could be a general equilibrium phenomenon that causes business cycle variables to fluctuate. Nevertheless, it is empirically difficult to test the direction of causality between sentiment measures and business cycle variables without a full-fledged general equilibrium model.

[3] Aggregate asset growth is computed as the value-weighted average of firm-level asset growth (Wen (2013)). The firm-level asset growth, defined in Cooper, Gulen, and Schill (2008), is the period-by-period growth rate of the book value of total assets.

investments, which have been shown in the literature to be closely linked to investor sentiment. For example, Baker and Wurgler (2000) show that equity share in new issues is linked to market timing and investor sentiment, whereas Arif and Lee (2013) find that corporate investments mirror some aspect of market-wide investor sentiment.[4] Second, unlike equity financing or corporate investments, asset growth is a comprehensive measure which may synergistically benefits from all subcomponents of growth. As a result, aggregate asset growth may better capture investor sentiment relative to any single component of growth.

We find that aggregate asset growth increases significantly following high investor sentiment. This is due to the strong effects of sentiment on the subcomponents of aggregate asset growth. From the financing decomposition, sentiment has the strongest effects on growth in equity financing which increases 200% (300%) in a one-quarter (two-quarter) horizon following high sentiment periods. From the investment decomposition, investor sentiment has strong effects on cash growth and growth in other assets (i.e., corporate investments). These findings suggest that the increase in investment in high sentiment states is in large part financed by an increase in external financing.

Our evidence also shows that aggregate asset growth captures major fluctuations in investor sentiment and it lines up well with the anecdotal accounts of bubbles and market crashes. For example, it reached a small peak in the biotech bubble of the early 1980s, and another peak in 1989Q2, perhaps associated with the end of President Ronald Reagan's Great Expansion or Reagan-era optimism. Aggregate asset growth fell in early 1990s during the Gulf war but rose again in late 1990s, reaching its peak during the tech bubble period. For the most recent periods, aggregate asset growth rose during the housing bubble and sub-prime securitization around early 2006. The index was generally low after the housing bubble bust but it rebounded back in early 2008 when U.S. government prepared to launch a series of bailouts to help firms in the sub-prime mortgage crisis. Aggregate asset growth reached the lowest point during the most recent financial crisis in early 2009.

[4] They find that corporate investments peak during periods of high investor sentiment, and provide further evidence that these investments might not be fully efficient.

If aggregate asset growth captures investor sentiment, then we should expect to observe stock returns consistent with its implications. We conduct a series of analyses to examine the role of aggregate asset growth in the stock market. One implication of investor sentiment is the market return predictability (Baker and Wurgler (2007)). We test whether aggregate asset growth provides new information about investor optimism (or pessimism) above and beyond the traditional sentiment measure. Our results suggest that aggregate asset growth remains a powerful predictor of stock market returns after controlling for investor sentiment index in Baker and Wurgler (2006). However, the predictive power for stock market returns is generally weak for the *individual components* of aggregate asset growth. These results suggest that aggregate asset growth better captures investor sentiment relative to any single component of growth, that is, the equity share in in issues (Baker and Wurgler (2000)) and corporate investments (Arif and Lee (2013)).

We test whether aggregate asset growth captures investors' biased belief about expected future cash flows, which is the nature of investor sentiment as described in Baker and Wurgler (2006). To the extent that managers are influenced by the same wave of "irrational exuberance" in a high sentiment period, their assessment of expected future cash flows might be excessively optimistic. If our results are driven by systematic errors in managerial expectations related to future performance, we would expect a negative relation between aggregate asset growth and these variables. We conduct a series of analyses by focusing on the association between aggregate asset growth and measures of ex-post fundamental performance. We find strong evidence that higher aggregate asset growth is associated with more negative analyst forecast errors and downward revisions. In other words, higher asset growth is associated with more optimistic ex-ante expectations of future corporate earnings, while the earnings realizations are lower in the future.

To formally test that aggregate asset growth captures investor sentiment, we examine its relation to the earnings announcement returns. We might expect that the average earnings announcement return would tend to be inversely related to investor sentiment, since errors in earnings expectations should account for some of the sentiment effects. If investors fail to anticipate the decrease in earnings following periods of high asset growth, they should be subsequently surprised by the earnings reversal when earnings are announced. Our results confirm all these findings. Aggregate asset growth is negatively related to future announcement returns, and this effect is particulary strong for announcement-window returns during the second and third quarter. However, the sentiment index in Baker and Wurgler (2006) *is not* associated with announcement returns. This result is surprising and casts doubt on the information content of the commonly used sentiment index. Overall, our evidence suggests that investors are not fully anticipating the lower earnings that are announced after periods of high aggregate asset growth. To the extent that short-window earnings announcement returns capture earnings surprise, aggregate asset growth seems to capture investors' errors in expectations.

Our last test examines the role of aggregate asset growth in a broad set of anomalies in cross-sectional stock returns, in a framework similar to Stambaugh, Yu, and Yu (2012). Stambaugh, Yu, and Yu (2012) derive three empirical predictions on investor sentiment and anomaly returns. First, the anomalies, to the extent they reflect mispricing, should be more prevalent when sentiment is high. Second, the returns on the short-leg portfolio of each anomaly should be lower following high sentiment, since the stocks in the short leg are relatively overpriced. Third, investor sentiment should not greatly affect returns on the long-leg portfolio of each anomaly. Our findings confirm all these predictions using aggregate asset growth. In the univariate regression, the coefficients on aggregate asset growth are statistically significant for nine of the eleven anomalies. More importantly, the predictive power of aggregate asset growth for anomaly returns does not weaken after we control for Baker and Wurgler (2006) sentiment index, which has been shown to contain rick information about economic fundamentals or rational risk premia (Sibley, Xing, and Zhang (2012)). These results suggest that the predictive power of aggregate asset growth for cross-sectional stock returns is less likely to be related to economic fundamentals or business-cycle variables.

Our results are not driven by the business cycle variations. To assess the potential for a risk-based explanation of our results , we orthogonalize aggregate asset growth index on a few macrovariables, and control for an additional set of macro-related variables that may be correlated with risk premium. We obtain qualitatively similar results.

Our work contributes to the literature on investor sentiment along several different dimensions. First, we propose a new measure of investor sentiment that aims to work as a behavioral variable unrelated to economic fundamentals, while the commonly used sentiment index seems to capture rich information about business cycle variables and might not be a pure behavioral measure of sentiment (Sibley, Xing, and Zhang (2012)). Second, we provide evidence that aggregate asset growth better capture investor sentiment relative to any single component of growth, that is, the equity issuance (Baker and Wurgler (2000)) and corporate investments (Arif and Lee (2013)). Third, we provide evidence that high aggregate asset growth is associated with more optimistic ex-ante expectations of future corporate earnings, while investors are subsequently surprised by the earnings reversal when earnings are announced. This is consistent with the nature of investor sentiment described in Baker and Wurgler (2006) in that sentiment should capture investors' biased belief about future cash flows. Fourth, we provide new evidence that aggregate asset growth predicts cross-sectional stock returns and the predictability is less likely to be related to economic fundamentals or business-cycle variables.

The paper is organized as follows. Section 2 introduces the data and the construction of aggregate asset growth. Section 3 describes the time-series behavior of aggregate asset growth. Section 4 presents empirical findings on asset growth and stock market returns. We also provide evidence that aggregate asset growth better captures investor sentiment than any individual components of growth. Section 5 examines aggregate asset growth and analyst forecasts. Section 6 examines aggregate asset growth and earnings announcement returns. Section 6 presents evidence on the role of aggregate asset growth in a broad set of anomalies in cross-sectional stock returns. Section 7 concludes.

2 Data and Variable Construction

2.1 Market returns

We obtain quarterly market returns (including distributions) from CRSP. We measure market returns as the value-weighted excess return.[5]

2.2 Accounting Data

Our sample of firm-level accounting information and the book value of total assets are obtained from COMPUSTAT quarterly files (from 1972Q1 to 2010Q4). The starting period is restricted by the availability of COMPUSTAT accounting data for the book value of total assets. Following Cooper, Gulen, and Schill (2008) and Wen (2013), we start by constructing the firm-level asset growth, computed as the quarter-on-quarter percentage change in the book value of total assets. We restrict our sample to firms with March, June, September, or December fiscal year ends, to ensure that fiscal quarters are aligned (Kothari, Lewellen, and Warner (2006)).[6] We exclude financial firms (SIC codes 6000 through 6999) from the sample. We then value-weight the firm-level asset growth by market capitalization as of the end of the fiscal quarter to obtain an aggregate measure.

2.3 Investor Sentiment

We obtain BW sentiment index (Baker and Wurgler (2006, 2007)) from Jeff Wurgler's website.[7] We also use the Michigan Consumer Sentiment Index (MCSI) from FRED St. Louis. as a proxy for investor sentiment(e.g., Lemmon and Portniaquina (2006); Bergman

[5] In untabulated results, we conduct robustness checks using other measures of market returns including the value-weighted real return, the S&P500 excess return, and the S&P500 real return.

[6] The sample represents about 90% of total market value of the CRSP universe.

[7] See http://people.stern.nyu.edu/jwurgler/.

and Roychowdhury (2008)).[8] The BW sentiment index captures the market-wide sentiment of investors in the financial market, while the focus of MCSI is mainly on the sentiment among consumers in the product market. The quarterly aggregate asset growth and the BW sentiment index span a period from 1972Q1 to 2010Q4, while the MCSI starts from 1978Q1.

2.4 Macro Variables

To capture macroeconomic conditions which are likely related to systematic risk, we obtain several macro variables from the Federal Reserve Statistical Release and the BEA National Income and Product Accounts. These variables include the growth in industrial production, growth in consumer durables, nondurables, and services, growth in employment, and a dummy variable for NBER recessions. Following Stambaugh, Yu, and Yu (2012) and Sibley, Xing, and Zhang (2012), we obtain an additional set of macro-related variables that seem reasonable to entertain as being correlated with a risk premium: the default premium, the term premium, the real interest rate, the inflation rate, and the consumption-wealth ratio (cay). The default premium is the difference between BAA and AAA-rated corporate bonds. The term premium is the the difference between long term yield on government bonds and the Treasury-bill. The real interest rate is defined as the difference between the 30-day T-bill return and the consumer price index inflation rate. For these variables we obtain the data from Goyal and Welch (2008).

3 The Behavior of Aggregate Asset Growth

3.1 Summary Statistics

Table 9 reports the summary statistics for aggregate asset growth and its subcomponents from investment and financing decomposition. Panel A shows that the quarterly aggregate

[8] See http://research.stlouisfed.org/fred2/series/UMCSENT/.

asset growth (AG) has an average of 3.35% and a standard deviation of 1.68%. Unlike scaled-price variables such as the earnings-to-price ratio or the book-to-market ratio which is highly persistent, aggregate asset growth shows a first-order autocorrelation of 0.58. The augmented Dickey-Fuller test rejects the null that aggregate asset growth has a unit root.

Panel B presents the correlations between aggregate asset growth and other commonly used sentiment measures: the Baker and Wurgler composite sentiment index ($SENT^{\perp}$), the Michigan Consumer Confidence Index (MCSI), the close-end fund discounts (CEFD), and the IPO first-day returns. The correlations in general suggest that higher aggregate asset growth is associated with higher investor sentiment index, lower close-end fund discounts and higher IPO first-day returns. This suggests that aggregate asset growth may capture some aspects of the market-wide investor sentiment.

3.2 Univariate Analysis

Table 10 reports the findings from our univariate tests. To conduct our univariate analyses we sort the sample into terciles using Baker and Wurgler (2006) sentiment index. We then compare average values of the asset growth and its subcomponents across the sentiment terciles at different time horizon.[9] The findings show that most variables are monotonically increasing in sentiment, especially at longer horizons. At one quarter horizon, aggregate asset growth increases by 25%, from 2.97% to 3.73% between the low and high sentiment states. At two quarter horizon, aggregate asset growth increases by 30%, from 2.91% to 3.78%. The effects are even greater with three to four quarter horizon. At three (four) quarter horizon, aggregate asset growth increases by 34% (32%). Each of these differences is statistically significant at the 5% or 1% level.

Table 10 further shows that investor sentiment has strong effects on the subcomponents of aggregate asset growth. From the investment decomposition, sentiment has the strongest effects on cash growth (ΔCash) and growth in other assets (ΔOthAssets). From

[9] The decomposition is implemented following Cooper, Gulen, and Schill (2008) and Wen (2013), from both the investment side and financing side of the balance sheet.

the financing decomposition, sentiment has strong effects on growth in equity financing (ΔStock). Equity issuance increases 202% (from 0.47% to 1.41%) at one-quarter horizon, and 290% (from 0.41% to 1.53%) at four-quarter horizon. These findings suggest that the increase in investment in high sentiment states is in large part financed by an increase in external financing. This is consistent with the idea that sentiment influences investment because it causes mispricing which in turn influences the cost of external finance (Mclean and Zhao (2013)).

Figure 1 plots aggregate asset growth and its subcomponents across high and low sentiment periods. Consistent with Table 10, Figure 4 suggests that the effect of investor sentiment on aggregate asset growth and its subcomponents is persistent.

3.3 Does Aggregate Asset Growth Capture the Anecdotal History of Investor Sentiment?

We plot quarterly Baker and Wurgler (2006) investor sentiment index ($\mathrm{SENT}^{\perp}$), aggregate asset growth (AG), and the Michigan Consumer Sentiment Index (MCSI) in Figure 2. We also consider the Michigan Consumer Sentiment Index (MCSI) an alternative to the BW sentiment measure used in this paper. A number of studies also use this series as a proxy for investor sentiment (e.g. Lemmon and Portniaquina (2006); Bergman and Roychowdhury (2008)). BW sentiment index captures the market-wide sentiment of investors in the financial market, while the focus of MCSI is mainly on the sentiment among consumers in the product market. AG and the BW sentiment index span a period from 1974Q4 to 2010Q4, while the MCSI starts from 1978Q1.

Figure 5 suggests that AG captures major fluctuations in investor sentiment. Figure 5 shows that AG generally succeeds in capturing most anecdotal accounts of fluctuations in market-wide sentiment. First, all measures of investor sentiment comove with each other, consistent with the concept that investor sentiment contains a market-wide component (e.g., Baker and Wurgler (2006, 2007)). Second, AG appears to line up well with the anecdotal accounts of bubbles and market crashes. For example, it reached a small peak in the biotech bubble of the early 1980s, and another peak in 1989Q2, perhaps associated with the end of President Ronald Reagan's Great Expansion or Reagan-era optimism. AG fell in early 1990s during the Gulf war but rose again in late 1990s, reaching its peak during the tech bubble period. For the most recent periods, AG rose during the housing bubble and sub-prime securitization around early 2006. The index was generally low after the housing bubble bust but it rebounded back in early 2008 when U.S. government prepared to launch a series of bailouts to help firms in the sub-prime mortgage crisis. AG reached the lowest point during the most recent financial crisis in early 2009.

4 Asset Growth, Investor Sentiment, and Stock Market Returns

If aggregate asset growth captures investor sentiment, then we should expect to observe stock returns consistent with its implications. We conduct a series of analyses to examine the role of aggregate asset growth in the stock market. One implication of investor sentiment is the market return predictability. Baker and Wurgler (2007) show that subsequent market returns are lower following high sentiment periods. In this section our tests below ask whether the aggregate asset growth captures the same information content as investor sentiment index, or provide additional information about investor optimism above and beyond the traditional sentiment measure.

4.1 Controlling for Investor Sentiment

Table 11 reports the regression results of stock market returns (e.g., the value-weighted excess returns) on aggregate asset growth and investor sentiment. To compare the economic significance, the independent variables are standardized to have zero mean and unit variance. In these regressions, aggregate asset growth remains a significant predictor of stock market returns, both in the univariate regression and after controlling for investor sentiment. For one-quarter-ahead market returns, the coefficient on asset growth is -2.27 ($t = -3.61$) in the univariate regression. Controlling for the commonly used sentiment index does not weaken the predictive power of aggregate asset growth, with coefficient on AG -2.25 ($t = -3.42$). In sum, these findings suggest that aggregate asset growth provide new information about market returns above and beyond the traditional measure of investor sentiment. In untabulated results, we control for the macrovariables in Stambaugh, Yu, and Yu (2012) and Sibley, Xing, and Zhang (2012). The results are qualitatively similar.

4.2 Asset Growth and its Subcomponents

Many of the individual components of asset growth have been identified in the literature as measures of investor sentiment. For example, Baker and Wurgler (2000) find that high equity share in new issues predicts low future stock market returns, and relate the predictability to the market timing behavior of firms and investor sentiment. Arif and Lee (2013) find that corporate investments in the U.S. peak during periods of investor sentiment, yet these high investment periods are followed by lower equity returns. They conclude that corporate investment is influenced by, and indeed mirrors, investor sentiment. However, our tests below suggest that after controlling for the commonly used investor sentiment index ($\text{SENT}^{\perp}$), the predictive power for stock market returns are generally weak for the individual components of aggregate asset growth. These results suggest that neither equity share or corporate investment contains new information above and beyond the traditional sentiment measures.

Table 12 reports the coefficients and t-statistics from time series regressions of stock market returns on the subcomponents of asset growth, from an investment and a financing decomposition. From an asset investment decomposition, growth in cash and other assets are associated with significant negative coefficients. In Panel A at one-quarter horizon, the coefficient on ΔCash is -1.91 ($t = -2.41$) and the coefficient on ΔOthAssets is -1.37

($t = -2.01$). Since all of the independent variables are standardized to have zero mean and unit variance, these coefficients are economically large as well. A coefficient of -1.91 implies that a one standard deviation increase in ΔCash is associated with about 1.91% decrease in one-quarter-ahead value-weighted market excess returns.

From an asset financing decomposition, growth in operating liability and equity financing are associated with significant negative coefficients. In Panel A, the coefficient on ΔOpLiab is -1.85 ($t = -2.09$) and the coefficient on ΔStock is -1.47 ($t = -2.51$). These results are consistent with the findings of Baker and Wurgler (2000) who find that equity issuance is a strong negative predictor of stock market returns. We obtain qualitatively similar results in other panels for different horizons.

Table 13 repeats the analysis in Table 12 by controlling for the investor sentiment index ($\text{SENT}^{\perp}$). We find that the predictive power for stock market returns gets weakened for these subcomponents of aggregate asset growth, especially for stock financing (ΔStock) which becomes insignificant. These results suggest that as a comprehensive measure of firm growth, asset growth synergistically benefits from the predictability of all subcomponents of growth, allowing aggregate asset growth to better capture investor sentiment relative to any single component of growth. Aggregate asset growth provides new information about market returns above and beyond the traditional measures of investor sentiment, while the individual components of growth do not.

5 Asset Growth, Investor Sentiment, and Analyst Forecasts

The evidence thus far indicates that aggregate asset growth mirrors investor sentiment, and provides new information about market returns above and beyond the traditional measure of investor sentiment. In this section we conduct a series of tests to examine the relation between aggregate asset growth and measures of ex-post fundamental performance. We test whether aggregate asset growth captures investors' biased belief about expected future cash flows, which is the nature of investor sentiment as described in Baker and Wurgler (2006). To the extent that our main results are driven by systematic errors in managerial expectations related to future performance, we would expect a negative relation between aggregate asset growth and these variables.

We begin by examining whether aggregate asset growth is associated with errors in expectations about future earnings. Following Wen (2013), we measure earnings news by constructing quarterly aggregate forecast errors or revisions from the Institutional Broker's Estimate System (IBES) summary unadjusted file.[10]

Table 14 examines the relation between aggregate asset growth, investor sentiment, and analyst forecast errors. The results suggest that higher asset growth (AG), or investor sentiment ($SENT^{\perp}$), is associated with negative forecast errors.[11] In other words, higher asset growth is associated with more optimistic ex-ante expectations of future corporate earnings but not associated with high future earning realizations.[12] It is interesting to note that both asset growth and investor sentiment index provide complementary power for analyst forecast errors, especially at one-quarter and two-quarter horizon. We obtain qualitatively similar results using analyst forecast revisions. Table 15 suggests that analysts tend to revise their earnings forecasts down in the direction of high past aggregate asset growth.

To summarize the results up to this point, we find that aggregate asset growth negatively predicts analyst forecast errors and forecast revisions. High aggregate asset growth is associated with more optimistic ex-ante expectations of future corporate earnings. This provides additional evidence that asset growth captures investors' biased belief about expected future cash flows, consistent with the nature of investor sentiment.

[10] Changes in analyst forecasts offer an attractive way to measure earnings news because they represent changes in the market's earnings expectations.

[11] Forecast error (FE), is defined as the realized difference between earnings as reported in Compustat and the prevailing consensus forecasts, scaled by price per share.

[12] In all regressions we control for past analyst forecast errors, since it is well documented that analyst forecast errors tend to be persistent (Abarbanell (1991); Lys and Sohn (1990).

6 Asset Growth, Investor Sentiment, and Earnings Announcement Returns

To formally test that aggregate asset growth captures investor sentiment, we examine its relation to the earnings announcement returns. We might expect that the average earnings announcement return would tend to be inversely related to investor sentiment, since errors in earnings expectations should account for some of the sentiment effects. If investors fail to anticipate the decrease in earnings following periods of high asset growth, they should be subsequently surprised by the earnings reversal when earnings are announced. Our results confirm all these findings. We construct an aggregate measure of abnormal earnings announcement returns using the quarterly COMPUSTAT and daily returns from CRSP. Table 16 reports the regression results of announcement returns on lagged aggregate asset growth and investor sentiment using an estimation window of [-250, -5] and an even window [-2,+2]. Table 16 suggests that aggregate asset growth is negatively related to future announcement returns, and this effect is particulary strong for announcement-window returns during the second and third quarter. Interestingly, investor sentiment index ($SENT^{\perp}$) is not significantly associated with future announcement returns. This result is surprising since errors in earnings expectations should account for some of the sentiment effects. As a result, if $SENT^{\perp}$ captures investor' biased belief about future cash flows, we might expect a negative relation between $SENT^{\perp}$ and announcement returns. Overall, our evidence suggests that investors are not fully anticipating the lower earnings that are announced after periods of high aggregate asset growth. To the extent that short-window earnings announcement returns capture earnings surprise, aggregate asset growth seems to capture investors' errors in expectations, consistent with the nature of investor sentiment as described in Baker and Wurgler (2006).

7 Asset Growth and the Cross-Section of Stock Returns

Baker and Wurgler (2006) provide evidence that investor sentiment may have significant effects on the cross section of stock returns. They argue that market-wide sentiment should exert stronger impacts on stocks that are difficult to value and hard to arbitrage. Combining the impediments to short selling as in Miller (1977), Stambaugh, Yu, and Yu (2012) explore the role of investor sentiment in a broad set of anomalies in cross-sectional stock returns, and find long-short strategies that exploit the anomalies exhibit profits consistent with this setting: each anomaly is stronger following high levels of sentiment and is mainly due to the underperformance of the short leg. However, a large percent of the total variation in Baker and Wurgler (2006) sentiment index is shown to be strongly correlated with contemporaneous and well-known business cycle variables. Sibley, Xing, and Zhang (2012) show that the power of the sentiment index to predict cross-sectional stock returns is mainly driven by the business-cycle component, while the component unrelated to business cycle conditions has little significance.

In this section, we examine the role of aggregate asset growth (AG) in a broad set of anomalies in cross-sectional stock returns. We control for the Baker and Wurgler (2006) sentiment index since it contains rich information about economic fundamentals or rational risk premia. If AG captures investor sentiment, then we should expect to observe anomaly returns consistent with its implication. Similar to Stambaugh, Yu, and Yu (2012), we use predictive regression to investigate whether AG predicts anomaly returns. Three empirical predictions are derived in Stambaugh, Yu, and Yu (2012). First, the anomalies, to the extent they reflect mispricing, should be more prevalent when sentiment is high. This hypothesis results from combining the presence of market-wide sentiment with the Miller (1977) short-sale argument. Second, the returns on the short-leg portfolio of each anomaly should be lower following high sentiment, since the stocks in the short leg are relatively overpriced.[13] Third, investor sentiment should not greatly affect returns on the long-leg portfolio of each anomaly.[14] Our findings confirm all these predictions.

We construct an aggregate asset growth index (AGI), defined as the moving average of the level of aggregate asset growth (AG) in the current quarter and previous three quarters. The aggregate asset growth index in quarter t is constructed as,

$$AGI_t = \frac{1}{4}\sum_{j=0}^{3} AG_{t-j}$$

The idea of using the moving average of AG is motivated by the empirical observation that investor sentiment is persistent. For example, the first (second) order autocorrelation of the BW quarterly sentiment index is 0.947 (0.876).[15] By using moving averages, we capture the persistence in AG and its effect on cross-sectional stock returns. The quarterly index, AGI, has a first (second) order autocorrelation of 0.926 (0.783), similar in magnitude to the BW sentiment index.

Our goal is to examine whether or not AGI captures market-wide investor sentiment by studying its relation to a broad set of anomalies surveyed in Stambaugh, Yu, and Yu (2012). These anomalies are previously documented and survive the adjustment for exposures to the Fama-French three factor model. The 11 anomalies are listed as the following,

- Failure Probability (Campbell, Hilscher, and Szilagyi (2008))
- O-score (Ohlson (1980); Dichev (1998))
- Net stock issuance (Ritter (1991), Loughran and Ritter (1995))
- Composite equity issuance (Daniel and Titman (2006))

[13] This prediction is also consistent with Baker and Wurgler (2006) who show that sentiment should affect stocks which are relatively hard to value and difficult to arbitrage. For example, younger, unprofitable, high-volatility, or distressed stocks. These stocks often fall into the short leg since they are relatively overvalued.

[14] Although it is still likely that when sentiment is high, the stocks in the long leg could be overpriced, but the long leg should contain the least degree of overpricing, compared to the short leg.

[15] Although it is highly persistent, the augmented Dickey-Fuller test rejects the null of unit root.

- Total accruals (Sloan (1996))
- Net operating assets (Hirshleifer, Hou, Teoh, and Zhang (2004))
- Momentum (Jegadeesh and Titman (1993))
- Gross profitability premium (Novy-Marx (2012))
- Asset growth (Cooper, Gulen, and Schill (2008))
- Return on assets (Fama and French (2006), Chen, Novy-Marx, and Zhang (2010))
- Investment-to-assets ratio (Titman, Wei, and Xie (2004))

Following Stambaugh, Yu, and Yu (2012), we construct value-weighted decile portfolio returns and a long-short strategy using the extreme deciles, 1 and 10, with the long leg being the higher-performing decile. Due to the availability of the data in AGI, the sample periods of the portfolio returns start from 1976Q1 to 2010Q2.

We run predictive regressions for the benchmark-adjusted returns by including the contemporaneous returns on the three Fama and French factors,

$$R_{i,t} = a + bAGI_{t-1} + cMKT_t + dSMB_t + eHML_t + u_t$$

where $R_{i,t}$ is the excess return (in percent) in quarter t for anomaly i, on either the long leg, the short leg, or the difference, and AGI is the aggregate asset growth index which is scaled to have zero mean and unit variance.[16]

7.1 Empirical Results: Long-Short Strategies

Table 17 reports results of regressing benchmark-adjusted anomaly returns on lagged BW sentiment index (Panel A), asset growth index (Panel B), as well as on both variables

[16]Our results remain qualitatively similar, and slightly weaker, if we just regress $R_{i,t}$ on lagged level of aggregate asset growth AG_{t-1}.

(Panel C). The results in Panel A are consistent with the findings in Stambaugh, Yu, and Yu (2012). However, Sibley, Xing, and Zhang (2012) show that these results are driven by the business cycle component of the sentiment index, while the component unrelated to business cycle has little significance.

Panel B and C in Table 17 provide new evidence on the role of asset growth index (AGI) in the cross-section of stock returns. If asset growth index captures investor sentiment, then we should expect to observe anomaly returns consistent with its implication. First, anomalies are stronger following high asset growth index and the profitability of each long-short spread is positively related to lagged AGI. In panel B, the coefficients on AGI for long-short spread are all positive for each of the anomalies, and eight of the individual coefficients are statistically significant in both tables at either 5% or 1% level. The combination strategy of all anomalies has a t-statistic of 5.12 in Table 17. To interpret the economic significance, the asset growth is scaled to have zero mean and unit standard deviation and anomaly returns are expressed in percent per quarter. As a result, the slope coefficient of 1.99 for the combination strategy in Table 17 indicates that a one standard deviation increase in asset growth index is associated with $0.0199 of additional long-short quarterly profit on a strategy with $1 in each leg of the spread.

Second, our results suggest that returns on the short-leg portfolio of each anomaly is lower following high aggregate asset growth. We find that the slope coefficients on AGI for short-leg are all negative for each of the anomaly, and nine of the individual coefficients are statistically significant in Table 17. The combination strategy has a t-statistic of -4.22.

The third hypothesis predicts that investor sentiment should not greatly affect returns on the long-leg portfolio of each anomaly. Consistent with this prediction, none of the coefficient is significantly negative in Panel B of Table 17 for the long-leg. This suggests that the long-leg contains the least degree of overpricing compared to the short-leg, when investor sentiment is high.

More importantly, the predictive power of aggregate asset growth for anomaly returns does not weaken after we control for Baker and Wurgler (2006) sentiment index, which has been shown to contain rick information about economic fundamentals or rational risk premia (Sibley, Xing, and Zhang (2012)). Results in Panel C suggest that AGI provides new information about investor sentiment above and beyond the BW sentiment index. The slope coefficient on AGI for long-short spread for the combination strategy is 1.65 with t-statistic of 4.10, while the coefficient on SENT$^{\perp}$ is 0.76 with t-statistic of 3.07. These results suggest that the predictive power of aggregate asset growth for cross-sectional stock returns is less likely to be related to economic fundamentals or business-cycle variables. To ensure the robustness of our results, we orthogonalize the asset growth index with a few macroeconomic variables in Sibley, Xing, and Zhang (2012), we obtain qualitatively similar results in Table 18.

In sum, results from the predictive regressions reported in Table 17 and 18 suggest that asset growth index captures market-wide investor sentiment, and we observe anomaly returns consistent with its implication in the cross-section of stock returns.

8 Conclusions

The commonly used measure of investor sentiment in Baker and Wurgler (2006) has been shown to capture rich information about economic fundamentals or business-cycle variables. After purging the effects of business-cycle variables, this index has little significance in predicting cross-sectional stock returns. As a result, the commonly used sentiment index may not be "sentimental".

In this paper, we propose a new measure of investor sentiment that aims to capture investors behavioral biases rather than economic fundamentals. Our measure lines up well with the anecdotal history of investor sentiment and better captures sentiment relative to any individual components of growth. Consistent with the nature of investor sentiment described in Baker and Wurgler (2006), our measure captures investors biased belief about expected future cash flows. Most importantly, unlike the commonly used sentiment index, the predictive power of our measure for cross-sectional stock returns is not driven by economic fundamentals or business-cycle variables.

Third Essay: Financial Distress Innovations and the Distress-Return Relation*

Mark Rachwalski Quan Wen†

Abstract

We examine the puzzling evidence that financial distress risk is negatively related to subsequent returns. We find that this negative relation lasts only for a year but after that financial distress risk is positively related to returns. We find that the negative relation in the first year is driven by innovations in financial risk during the prior year and not by the level of risk. The evidence indicates that distress risk commands a positive risk premium although investors initially underreact to distress risk innovations. We also find that the positive distress risk premium explains the size effect.

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†Goizueta Business School, Emory University, 1300 Clifton Rd., Atlanta, GA 30322.

1 Introduction

Is financial distress risk priced? Although the CAPM prescribes a single priced risk, a mismeasured market portfolio (Ferguson and Schockley (2003)) or time-varying investment opportunities (Merton (1973)) leaves open the possibility of additional priced risks. Chan and Chen (1991) and Fama and French (1996) have suggested that distress risk may explain the nonzero returns of of the size and value anomalies. This has motivated a large number of researchers to search for priced distress risk, often by examining the relationship between predicted default probability and subsequent returns. A robust result from these studies is that financial distress is negatively related to subsequent returns (see Dichev (1998), Campbell, Hilscher, and Szilagyi (2008), henceforth CHS (2008), Avramov, Chordia, Jostova, and Philipov (2009), George and Hwang (2010), Garlappi and Yan (2011), and Gao, Parson, and Shen (2012))[1]. This is a counterintuitive result because distressed stocks are likely riskier than non-distressed stocks (in addition to the a priori appeal of this idea, CHS (2008) document that distressed stocks have higher standard deviations, market betas, and loadings on the size and value factors than non-distressed stocks). Then, we should expect distressed stocks to offer an expected return at least as large as non-distressed stocks. Therefore, a better understanding of distress risk is important not just as a potential explanation of the size and book-to-market anomalies, but also in explaining the surprising negative relation between predicted default probability and returns.

In this paper, we estimate the price of distress risk using the cross section of

[1]Vassalou and Xing (2004) find that distress risk is positively priced, although this result appears to be driven by short-term return reversals (see Da and Gao (2010)). Using implied cost of capital to proxy for expected returns, Chava and Purnanandam (2010) find a positive cross-sectional relationship between expected stock returns and default risk. Gao, Parson, and Shen (2012) document a robust worldwide distress anomaly, particularly among small firms.

stocks. We build on previous work that relates predicted default probability and expected returns. However, we are concerned that investors may underreact to distress risk innovations, which can lead to misleading inference about the price of distress risk. This concern is motivated by ample evidence of underreaction in other settings.[2] If distress risk is priced, underreaction to distress risk innovations should lead to predictable patterns in returns.

In the presence of underreaction, the expected distress risk-return relation will be somewhat complicated. For example, suppose that distress risk is positively priced and that investors underreact to distress risk innovations. Then, immediately after a positive shock to a stock's distress risk, the representative investor's forecast of distress risk will be too low and the price of the stock will be too high. However, if underreaction is temporary, investors will eventually arrive at the correct distress risk forecast and stock price. Therefore, for some period of time after the shock, expected returns will be low as investors "correct" their underreaction. After the shock is fully priced, the stock's expected return will be higher than the pre-shock expected return because risk is higher. We build a simple model to develop this intuition.

Our model suggests that, in the presence of underreaction and a positive price of distress risk, stocks with high distress risk will earn high returns, although stocks with recent increases in distress risk will earn temporarily low returns. To test the implications of our model, we estimate recent distress risk (predicted default

[2]Prior research suggests that investors underreact to earnings announcements (Ball and Brown (1968), Bernard and Thomas (1989)), prior returns (Jegadeesh and Titman (1993)), dividend news (Michaely, Thaler, and Womack (1995)), share repurchases (Ikenberry, Lakonishok, and Vermaelen (1995)), seasoned equity offerings (Loughran and Ritter (1995), Spiess and Affleck-Graves (1995)), increased R&D expenditures (Eberhart, Maxwell, and Siddique (2004)), predictable demographic trends (DellaVigna and Pollet (2007)), and news about related firms (Cohen and Frazzini (2008)). Barberis, Shleifer, and Vishny (1997), Daniel, Hirshleifer, and Subrahmanyam (1998), and Hong and Stein (1999) develop models with investor underreaction.

probability using the most recent data) and distant distress risk (lagged predicted default probability) for each stock-month observation in our sample. Our model suggests that recent distress should be negatively related to subsequent returns, while distant distress should be positively related to subsequent returns. We confirm these predictions.

Our model suggests that, provided the underlying price of distress risk is positive, any negative distress risk-return relationship should be temporary. Stocks with high distress risk may exhibit temporarily low returns because the level and recent change in distress risk are likely correlated. However, in the long-run (i.e. after the effects of temporary underreaction), the distress risk-return relation should be positive. We examine the returns of distress-sorted hedge portfolios for up to five years after portfolio formation and observe this return pattern. Returns of some distress-sorted hedge portfolios are significantly negative for about a year. However, after this year, hedge portfolio returns are positive. This suggests that, after the temporary effects of underreaction have run their course, the underlying distress risk-return relation is positive. Prior studies fail to detect this long run relation because these studies generally focus on returns immediately after portfolio formation; these studies miss the long-run positive distress risk-return relation and may incorrectly infer that distress risk is negatively priced.

Our results are not driven by well-known return patterns (short-term reversals, momentum, and liquidity). Our results are robust to alternative measures of financial distress (use of Ohlson (1980)'s O-score rather than the predicted default measure of CHS (2008)), data filters that remove the smallest or most illiquid stocks from the sample, and alternative distant distress lag lengths. Finally, we generally report both equal- and value-weighted portfolio returns; inference is generally similar.

One limitation of our approach is that we do not observe investors' distress risk forecasts; this means that we cannot directly test whether or not these forecasts are consistent with the observed return patterns. Instead, we rely on return patterns to provide indirect support for our underreaction explanation of the distress risk-return relation. This leaves open the possibility that another stock characteristic, related to distress in the cross-section, is driving our results. To address this, we directly control for well-documented return patterns that could potentially fit the results. Also, we note that many alternative explanations are not likely to fully explain the dynamic nature of our results (i.e. distress risk is sometimes negatively and sometimes positively related to subsequent returns). For example, suppose that high distress risk stocks tend to be firms with overly optimistic investors and short sale constraints. Then, the returns of high distress stocks will be low when investors correct their excessive optimism, but there is no reason to expect that long-run returns will be high.

We explore the relation between the size (SMB) and book-to-market (HML) hedge portfolios and distress risk. We construct a traded distress factor; this factor is a zero-cost hedge portfolio formed by taking a long position in stocks with high distant distress and a short position in stocks with low distant distress, controlling for recent distress (and underreaction). We find that SMB loads positively on distress risk. This is consistent with Chan and Chen (1991), who suggest that the size anomaly may be related to financial distress. However, we find that the HML portfolio loads negatively on the distress factor. Therefore, our distress factor cannot explain the value premium.

Our paper contains several contributions to the literature relating financial distress and asset returns. First, we empirically document a positive relation between distress risk and long-run returns. We find that, starting in the second year after portfolio formation, returns of some distress-sorted hedge portfolios are positive. Documenting a positive long-run relation is important because distressed stocks are likely riskier than non-distressed stocks. Therefore, distressed stocks should earn a return at least as large as non-distressed stocks. Our results are consistent with this intuition.

Second, we show that the sign of the distress risk-return relation is dynamic. This empirical fact should be useful when evaluating potential explanations of the distress risk-return relation. Potential explanations of the negative relation between predicted default probability and expected returns include firm's endogenous choice of leverage (George and Hwang (2010)), violations of shareholder priority in bankruptcy (Garlappi and Yan (2011)), and investors' preference for skewness (Conrad, Kapadia, and Xing (2012)). Such explanations do not address the dynamic nature of the distress risk-return relation, and may be inconsistent with a positive long-run distress risk-return relation. A satisfactory explanation of the distress risk-return relation should capture the dynamic nature of the relation. Our underreaction framework is a simple way to understand this relation. Also, our underreaction framework allows us to reconcile a short-run negative distress risk-return relation with a positive underlying price of distress risk.

Third, we explore the relation between distress risk and the size and book-to-market anomalies. Because we find that distress risk is positively related to subsequent returns after controlling for the effects of underreaction, we can empirically test the contention that the size and value premiums are due to financial distress risk. We find that distress risk is a plausible economic explanation of the nonzero returns of the SMB portfolio. However, we find no evidence that distress risk can explain the nozero returns of the HML portfolio.

The paper proceeds as follows. Secion I presents a simple model highlighting the interaction of risk innovations and underreaction, and discuss distress risk and underreaction in additional detail. Section II describes the data and our measures of recent and distant financial distress, and the empirical setup. Section III presents our empirical results, where we estimates the cross-sectional price of financial distress and explores the dynamic nature of the distress risk-return relationship. Section IV explores the relation between the distress factor and size and value anomalies. Section V concludes.

2 Financial distress, Risk Innovations, and Underreaction

2.1 A Simple Model of Investor Underreaction to Risk Innovations

In this section, we present a simple model of investor underreaction to distress risk innovations to help develop the intuition behind this paper.[3] The model is focused on the interaction of underreaction and risk innovations. We do not address the limits to arbitrage that allow underreaction to exist. Instead, we rely on previous research (e.g. Long, Shleifer, Summers, and Waldmann (1990), Shleifer and Vishny (1997)). Prior studies have found evidence of apparent underreaction in a wide variety of settings (see Footnote 2). This evidence is consistent with binding limits to arbitrage and serves to motivate our study of underreaction and distress risk.

Because we are focused on risk, rather than cash flows, we adopt a dividend discount model, where expected cash flows are held constant throughout. We assume

[3]This section closely follows Rachwalski and Wen (2012), where a nearly identical model is developed in the context of idiosyncratic volatility.

that the expected return of a stock is determined solely by distress risk, and that the distress risk-return relation is positive. Then,

$$p_t = \frac{d}{r_t} = \frac{d}{\gamma FD_t^*} \tag{1}$$

where p_t is the price, d is the dividend, r_t is the expected return, and FD_t^* is distress risk as perceived by investors.

Under our model, perceived distress risk (FD_t^*) may differ from true distress risk (FD_t). We assume that the log of FD follows a random walk,

$$log(FD_{t+1}) = log(FD_t) + \epsilon_{t+1} \tag{2}$$

We obtain similar results, but a more complicated model, if we assume an AR(1) process.

We assume that the representative investor cannot, or does not, observe ϵ in real time. Therefore, this information cannot be incorporated into risk estimates. We assume that the representative investor's distress risk estimate (FD^*), which is used to set the stock price, evolves according to

$$FD_{t+1}^* = FD_t^* + \Theta(FD_t - FD_t^*) \tag{3}$$

Investors base their distress risk estimates on last period's forecast (FD_t^*) and the forecast error $FD_t - FD_t^*$. (We obtain qualitatively similar results if we allow investors to partially react to ϵ.) Θ governs the speed with which investors correct their forecasts. We consider $\Theta \in (0, 1)$, so the representative investor's risk estimate will eventually converge to the correct level (in the absence of additional shocks). Thus, investors temporarily underreact to risk innovations.

Under our model, the expected gross return,

$$E_t[\frac{p_{t+1}+d}{p_t}] = \frac{FD_t^*}{FD_t^* + \Theta(FD - FD_t^*)} + \gamma FD_t^*, \tag{4}$$

will depend on the representative investor's distress risk forecast error $(FD_t - FD_t^*)$ as well as the perceived level of financial distress (FD_t^*). It is straightforward to show that if the distress risk forecast from period t is too low (i.e., $FD > FD_t^*$), then the time $t+1$ expected gross return will be low (relative to the case where $FD_t = FD_t^*$). This low expected return corresponds to investors revising their distress risk estimate higher, which reduces the price of the stock. Also, holding the forecast error constant, higher perceived distress risk will be associated with higher expected returns.

We can state the empirical implications of our model as

$$\frac{\partial E_t[R_{t+1}]}{\partial FD_t} < 0 \tag{5}$$

and

$$\frac{\partial E_t[R_{t+1}]}{\partial FD_t^*} > 0, \tag{6}$$

where R_{t+1} is the time $t+1$ gross return. Prior literature often focuses on tests of the relationship between a single measure of financial distress and subsequent returns. Such a test can be expressed as

$$\frac{\partial E_t[R_{t+1}]}{\partial X_t} \neq 0, \tag{7}$$

where X is some proxy for financial distress. Our framework does not offer a clear prediction of the sign of this relation because X could be positively correlated with both FD_t^* and $FD_t - FD_t^*$, which have opposing relations with subsequent returns. Indeed, later in the paper we will show that, for some X, subsequent returns are sometimes negatively and sometimes positively related to the proxy.

2.2 Underreaction and Distress Risk

There are reasons to believe that underreaction is particularly likely in this application. First, distress risk estimates are not released in an easily processed form at a scheduled time (unlike, say, earnings). Instead, distress risk must be estimated from a variety of sources including market and accounting data. The relevant information set could easily be large, diverse, and continuously changing. Monitoring this information set in real time is likely a challenging task. If some of this information set is not monitored in real time, perhaps due to investor distraction (see Hirshleifer, Lim, and Teoh (2009), DellaVigna and Pollet (2009)), then investors could easily underreact to risk innovations. Second, standard valuation techniques (e.g. discounting expected cash flows) may not be well-suited for distressed stocks, as many distressed stocks have negative earnings, high leverage, and volatile cash flows. Distressed stocks also have lower analyst coverage and institutional ownership (see CHS (2008)). This suggests that few investors have the skill to value these stocks correctly (see Baker and Wurgler (2006), Eisdorfer, Goyal, and Zhdanov (2011)), and that risk estimates of distressed stocks are relatively uncertain. This uncertainty, in particular the uncertainty associated with estimating default probabilities, may exacerbate underreaction (Zhang (2006) shows that uncertainty may exacerbate underreaction).

Underreaction could easily influence the conclusions reached by empirical researchers. For example, empirical studies may focus on a measure of financial distress that is more highly correlated with the recent innovation in financial distress than distant financial distress. Then, Equations 5 and 6 suggest that these empirical studies could uncover a negative relation between financial distress and subsequent returns. However, this does not imply that financial distress risk is negatively priced, as the negative relation could be attributable to the effects of underreaction.

It is interesting to note that, in the presence of underreaction, an empirical study may possess more power detecting returns associated with underreaction than changing risk premiums (or even the level of risk premiums). This could occur because a persistent change in required returns has a large effect on current prices (see Campbell (1991), who shows that the contemporaneous return associated with a change in expected returns is equal to the sum of the discounted expected return changes).

For example, consider a stock that pays a dividend of one dollar annually in perpetuity. If the discount rate is 10%, the value of the stock is 10. If the discount rate increases by 1%, the new value of the stock is 9.09. If prices fully adjust to the risk innovation within one month, then the stock will return -9.1% subsequent to the risk innovation. Suppose half of the change in the required return occurs with a delay but within a month; this is a return of -4.55% in a month. A monthly return of -4.55% should be easier to empirically detect than the change in risk premia, equal to 1% annually or 0.08% monthly. A monthly return of -4.55% should also be easier to detect than the absolute level of the new risk premium, which will be less than 0.92% monthly (assuming the risk-free rate is greater than 0).

3 Data

3.1 Stock Sample, Filters

We obtain stock data from CRSP and Compustat. Following CHS (2008), we e-liminate all stocks with a lagged price less than one dollar from the sample. This sort of filter is intended to remove the smallest and most illiquid stocks from the sample. The filter also partially addresses concerns that the distress anomaly may be confined to a small subset of the stock market (and may be difficult to exploit due to short selling constraints and low liquidity associated with this subset). We use CRSP delisting returns where appropriate (following Shumway (1997) and Price, Beaver, and McNichols (2007)). We exclude financial firms (SIC codes 6000 through 6999). We require that each stock-month observation has sufficient accounting and market data to compute recent and distant financial distress defined as below.

3.2 Measures of Financial Distress

We primarily measure financial distress using CHS's (2008) failure probability. CHS show this measure is a relatively accurate predictor of corporate default.[4] However, as a robustness check, we also report results using Ohlson's (1980) O-score.

3.3 "Recent" and "Distant" Financial Distress

If underreaction is important, the choice of the historical data used to calculate financial distress will be important. For this reason we distinguish between "recent" financial distress (RD, defined as predicted default probability using all information

[4]CHS show their measure predicts corporate failure more accurately, at both short and long horizons, than either static models (Beaver (1966), Altman (1968), and Ohlson (1980)) or the structural default model of Merton (1974).

up to the current quarter t) and "distant" financial distress (DD, defined as the predicted default probability using information up to quarter $t-s$). We will refer to s as the RD-DD threshold, as s separates the data into partitions used to estimate RD and DD. Although we will focus on a four-quarter RD-DD threshold throughout much of the paper, we will also examine thresholds of 6 and 8 quarters. To illustrate, when $s = 4$, RD is the predicted default probability calculated using data up to the current quarter (time t). DD is the predicted default probability calculated using data up to time $t - 4$. Note that the threshold is equal to the DD lag length (e.g. when $s = 4$, DD equals RD lagged 4 quarters).

We use RD and DD to test Equations 5 and 6. We measure FD^*, perceived financial distress, with DD. Provided the RD-DD threshold is sufficiently long, investors will have fully incorporated the information contained in DD into prices. We measure FD with RD. In the presence of underreaction, investors may have not fully assimilated the information contained in RD into prices. Then RD contains information about subsequent returns related to predictable corrections to underreaction.

3.4 RD- and DD-Sorted Portfolios

In this section we examine the mean returns of RD- and DD-sorted portfolios. This section highlights the conditional nature of distress risk-return relation. Each month, we identify firms that release earnings. We use the information from the earnings report and market data to calculate recent distress (RD) for each of these firms. We also record financial distress calculated one year prior (DD) for each of these firms. We then form sequentially-sorted portfolios (by RD then DD, and separately by DD then RD).[5]

Table 19 reports mean equal-weighted portfolio returns for the month subsequent to portfolio formation.[6] Financial distress is measured by CHS failure probability in Panel 1 and O-score in Panel 2. Our discussion focuses on CHS failure probability, although results are similar when using O-score.

Table 19 demonstrates that sequential sorts are helpful in clarifying the relationship between distress risk and mean returns. The column means of Panel 1A (where stocks are sorted by DD, then RD) reveal little relation between DD and subsequent returns. The extreme DD portfolios exhibit little difference in mean returns (0.72 for DD1, 0.68 for DD5). Therefore, an unconditional sort on DD suggests that DD is unrelated to subsequent returns. However, the column means of Panel 1B (where stocks are sorted by RD, then DD) reveal an economically large and monotonic relation between DD and subsequent returns (with extreme portfolio returns of 0.50 and 1.31). The column means of Panel 1B are formed using a sequential sort, where stocks are sorted into RD quintiles then DD quintiles within each RD quintile. Because the first sort is on RD, each DD quintile must contain stocks from each RD quintile; this is one way to control for RD when examining the DD-return relation. In Panel 1A, the first sort is on DD, so there is no such control for RD. Therefore, controlling for RD reveals a positive DD-return relation.

Similarly, controlling for DD reveals a stronger relation between RD and subsequent returns. Comparing the row means of Panel 1A and 1B, controlling for DD increases the absolute value of the difference in the extreme portfolio mean returns (from 0.74 to 1.21). However, the negative RD-return relation is economically

[5]We use a sequential sort rather than an independent sort because RD and DD are highly correlated. An independent sort leaves certain portfolios (e.g. RD1, DD5) sparsely populated.

[6]The sample period for our study is 1977 to 2010; quarterly Compustat data is sparse before this date.

large even when using a single sort on RD (this is consistent with prior work, such as Dichev (1998) and CHS (2008)). Importantly, RD and DD have opposing conditional relationships with subsequent returns, although the DD-return relation is only apparent when appropriate controls are applied.

We will refer to the portfolios corresponding to the row means of Panel 1A and the column means of Panel 1B as RDS1-RDS5 and DDS1-DDS5, respectively. The "S" indicates a sequential sort. These portfolios are constructed to induce variation in RD while controlling for DD or induce variation in DD while controlling for RD.

3.5 Descriptive Statistics

Table 20 reports descriptive statistics of the sequentially- and single-sorted DD and RD portfolios (again, using a four-quarter RD-DD threshold). The DD and RD columns report the annualized 12-month failure probability (CHS (2008)) associated with each portfolio (e.g. the RD5 portfolio contains stocks with an average failure probability of 1.14% based on recent distress and 0.63% based on distant distress). Table 20 offers evidence that predicted failure probability tracks realized corporate failures. The DELIST column reports the share of firms delisted from CRSP due to bankruptcy, liquidation or performance within 12 months of portfolio formation for each quintile. For example, on average 77.4% of delisted firms are in the RD5 quintile while 2.27% are in the RD1 quintile. Therefore, high predicted failure probability is associated with high future corporate failures (as demonstrated by CHS).

Table 20 demonstrates that a single sort on DD is very similar to a sort on RD (and the reverse); both DD and RD increase in a similar way from RD1 to RD5 and from DD1 to DD5. This occurs because financial distress, not surprisingly, exhibits positive autocorrelation. Sequential sorts break the tight link between DD and RD. The DDS portfolios exhibit substantial variation in DD and little variation in RD.

Similarly, the RDS portfolios exhibit substantial variation in RD but little variation in DD.

Persistence in distress risk implies that DD and RD are correlated. Empirically, the correlation is quite high; the time series average of the DD-RD cross-sectional correlation is 0.85. Because DD and RD are positively correlated but have opposing partial relationships with mean returns, a single measure of financial distress (e.g. calculating financial distress over the most recent quarter) cannot fully reveal the relation between distress and subsequent returns.

Table 20 contains additional portfolio descriptive statistics. On average, distressed stocks are small, volatile, have positive skewness, and are illiquid. Also, distressed stocks exhibit positive skewness, which may appeal to certain investors (Barberis and Huang (2008), Bali, Cakici, and Whitelaw (2011)).

4 The Cross-Sectional Price of Financial Distress

4.1 Empirical Setup

In this section, we test for a conditional distress risk-return relation consistent with our underreaction framework and a positive price of distress risk. We examine the mean returns of distress-sorted hedge portfolios. We also consider Fama and MacBeth (1973) cross-sectional regressions of the following form:

$$r_{i,t+1} = \alpha + \beta_{t,DD} DD_{i,t} + \beta_{t,RD} RD_{i,t} + \gamma_t X_t + \epsilon_{i,t}, \tag{8}$$

where X is a vector of controls. This specification allows us to examine the partial RD- and DD-return relations (as do the DDS and RDS hedge portfolios), and can be interpreted as a test for a conditional distress risk-return relation. As discussed above, Equation 4 suggests that RD should be negatively related to subsequent stock returns and that DD should be positively related to subsequent stock returns.

Note that Equation 8 can be rewritten as

$$r_{i,t+1} = \alpha + \delta_{t,DD} DD_{i,t} + \beta_{t,RD}(RD_{i,t} - DD_{i,t}) + \gamma_t X_t + \epsilon_{i,t}, \tag{9}$$

where expected returns depend on the level of distant financial distress and the change in financial distress. This corresponds to Equation 4, where expected returns depend on perceived distress risk (measured by DD) and the forecast error (measured by RD-DD).

The anticipated RD- and DD-return relations will only hold under a suitable RD-DD threshold. For example, if the RD-DD threshold is very short, then the DD-return relation may reflect both the effects of underreaction and the distress risk premium. In this case, we may expect the DD parameter (or the DDS hedge portfolio mean return) to be small and insignificant. If the RD-DD threshold is very long, then the information conveyed by DD may be too dated to be useful. However, we find that distress is sufficiently persistent that DD is useful under reasonable thresholds. Therefore, under our underreaction framework, we expect the estimated DD parameter to vary in a systematic way as we alter the threshold. In particular, the DD-return relation should be weak when using a short RD-DD threshold.

4.2 Sorted Stock Portfolio Returns

Table 21 reports mean returns of the hedge (high minus low distress) portfolio for each sorting procedure (DD, RD, DDS and RDS). Equal- and value-weighted returns are reported for four RD-DD thresholds. Focusing on Panel 1, where distress is measured by CHS failure probability, the DD hedge portfolio returns are often negative and never statistically significant. In contrast, the DDS hedge portfolio returns are always positive and highly significant for all thresholds. After controlling for predictable returns related to the adjustment period (captured by RD), the DD-return relation is positive. This is consistent with a positive price of distress risk.

The RD hedge portfolio returns are significant for most thresholds and always negative. This is consistent with Dichev (1998) and CHS (2008), who find that firms with high financial distress deliver abnormally low returns. The RDS hedge portfolio returns are always more negative, more significant, and larger in absolute value than the corresponding RD hedge portfolio returns. For example, in Panel 1 the equal-weighted RDS hedge portfolio using a four-quarter RD-DD threshold exhibits a return of -1.21% per month, while the RD hedge portfolio exhibits a return of -0.71%. By controlling for distant financial distress, we uncover a stronger negative relationship between recent financial distress and stock returns. Results are similar in Panel 2, where distress is measured by O-score.

Table 22 reports regressions of the RDS and DDS hedge portfolio returns on the Fama and French (1996) factors (MKT, SMB, and HML) and the Fama and French factors with a momentum factor (WML). As above, results are reported for both equal- and value-weighted returns and for thresholds of 4, 6, and 8 quarters. Alphas are similar to the raw portfolio returns. The DDS hedge portfolio earns a significant positive returns for most of the thresholds. The RDS hedge portfolio always earns highly significant negative returns. For example, when using the CHS predicted failure probability and a four-quarter threshold, the DDS hedge portfolio generates an equal-weighted three-factor alpha of 0.69% monthly (with a robust t-statistic of 4.08). Using the same setup, the RDS hedge portfolio generates an equal-weighted three-factor alpha of -1.49% monthly. Overall, these results suggest that commonly-used factors cannot explain the nonzero mean returns of the RDS and DDS hedge portfolios.

Although a positive DD-return relation is consistent with a positive distress risk-return relation, we are not comfortable asserting that the price of distress risk is positive based on the results of this section. It remains possible that distress risk is not priced, but distress risk shocks are correlated with another priced stock characteristic. For example, suppose that distress risk is not priced, but the change in distress risk is correlated with some stock characteristic associated with subsequent returns (e.g. through return reversals or underreaction to cash flow news). Then, $RD - DD$ will be correlated with subsequent returns, and the partial relations between RD and DD and subsequent returns will be nonzero (i.e. a regression of returns on lagged $RD - DD$, or on RD and DD, should yield nonzero parameters).

Therefore, the return patterns of Table 22 do not imply that distress risk is priced. One could conceivably address this by running a regression of returns on $RD - DD$ and DD and testing for a nonzero DD parameter. However, such a regression may suffer from measurement error. Measurement error is a concern given that (1) we do not know the "correct" RD-DD threshold, so $RD - DD$ likely mismeasures the forecast error, (2) the distress risk premium, and degree of underreaction, likely varies across firms, and (3) both RD and DD measure expected distress risk with error. Also, because DD and $RD - DD$ are almost certainly correlated, the measurement errors may interact. Therefore, in the next section, we take an alternative approach to estimating the underlying price of distress risk.

4.3 Longer Holding Periods

Under our model of underreaction, prices diverge from rational values. However, the mispricing is temporary. Eventually investors arrive at the correct risk premium.

This suggests that one could estimate the underlying price of distress risk by examining distress-sorted hedge portfolios for many months after portfolio formation. Although underreaction may influence the returns of these portfolios for some time after portfolio formation, eventually the effects of underreaction should dissipate, and the mean returns of the portfolios should reflect compensation for risk.

Examining long-run returns will only be useful if distress risk is persistent. If financial distress is not very persistent, then distress-sorted portfolios formed using year t financial distress will not exhibit much dispersion in financial distress in, say, year $t + 5$. Then, any difference in year $t + 5$ mean returns cannot reasonably be attributed to distress risk. However, we find that financial distress is quite persistent. Using predicted default probability as a measure of financial distress, the time series average of the cross-sectional correlation between financial distress and one-, three-, and five-year subsequent financial distress is .78, .72, and .68, respectively. Therefore, our measure of financial distress can be reasonably used to form portfolios with systematically varying distress risk, even if returns are measured long after portfolio formation.

We report the average six-month equal-weighted returns of distress-sorted hedge portfolios for up to five years after portfolio formation in Table 23. First, we note that the return patterns documented in Table 21 are not very persistent. In both panels of Table 23, the negative returns of the distress hedge portfolio persist for about a year after portfolio formation then become positive. This can also be seen in Figure 6, which plots the cumulative returns of distress-sorted hedge portfolio for 60 months after the portfolio formation. The returns of the distress hedge portfolio are negative for about a year after portfolio formation. After a year, the returns are always positive.

We find that, for each measure of financial distress, the returns of the distress-sorted portfolios are always positive starting one year after portfolio formation (although these returns are not always significantly positive). This provides direct evidence that the distress risk-return relation is dynamic (RD is sometimes positively and sometimes negatively related to subsequent returns, depending on the post-formation period return being measured). Also, this is consistent with the notion that distressed stocks are likely riskier than non-distressed stocks, and distress risk should carry a positive premium. Indeed, compensation for risk seems a particularly appealing explanation for the long-run positive returns of Table 23, as most types of mispricing are likely corrected within five years. Overall, these results are consistent with our underreaction framework.

The results of this section can be used to distinguish among explanations of the distress risk-return relation. For example, authors have attempted to explain the negative distress risk-return relation documented by Dichev (1998), and Campbell, Hilscher, and Szilagyi (2008) by appealing to firm's endogenous choice of leverage (George and Hwang (2010)), violations of shareholder priority in bankruptcy (Garlappi and Yan (2011)), and investors' preference for skewness (Conrad, Kapadia, and Xing (2012)). These explanations may explain the negative relation between recent distress and returns but are then inconsistent with the long-run positive relation. The evidence presented in this paper suggests that a satisfactory explanation of the distress risk-return relation must address both short-run negative and long-run positive returns.

4.4 Fama-Macbeth Analysis

In this section, we use Fama and MacBeth (1973) cross-sectional regressions to estimate the relationship between financial distress and subsequent returns. The procedure is an alternative to the sorted portfolio approach examined above and can be interpreted as a robustness test. One advantage of the Fama-MacBeth procedure is that it is easy to simultaneously control for many other characteristics. However, many of the standard controls used in cross-sectional regressions plausibly capture information about distress risk, which is not desirable when examining the distress risk-return relation. In particular, high book-to-market stock may earn a premium because they are in distress (as suggested by Fama and French (1996)). Other characteristics are plausibly related to financial distress as well.[7] For this reason, we report results from a cross-sectional regression with only RD and DD and results from a cross-sectional regression with RD, DD, and controls.

We perform the Fama-MacBeth procedure using both OLS and WLS (with weights equal to market capitalizations). The OLS and WLS regressions correspond to an equal-weighted and value-weighted approach (respectively). Under the WLS regressions, each observation receives a weight equal to the stock's share of total market capitalization.[8] Stock characteristics included as controls are market capitalization, book-to-market ratio, prior return from month -6 to month -2, prior return over month -1 and illiquidity.[9] We focus on a four-quarter threshold in this section, although results are robust to using other thresholds.[10]

Results are reported in Table 24. Focusing on Panel 1, where distress is measured by failure probability, RD is always highly significant and negatively related to subsequent stock returns while DD is always highly significant and positively related

[7]Suppose distress risk is positively priced. Then small stocks may earn higher returns because small stocks are more likely to be distressed. Illiquid stocks may earn high returns because illiquid stocks are more likely to be distressed.

[8]Under WLS, we minimize $\sum w_i e_i^2$, where w_i is market capitalization and e_i is the difference between the actual and fitted return. Under OLS, $w_i = 1$.

[9]Illiquidity is calculated as the log of the trailing one-year average of daily $|R_{i,t}|/DVOL_{i,t}$, where $R_{i,t}$ is the return of stock i on day t and $DVOL$ is dollar volume. This follows Amihud (2002).

[10]Our results are also robust to using the expected skewness as constructed by Boyer, Mitton, and Vorkink (2010) and historical skewness.

to subsequent stock returns. Results are similar when distress is measured by O-score.

Many of the characteristics exhibit a weaker relation with returns when using WLS. In Panel 1, book-to-market is an important characteristic both economically and statistically in the OLS regression, although not in the WLS regression (the book-to-market parameter estimate is 0.274 in the equal-weighted regressions (with a t-statistic of 3.11) and 0.159 in the value-weighted regression (with a t-statistic of 1.35)). Similarly, the economic and statistical significance of one-month prior return is attenuated in the value-weighted regressions. In contrast, the DD and RD parameters have similar magnitudes in the equal- and value-weighted regressions. This suggests that the relationship between financial distress and returns is pervasive (i.e. not only found in small stocks). Also, this suggests the the return patterns associated with financial distress are not likely to be explained by return patterns primarily associated with small stocks (e.g. bid-ask bounce or short-term reversals). Overall, these results are consistent with the sorted portfolio results.

5 Distress Risk and the Size and Value Premiums

The previous section shows that the distress risk-return relation is dynamic. In this section we examine whether financial distress risk, expunged of the effects of underreaction, can explain the size or value premium as suggested by Chan and Chen (1991) and Fama and French (1996). To do this, we examine the ability of traded market and distress factors to explain the nonzero returns of size- and value-sorted portfolios.

In this application, we use CHS (2008) failure probability as a measure of distress. The distress factor (FD) is the equal-weighted DDS hedge portfolio return, using a four-quarter RD-DD threshold.[11] Panel A of Table 25 reports summary statistics for FD, the Fama-French factors (MKT, SMB, and HML), and the momentum factor (WML). The average return of FD is 0.805% monthly. Panel B reports factor correlation coefficients. FD is not highly correlated with any of the other factors, although most of the correlations are statistically significant.[12]

Panel C reports time-series regressions of the SMB, HML, and WML factors on MKT and FD. FD may explain a substantial portion of SMB returns. Adding the distress factor attenuates the SMB alpha from 0.191% to -0.019%, although neither alpha is significant (this is likely a result of our short time series, 1977-2010). However, the SMB hedge portfolio has a highly significant and positive FD loading.

In contrast to the SMB hedge portfolio, we find no evidence that HML is related to distress. Adding FD to the HML regression slightly increases the alpha. Also, HML does not load significantly on FD. Therefore, we find no evidence that financial distress can explain the value premium.

Table 26 reports results when we use GMM to simultaneously examine all of the size- or book-to-market-sorted portfolios, rather than a hedge portfolio formed from the extreme quintile portfolios. The p-value associated with testing overidentifying restrictions is reported. Panel A of Table 26 provides additional evidence that distress risk explains the anomalous returns of the size-sorted portfolio. The intercepts are generally not significant and we fail to reject the null hypothesis that the intercepts are jointly zero (p-value=0.271). The loadings on the distress factor monotonically decrease as size increases. Small firms (quintile 1) have positive and

[11] We obtain qualitatively similar results if we use value-weighted returns.

[12] We also examined the correlation between FD and the default yield, defined as the return difference between BAA and AAA-rated corporate bonds. The correlation is -0.05, which suggests that the default spread and distress factor share little information.

significant loadings on the distress factor while large firms (quintile 5) have negative and significant loadings. Overall, this result is consistent with the suggestion of Chan and Chen (1991); the size premium appears to be related to financial distress.

Panel B of Table 26 reports results for the book-to-market-sorted portfolios. We find a non-monotonic relation between book-to-market and FD loading, consistent with Dichev (1998) and Griffin and Lemmon (2002). If the source of the value premium is distress risk, then firms with high book-to-market should have greater loadings on the distress factor than firms with low book-to-market. However, we find that the loadings on the distress factor for low and high book-to-market firms have similar magnitudes: 0.277 for the low book-to-market quintile and 0.286 for the high book-to-market quintile. The middle quintiles (2, 3, and 4) have the lowest FD loading. The non-monotonic loading pattern of Panel B suggests that market-to-book portfolios are related to distress, although the relation appears to be more complicated than a simple linear relation between market-to-book and financial distress.[13]

6 Summary

In this paper, we show that the distress risk-return relation is dynamic. In the cross section of stocks, recent innovations in distress risk (and the level of recent financial distress) are negatively related to subsequent returns. However, controlling for recent financial distress, distant financial distress is positively related to subsequent returns. We find that the negative distress risk-return relation documented in prior studies is short-lived, lasting about a year. In the long-run, we find that the distress

[13] Kapadia (2011) finds that stock's covariation with an aggregate firm failure index can be used to construct a distress factor that is related to the value premium. Kapadia does not address the relation between predicted default probability and subsequent returns.

risk-return relation is positive. Prior studies fail to detect this long run relation because such studies generally focus on one-year returns immediately after portfolio formation.

These empirical findings can be used to discriminate among potential explanations of the negative distress risk-return relation. Many such explanations do not address the dynamic nature of the distress risk-return relation. A complete explanation of the distress risk-return relation should explain why two different proxies for distress could have differing relations with subsequent returns. Also, a complete explanation should explain why the same proxy for distress risk could exhibit a negative relation with short-run returns and a positive relation with long-run returns.

We develop a simple model that examines the interaction of distress risk and investor underreaction. Our empirical findings are consistent with a positive price of distress risk and temporary investor underreaction to risk innovations. This allows us to reconcile our findings, and those of Dichev (1998), and Campbell, Hilscher, and Szilagyi (2008), with intuition that suggests that distress risk should carry a nonnegative price.

Our inability to measure investors' estimates of distress risk prevents us from directly testing our underreaction framework. To address this, we rule out many alternative explanations of our results. Although it remains possible that some omitted stock characteristic, correlated with financial distress, may explain our findings, such an explanation would need to address the dynamic nature of the distress risk-return relation.

Our empirical findings can be interpreted as evidence against any explanation of the return patterns associated with financial distress that rely on a persistent explanatory variable. Overall, we find a positive price of distress risk and investor underreaction to distress risk innovations to be a compelling explanation of thes returns patterns.

We explore the relation between distress risk and the size and book-to-market anomalies. We find that distress risk is a plausible explanation of the anomalous returns of the SMB portfolio. However, we find no evidence that distress risk can explain the anomalous returns of the HML portfolio. Therefore, researchers may need to look elsewhere when attempting to explain the value premium.

Appendix

The CHS distress index is the predicted failure probability of the firm. This measure tracks realized failure rates (CHS (2008)). The CHS distress index and failure probability are calculated as

$$\begin{aligned} CHS_{i,t} \;=\; & -9.164 - 20.264 NIMTAAVG_{t-1,t-12} + 1.416 TLMTA_{t-1} \\ & -7.129 EXRETAVG_{t-1,t-12} + 1.411 SIGMA_{t-1,t-3} - 0.045 RSIZE_{t-1} \\ & -2.132 CASHMTA_{t-1} + 0.075 MB_{t-1} - 0.058 PRICE_{t-1} \end{aligned}$$

$$P\_CHS = Failure\ Probability = P_{t-1}(Y_{i,t}=1) = \frac{1}{1+exp(-CHS_{i,t-1})} \tag{19}$$

$$NIMTAAVG_{t-1,t-12} = \frac{1-\phi^3}{1-\phi^{12}}(NIMTA_{t-1,t-3} + ... + \phi^9 NIMTA_{t-10,t-12})$$

$$EXRETAVG_{t-1,t-12} = \frac{1-\phi^3}{1-\phi^{12}}(EXRET_{t-1} + ... + \phi^{11} EXRET_{t-12})$$

in which $\phi = 2^{-1/3}$. $NIMTAAVG$ is a geometrically declining average of past values of the ratio of net income to the market value of total assets. Market value of assets equals the book value of assets plus the market value of common stock less the sum of book value of common stock and balance sheet deferred taxes. $NIMTA$ is the ratio of net income to the market value of total assets. $NIMTAAVG$ is calculated as a moving average to capture the intuition that a long history of losses is a better predictor of bankruptcy than one large quarterly loss. $TLMTA$ is the ratio of total liabilities to the market value of total assets. $EXRETAVG$ is a geometrically declining average of monthly log excess return over the

S&P 500 index. $EXRET_{i,t} = log(1 + R_{i,t}) - log(1 + R_{S\&P500,t})$ is the monthly log excess return relative to the S&P500 index. $SIGMA_{i,t-1,t-3} = (252 * \frac{1}{N-1} \sum_{k \in \{t-1,t-3\}} r_{i,k}^2)^{\frac{1}{2}}$ is the annualized standard deviation of daily stock returns over the previous three months. This standard deviation is centered around zero rather than the rolling 3-month mean and is coded as missing if there are less than 5 observations. $RSIZE$ is the log of the ratio of market capitalization to the market value of the S&P 500 index. $CASHMTA$ is the ratio of cash holdings and short term investments to the market value of total assets. MB is the market-to-book ratio. Book equity is defined as in Davis, Fama and French (2000), which equals to the stockholders' equity, plus balance sheet deferred taxes. If this data is unavailable, we measure stockholders'equity as the book value of common equity. Following CHS, we adjust the book value of equity by adding 10% of the difference between market and book equity to the book value of equity. This adjustment increases extremely small (or negative) book values that are likely mismeasured, which can result in outliers when calculating financial ratios. $PRICE$ is the log price per share. To further reduce the influence of outliers, we follow CHS and winsorize all variables at 5th and 95th percentiles of their pooled distribution. P_CHS is the failure probability from the estimated dynamic logit model. The sample is restricted to firm-quarters with complete data for profitability ($NIMTA$) and leverage ($TLMTA$), with no missing monthly stock returns or quarterly accounting items.

We follow Ohlson (1980) to construct the O-score. The O-score is the predicted value from a dynamic logit regression of bankruptcy on financial ratios. High O-score is associated with high financial distress. O-score is calculated as

$$
\begin{aligned}
O\,score &= -1.32 - 0.407 * log(\frac{MKTASSET}{CPI}) + 6.03 * TLTA \\
&\quad -1.43 * WCTA + 0.076 * CLCA - 1.72 * OENEG \\
&\quad -1.83 * FUTL + 0.285 * INTWO - 0.521 * CHIN \\
&\quad -2.37 * NITA
\end{aligned} \tag{20}
$$

where $MKTASSET$ is the total market value of asset, CPI is the consumer price index. $TLTA$ is the leverage ratio, defined as the the book value of debt ($DLCQ$ plus $DLTTQ$) divided by market value of assets. $WCTA$ is the working capital, defined as the difference between current assets ($ACTQ$) and current liabilities ($LCTQ$). $CLCA$ is ratio of current liabilities to current assets. $OENEG$ is a dummy variable that equals to one if total liabilities (LTQ) exceeds total assets (ATQ) and is zero otherwise. $NITA$ is net income (NIQ) divided by market assets. $FUTL$ is the ratio of funds provided by operations (PIQ) to liabilities (LTQ). $INTWO$ is a dummy variable that equals to one if net income (NIQ) is negative for the measurement horizon and zero otherwise. $CHIN = (NI_t - NI_{t-1})/(|NI_t| + |NI_{t-1}|)$ is the change in net income over the measurement horizon. All inputs are winsorized at the 5th and 95th percentiles of their pooled distributions.

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Table 1

Summary Statistics for Market Returns, Aggregate Asset Growth, and Other Predictors

The table reports the summary statistics for market returns, aggregate asset growth and other return predictors. Quarterly market returns (in logarithm) are computed by compounding monthly returns for each quarter. VWRET is the value-weighted excess return. EWRET is the equal-weighted excess return. SPRET is the SP500 excess return. AG is the value-weighted averages of firm-level asset growth, defined as the quarter-on-quarter percentage change in the book value of total assets. Other predictive variables follow the definition of Goyal and Welch (2008). EP is the log earnings-to-price ratio. DP is the log dividend-to-price ratio. BM is the book-to-market ratio. TBL is the 30-day T-bill rate. TMS is the difference between long term yield on government bonds and the Treasury-bill. DFY is the difference between BAA and AAA-rated corporate bonds. NTIS is the net equity issuance. SVAR is the equity variance. IK is the investment-to-capital ratio. CAY is the consumption-wealth ratio. p(ADF) is the p-value associated with the augmented Dickey-Fuller test of unit root. The sample period is 1972Q1-2011Q4.

Panel A: Summary statistics and autocorrelations

Name	Mean	std. dev	Q1	Median	Q3	Autocorrelation 1	Autocorrelation 2	Autocorrelation 3	p(ADF)
VWRET	0.010	0.091	-0.032	0.024	0.066	0.06	-0.07	-0.04	0.00
EWRET	0.016	0.121	-0.055	0.020	0.095	0.03	-0.09	-0.05	0.00
SPRET	0.003	0.086	-0.040	0.014	0.055	0.09	-0.05	-0.04	0.00
AG	0.034	0.017	0.025	0.032	0.039	0.56	0.38	0.33	0.00
EP	-2.816	0.513	-3.106	-2.831	-2.462	0.94	0.84	0.74	0.02
DP	-3.593	0.450	-4.008	-3.553	-3.206	0.98	0.96	0.93	0.69
BM	0.512	0.297	0.282	0.402	0.746	0.98	0.96	0.94	0.70
TBL	0.054	0.033	0.035	0.052	0.072	0.93	0.88	0.85	0.47
TMS	0.020	0.015	0.010	0.023	0.033	0.81	0.66	0.59	0.00
DFY	0.011	0.005	0.008	0.010	0.013	0.84	0.68	0.57	0.01
NTIS	0.010	0.020	0.001	0.013	0.024	0.91	0.80	0.66	0.01
SVAR	0.008	0.012	0.003	0.005	0.008	0.40	0.16	0.09	0.00
IK	0.036	0.004	0.033	0.036	0.038	0.97	0.90	0.81	0.01
CAY	0.002	0.023	-0.014	-0.002	0.025	0.95	0.91	0.87	0.25

Panel B: Correlations between one-quarter-ahead market returns and AG

	VWRET	EWRET	SPRET	AG
VWRET	1	0.87	0.99	-0.25
EWRET		1	0.82	-0.22
SPRET			1	-0.24
AG				1

Table 2

Univariate Regression Results

The table reports the time series regression of multi-quarter-ahead stock market returns on aggregate asset growth:

$$R_{t+\tau} = \alpha + \beta AG_t + u_t$$

Panel A reports the results for contemporaneous stock market returns ($\tau = 0$), and Panel B to E report the results for multi-quarter-ahead stock market returns ($\tau = 1, 2, 3, 4$). VWRET is the value-weighted excess return. EWRET is the equal-weighted excess return. SPRET is the SP500 excess return. AG is the value-weighted averages of firm-level asset growth, defined as the quarter-on-quarter percentage change in book value of total assets. The coefficients are multiplied by 100 and expressed in percentage. The independent variable is standardized to have zero mean and unit variance. t-statistics are computed using Newey-West standard errors. Rand.p is the bootstrap p-value calculated following Nelson and Kim (1993). *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The sample period is 1972Q1-2011Q4.

Returns	α in %	$t(\alpha)$	β in %	$t(\beta)$	Rand.p	Adj.R^2(%)
			Panel A: $\tau = 0$			
VWRET	1.07	1.53	1.20	1.28	0.12	1.24
EWRET	1.69	1.88	0.47	0.40	0.21	-0.46
SPRET	0.29	0.42	1.22	1.38	0.11	1.49
			Panel B: $\tau = 1$			
VWRET	1.03	1.51	-2.27***	-3.69	0.01	5.75
EWRET	1.64	1.83	-2.61***	-3.04	0.01	4.10
SPRET	0.26	0.38	-2.05***	-3.53	0.01	5.18
			Panel C: $\tau = 2$			
VWRET	1.03	1.54	-1.30**	-2.49	0.02	1.48
EWRET	1.64	1.85	-1.55**	-2.09	0.04	1.03
SPRET	0.26	0.38	-1.11**	-2.44	0.02	1.08
			Panel D: $\tau = 3$			
VWRET	1.00	1.45	-0.56	-0.71	0.28	-0.25
EWRET	1.57	1.67	0.45	0.61	0.32	-0.50
SPRET	0.23	0.34	-0.48	-0.67	0.30	-0.32
			Panel E: $\tau = 4$			
VWRET	1.01	1.42	-0.15	-0.26	0.38	-0.61
EWRET	1.63	1.71	0.98	1.48	0.13	0.02
SPRET	0.24	0.35	-0.23	-0.41	0.35	-0.57

Table 3

Multivariate Regression Results

The table reports the coefficients and t-statistics from time series regressions of multi-quarter-ahead ($\tau = 1, 2$) stock market returns on the aggregate asset growth and other return predictors:

$$R_{t+\tau} = \alpha + \beta_1 AG_t + \beta_2 EP_t + \beta_3 DP_t + \beta_4 BM_t + \beta_5 TBL_t + \beta_6 TMS_t + \beta_7 DFY_t + \beta_8 NTIS_t + \beta_9 SVAR_t + \beta_{10} IK_t + \beta_{11} CAY_t$$

VWRET is the value-weighted excess return. EWRET is the equal-weighted excess return. SPRET is the SP500 excess return. AG is the value-weighted averages of firm-level asset growth, defined as the quarter-on-quarter percentage change in book value of total assets. The independent variables are defined in Table 1 and standardized to have zero mean and unit variance. The coefficients are multiplied by 100 and expressed in percentage. t-statistics are computed using Newey-West standard errors. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The sample period is 1972Q1 to 2011Q4.

Returns		α	AG	EP	DP	BM	TBL	TMS	DFY	NTIS	SVAR	IK	CAY	Adj.R^2(%)
Panel A: $\tau = 1$														
VWRET	Coef.	1.04	-2.81***	2.12	-8.58	8.52	-4.72	-2.86	1.93	-0.89	-0.19	0.36	5.89	11.50
	t-stat	1.70	-3.42	0.90	-2.07	2.00	-2.57	-2.57	1.30	-1.21	-0.18	0.30	4.10	
EWRET	Coef.	1.62	-2.89***	1.81	-13.40	15.21	-7.94	-4.38	3.34	-0.75	0.38	0.25	8.63	8.63
	t-stat	2.15	-3.02	0.69	-2.87	3.06	-3.57	-3.24	1.69	-0.82	0.23	0.17	5.27	
SPRET	Coef.	0.27	-2.64***	2.04	-7.77	7.24	-4.51	-2.81	1.92	-0.81	-0.44	0.44	5.57	11.05
	t-stat	0.45	-3.36	0.89	-1.88	1.71	-2.48	-2.54	1.38	-1.12	-0.46	0.37	3.90	
Panel B: $\tau = 2$														
VWRET	Coef.	1.09	-1.31**	1.65	-7.46	7.93	-4.12	-2.75	1.91	-0.16	0.98	-0.23	5.75	8.71
	t-stat	1.85	-2.19	1.01	-1.92	2.05	-2.28	-2.67	1.78	-0.19	1.50	-0.20	3.89	
EWRET	Coef.	1.73	-1.54*	1.32	-13.41	15.61	-6.45	-4.27	2.59	-0.01	1.97	-0.62	8.72	14.40
	t-stat	2.57	-1.91	0.84	-3.17	3.72	-2.91	-3.28	1.60	-0.01	1.77	-0.47	5.45	
SPRET	Coef.	0.31	-1.14**	1.65	-6.48	6.56	-4.02	-2.60	1.89	-0.14	0.78	-0.09	5.40	7.97
	t-stat	0.53	-2.20	0.98	-1.68	1.70	-2.26	-2.61	1.88	-0.18	1.33	-0.08	3.75	

Table 4

Out-of-Sample Results: Aggregate Asset Growth and Stock Market Returns

The table reports results from one step ahead out-of-sample forecasts of quarterly market returns. The sample period is 1972Q1 to 2011Q4. Recursive (expanding window) forecasts are made for four out-of-sample forecast periods: 1985Q1 to 2011Q4, 1990Q1 to 2011Q4, and 1995Q1 to 2011Q4, and 2000Q1 to 2011Q4. AG is the aggregate asset growth and other predictive variables are defined in Table 1. OOS R^2 is the Campbell and Thomson (2008) out-of-sample statistic. Statistical significance for the OOS R^2 is based on the p-value from the Clark and West (2007) out-of-sample MSPE-adjusted statistic. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Returns	OOS Statistics	AG	EP	DP	BM	TBL	TMS	DFY	NTIS	SVAR	IK	CAY
Panel A: 1985Q1-2011Q4 out-of-sample period												
VWRET	OOS R^2 (%)	2.67***	-6.26	-6.97	-8.74	-1.23	-1.95	-4.65	-4.83	-42.75	-2.55	1.21**
	p-value	0.01	0.82	0.68	0.92	0.72	0.44	0.87	0.32	0.36	0.40	0.02
EWRET	OOS R^2 (%)	0.52***	-9.73	-9.55	-10.86	-0.57	-0.55	-1.76	-4.54	-55.11	-2.63	-1.48
	p-value	0.01	0.65	0.40	0.54	0.36	0.26	0.26	0.63	0.20	0.27	0.18
SPRET	OOS R^2 (%)	1.09***	-4.88	-6.02	-7.27	-1.15	-2.39	-5.23	-4.53	-40.91	-3.08	2.44***
	p-value	0.01	0.96	0.87	0.98	0.56	0.47	0.97	0.26	0.48	0.45	0.01
Panel B: 1990Q1-2011Q4 out-of-sample period												
VWRET	OOS R^2 (%)	6.00***	-5.25	-6.57	-2.48	-1.44	-1.66	-5.66	-7.75	-5.36	-2.08	0.26**
	p-value	0.01	0.76	0.80	0.80	0.71	0.43	0.92	0.97	0.89	0.34	0.04
EWRET	OOS R^2 (%)	2.31**	-11.57	-13.13	-7.06	-0.42	0.63	-3.58	-3.06	-6.41	-0.55	0.89*
	p-value	0.03	0.84	0.72	0.71	0.33	0.16	0.42	0.95	0.62	0.15	0.10
SPRET	OOS R^2 (%)	4.83***	-3.67	-5.08	-1.76	-1.54	-2.35	-6.26	-9.44	-4.88	-3.32	0.34**
	p-value	0.01	0.86	0.93	0.80	0.58	0.50	0.99	0.98	0.92	0.46	0.03
Panel C: 1995Q1-2011Q4 out-of-sample period												
VWRET	OOS R^2 (%)	6.18**	-4.09	-5.90	-1.78	-1.64	-2.06	-5.46	-6.07	-6.22	-1.58	3.30***
	p-value	0.02	0.75	0.90	0.96	0.76	0.58	0.97	0.97	0.91	0.42	0.01
EWRET	OOS R^2 (%)	0.13*	-6.57	-10.28	-3.86	-0.98	0.03	-2.76	-2.37	-7.93	-0.73	2.66**
	p-value	0.10	0.79	0.71	0.74	0.43	0.27	0.47	0.91	0.64	0.21	0.03
SPRET	OOS R^2 (%)	5.19**	-3.22	-4.71	-1.39	-1.76	-2.87	-5.88	-7.15	-5.57	-2.86	3.43***
	p-value	0.02	0.83	0.99	0.79	0.64	0.67	1.00	0.98	0.93	0.59	0.01
Panel D: 2000Q1-2011Q4 out-of-sample period												
VWRET	OOS R^2 (%)	13.67***	-2.81	1.27	-0.15	-3.31	-1.59	-1.36	-6.64	-9.46	3.24*	1.48*
	p-value	0.00	0.59	0.21	0.52	0.93	0.49	0.67	0.96	0.96	0.10	0.06
EWRET	OOS R^2 (%)	7.73**	-5.26	-1.02	-0.38	-1.55	0.15	0.76	-2.88	-11.17	2.97*	2.30*
	p-value	0.02	0.74	0.42	0.45	0.48	0.27	0.29	0.91	0.73	0.10	0.07
SPRET	OOS R^2 (%)	12.63***	-3.63	-1.22	-2.50	-4.55	-2.14	-1.70	-7.48	-8.48	2.90	0.60*
	p-value	0.00	0.80	0.71	0.99	0.90	0.54	0.86	0.96	0.98	0.11	0.07

Table 5

Regression of Stock Market Returns on the Subcomponents of Asset Growth: Asset and Financing Decompositions

The table reports the coefficients and t-statistics (in parentheses) from time series regressions of one-quarter-ahead stock market returns on the subcomponents of aggregate asset growth, from an asset and a financing decomposition. In the asset decomposition, asset growth is the sum of : (1) ΔCash (growth in cash), (2) ΔCurAsst (growth in noncash current assets), (3) ΔPPE (growth in property, plant, and equipment), (4) ΔOthAssets (growth in other assets). In the financing decomposition, asset growth is the sum of : (1) ΔOpLiab (growth in operating liabilities), (2) ΔDebt (growth in debt financing), (3) ΔStock (growth in equity financing) (4) ΔRE (growth in retained earnings). VWRET is the value-weighted excess return. EWRET is the equal-weighted excess return. SPRET is the SP500 excess return. The independent variables are standardized to have zero mean and unit variance. The coefficients are multiplied by 100 and expressed in percentage. t-statistics are computed using Newey-West standard errors. The sample period is 1974Q4-2011Q4.

Asset Decomposition						Financing Decomposition					
Constant	ΔCash	ΔCurAsst	ΔPPE	ΔOthAssets	Adj R^2 (%)	Constant	ΔOpLiab	ΔDebt	ΔStock	ΔRE	Adj R^2 (%)
Panel A: Dependent variable = VWRET											
1.53	-1.91***				4.09	1.55	-1.85**				3.78
(2.17)	(-2.41)					(2.24)	(-2.09)				
1.53		-1.19			1.17	1.90		-0.01			0.33
(2.13)		(-1.22)				(2.75)		(-0.02)			
1.53			-0.69		-0.08	1.69			-1.47***		1.94
(2.12)			(-0.75)			(2.50)			(-2.51)		
1.54				-1.37**	1.75	1.53				-0.85	-0.70
(2.20)				(-2.01)		(2.12)				(-1.01)	
Panel B: Dependent variable = EWRET											
1.87	-1.95***				4.32	1.88	-1.82**				3.64
(2.63)	(-2.51)					(2.69)	(-2.03)				
1.87		-1.20			1.19	2.17		0.07			0.45
(2.58)		(-1.26)				(3.16)		(0.09)			
1.87			-0.66		-0.13	1.95			-1.34***		1.58
(2.56)			(-0.77)			(2.84)			(-2.22)		
1.88				-1.29*	1.47	1.87				-0.96	-0.70
(2.65)				(-1.93)		(2.57)				(-1.18)	
Panel C: Dependent variable = SPRET											
0.68	-1.64**				3.26	0.69	-1.63**				3.16
(0.96)	(-2.20)					(1.00)	(-2.01)				
0.68		-1.21			1.45	0.97		0.08			0.79
(0.96)		(-1.32)				(1.42)		(0.12)			
0.68			-0.90		0.48	0.78			-1.08*		0.99
(0.96)			(-1.03)			(1.14)			(-1.81)		
0.69				-1.06	0.93	0.68				-1.01	-0.70
(0.97)				(-1.62)		(0.95)				(-1.32)	

Table 6

Tests of Q-theory with Investment Frictions: Asset Growth and Time-Varying Predictability

The table reports the coefficients and t-statistics (in parentheses) from time series regressions of multi-quarter-ahead market returns ($\tau = 1, 2, 3, 4$) on aggregate asset growth.

$$R_{t+\tau} = \alpha + \beta AG_t + \gamma AG_t * Recession + u_t$$

where recession equals one if in recession and zero otherwise. VWRET is the value-weighted excess return. EWRET is the equal-weighted excess return. SPRET is the SP500 excess return. The independent variables are standardized to have zero mean and unit variance. The coefficients are multiplied by 100 and expressed in percentage. t-statistics are computed using Newey-West standard errors. The sample period is 1972Q1-2011Q4. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Returns	α in %	$t(\alpha)$	β in %	$t(\beta)$	γ in %	$t(\gamma)$	Adj.R^2(%)
			Panel A: $\tau = 1$				
VWRET	1.17	1.80	-1.82***	-3.35	-5.85**	-2.38	8.14
EWRET	1.80	2.05	-2.10***	-3.22	-6.78**	-2.15	5.73
SPRET	0.40	0.61	-1.60***	-3.22	-5.89***	-2.42	7.97
			Panel B: $\tau = 2$				
VWRET	1.11	1.71	-1.04*	-1.91	-3.43	-1.23	1.88
EWRET	1.78	2.04	-1.10	-1.54	-5.95	-1.60	2.13
SPRET	0.34	0.52	-0.86*	-1.85	-3.32	-1.31	1.53
			Panel C: $\tau = 3$				
VWRET	0.95	1.32	-0.72	-0.86	2.15	0.77	-0.49
EWRET	1.44	1.49	0.05	0.07	5.18	1.45	0.17
SPRET	0.19	0.27	-0.60	-0.78	1.63	0.60	-0.70
			Panel D: $\tau = 4$				
VWRET	1.04	1.46	-0.07	-0.11	-1.09	-0.42	-1.16
EWRET	1.60	1.67	0.89	1.42	1.13	0.34	-0.56
SPRET	0.28	0.40	-0.12	-0.20	-1.43	-0.57	-1.02

Table 7

Asset Growth, Analyst Forecast Errors and Revisions

The table reports the coefficients (β) and t-statistics from time series regression of aggregate analyst forecast revisions (Panel A) and forecast errors (Panel B) on lagged aggregate asset growth, at different time horizon τ, where τ=1, 2, 3, or 4 quarters,

$$\begin{aligned} FE_t &= \alpha + \beta AG_{t-\tau} + \gamma FE_{t-1} + u_t \\ REV_t &= \alpha + \beta AG_{t-\tau} + \gamma REV_{t-1} + u_t \end{aligned}$$

Analyst forecast errors (FE) or revisions (REV) are the equal- or value-weighted averages of the firm-level forecast errors or revisions. Forecast error (FE), is defined as the realized difference between earnings and the prevailing consensus forecasts, scaled by price per share. Forecast revision (REV), is defined as the quarter-on-quarter percentage change in consensus forecasts. AG is the aggregate asset growth. The regressions include past forecast errors or revisions as control variables. t-statistics are computed using heteroskedasticity and auto-correlation consistent standard errors. The sample period starts from 1976Q1 to 2011Q4.

Panel A: Forecast Revisions

	$\tau = 1$	$\tau = 2$	$\tau = 3$	$\tau = 4$
	A.1: Equal-weighted REV			
Coef. $\hat{\beta}$	-0.14***	-0.13**	0.02	0.02
t-stat	(-2.22)	(-2.02)	(0.21)	(0.23)
	A.2: Value-weighted REV			
Coef. $\hat{\beta}$	-0.22***	-0.15*	-0.08	-0.09
t-stat	(-3.46)	(-1.81)	(-0.93)	(-0.95)

Panel B: Forecast Errors

	$\tau = 1$	$\tau = 2$	$\tau = 3$	$\tau = 4$
	B.1: Equal-weighted FE			
Coef. $\hat{\beta}$	-0.24***	-0.22***	-0.04	-0.10
t-stat	(-3.00)	(-2.77)	(-0.28)	(-0.70)
	B.2: Value-weighted FE			
Coef. $\hat{\beta}$	-0.49***	-0.32**	-0.30	-0.30
t-stat	(-2.45)	(-2.19)	(-1.32)	(-1.44)

Table 8

Asset Growth and Cumulative Abnormal Returns around Earnings Announcements

The table reports the coefficients (β) and t-statistics from time series regressions of quarterly cumulative abnormal returns (CARs) around the earnings announcements on the aggregate asset growth, at different time horizon τ, where τ=1, 2, 3, or 4 quarters

$$CAR_t = \alpha + \beta AG_{t-\tau} + u_t \quad \tau = 1, 2, 3, 4$$

The quarterly CARs is the equal- or value-weighted average CARs of the S&P500 firms whose earnings announcements fall into the corresponding quarter. Panel A reports the results for the event window [-1,+1] where day 0 is the earnings announcement day. Panel B reports the results for the event window [-2,+2]. Three benchmark models are used: CAPM, Fama-French three factor model (FF), and Carhart four factor model. The estimation window is [-250, -5]. The independent variable is standardized to have zero mean and unit variance. The coefficients are multiplied by 100 and expressed in percentage. t-statistics are computed using heteroskedasticity and auto-correlation consistent standard errors. The sample period is 1972Q1 to 2011Q4. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Model	$\tau = 1$	$\tau = 2$	$\tau = 3$	$\tau = 4$
		Panel A: Event window [-1, +1]		
		A.1: Equal-weighted CARs		
CAPM	-0.04	-0.03	-0.00	0.03
t-stat	(-1.53)	(-1.20)	(-0.12)	(0.92)
3-factor	-0.04**	-0.04*	-0.04	0.02
t-stat	(-2.15)	(-1.98)	(-1.29)	(0.95)
4-factor	-0.05***	-0.05**	-0.04	0.02
t-stat	(-2.44)	(-2.23)	(-1.48)	(0.76)
		A.2: Value-weighted CARs		
CAPM	-0.07***	-0.04	0.00	-0.03
t-stat	(-2.71)	(-0.95)	(-0.03)	(-1.19)
3-factor	-0.06***	-0.06	-0.02	-0.02
t-stat	(-2.51)	(-1.58)	(-0.34)	(-0.79)
4-factor	-0.07**	-0.08	-0.04	-0.02
t-stat	(-2.23)	(-1.58)	(-0.60)	(-0.66)
		Panel B: Event window [-2, +2]		
		B.1: Equal-weighted CARs		
CAPM	-0.05	-0.03	0.03	0.03
t-stat	(-1.54)	(-0.76)	(1.04)	(0.86)
3-factor	-0.06***	-0.04*	-0.03	0.02
t-stat	(-2.51)	(-1.97)	(-0.75)	(0.76)
4-factor	-0.06***	-0.05***	-0.03	0.02
t-stat	(-2.68)	(-2.37)	(-0.90)	(0.76)
		B.2: Value-weighted CARs		
CAPM	-0.09***	-0.03	0.04	-0.04
t-stat	(-2.87)	(-0.80)	(0.60)	(-1.09)
3-factor	-0.07***	-0.05	0.01	-0.01
t-stat	(-2.79)	(-1.71)	(0.18)	(-0.47)
4-factor	-0.08***	-0.07*	-0.01	-0.01
t-stat	(-2.56)	(-1.84)	(-0.23)	(-0.42)

Table 9: Summary Statistics

Panel A reports the summary statistics for aggregate asset growth (AG) and its components. In the investment decomposition, asset growth is the sum of : (1) ΔCash (growth in cash), (2) ΔCurAsst (growth in noncash current assets), (3) ΔPPE (growth in property, plant, and equipment), (4) ΔOthAssets (growth in other assets). In the financing decomposition, asset growth is the sum of : (1) ΔOpLiab (growth in operating liabilities), (2) ΔRE (growth in retained earnings), (3) ΔStock (growth in equity financing), (4) ΔDebt (growth in debt financing). Panel B reports quarterly spearman correlation between aggregate asset growth and investor sentiment index ($SENT^{\perp}$) as in Baker and Wurgler (2006), and the Michigan Consumer Sentiment Index (MCSI), close-end fund discounts (CEFD), and IPO first-day returns (RIPO). Aggregate asset growth and $SENT^{\perp}$ span a period from 1972Q1 to 2010Q4, while the MCSI starts from 1978Q1. $SENT^{\perp}$ is constructed using the first principal component of six proxies: the trading volume, the dividend premium, the closed-end fund discount, the number and first-day returns on IPOs, and the equity new issuance. $SENT^{\perp}$ is orthogonalized with respect to a set of macroeconomic variables. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Summary statistics and autocorrelations

Name	Mean	std. dev	Q1	Median	Q3	Autocorrelation 1	Autocorrelation 2	Autocorrelation 3	p(ADF)
AG	3.35	1.68	2.48	3.16	3.88	0.58	0.39	0.33	0.00
Investment Decomposition									
ΔCash	0.40	0.56	0.07	0.39	0.68	0.41	0.13	0.18	0.00
ΔCurAsst	0.83	0.62	0.51	0.80	1.17	0.43	0.34	0.10	0.01
ΔPPE	1.04	0.59	0.64	0.94	1.35	0.62	0.54	0.47	0.05
ΔOthAsset	0.82	0.76	0.38	0.64	1.05	0.74	0.60	0.49	0.00
Financing Decomposition									
ΔOpLiab	1.57	0.89	0.98	1.42	1.98	0.24	0.01	0.15	0.01
ΔRE	0.87	0.60	0.60	0.91	1.23	0.38	0.08	0.13	0.00
ΔStock	0.98	1.22	0.34	0.56	1.16	0.84	0.68	0.59	0.01
ΔDebt	0.18	0.28	0.01	0.19	0.33	0.38	0.12	0.08	0.00

Panel B: Correlations between AG and other sentiment measures

	AG	$SENT^{\perp}$	MCSI	CEFD	RIPO
AG	1	0.172**	0.320***	-0.177**	0.172**
$SENT^{\perp}$		1	0.368***	-0.520***	0.201***
MCSI			1	-0.241***	0.226***
CEFD				1	-0.047
RIPO					1

Table 10: Asset Growth and its Subcomponents across Sentiment Terciles

The table reports average levels of aggregate asset growth (AG) and its subcomponents across sentiment terciles at different time horizon τ, from an investment and a financing decomposition. $SENT^{\perp}$ is the sentiment index from Baker and Wurgler (2006). "High-Low" is the difference in average values between the high sentiment periods and low sentiment periods. In the asset decomposition, asset growth is the sum of : (1) ΔCash (growth in cash), (2) ΔCurAsst (growth in noncash current assets), (3) ΔPPE (growth in property, plant, and equipment), (4) ΔOthAssets (growth in other assets). In the financing decomposition, asset growth is the sum of : (1) ΔOpLiab (growth in operating liabilities), (2) ΔRE (growth in retained earnings), (3) ΔStock (growth in equity financing), (4) ΔDebt (growth in debt financing). The subcomponents of asset growth are the quarter-by-quarter changes in these variables, scaled by total assets in previous quarter, to maintain the asset growth identity. The subcomponents of asset growth are in aggregate level, defined as the value-weighted averages of firm-level variables. The sample period is 1974Q2 to 2010Q4. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

		Investment Decomposition				Financing Decompostion			
$SENT_t^{\perp}$	$AG_{t+\tau}$	$\Delta Cash_{t+\tau}$	$\Delta CurAsst_{t+\tau}$	$\Delta PPE_{t+\tau}$	$\Delta OthAssets_{t+\tau}$	$\Delta OpLiab_{t+\tau}$	$\Delta RE_{t+\tau}$	$\Delta Stock_{t+\tau}$	$\Delta Debt_{t+\tau}$
Panel A: $\tau = 1$									
Low	2.97	0.34	0.87	1.17	0.52	1.36	0.98	0.47	0.47
Medium	3.36	0.38	0.86	0.84	0.95	1.58	0.90	1.03	1.03
High	3.73	0.51	0.77	1.12	0.99	1.79	0.76	1.41	1.41
High - Low	0.76**	0.17	-0.10	-0.08	0.49***	0.43***	-0.23*	0.95***	0.07
***t*-stat**	2.07	1.60	-0.73	-0.73	3.31	2.46	-1.90	3.92	1.15
Panel B: $\tau = 2$									
Low	2.91	0.28	0.83	1.15	0.47	1.39	0.89	0.41	0.16
Medium	3.35	0.40	0.88	0.84	0.96	1.56	0.89	1.05	0.19
High	3.78	0.52	0.79	1.14	1.00	1.76	0.82	1.44	0.18
High - Low	0.88***	0.25***	-0.04	-0.07	0.55***	0.36*	-0.09	1.06***	0.03
***t*-stat**	2.34	2.39	-0.28	-0.65	3.64	1.97	-0.73	4.29	0.50
Panel C: $\tau = 3$									
Low	2.83	0.26	0.81	1.13	0.47	1.45	0.82	0.39	0.16
Medium	3.44	0.47	0.86	0.86	0.95	1.54	0.94	1.08	0.19
High	3.80	0.47	0.83	1.16	1.03	1.74	0.85	1.44	0.18
High - Low	0.97***	0.23**	0.02	-0.05	0.60***	0.29	-0.01	1.11***	0.02
***t*-stat**	2.59	2.19	0.12	-0.47	3.69	1.58	-0.07	4.37	0.38
Panel D: $\tau = 4$									
Low	2.93	0.25	0.84	1.15	0.49	1.45	0.86	0.41	0.18
Medium	3.28	0.47	0.82	0.84	0.90	1.57	0.89	0.97	0.18
High	3.87	0.48	0.86	1.17	1.04	1.71	0.86	1.53	0.18
High - Low	0.93***	0.25***	-0.02	-0.06	0.60***	0.26	-0.05	1.21***	0.00
t-stat	2.47	2.30	-0.13	-0.63	3.61	1.39	-0.35	4.64	0.03

Table 11: Asset Growth and Stock Market Returns

The table reports the coefficients and t-statistics (in parentheses) from time series regressions of future market returns (the value-weighted excess return) on aggregate asset growth (AG) and investor sentiment ($\text{SENT}^{\perp}$), at different time horizon τ. The independent variables are standardized to have zero mean and unit variance. The coefficients are multiplied by 100 and expressed in percentage. t-statistics are computed using Newey-West standard errors. The sample period is 1974Q4-2010Q4. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

α	AG	$\text{SENT}^{\perp}$	Adj R^2 (%)
	Panel A: $\tau = 1$		
1.08	-2.27***		5.65
(1.55)	(-3.61)		
1.08	-2.25***	-0.08	5.05
(1.54)	(-3.42)	(-0.11)	
	Panel B: $\tau = 2$		
1.06	-1.27**		1.31
(1.54)	(-2.21)		
1.06	-1.21**	-0.34	2.81
(1.53)	(-2.09)	(-0.51)	
	Panel C: $\tau = 3$		
1.02	-0.85		0.23
(1.46)	(1.17)		
1.02	-0.83	-0.13	-0.41
(1.45)	(-1.11)	(-0.18)	
	Panel D: $\tau = 4$		
1.03	-0.19		-0.61
(1.41)	(0.32)		
1.04	-0.15	-0.26	-1.20
(1.41)	(-0.24)	(-0.38)	

Table 12: Asset Growth and Stock Market Returns: Investment and Financing Decompositions

The table reports the coefficients and t-statistics (in parentheses) from time series regressions of future market returns on the subcomponents of aggregate asset growth, from an asset and a financing decomposition at different time horizon τ. In the asset decomposition, asset growth is the sum of : (1) ΔCash (growth in cash), (2) ΔCurAsst (growth in noncash current assets), (3) ΔPPE (growth in property, plant, and equipment), (4) ΔOthAssets (growth in other assets). In the financing decomposition, asset growth is the sum of : (1) ΔOpLiab (growth in operating liabilities), (2) ΔDebt (growth in debt financing), (3) ΔStock (growth in equity financing) (4) ΔRE (growth in retained earnings). The subcomponents of asset growth used in the regressions are the quarter-by-quarter changes in these variables, scaled by total assets in previous quarter, to maintain the asset growth identity. The subcomponents of asset growth are in aggregate level, defined as the value-weighted averages of firm-level variables. The independent variables are standardized to have zero mean and unit variance. The coefficients are multiplied by 100 and expressed in percentage. t-statistics are computed using Newey-West standard errors. The sample period is 1974Q4-2010Q4.

Investment decompsition						Financing decomposition					
α	ΔCash	ΔCurAsst	ΔPPE	ΔOthAssets	Adj R^2 (%)	α	ΔOpLiab	ΔRE	ΔStock	ΔDebt	Adj R^2 (%)
Panel A: $\tau = 1$											
1.53	-1.91***				4.09	1.55	-1.85**				3.78
(2.17)	(-2.41)					(2.24)	(-2.09)				
1.53		-1.19			1.17	1.90		-0.85			0.33
(2.13)		(-1.22)				(2.75)		(-1.01)			
1.53			-0.69		-0.08	1.69			-1.47***		1.94
(2.12)			(-0.75)			(2.50)			(-2.51)		
1.54				-1.37**	1.75	1.53				-0.01	-0.70
(2.20)				(-2.01)		(2.12)				(-0.02)	
Panel B: $\tau = 2$											
1.40	-1.32*				1.66	1.42	-1.50***				2.31
(2.04)	(-1.92)					(2.12)	(-2.58)				
1.40		-0.20			-0.65	1.87		-0.37			-0.32
(1.99)		(-0.29)				(3.17)		(-0.49)			
1.40			-0.43		-0.46	1.59			-1.28***		1.21
(1.99)			(-0.69)			(2.58)			(-2.35)		
1.40				-1.82***	3.80	1.40				0.04	-0.71
(2.10)				(-3.39)		(1.97)				(0.08)	

		Investment decompsition						Financing decomposition			
α	ΔCash	ΔCurAsst	ΔPPE	ΔOthAssets	Adj R^2 (%)	α	ΔOpLiab	ΔRE	ΔStock	ΔDebt	Adj R^2 (%)
					Panel C: $\tau = 3$						
1.31	-0.47				-0.41	1.31	0.05				-0.71
(1.87)	(0.52)					(1.85)	(0.05)				
1.30		0.63			-0.16	1.47		0.01			-0.71
(1.79)		(0.99)				(2.42)		(0.02)			
1.31			-0.18		-0.67	1.30			-0.86		0.31
(1.86)			(-0.24)			(2.02)			(-1.28)		
1.31				-1.30	1.61	1.31				-0.59	-0.24
(1.97)				(-2.18)		(1.87)				(-0.89)	
					Panel D: $\tau = 4$						
1.42	-0.30				-0.59	1.42	-0.11				-0.70
(2.00)	(0.49)					(1.99)	(0.22)				
1.42		-0.18			-0.68	1.65		0.55			-0.30
(1.99)		(-0.27)				(2.53)		(0.72)			
1.41			0.62		-0.18	1.48			-1.10		1.00
(1.91)			(0.84)			(2.33)			(1.97)		
1.42				-0.48	-0.40	1.41				0.36	-0.54
(2.04)				(-0.66)		(1.95)				(0.63)	

Table 13: Asset Growth Subcomponents and Stock Market Returns, Controlling for Investor Sentiment

The table reports the coefficients and t-statistics (in parentheses) from time series regressions of future market returns on the subcomponents of aggregate asset growth, controlling for investor sentiment (SENT$^{\perp}$). In the asset decomposition, asset growth is the sum of : (1) ΔCash (growth in cash), (2) ΔCurAsst (growth in noncash current assets), (3) ΔPPE (growth in property, plant, and equipment), (4) ΔOthAssets (growth in other assets). In the financing decomposition, asset growth is the sum of : (1) ΔOpLiab (growth in operating liabilities), (2) ΔDebt (growth in debt financing), (3) ΔStock (growth in equity financing) (4) ΔRE (growth in retained earnings). The subcomponents of asset growth used in the regressions are the quarter-by-quarter changes in these variables, scaled by total assets in previous quarter, to maintain the asset growth identity. The subcomponents of asset growth are in aggregate level, defined as the value-weighted averages of firm-level variables. The independent variables are standardized to have zero mean and unit variance. The coefficients are multiplied by 100 and expressed in percentage. t-statistics are computed using Newey-West standard errors. The sample period is 1974Q4-2010Q4.

Investment decompsition							Financing decomposition						
α	SENT$^{\perp}$	Cash	CurAsst	PPE	OthAssets	Adj R^2 (%)	α	SENT$^{\perp}$	OpLiab	RE	Stock	Debt	Adj R^2 (%)
Panel A: $\tau = 1$													
1.61	-0.85	-1.76**				4.32	1.63	-0.91	-1.72**				4.16
(2.36)	(-1.37)	(-2.29)					(2.43)	(-1.43)	(-2.02)				
1.65	-1.26		-1.29			2.54	1.65	-1.34		-1.10			1.93
(2.42)	(-1.80)		(-1.45)				(2.43)	(-1.94)		(-1.50)			
1.65	-1.29			-0.88		1.35	1.60	-0.75			-1.15		1.89
(2.42)	(-1.80)			(-1.12)			(2.37)	(-1.05)			(-1.62)		
1.61	-0.85				-1.14	1.94	1.63	-1.16				0.02	0.36
(2.36)	(-1.21)				(-1.57)		(2.39)	(-1.69)				(0.03)	
Panel B: $\tau = 2$													
1.46	-0.60	-1.21				1.43	1.47	-0.61	-1.41***				2.11
(2.19)	(-0.98)	(-1.79)					(2.27)	(-1.02)	(-2.50)				
1.47	-0.84		-0.27			-0.42	1.48	-0.93		-0.68			0.10
(2.21)	(-1.30)		(-0.41)				(2.25)	(-1.36)		(-0.92)			
1.48	-0.90			-0.56		-0.10	1.44	-0.45			-1.03		0.75
(2.25)	(-1.26)			(-0.78)			(2.21)	(-0.67)			(-1.45)		
1.43	-0.35				-1.73*	3.26	1.47	-0.82				0.07	-0.51
(2.19)	(-0.54)				(-1.87)		(2.18)	(-1.26)				(-0.11)	

Investment decompsition							Financing decomposition						
α	SENT$^{\perp}$	Cash	CurAsst	PPE	OthAssets	Adj R^2 (%)	α	SENT$^{\perp}$	OpLiab	RE	Stock	Debt	Adj R^2 (%)
Panel C: $\tau = 3$													
1.33	-0.20	-0.43				-1.09	1.34	-0.29	0.09				-1.32
(1.96)	(-0.30)	(-0.47)					(1.94)	(-0.44)	(0.10)				
1.33	-0.23		0.62			-0.81	1.34	-0.28		-0.06			-1.33
(1.89)	(-0.33)		(0.96)				(1.97)	(-0.42)		(-0.09)			
1.34	-0.31			-0.23		-1.26	1.31	0.04			-0.88		-0.40
(2.00)	(-0.43)			(-0.28)			(1.97)	(0.06)			(-1.20)		
1.30	0.09				-1.33	0.91	1.34	-0.26				-0.58	-0.87
(2.01)	(0.14)				(-2.09)		(1.98)	(-0.39)				(-0.88)	
Panel D: $\tau = 4$													
1.46	-0.49	-0.21				-0.99	1.47	-0.53	-0.03				-1.05
(2.14)	(-0.69)	(-0.33)					(2.12)	(-0.75)	(-0.06)				
1.48	-0.55		-0.22			-0.98	1.47	-0.46		0.48			-0.74
(2.15)	(-0.77)		(-0.35)				(2.07)	(-0.66)		(0.61)			
1.45	-0.45			0.55		-0.63	1.43	-0.16			-1.05		0.32
(2.05)	(-0.63)			(-0.73)			(2.16)	(-0.24)			(-1.75)		
1.46	-0.43				-0.36	-0.88	1.46	-0.54				0.37	-0.86
(2.13)	(-0.61)				(-0.46)		(2.10)	(-0.80)				(0.68)	

Table 14: Asset Growth, Investor Sentiment, and Forecast Errors

The table reports the coefficients and t-statistics from time series regression of aggregate analyst forecast errors on lagged aggregate asset growth (AG) and investment sentiment ($SENT^{\perp}$), at different time horizon τ, where τ=1, 2, 3, or 4 quarters. Analyst forecast errors (FE) are the equal- or value-weighted averages of the firm-level forecast errors. Forecast error (FE), is defined as the realized difference between earnings and the prevailing consensus forecasts, scaled by price per share. All regressions include lagged forecast errors as control variables (coefficient not reported). t-statistics are computed using heteroskedasticity and auto-correlation consistent standard errors. The sample period starts from 1976Q1 to 2010Q4. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Value-weighted FE				Equal-weighted FE			
α	AG	$SENT^{\perp}$	Adj R^2 (%)	α	AG	$SENT^{\perp}$	Adj R^2 (%)
Panel A: $\tau = 1$							
-1.13	-0.49***		30.21	-0.88	-0.24***		52.17
(-3.71)	(-2.45)			(-4.44)	(-3.00)		
-0.98		-0.54***	29.89	-1.02		-0.48***	54.58
(-5.65)		(-4.87)		(-5.83)		(-4.37)	
-1.24	-0.50***	-0.55***	35.54	-1.13	-0.23***	-0.47***	56.01
(-4.39)	(-2.42)	(-4.42)		(-6.24)	(-2.84)	(-3.81)	
Panel B: $\tau = 2$							
-0.93	-0.32**		33.83	-1.02	-0.25***		45.32
(-4.53)	(-2.19)			(-4.69)	(-2.77)		
-0.83		-0.35**	33.77	-1.17		-0.49***	47.90
(-3.85)		(-2.08)		(-6.58)		(-3.34)	
-1.00	-0.32**	-0.36**	35.86	-1.29	-0.24***	-0.48***	49.46
(-5.29)	(-2.15)	(-2.12)		(-7.54)	(-2.53)	(-3.05)	
Panel C: $\tau = 3$							
-1.28	-0.30		14.83	-1.22	-0.04		29.74
(-3.81)	(-1.32)			(-4.63)	(-0.28)		
-1.22		-0.49***	17.29	-1.51		-0.54***	35.49
(-5.62)		(-3.72)		(-6.99)		(-2.83)	
-1.38	-0.31	-0.50***	19.06	-1.52	-0.02	-0.54***	35.03
(-4.67)	(-1.30)	(-3.62)		(-7.00)	(-0.16)	(-2.80)	
Panel D: $\tau = 4$							
-1.15	-0.30		20.96	-1.13	-0.10		35.46
(-4.39)	(-1.45)			(-4.61)	(-0.70)		
-1.04		-0.27	20.09	-1.26		-0.31	36.94
(-5.08)		(-1.45)		(-5.15)		(-1.35)	
-1.20	-0.30	-0.27	21.81	-1.31	-0.10	-0.30	36.79
(-5.13)	(-1.44)	(-1.44)		(-5.21)	(-0.63)	(-1.30)	

Table 15: Asset Growth, Investor Sentiment, and Forecast Revisions

The table reports the coefficients and t-statistics from time series regression of aggregate analyst forecast revisions on lagged aggregate asset growth (AG) and investment sentiment ($SENT^{\perp}$), at different time horizon τ, where τ=1, 2, 3, or 4 quarters. Analyst forecast revisions (REV) are the equal- or value-weighted averages of the firm-level forecast revisions. Forecast revision (REV), is defined as the change in consensus forecasts over the period starting one month after previous earnings announcement, to the period one month before next earnings announcement, scaled by price per share. All regressions include lagged forecast revisions as control variables (coefficient not reported). t-statistics are computed using heteroskedasticity and auto-correlation consistent standard errors. The sample period starts from 1976Q1 to 2010Q4. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Value-weighted REV				Equal-weighted REV			
α	AG	$SENT^{\perp}$	Adj R^2 (%)	α	AG	$SENT^{\perp}$	Adj R^2 (%)
Panel A: $\tau = 1$							
-0.70	-0.22***		29.48	-0.60	-0.13***		50.76
(-4.11)	(-3.46)			(-4.82)	(-2.22)		
-0.70		-0.33***	31.23	-0.71		-0.27***	52.76
(-4.02)		(-3.70)		(-4.58)		(-3.00)	
-0.77	-0.19***	-0.31***	33.58	-0.73	-0.10	-0.25***	53.19
(-4.50)	(-3.03)	(-3.17)		(-5.20)	(-1.57)	(-2.56)	
Panel B: $\tau = 2$							
-0.76	-0.15*		21.85	-0.77	-0.14**		39.60
(-4.42)	(-1.81)			(-5.17)	(-2.22)		
-0.79		-0.33***	25.43	-0.91		-0.32***	42.65
(-4.57)		(-2.81)		(-5.63)		(-2.63)	
-0.83	-0.13	-0.32***	26.16	-0.93	-0.11	-0.30***	43.13
(-4.84)	(-1.51)	(-2.58)		(-6.19)	(-1.60)	(-2.31)	
Panel C: $\tau = 3$							
-0.79	-0.08		16.18	-0.87	0.02		29.37
(-4.12)	(-0.93)			(-4.91)	(0.21)		
-0.84		-0.30***	20.11	-1.05		-0.30**	33.55
(-4.58)		(-2.30)		(-5.78)		(-2.10)	
-0.86	-0.06	-0.29***	19.75	-1.04	0.05	-0.31***	33.27
(-4.57)	(-0.64)	(-2.23)		(-5.64)	(-0.63)	(-2.27)	
Panel D: $\tau = 4$							
-0.86	-0.09		12.71	-0.81	0.02		32.73
(-4.57)	(-0.95)			(-5.15)	(0.23)		
-0.88		-0.25*	15.19	-0.91		-0.18	34.21
(-4.94)		(-1.86)		(-5.03)		(-1.17)	
-0.91	-0.07	-0.24*	14.93	-0.91	0.04	-0.19	33.83
(-5.01)	(-0.74)	(-1.78)		(-4.95)	(-0.47)	(-1.25)	

Table 16: Asset Growth, Investor Sentiment, and CARs

The table reports the coefficients and t-statistics from time series regressions of quarterly cumulative abnormal returns (CARs) around the earnings announcements on lagged aggregate asset growth (AG), and investor sentiment (SENT$^{\perp}$), at different time horizon τ, where τ=1, 2, 3, or 4 quarters. The quarterly CARs is the equal- or value-weighted average CARs of the S&P500 firms whose earnings announcements fall into the corresponding quarter. The estimation window is [-250, -5] and the even window is [-2,+2]. The benchmark is the Carhart four factor model. The independent variables are standardized to have zero mean and unit variance. The coefficients are multiplied by 100 and expressed in percentage. t-statistics are computed using heteroskedasticity and auto-correlation consistent standard errors. The sample period is 1972Q1 to 2010Q4. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Value-weighted CARs				Equal-weighted CARs			
α	AG	SENT$^{\perp}$	Adj R^2 (%)	α	AG	SENT$^{\perp}$	Adj R^2 (%)
Panel A: $\tau = 1$							
0.09	-0.07***		2.85	0.16	-0.06***		2.21
(2.49)	(-2.39)			(4.15)	(-2.99)		
0.09		-0.02	-0.45	0.16		-0.03	-0.60
(2.46)		(-0.60)		(4.17)		(-1.24)	
0.09	-0.07***	-0.02	2.22	0.16	-0.06***	-0.03	1.57
(2.49)	(-2.27)	(-0.56)		(4.17)	(-2.71)	(-1.07)	
Panel B: $\tau = 2$							
0.09	-0.07**		1.93	0.16	-0.06***		1.90
(2.58)	(-2.02)			(4.16)	(-2.49)		
0.09		-0.01	-0.54	0.15		-0.02	-0.32
(2.45)		(-0.52)		(4.14)		(-0.72)	
0.09	-0.07*	0.00	2.56	0.16	-0.06**	-0.01	1.36
(2.57)	(-1.98)	(-0.04)		(4.16)	(-2.28)	(-0.37)	
Panel C: $\tau = 3$							
0.07	-0.02		-0.41	0.16	-0.04		0.30
(2.36)	(-0.32)			(4.09)	(-0.97)		
0.09		-0.02	-0.44	0.15		-0.01	0.30
(2.44)		(-0.78)		(4.12)		(-0.25)	
0.07	-0.02	0.00	-0.92	0.16	-0.03	0.00	1.57
(2.35)	(-0.28)	(-0.05)		(4.08)	(-0.85)	(-0.06)	
Panel D: $\tau = 4$							
0.07	-0.02		-0.50	0.15	0.01		-0.51
(2.18)	(-0.56)			(4.02)	(-0.50)		
0.09		-0.01	-0.63	0.15		0.01	-0.61
(2.44)		(-0.26)		(4.11)		(-0.19)	
0.07	-0.01	0.00	-1.15	0.15	0.01	0.01	-1.13
(2.18)	(-0.53)	(-0.17)		(4.01)	(-0.44)	(-0.19)	

Table 17: Aggregate Asset Growth Index (AGI) and Anomalies: Predictive Regressions for Benchmark-Adjusted Returns on Long-Short Strategies

The table reports predictive regressions for benchmark adjusted returns on long-short strategies for the 11 anomalies, and returns on a strategy that equally combines all the strategies (Combination). Panel A reports coefficient estimates of excess returns on the BW sentiment index (SENT$^{\perp}$),

$$R_{i,t} = a + bSENT^{\perp}_{t-1} + cMKT_t + dSMB_t + eHML_t + u_t$$

Panel B reports coefficient estimates of excess returns on aggregate asset growth index, defined as the moving averages of unexpected aggregate asset growth in previous four quarters ($AGI_t = \frac{1}{4}\sum_{j=0}^{3} AG_{t-j}$),

$$R_{i,t} = a + bAGI_{t-1} + cMKT_t + dSMB_t + eHML_t + u_t$$

Panel C reports coefficient estimates of excess returns on both BW sentiment index and aggregate asset growth index,

$$R_{i,t} = a + b_1 SENT^{\perp}_{t-1} + b_2 AGI_{t-1} + cMKT_t + dSMB_t + eHML_t + u_t$$

The sample period is 1976Q1 to 2010Q2. t-statistics are computed using heteroskedasticity and auto-correlation consistent standard errors.

Anomaly	Failure Probability	O-score	Net Stock Issuance	Composite Stock Issuance	Total Accruals	Net Operating Assets	Momentum	Gross Profitability	Asset Growth	Return on Assets	Investment to assets	Combination
Panel A: $R_{i,t} = a + bSENT^{\perp}_{t-1} + cMKT_t + dSMB_t + eHML_t + u_t$												
Long Leg												
$\hat{b}$	0.08	-0.06	0.10	-0.15	-0.33	-0.02	-0.34	0.51	0.02	0.18	-0.38	-0.04
t-stat	0.26	-0.37	0.47	-0.61	-0.70	-0.08	-1.35	1.86	0.04	0.84	-1.27	-0.29
Short Leg												
$\hat{b}$	-2.59	-2.19	-1.25	-0.53	-1.43	-1.44	-1.76	-0.87	-1.21	-1.95	-1.16	-1.49
t-stat	-2.27	-3.43	-4.08	-1.92	-2.24	-4.58	-2.34	-2.03	-3.89	-2.32	-2.75	-3.58
Long-Short												
$\hat{b}$	2.67	2.13	1.34	0.38	1.11	1.42	1.43	1.38	1.23	2.13	0.77	1.45
t-stat	2.02	3.53	3.35	1.09	1.18	4.02	1.81	2.75	2.19	2.37	1.94	3.14

Anomaly	Failure Probability	O-score	Net Stock Issuance	Composite Stock Issuance	Total Accruals	Net Operating Assets	Momentum	Gross Profitability	Asset Growth	Return on Assets	Investment to assets	Combination
Panel B: $R_{i,t} = a + bAGI_{t-1} + cMKT_t + dSMB_t + eHML_t + u_t$												
Long Leg												
$\hat{b}$	0.79	-0.15	0.55	0.35	0.65	-0.19	0.22	0.55	1.27	0.15	0.12	0.39
t-stat	1.57	-0.62	3.54	1.42	1.36	-0.76	0.53	1.89	2.54	0.70	0.37	3.47
Short Leg												
$\hat{b}$	-3.94	-2.19	-1.11	-0.03	-1.87	-0.81	-2.42	-1.05	-0.74	-3.05	-0.36	-1.60
t-stat	-2.87	-3.52	-3.58	-0.08	-2.47	-2.07	-3.92	-2.55	-2.06	-3.69	-0.96	-4.22
Long-Short												
$\hat{b}$	4.73	2.03	1.67	0.38	2.52	0.62	2.64	1.59	2.01	3.20	0.48	1.99
t-stat	2.76	3.41	4.43	0.98	2.45	1.36	4.11	3.32	3.40	3.42	1.20	5.12
Panel C: $R_{i,t} = a + b_1 SENT^{\perp}_{t-1} + b_2 AGI_{t-1} + cMKT_t + dSMB_t + eHML_t + u_t$												
Long Leg												
$\hat{b}_1$	-0.31	0.01	-0.17	-0.36	-0.74	0.08	-0.53	0.34	-0.64	0.14	-0.54	-0.25
t-stat	-1.26	0.05	-1.01	-1.37	-1.88	0.31	-1.82	1.07	-1.62	0.56	-1.68	-1.86
$\hat{b}_2$	0.93	-0.16	0.63	0.52	0.98	-0.23	0.46	0.39	1.56	0.09	0.36	0.50
t-stat	1.69	-0.56	3.42	2.00	1.92	-0.87	1.02	1.16	3.29	0.35	1.22	3.90
Short Leg												
$\hat{b}_1$	-1.14	-1.56	-0.96	-0.63	-0.79	-1.35	-0.91	-0.53	-1.11	-0.82	-1.24	-1.00
t-stat	-1.81	-3.69	-2.78	-1.97	-2.20	-3.87	-1.56	-1.20	-3.36	-1.53	-2.44	-3.67
$\hat{b}_2$	-3.43	-1.49	-0.68	0.25	-1.52	-0.21	-2.02	-0.81	-0.25	-2.68	0.19	-1.15
t-stat	-2.35	-2.49	-1.86	0.58	-2.03	-0.49	-3.28	-1.84	-0.63	-3.06	0.44	-3.07
Long-Short												
$\hat{b}_1$	0.83	1.57	0.79	0.27	0.05	1.43	0.38	0.88	0.47	0.96	0.70	0.76
t-stat	1.21	4.07	2.04	0.72	0.14	3.45	0.61	1.64	0.95	1.53	1.66	3.07
$\hat{b}_2$	4.36	1.33	1.31	0.26	2.50	-0.02	2.48	1.20	1.81	2.77	0.17	1.65
t-stat	2.34	2.46	2.95	0.61	2.52	-0.04	3.61	2.25	2.91	2.80	0.39	4.10

Table 18: Orthogonalized Aggregate Asset Growth Index ($AGI^{\perp}$) and Anomalies: Predictive Regressions for Benchmark-Adjusted Returns on Long-Short Strategies

Panel A of the table reports coefficient estimates of benchmark-adjusted returns on the orthogonalized aggregate asset growth index (AGI$^{\perp}$), with respect to macrovariables in Sibley, Xing, and Zhang (2012). Panel B reports coefficient estimates of excess returns on both BW sentiment index and AGI$^{\perp}$. The sample period is 1976Q1 to 2010Q2. t-statistics are computed using heteroskedasticity and auto-correlation consistent standard errors.

Anomaly	Failure Probability	O-score	Net Stock Issuance	Composite Stock Issuance	Total Accruals	Net Operating Assets	Momentum	Gross Profitability	Asset Growth	Return on Assets	Investment to assets	Combination
						Long Leg						
$\hat{b}$	0.79	-0.14	0.58	0.30	0.59	-0.18	0.18	0.57	1.32	0.17	0.11	0.39
t-stat	1.61	-0.57	3.70	1.15	1.25	-0.70	0.43	1.97	2.66	0.74	0.36	3.41
						Short Leg						
$\hat{b}$	-3.84	-2.17	-1.19	-0.09	-1.94	-0.86	-2.41	-1.04	-0.81	-3.02	-0.45	-1.62
t-stat	-2.70	-3.31	-4.06	-0.24	-2.67	-2.22	-3.86	-2.47	-2.26	-3.45	-1.15	-4.23
						Long-Short						
$\hat{b}$	4.63	2.03	1.78	0.39	2.53	0.68	2.59	1.61	2.13	3.19	0.56	2.01
t-stat	2.64	3.25	5.00	1.00	2.49	1.49	3.86	3.33	3.66	3.27	1.34	5.07
						Panel B: $R_{i,t} = a + b_1 SENT^{\perp}_{t-1} + b_2 AGI^{\perp}_{t-1} + cMKT_t + dSMB_t + eHML_t + u_t$						
						Long Leg						
$\hat{b}_1$	-0.32	0.00	-0.18	-0.34	-0.71	0.07	-0.51	0.33	-0.66	0.13	-0.53	-0.25
t-stat	-1.29	0.01	-1.12	-1.31	-1.78	0.29	-1.72	1.03	-1.63	0.53	-1.63	-1.79
$\hat{b}_2$	0.93	-0.14	0.66	0.45	0.91	-0.21	0.40	0.43	1.61	0.11	0.35	0.50
t-stat	1.74	-0.50	3.59	1.67	1.80	-0.81	0.89	1.26	3.46	0.40	1.21	3.77
						Short Leg						
$\hat{b}_1$	-1.20	-1.57	-0.92	-0.60	-0.76	-1.32	-0.92	-0.54	-1.07	-0.84	-1.19	-0.99
t-stat	-1.93	-3.73	-2.64	-1.92	-2.19	-3.86	-1.60	-1.20	-3.41	-1.60	-2.38	-3.80
$\hat{b}_2$	-3.31	-1.46	-0.79	0.17	-1.60	-0.27	-2.00	-0.80	-0.34	-2.65	0.08	-1.18
t-stat	-2.23	-2.35	-2.27	0.39	-2.25	-0.65	-3.25	-1.80	-0.87	-2.89	0.18	-3.18
						Long-Short						
$\hat{b}_1$	0.88	1.57	0.73	0.26	0.05	1.39	0.41	0.87	0.41	0.97	0.66	0.75
t-stat t-stat	1.31	4.13	1.91	0.73	0.13	3.38	0.65	1.59	0.84	1.56	1.59	3.09
$\hat{b}_2$	4.24	1.33	1.45	0.28	2.51	0.06	2.41	1.23	1.95	2.75	0.27	1.68
t-stat	2.26	2.37	3.49	0.66	2.58	0.12	3.35	2.28	3.28	2.71	0.61	4.14

Table 19

Financial Distress-Sorted Portfolio Mean Returns

This table reports mean excess return of stock portfolios formed by sequentially sorting on distant financial distress then recent financial distress (and the reverse). Financial distress is measured by CHS (2008) failure probability in Panel 1 and O-score as in Ohlson (1980) in Panel 2. Recent financial distress (RD) is defined as the predicted default probability in the current quarter t. Distant financial distress (DD) is defined as the predicted default probability in quarter $t-4$. Each month, firms whose most recent public earnings announcement date fall into this month are obtained and portfolios are formed at the beginning of month t+1. Portfolios are held for one month and rebalanced monthly. Portfolio returns are equal-weighted, monthly, and span 1977-2010.

Panel 1: Distress measured by failure probability

1A: DD, then RD

	DD1	DD2	DD3	DD4	DD5	Row Mean
RDS1	1.08	1.42	1.57	1.41	1.70	1.44
RDS2	0.90	0.89	1.20	0.98	1.00	0.99
RDS3	0.64	0.82	0.69	0.78	0.75	0.73
RDS4	0.50	0.47	0.55	0.48	0.41	0.48
RDS5	0.45	0.50	0.36	0.27	-0.46	0.22
Column Mean	0.72	0.82	0.87	0.78	0.68	

1B: RD, then DD

	DDS1	DDS2	DDS3	DDS4	DDS5	Row Mean
RD1	0.89	0.81	0.95	1.18	1.80	1.13
RD2	0.57	0.73	0.79	1.16	1.48	0.94
RD3	0.61	0.54	0.68	0.81	1.37	0.80
RD4	0.53	0.58	0.56	0.75	1.17	0.72
RD5	-0.09	0.38	0.53	0.40	0.74	0.39
Column Mean	0.50	0.61	0.70	0.86	1.31	

Panel 2: Distress measured by O-score

2A: DD, then RD

	DD1	DD2	DD3	DD4	DD5	Row Mean
RDS1	0.75	1.48	1.68	1.75	1.38	1.41
RDS2	1.04	1.21	1.37	1.16	0.96	1.15
RDS3	0.92	0.95	0.76	0.54	1.07	0.85
RDS4	0.56	0.63	0.52	0.67	0.66	0.61
RDS5	0.40	-0.01	-0.36	-0.15	0.00	-0.02
Column Mean	0.73	0.85	0.79	0.79	0.81	

2B: RD, then DD

	DDS1	DDS2	DDS3	DDS4	DDS5	Row Mean
RD1	0.64	0.72	0.99	1.18	1.53	1.01
RD2	0.63	0.99	1.12	1.44	1.80	1.20
RD3	0.43	0.67	0.84	0.92	1.49	0.87
RD4	-0.05	0.37	0.57	1.01	1.03	0.59
RD5	-0.52	0.23	0.63	0.63	0.85	0.36
Column Mean	0.23	0.60	0.83	1.04	1.34	

Table 20

Sorted Portfolio Descriptive Statistics

This table reports time series averages of sorted stock portfolio mean characteristics. Characteristics are mean excess returns (RET), standard deviation (SD) and skewness (SKEW), distant financial distress (DD), recent financial distress (RD), the portfolio share of firms delisted from CRSP due to bankruptcy, liquidation or performance within 12 months of portfolio formation (DELIST), log of the market value of equity (ME), book-to-market ratio (BM), 6-month prior returns (PRET6), the average of the absolute value of the daily return divided by dollar vol over the last year (ILLIQ, see Amihud (2002)), and the share of the aggregate market capitalization. Financial distress is the annualized 12-month failure probability following CHS (2008). We use a four-quarter RD-DD threshold. DD and RD quintile portfolios are formed by sorting stocks by DD and RD (respectively). DDS quintile portfolios are formed by sequentially sorting stocks into RD then DD quintiles. Corresponding DD quintile portfolios are then aggregated to form DDS portfolios. The RDS hedge portfolio is formed similarly. Data spans 1977-2010.

	RET (%)	SD	SKEW	DD (%)	RD (%)	DELIST (%)	ME	BM	PRET6 (%)	ILLIQ	Cap. Share
DD1	0.72	11.74	0.84	0.01	0.03	2.97	5.74	0.67	7.87	0.83	0.24
DD2	0.82	13.22	1.44	0.03	0.07	4.75	5.53	0.76	6.73	1.21	0.23
DD3	0.87	15.35	1.76	0.05	0.14	10.30	4.95	0.86	5.87	2.23	0.21
DD4	0.78	18.48	3.18	0.12	0.30	22.22	4.29	0.90	6.59	4.35	0.18
DD5	0.68	22.96	5.71	0.81	0.85	59.76	3.41	0.70	11.52	11.27	0.14
RD1	1.13	11.42	1.10	0.03	0.01	2.27	5.71	0.65	16.56	0.69	0.24
RD2	0.94	12.61	1.51	0.05	0.03	2.14	5.58	0.72	13.30	1.02	0.23
RD3	0.80	14.87	2.40	0.09	0.05	4.79	4.99	0.84	9.58	2.01	0.21
RD4	0.72	18.10	2.73	0.21	0.15	13.41	4.32	0.91	5.48	4.14	0.18
RD5	0.39	24.44	5.10	0.63	1.14	77.40	3.32	0.78	-6.51	12.05	0.14
DDS1	0.50	6.17	-0.54	0.03	0.19	14.67	4.82	0.85	-2.54	2.79	0.21
DDS2	0.61	5.90	-0.58	0.05	0.20	16.43	4.87	0.87	1.55	3.28	0.21
DDS3	0.70	5.85	-0.56	0.09	0.23	18.66	4.77	0.87	5.53	3.84	0.21
DDS4	0.86	6.06	-0.77	0.17	0.23	21.17	4.51	0.84	11.29	5.01	0.20
DDS5	1.31	6.92	-0.49	0.60	0.37	29.08	3.99	0.74	24.96	7.29	0.17
RDS1	1.44	5.60	-0.86	0.14	0.03	3.94	4.82	0.76	24.91	1.96	0.21
RDS2	0.99	5.57	-1.07	0.14	0.06	6.12	4.95	0.82	15.39	2.60	0.22
RDS3	0.73	5.88	-0.67	0.17	0.11	10.46	4.82	0.86	8.91	3.54	0.21
RDS4	0.48	6.41	-0.49	0.21	0.22	20.27	4.52	0.90	2.24	5.18	0.20
RDS5	0.22	8.04	0.05	0.29	0.86	59.21	3.87	0.84	-10.70	9.00	0.17

Table 21

Hedge Portfolio Returns

This table reports the monthly hedge portfolio excess returns. Financial distress is measured by CHS (2008) failure probability in Panel 1 and O-score as in Ohlson (1980) in Panel 2. Table reports mean returns of DD, RD, DDS, RDS hedge portfolios using various sample thresholds. DD and RD quintile portfolios are formed by sorting stocks by DD and RD (respectively). DDS quintile portfolios are formed by sequentially sorting stocks into RD then DD quintiles. Corresponding DD quintile portfolios are then aggregated to form DDS portfolios. The RDS hedge portfolio is formed similarly. For each portfolio, the return is reported above the estimated standard error. ***, **, * indicates significance at the 1%, 5%, and 10% level, respectively. Data spans 1977 to 2010.

Panel 1: Distress measured by failure probability

Equal-Weighted				Value-Weighted			
DD	RD	DDS	RDS	DD	RD	DDS	RDS
Four-Quarter Threshold							
0.16	-0.71**	0.81***	-1.21***	0.34	-0.79***	0.85***	-1.05***
(0.26)	(0.35)	(0.18)	(0.26)	(0.34)	(0.43)	(0.25)	(0.37)
Six-Quarter Threshold							
-0.10	-0.65*	0.45***	-0.90***	0.11	-0.63	0.51**	-0.99***
(0.25)	(0.34)	(0.17)	(0.27)	(0.40)	(0.44)	(0.23)	(0.35)
Eight-Quarter Threshold							
0.03	-0.56*	0.47***	-0.92***	0.02	-0.58	0.45*	-1.14***
(0.24)	(0.34)	(0.17)	(0.27)	(0.33)	(0.44)	(0.25)	(0.34)

Panel 2: Distress measured by O-score

Equal-Weighted				Value-Weighted			
DD	RD	DDS	RDS	DD	RD	DDS	RDS
Four-Quarter Threshold							
0.11	-0.68***	1.11***	-1.43***	0.26	-0.33	0.92***	-1.07***
(0.18)	(0.21)	(0.15)	(0.17)	(0.23)	(0.28)	(0.21)	(0.22)
Six-Quarter Threshold							
-0.06	-0.65***	0.46***	-0.87***	0.20	-0.37	0.43**	-0.55**
(0.18)	(0.21)	(0.15)	(0.18)	(0.24)	(0.26)	(0.19)	(0.22)
Eight-Quarter Threshold							
-0.01	-0.63***	0.52***	-1.00***	-0.01	-0.30	0.55***	-0.74***
(0.18)	(0.22)	(0.16)	(0.19)	(0.23)	(0.29)	(0.20)	(0.24)

Table 22

Financial Distress Hedge Portfolio Returns Regressed on Factor Returns

The table reports the DDS and RDS hedge portfolios which are regressed on contemporaneous factors. Financial distress is measured by CHS (2008) failure probability in Panel 1 and O-score as in Ohlson (1980) in Panel 2. Financial distress is measured by CHS (2008) failure probability in Panel 1 and O-score as in Ohlson (1980) in Panel 2. Recent financial distress (RD) is defined as the predicted default probability in the current quarter t. Distant financial distress (DD) is defined as the predicted default probability in quarter $t-4$. DDS quintile portfolios are formed by sequentially sorting stocks into RD then DD quintiles. DDS portfolio returns are the simple average of the five corresponding DD quintile returns (one for each RD quintile). RDS portfolio returns are formed similarly. Hedge portfolio returns equal the high quintile return less the low quintile return. For each explanatory variable, point estimates are reported above heteroskedasticity-robust standard errors. Data is monthly and spans 1977-2010. ***, **, * indicates intercepts significant at the 1%, 5%, and 10% level, respectively.

Panel 1: Distress measured by failure probability

DDS Hedge Portfolio

Equal-Weighted					Value-Weighted				
INT	MKT	SMB	HML	WML	INT	MKT	SMB	HML	WML
Four-Quarter Threshold									
0.69***	0.03	0.37	-0.03		0.75***	-0.02	0.44	-0.06	
(0.17)	(0.04)	(0.06)	(0.06)		(0.25)	(0.06)	(0.08)	(0.09)	
0.50***	0.07	0.35	0.04	0.21	0.41*	0.05	0.41	0.07	0.37
(0.17)	(0.04)	(0.05)	(0.06)	(0.04)	(0.24)	(0.05)	(0.08)	(0.08)	(0.05)
Six-Quarter Threshold									
0.37*	0.06	0.30	-0.09		0.40*	-0.04	0.54	-0.08	
(0.17)	(0.04)	(0.06)	(0.06)		(0.22)	(0.05)	(0.07)	(0.08)	
0.16	0.10	0.28	-0.01	0.23	0.05	0.03	0.50	0.06	0.39
(0.16)	(0.04)	(0.05)	(0.06)	(0.03)	(0.20)	(0.05)	(0.07)	(0.07)	(0.04)
Eight-Quarter Threshold									
0.45***	-0.01	0.32	-0.19		0.43*	-0.06	0.53	-0.29	
(0.16)	(0.04)	(0.05)	(0.06)		(0.23)	(0.05)	(0.08)	(0.08)	
0.20	0.04	0.30	-0.10	0.27	0.02	0.03	0.49	-0.13	0.44
(0.15)	(0.03)	(0.05)	(0.05)	(0.03)	(0.21)	(0.05)	(0.07)	(0.07)	(0.05)

RDS Hedge Portfolio

Equal-Weighted					Value-Weighted				
INT	MKT	SMB	HML	WML	INT	MKT	SMB	HML	WML
Four-Quarter Threshold									
-1.49***	0.31	0.31	0.07		-1.41***	0.37	0.61	-0.02	
(0.25)	(0.06)	(0.08)	(0.09)		(0.35)	(0.08)	(0.12)	(0.12)	
-0.93***	0.19	0.37	-0.15	-0.62	-0.58**	0.20	0.69	-0.34	-0.91
(0.21)	(0.05)	(0.07)	(0.07)	(0.05)	(0.29)	(0.07)	(0.09)	(0.10)	(0.06)
Six-Quarter Threshold									
-1.22***	0.30	0.41	0.09		-1.46***	0.42	0.66	0.20	
(0.25)	(0.06)	(0.08)	(0.09)		(0.33)	(0.08)	(0.11)	(0.12)	
-0.64***	0.17	0.47	-0.13	-0.65	-0.64**	0.25	0.74	-0.12	-0.91
(0.21)	(0.05)	(0.07)	(0.07)	(0.04)	(0.26)	(0.06)	(0.09)	(0.09)	(0.06)
Eight-Quarter Threshold									
-1.25***	0.29	0.43	0.14		-1.63***	0.39	0.64	0.28	
(0.26)	(0.06)	(0.09)	(0.09)		(0.32)	(0.07)	(0.10)	(0.11)	
-0.69***	0.17	0.49	-0.07	-0.61	-0.95***	0.25	0.70	0.02	-0.75
(0.23)	(0.05)	(0.07)	(0.08)	(0.05)	(0.27)	(0.06)	(0.09)	(0.09)	(0.06)

Panel 2: Distress measured by O-score

DDS Hedge Portfolio

Equal-Weighted					Value-Weighted				
INT	MKT	SMB	HML	WML	INT	MKT	SMB	HML	WML
Four-Quarter Threshold									
1.16***	-0.12	0.24	-0.15		0.93***	-0.14	0.38	-0.13	
(0.15)	(0.03)	(0.05)	(0.05)		(0.20)	(0.05)	(0.07)	(0.07)	
0.88***	-0.06	0.21	-0.05	0.31	0.49***	-0.05	0.33	0.05	0.49
(0.14)	(0.03)	(0.04)	(0.05)	(0.03)	(0.17)	(0.04)	(0.06)	(0.06)	(0.04)
Six-Quarter Threshold									
0.47***	-0.08	0.24	-0.11		0.40**	-0.10	0.40	-0.10	
(0.15)	(0.03)	(0.05)	(0.05)		(0.19)	(0.04)	(0.06)	(0.07)	
0.26*	-0.03	0.22	-0.03	0.23	0.10	-0.03	0.37	0.01	0.33
(0.15)	(0.03)	(0.05)	(0.05)	(0.03)	(0.17)	(0.04)	(0.06)	(0.06)	(0.04)
Eight-Quarter Threshold									
0.54***	-0.05	0.23	-0.17		0.55***	-0.07	0.39	-0.22	
(0.15)	(0.03)	(0.05)	(0.05)		(0.19)	(0.04)	(0.06)	(0.07)	
0.30**	0.00	0.21	-0.08	0.26	0.18	0.00	0.35	-0.08	0.40
(0.14)	(0.03)	(0.05)	(0.05)	(0.03)	(0.17)	(0.04)	(0.06)	(0.06)	(0.04)

RDS Hedge Portfolio

Equal-Weighted					Value-Weighted				
INT	MKT	SMB	HML	WML	INT	MKT	SMB	HML	WML
Four-Quarter Threshold									
-1.60***	0.05	-0.01	0.44		-1.32***	0.12	0.00	0.55	
(0.16)	(0.04)	(0.05)	(0.06)		(0.21)	(0.05)	(0.07)	(0.07)	
-1.27***	-0.02	0.02	0.31	-0.35	-0.81***	0.01	0.05	0.36	-0.56
(0.14)	(0.03)	(0.05)	(0.05)	(0.03)	(0.17)	(0.04)	(0.06)	(0.06)	(0.04)
Six-Quarter Threshold									
-1.06***	0.04	0.04	0.48		-0.86***	0.09	0.08	0.70	
(0.17)	(0.04)	(0.06)	(0.06)		(0.21)	(0.05)	(0.07)	(0.07)	
-0.74***	-0.02	0.07	0.35	-0.35	-0.43**	0.00	0.12	0.54	-0.47
(0.15)	(0.03)	(0.05)	(0.05)	(0.03)	(0.18)	(0.04)	(0.06)	(0.06)	(0.04)
Eight-Quarter Threshold									
-1.23***	0.05	0.07	0.54		-1.10***	0.10	0.15	0.78	
(0.18)	(0.04)	(0.06)	(0.06)		(0.22)	(0.05)	(0.07)	(0.08)	
-0.92***	-0.01	0.11	0.42	-0.34	-0.61***	0.00	0.20	0.59	-0.54
(0.16)	(0.04)	(0.05)	(0.06)	(0.03)	(0.18)	(0.04)	(0.06)	(0.06)	(0.04)

Table 23

Longer Horizon Returns of Distress-Sorted Hedge Portfolios for Five Years after Portfolio Formation

This table reports average monthly returns of equal-weighted distress hedge portfolio for month 1-60 subsequent to portfolio formation. Hedge portfolios are formed by single sorts on recent financial distress (RD) in the current quarter t. Financial distress is measured by CHS (2008) failure probability in Panel 1 and O-score as in Ohlson (1980) in Panel 2. Sample period corresponds to 1977 to 2010. Newey-West standard error are reported below each mean return. ***, **, * indicates intercepts significant at the 1%, 5%, and 10% level, respectively.

Panel 1: Distress measured by failure probability

Month 1 to 6	Month 7 to 12	Month 13 to 18	Month 19 to 24	Month 25 to 30	Month 31 to 36	Month 37 to 42	Month 43 to 48	Month 49 to 54	Month 55 to 60
-0.86***	-0.28**	0.19	0.17	0.17	0.09	0.12	0.26**	0.29**	0.26***
(0.17)	(0.12)	(0.18)	(0.17)	(0.15)	(0.14)	(0.11)	(0.11)	(0.14)	(0.10)

Panel 2: Distress measured by O-score

Month 1 to 6	Month 7 to 12	Month 13 to 18	Month 19 to 24	Month 25 to 30	Month 31 to 36	Month 37 to 42	Month 43 to 48	Month 49 to 54	Month 55 to 60
-0.54**	0.05	0.09	0.14	0.02	0.05	0.03	0.24**	0.11	0.21**
(0.10)	(0.10)	(0.13)	(0.12)	(0.16)	(0.11)	(0.14)	(0.12)	(0.15)	(0.10)

Table 24

Fama-MacBeth Estimation of the Price of Distress Risk

Table reports results from Fama-MacBeth regressions of stock returns on stock characteristics. Characteristics are distant financial distress(DD), recent financial distress (RD), the log of the market value of equity (ME), the log of the book-to-market ratio (BM), 1- and 6-month prior returns (PRET1 and PRET6), a measure of illiquidity (ILLIQ) based on Amihud (2002). Financial distress is measured by CHS (2008) failure probability in Panel 1 and O-score as in Ohlson (1980) in Panel 2. Distant financial distress (DD) and recent financial distress (RD) are calculated using four-quarter threshold. For each characteristic, point estimates are reported above standard errors. Data is monthly and spans 1977-2010. ***, **, * indicates significance at the 1%, 5%, and 10% level, respectively.

Panel 1: Distress measured by failure probability

Equal-Weighted Cross-Sectional Regression

DD	RD	ME	BM	PRET6	PRET1	ILLIQ
0.413***	-0.462***					
(0.068)	(0.094)					
0.479***	-0.695***	-0.112	0.274***	0.001	-0.033***	0.025
(0.060)	(0.085)	(0.089)	(0.088)	(0.002)	(0.004)	(0.059)

Value-Weighted Cross-Sectional Regression

DD	RD	ME	BM	PRET6	PRET1	ILLIQ
0.442***	-0.591***					
(0.144)	(0.177)					
0.320**	-0.618***	0.015	0.159	0.001	-0.011*	0.083
(0.124)	(0.146)	(0.106)	(0.118)	(0.003)	(0.007)	(0.073)

Panel 2: Distress measured by O-score

Equal-Weighted Cross-Sectional Regression

DD	RD	ME	BM	PRET6	PRET1	ILLIQ
0.679***	-0.613***					
(0.082)	(0.091)					
0.531***	-0.712***	-0.110	0.335***	0.011***	-0.053***	0.106*
(0.068)	(0.076)	(0.096)	(0.089)	(0.002)	(0.005)	(0.056)

Value-Weighted Cross-Sectional Regression

DD	RD	ME	BM	PRET6	PRET1	ILLIQ
0.389***	-0.364**					
(0.139)	(0.159)					
0.215***	-0.279**	-0.037	0.180*	0.007***	-0.036***	0.041
(0.090)	(0.121)	(0.146)	(0.102)	(0.003)	(0.008)	(0.097)

Table 25

Distress Factor and the Fama-French Factors

This table reports summary statistics of the distress factor (FD). The distress factor is the equal-weighted DDS hedge portfolio return, using a four-quarter RD-DD threshold. MKT, SMB, and HML are the Fama and French (1996) factors; WML is the momentum factor. "Auto" refers to the first-order autocorrelation. In all regressions, standard errors are adjusted for heteroskedasticity and serial correlation. Data is monthly and spans 1977-2010. ***, **, * indicates significance at the 1%, 5%, and 10% level, respectively.

Panel A: Summary Statistics

	Mean (%)	Std (%)	Skew	Kurt	Auto
FD	0.805	3.551	1.216	9.210	0.133
MKT	0.539	4.593	-0.783	5.280	0.093
SMB	0.284	3.139	0.522	10.669	-0.003
HML	0.333	3.078	0.004	5.451	0.155
WML	0.713	4.650	-1.499	14.073	0.086

Panel B: Correlations

	FD	MKT	SMB	HML	WML
FD	1				
MKT	0.130***	1			
SMB	0.344***	0.250***	1		
HML	-0.141***	-0.345***	-0.310***	1	
WML	0.286***	-0.091*	0.087*	-0.187***	1

Panel C: Time-Series Regressions for the Fama-French Factors

Dep. var	α	MKT	FD	Adj. R^2
SMB	0.191	0.171***		6.01%
	(0.146)	(0.035)		
SMB	-0.019	0.143***	0.280***	15.71%
	(0.154)	(0.036)	(0.105)	
HML	0.457**	-0.231***		11.70%
	(0.188)	(0.068)		
HML	0.521***	-0.223***	-0.085	12.43%
	(0.175)	(0.070)	(0.093)	
WML	0.763***	-0.092		0.59%
	(0.223)	(0.110)		
WML	0.465**	-0.132	0.397***	9.41%
	(0.236)	(0.104)	(0.120)	

Table 26

Time-Series Regressions on the Size and Book-to-Market-Sorted Portfolios

This table reports GMM estimates of the intercepts (in % per month) and factor loadings from time-series regressions of size and book-to-market-sorted portfolios on the market (MKT) and distress factor (FD). The distress factor is the equal-weighted DDS hedge portfolio return, using a four-quarter RD-DD threshold. In all regressions, standard errors are adjusted for heteroskedasticity and serial correlation. The p-values to test the joint significance of the intercepts are reported. Sample spans 1977-2010. **, **, * indicates significance at the 1%, 5%, and 10% level, respectively.

Table 1:

Panel A: Size-Sorted Portfolios

	α	MKT	FD	Adj. R^2
Small	0.126	1.004	0.362***	61.78%
	(0.220)	(0.050)	(0.109)	
2	0.059	1.184	0.095	79.84%
	(0.154)	(0.039)	(0.065)	
3	0.150	1.165	0.002	85.62%
	(0.121)	(0.033)	(0.049)	
4	0.145	1.125	-0.035	91.74%
	(0.089)	(0.021)	(0.026)	
Big	0.120**	1.039	-0.113***	95.36%
	(0.057)	(0.018)	(0.031)	
p-value ($H_0: \alpha = 0$)	0.271			

Panel B: Book-to-Market-Sorted Portfolios

	α	MKT	FD	Adj. R^2
Low B/M	-0.507***	1.286	0.277**	72.80%
	(0.198)	(0.056)	(0.127)	
2	0.173	1.098	0.174***	77.07%
	(0.160)	(0.036)	(0.060)	
3	0.355**	0.987	0.150***	77.59%
	(0.157)	(0.041)	(0.048)	
4	0.438***	0.878	0.174***	72.78%
	(0.157)	(0.044)	(0.056)	
High B/M	0.642***	0.920	0.286***	61.88%
	(0.212)	(0.061)	(0.087)	
p-value ($H_0: \alpha = 0$)	0.000			

Figure 1

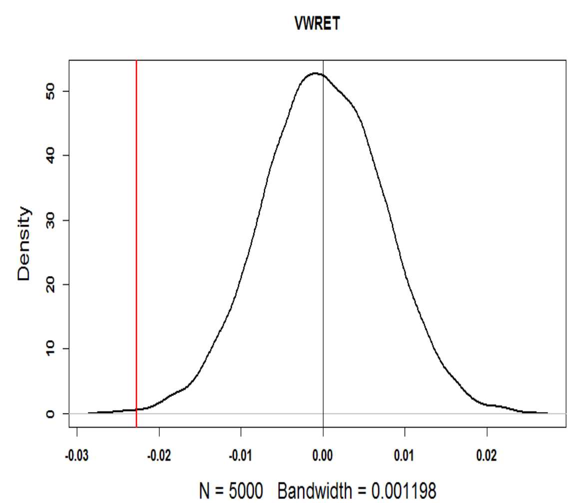
Density Plots of Predictive Coefficients Under the Null of No Predictability

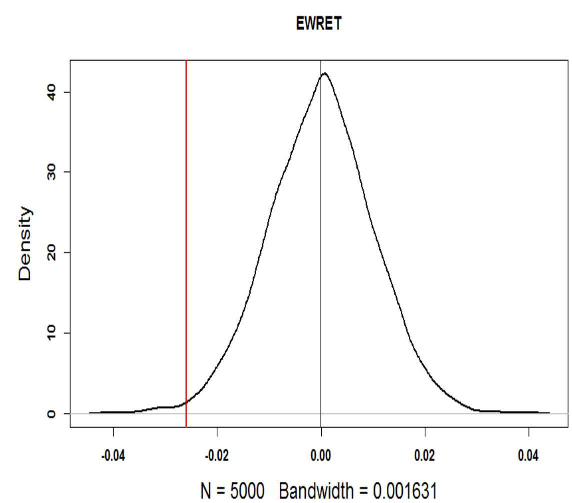
We plot the estimated predictive coefficients β from regressing simulated market returns on aggregate asset growth, under the null of no predictability. The randomization is conducted for 5,000 iterations. Randomization p-value is computed based on the empirical distribution of estimated coefficients β (in percent). Vertical red line reports the actual β (in percent).

Panel A: Simulation V.S. actual results

Returns	Average estimated β	Actual β	Average/Actual	Rand.p
VWRET	-0.022	-2.27	0.10%	0.001
EWRET	-0.019	-2.61	0.07%	0.006
SPRET	-0.028	-2.05	1.30%	0.002

Panel B: Density plots of estimated predictive coefficients





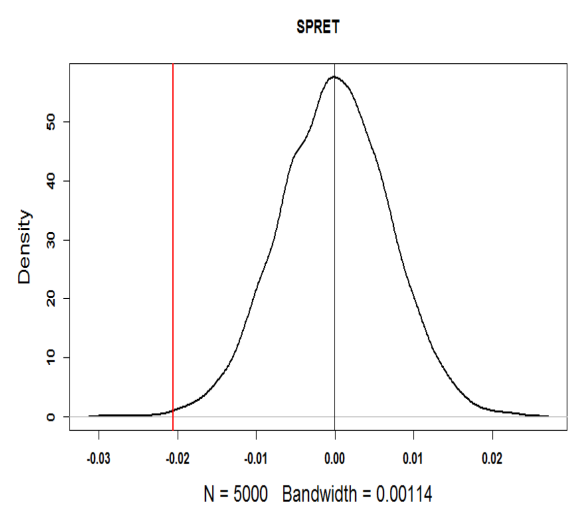
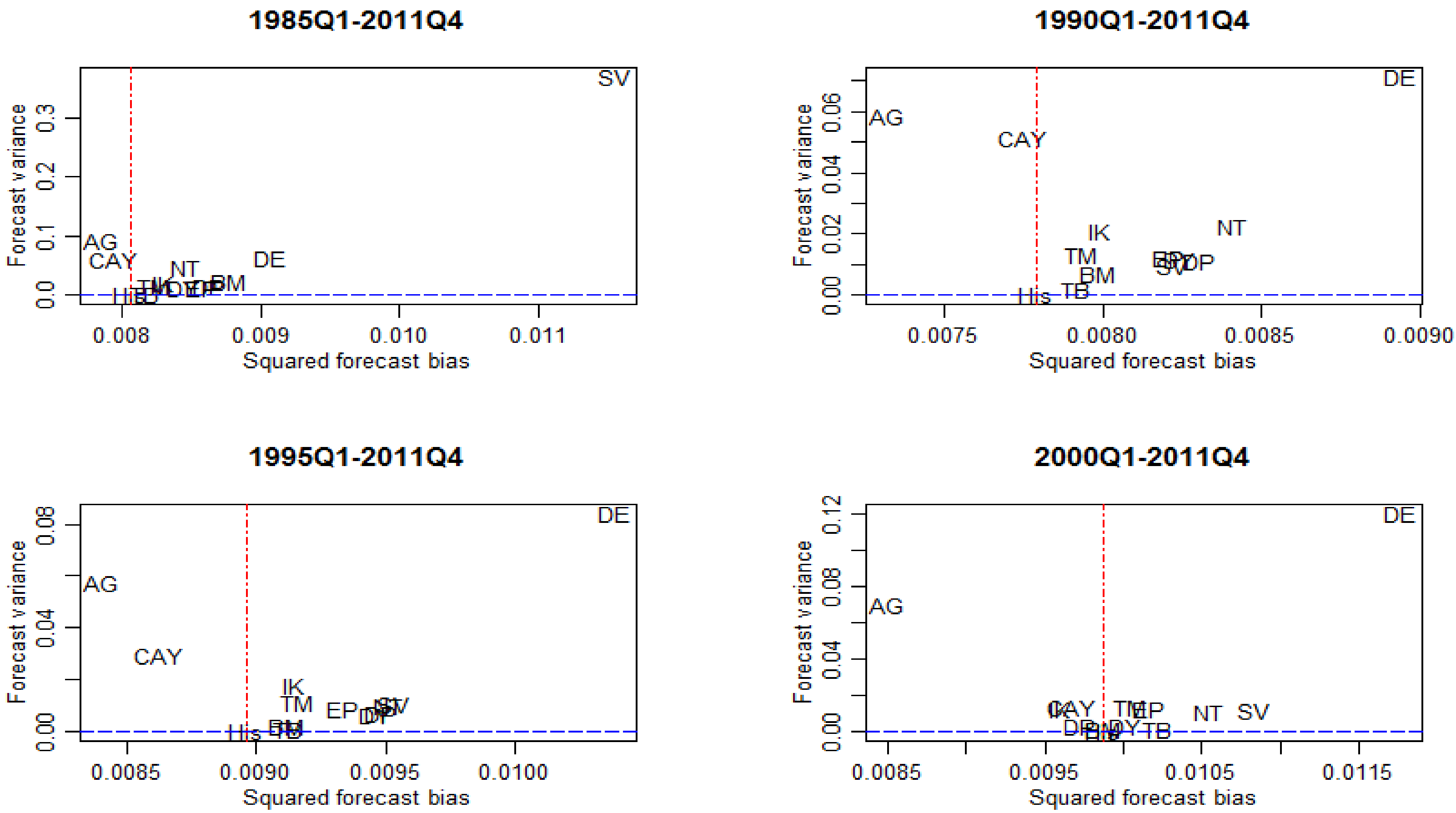


Figure 2

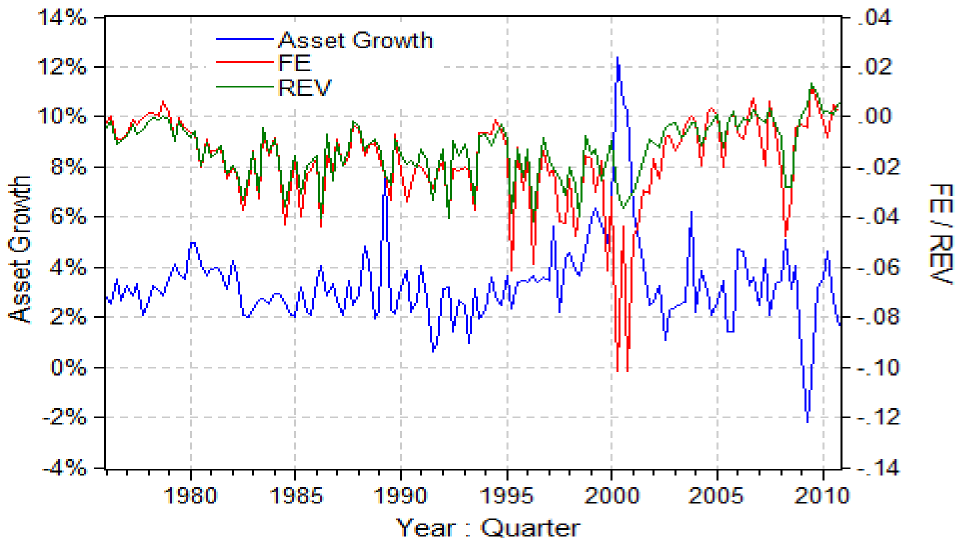
Scatterplots of Forecast Variance and Squared Forecast Bias



This figure plots the forecast variance and squared forecast bias for asset growth (AG) and other predictive variables, for different out-of-sample periods. The dotted (horizontal) and dashed (vertical) lines represents the historical average benchmark. The sample period is 1972Q1 to 2011Q4.

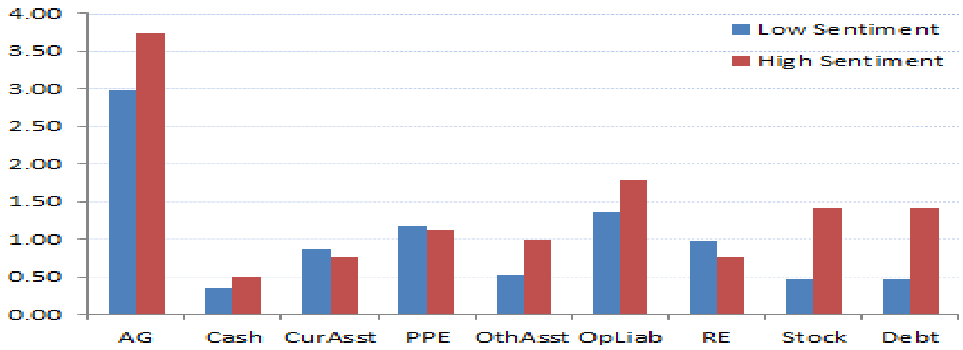
Figure 3

Aggregate Asset Growth, Analyst Forecast Errors and Revisions

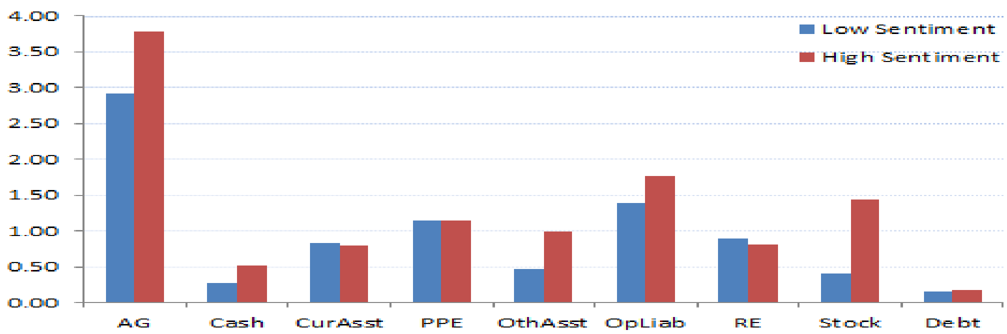


This figure plots quarterly aggregate asset growth (AG), analyst forecast errors (FE) and revisions (REV). Analyst forecast errors (FE) or revisions (REV) is the equal-or value-weighted averages of the firm-level forecast errors or revisions. Forecast error (FE), is defined as the realized difference between earnings and the prevailing consensus forecasts, scaled by price per share. Forecast revision (REV), is defined as the change in consensus forecasts over the period starting one month after previous earnings announcement, to the period one month before next earnings announcement, scaled by price per share. The sample period starts from 1976Q1 to 2011Q4.

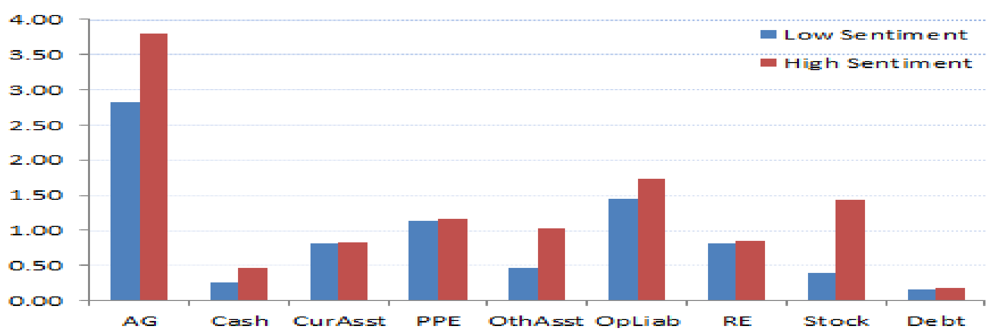
Figure 4: Asset Growth and its Components across High and Low Sentiment Periods



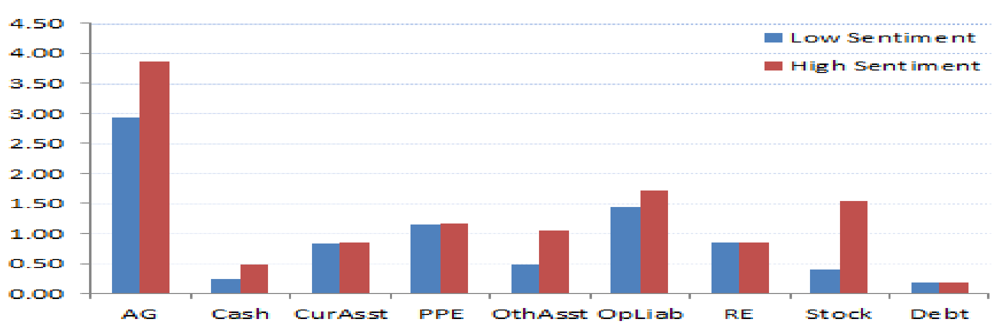
$\tau = 1$



$\tau = 2$



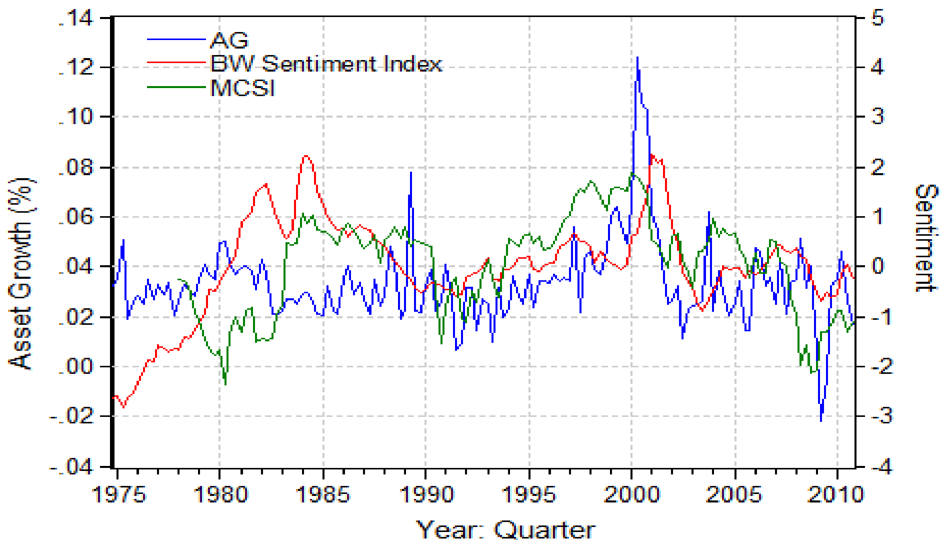
$\tau = 3$



$\tau = 4$

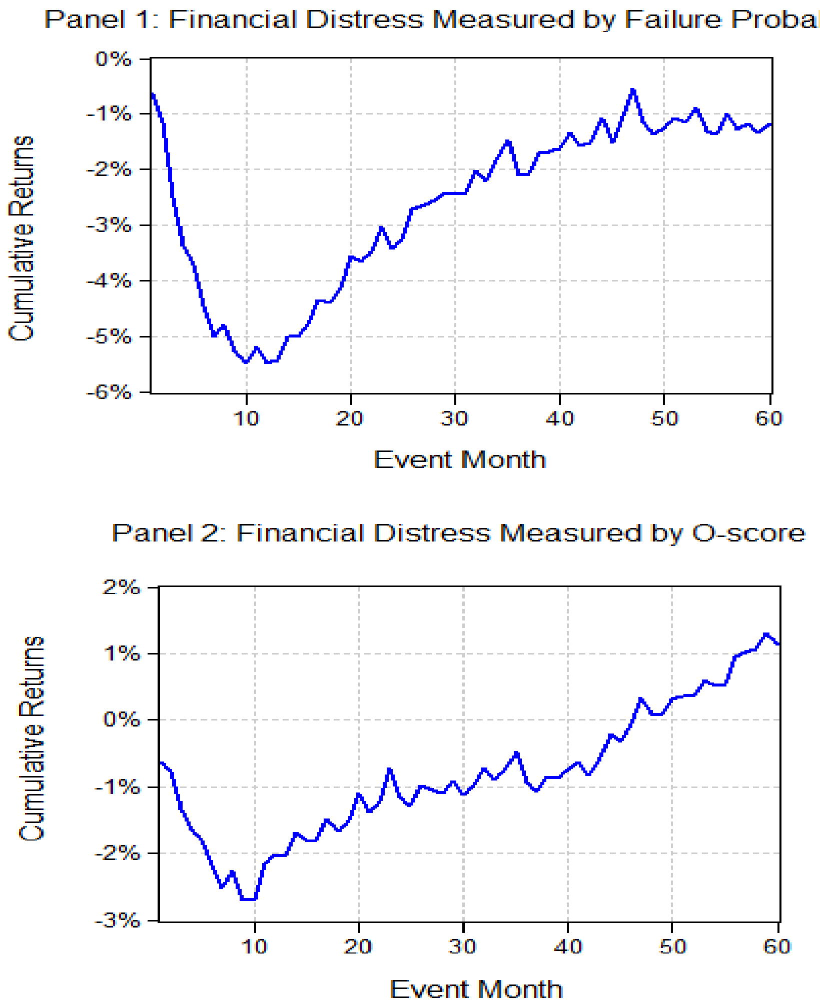
This figure plots average level of aggregate asset growth (AG) and its subcomponents across high and low sentiment periods, at different time horizon τ. The sample period is 1974Q2 to 2010Q4.

Figure 5: The Investor Sentiment Index and Aggregate Asset Growth



This figure plots quarterly Baker and Wurgler (2006) investor sentiment index, aggregate asset growth (AG), and the Michigan Consumer Sentiment Index (MCSI). AG and BW sentiment index span a period from 1974Q4 to 2010Q4, while the MCSI starts from 1978Q1.

Figure 6: Cumulative Returns of Distress-Sorted Hedge Portfolio



Notes - This figure presents cumulative hedge portfolio returns sorted on financial distress, by months after portfolio formation. The sample period is 1977-2010. Financial distress is measured by CHS (2008) failure probability in Panel 1 and O-score as in Ohlson (1980) in Panel 2.