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

Quan Wen†

Goizueta Business School

Emory University

Job Market Paper

This version: December 2013

*I thank Tarun Chordia, Ilia Dichev, Clifton Green, Hui Guo, Ravi Jagannathan, David Hirshleifer, Narasimhan Jegadeesh, Mark Rachwalski, Breno Schmidt, Jay Shanken, Bhaskaran Swaminathan, Soojin Yim, Dexin Zhou, seminar participants at Emory University, the 2012 Western Finance Association Meeting, and the 2013 FMA Doctoral Consortium for very helpful comments. This paper has also benefited from helpful discussions with Amiyatosh Purnanandam (WFA discussant). All errors are my own.

†Goizueta Business School, Emory University, 1300 Clifton Rd., Atlanta, GA 30322, USA. Tel: +1 (404) 273-4774. Email: quan.wen@emory.edu.

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. In addition, aggregate asset growth provides complementary power to predict cross-sectional anomalies above and beyond the commonly used measures of investor sentiment. These findings suggest that aggregate asset growth indirectly mirrors or captures investor sentiment, consistent with the catering theory of investment.

JEL Classification: C22, C53, C58, G02, G10, G17

Key words: Asset growth, return predictability, analyst forecasts, investor sentiment, cross-sectional anomalies

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 to 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 (2009a); Da and Warachka (2009a)) 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 results suggest that investors excessively extrapolate past growth into future and are subsequently surprised by the earnings reversal. These findings are consistent with DeLong, Shleifer, Summers, and Waldmann (1990) that investors are subject to sentiment. Investor sentiment, defined in Baker and Wurgler (2006, 2007), is a belief about future cash flows and investment risks that is not justified by the facts at hand. Baker and Wurgler (2006), and Stambaugh, Yu, and Yuan (2012) provide evidence that investor sentiment may have significant effects on the cross section of stock returns. We examine 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 Yuan (2012). We find that aggregate asset growth provides complementary power for the cross-sectional stock returns, above and beyond the commonly used measure of investor sentiment.

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 s-tock 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. (d) we provide new evidence that aggregate asset growth provides complementary power for the cross-sectional stock returns, above and beyond the commonly used measure of investor sentiment.

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 examines the relation between aggregate asset growth, investor sentiment, and the cross-sectional stock returns. Section 8 concludes. Section 9 provides additional analysis on the source of the aggregate asset growth effect.

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

$$AG_{j,t} = \frac{AT_{j,t-1} - AT_{j,t-2}}{AT_{j,t-2}}$$

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

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

[9]We obtain qualitatively similar results without winsorization.

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 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

[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.

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 one-year-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. 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 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. In the next section we apply Giacomini and White (2006) approach to examine the time-varying forecasting performance for asset growth over the entire time path.

4.4 Time Path of Forecasting Performance

Giacomini and White (2006) test complements the existing approaches in comparing forecasting performance of different models. One of the appealing properties of Giacomini and White approach is that it allows researchers to assess the relative performance of different models at different times, which is the first step to examine the sources of forecasting performance. We apply their approach to study models' forecasting performance over the entire time path. Let $\triangle L_{m,t+h}|\mathcal{F}_t$ denote the difference of loss functions between the h-steps-ahead forecasts of method g and f. m is the length of estimation window, and $\mathcal{F}_t$ is the information available at time t. In our empirical setup, we have $h = 1$. The loss functions, L_{t+1}, can be measured in many ways and we use squared forecast errors. The null hypothesis of equal predictive ability can be tested as $H_0 :\ E(\triangle L_{t+1}) = 0$ or $H_0 :\ E(h_t\triangle L_{t+1}) = 0$, where h_t is a $q \times 1$ $\mathcal{F}_t$-measurable vector as the test function. The test statistic for the null hypothesis at the level α follows a $\chi^2_{q,1-\alpha}$ distribution.

Giacomini and White (2006) propose a two-step procedure for adaptively selecting a forecasting method. In step 1, we regress $\triangle L_{t+1} = L_{t+1}\left(\hat{f}_t\right) - L_{t+1}\left(\hat{g}_t\right)$ on h_t over the out-of-sample period and let $\hat{\delta}$ denote the regression coefficients. Then apply the tests for the null hypothesis of equal conditional predictive ability. In step 2, in case of rejection, we use the following decision rule: uses g if $\hat{\delta}h_t > c$ and uses f if $\hat{\delta}h_t < c$, with c a user-specified threshold. In general, the plots of out-of-sample period predicted loss differences $\left\{\hat{\delta}' h_t\right\}_{t=m}^{T-h}$ are useful for assessing the relative performance of f and g at different times. One can further summarize relative out-of-sample performance by computing the proportion of times the foregoing decision rule chooses g, i.e., $I_c = \frac{1}{T-R}\sum_{t=R}^{T-h} 1\left(\hat{\delta}' h_t > c\right)$, where $1(\cdot)$ is an indicator function.

Figure 3-6 present the predicted loss difference for assessing forecasting performance of asset growth over the entire out-of-sample periods. We use the historical average model as the benchmark. The solid lines represent the zero level. A positive value above zero indicates the specific time periods in which the predictive variables outperform the benchmark model out-of-sample, and vice versa. The results in Figure 3-6 consistently show that many of the predictive variables perform worse than the benchmark over the entire sample periods. However, asset growth consistently delivers positive out-of-sample forecasting 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 year'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 for firms with December fiscal year ends in year $t-1$, using market capitalization at the end of year $t-1$ 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.[11] 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.

[11] 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 (2009a); Da and Warachka (2009a)). 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.[12]

[12] 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 7 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.[13] 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.[14] 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,

[13]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.

[14]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 10, 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 Aggregate Asset Growth, Investor Sentiment, and Stock Returns

Our results suggest that investors excessively extrapolate past growth into future and are subsequently surprised by the earnings reversal. These findings are consistent with DeLong, Shleifer, Summers, and Waldmann (1990) that investors are subject to sentiment. Investor sentiment, defined in Baker and Wurgler (2007), is a belief about future cash flows and investment risks that is not justified by the facts at hand. In this section, we examine the relation between aggregate asset growth, investor sentiment, and stock returns.

7.1 Asset Growth and the Cross-Section of Stock Returns

In this section, we examine the relation between aggregate asset growth and its role in a broad set of asset pricing anomalies in cross-sectional stock returns. Baker and Wurgler (2006) provide evidence that investor sentiment may have significant effects on the cross section of stock returns. Combining the impediments to short selling as in Miller (1977), Stambaugh, Yu, and Yuan (2012) explore the role of investor sentiment in a broad set of anomalies in cross-sectional stock returns. They find evidence that long-short strategies associated with 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. In this section, the results suggest that aggregate asset growth captures market-wide sentiment and we observe anomaly returns consistent with its implication in the cross-section of stock returns.

7.1.1 Research Design

Similar to Stambaugh, Yu, and Yuan (2012), we use predictive regression to investigate whether aggregate sentiment predicts anomaly returns. Three empirical predictions are derived in Stambaugh, Yu, and Yuan (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.[15] Third, investor sentiment should not greatly affect returns on the long-leg portfolio of each anomaly.[16] 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 BW quarterly sentiment index is 0.947 (0.876).[17] By using moving averages, we capture the persistence in AG and its effect on cross-sectional stock returns. The quarterly index, AGI_t, 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 our measure captures market-wide investor sentiment by studying its relation to a broad set of anomalies surveyed in Stambaugh, Yu, and Yuan (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))

[15]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.

[16]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.

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

- O-score (Ohlson (1980); Dichev (1998))
- Net stock issuance (Ritter (1991), Loughran and Ritter (1995))
- Composite equity issuance (Daniel and Titman (2006))
- Total accruals (Sloan (1996))
- Net operating assets (Hirshleifer, Hou, Teoh, and Zhang (2004))
- Momentum (Jegadeesh and Titman (1993))
- Gross profitability premium (Novy-Marx (2013))
- 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 Yuan (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 our aggregate measure, the sample periods of the portfolio returns start from 1972Q2 to 2010Q2.

We run predictive regression of anomaly returns on lagged aggregate asset growth index,

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

where here $R_{i,t}$ is the excess return (in percent) in quarter t for anomaly i, on either the long leg, the short leg, or the difference. AGI is the aggregate asset growth index which is scaled to have zero mean and unit variance.[18] We also include the contemporaneous returns on the three Fama and French factors to investigate the ability of AGI to predict benchmark-adjusted returns.

[18] 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}.

It is likely that AG (and AGI) contains some macro-related variations. For example, during expansions aggregate asset growth generally goes up (with about two or three quarters lag) but during recessions it is usually low. To distinguish between a common sentiment component and a common business cycle component, we follow Baker and Wurgler (2006) and explicitly remove business cycle variations. Specifically, we regress AG on six macrovariables: the growth in industrial production, growth in consumer durables, nondurables, and services, growth in employment, and a dummy variable for NBER recessions.[19] The residuals from this regression, labeled with a subscript $\perp$, are orthogonal to the macro variables.[20] The orthogonalized aggregate asset growth index is constructed as,

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

We find that orthogonalizing to macro variables does not qualitatively affect the overall index. The correlation between AGI and $AGI^{\perp}$ is 0.90. The orthogonalized index exhibit similar time series variations as the raw index.

7.1.2 Empirical Results: Long-Short Strategies

Table 9 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 (Panel C). The results in Panel A are consistent with the findings in Stambaugh, Yu, and Yuan (2012): each anomaly is stronger following high levels of sentiment and is mainly due to the underperformance of the short leg. Focusing on Panel B where asset growth is used as the explanatory variable, we obtain qualitatively similar results.

First, anomalies are stronger following high AGI and the profitability of each long-short

[19] The industry production index is available at the Federal Reserve Statistical Release G.17. The quarterly growth rate of industry production is computed by $log(IP_t) - log(IP_{t-1})$. The consumer durables, nondurables, and services data are available at the BEA National Income and Product Accounts Table 1.1.1. The NBER recession dates come from FRED st. Louis.

[20] We obtain qualitatively similar results if we orthogonalize aggregate asset growth with respect to the macroeconomic factors in Chen, Roll, and Ross (1986). These factors include the growth rate of industrial production, unexpected inflation, term premium, and the default premium.

spread is positively related to lagged sentiment. In Panel B, the coefficients on AGI for each long-short spread are all positive for each of the anomalies, and ten of the individual coefficients are statistically significant. The combination strategy of all anomalies has a coefficient of 1.99 with t-statistic of 5.12. To interpret the economic significance, AGI 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 Panel B indicates that a one standard deviation increase in aggregate sentiment 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 AGI. In Panel B, we find that the slope coefficients on AGI for each short-leg are all negative for each of the anomaly, and nine of the individual coefficients are statistically significant. The combination strategy has a negative coefficient of -1.60 and 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 coefficients on AGI is significantly negative for each long-leg in Panel B. 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. 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 $\mathrm{SENT}^{\perp}$ is 0.76 with t-statistic of 3.07. These results suggest that aggregate asset growth provides complementary power for cross-sectional stock returns.

8 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.

Our further analysis shows that aggregate asset growth is correlated and provides complementary power for the cross-sectional stock returns, above and beyond the commonly used measure of investor sentiment. 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.

9 Appendix

The appendix provides additional analysis on the source of return predictability by aggregate asset growth. In the first section, we provide new evidence that asset growth is highly correlated with measures of investor optimism. In the second section, we use analyst earnings forecast to separate cash flow and discount rate components of returns. We then distinguish the source of return predictability by asset growth. Our evidence supports the evidence that asset growth largely predicts the cash flow component of returns, implying that this variable may capture investors' biases in projecting aggregate future cash flows.

9.1 Does Asset Growth Capture Investor Optimism?

In this section we examine the relation between asset growth and other measures of investor optimism. This is motivated by Baker and Wurgler (2006, 2007) who describe investor sentiment as a belief about future cash flows and investment risks that is not justified by the facts at hand. Following their logic, we use analyst consensus forecasts from IBES to measure investors' belief about the future earnings prospects of the firm. To measure the "facts at hand" we consider the benchmark model of regression-based earnings forecasts or statistical forecasts. Following So (2013), we define investor optimism or sentiment as the difference between AF and the benchmark forecasts, scaled by the total assets per share. We scale the difference by total assets rather than equity price to avoid spurious cross-sectional variation in the sentiment measure (Ball (2011), Cheong and Thomas (2011)).

$$SENT_{SF} = \frac{AF - SF}{TA} \tag{10}$$

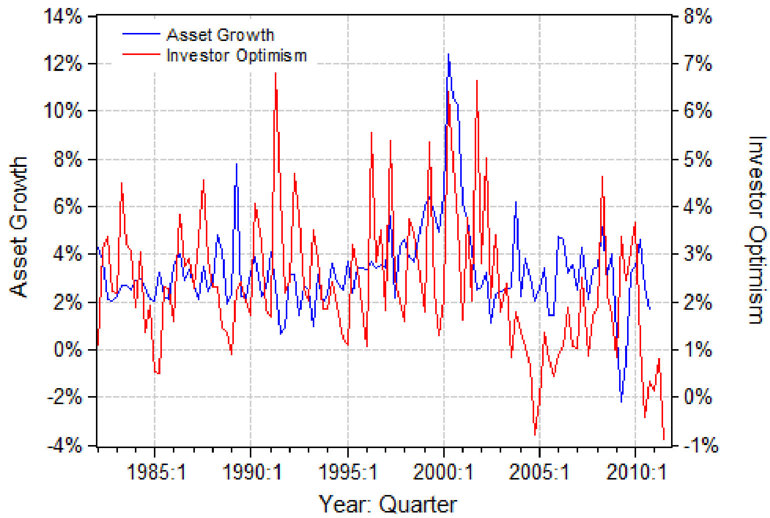
We adopt cross-sectional regressions to predict earnings in that they allow researchers to generate earnings forecasts for firms that do not have long time series of earnings (Hou, Dijk, and Zhang (2011)). We construct statistical forecasts (SF) following Fama and French (2006), Hou, Dijk, and Zhang (2011) and So (2013). Statistical forecasts are computed based on the predicted forecasts estimated from past firm characteristics. Specifically, we estimate the following cross-sectional regression for all firms reporting earnings in calendar year t,

$$\begin{aligned} E_{j,t} &= \beta_0 + \beta_1 E^{+}_{j,t-1} + \beta_2 NEGE_{j,t-1} + \beta_3 ACC^{+}_{j,t-1} + \beta_4 ACC^{-}_{j,t-1} \\ &\quad + \beta_5 AG_{j,t-1} + \beta_6 DD_{j,t-1} + \beta_7 DIV_{j,t-1} + \beta_8 MB_{j,t-1} \\ &\quad + \beta_9 PRICE_{j,t-1} + \epsilon_{j,t-1} \end{aligned} \tag{11}$$

where $E_{j,t}$ is a firm's earnings per share. Equation (11) expresses earnings in year t as a linear function of the following lagged firm characteristics from year $t-1$: earnings per share when earnings are positive and zero otherwise (E^{+}), a dummy variable that is one for firms that have negative earnings and zero otherwise ($NEGE$), accruals per share when accruals are positive and zero otherwise (ACC^{+}), accruals per share when accruals are negative and zero otherwise (ACC^{-}), the total asset growth (AG), a dummy variable that is one for firms with zero dividends and zero otherwise (DD), dividends per share (DIV), market-to-book (MB), and end-of-fiscal-year share price ($PRICE$). These accounting fundamentals have been shown in Fama and French (2006) to predict future earnings or profitability.

We estimate Equation (11) for each firm-year in Compustat with non-missing values of the nine characteristics. We then apply historically estimated coefficients to current firm characteristics and obtain statistic forecasts on an *ex-ante* basis, prior to observing realized FY1 earnings. The year t statistical earnings forecast for firm j in year $t+1$ is computed as,

Appendix Figure 1: Asset Growth and Investor Optimism



$$
\begin{aligned}
SF_{j,t} &= \hat{\beta}_0 + \hat{\beta}_1 E^{+}_{j,t} + \hat{\beta}_2 NEGE_{j,t} + \hat{\beta}_3 ACC^{+}_{j,t} + \hat{\beta}_4 ACC^{-}_{j,t} \\
&\quad + \hat{\beta}_5 AG_{j,t} + \hat{\beta}_6 DD_{j,t} + \hat{\beta}_7 DIV_{j,t} + \hat{\beta}_8 MB_{j,t} \\
&\quad + \hat{\beta}_9 PRICE_{j,t} \qquad (12)
\end{aligned}
$$

where $SF_{j,t}$ measures the statistical forecast of year $t+1$ earnings.

To obtain an aggregate measure of investor sentiment, we restrict our sample to firms with March, June, September, or December fiscal year ends, to ensure that fiscal quarters are aligned. We exclude financial firms (SIC codes 6000 through 6999) from the sample. We then equal- or value-weight the firm-level sentiment measure by the market capitalization as of the end of the fiscal quarter to obtain an aggregate measure (Kothari, Lewellen, and Warner (2006); Hirshleifer, Hou, and Teoh (2009)). The above figure shows the correlation between aggregate asset growth and the value-weighted investor optimism.

9.2 Does Asset Growth Capture Investors' Biased Belief About Future Cash Flows?

In this section, we follow Wen and Zhou (2013) and use analyst earnings forecast to separate cash flow and discount rate components of returns. We then distinguish the source of return predictability by asset growth. Our evidence supports the evidence that asset growth largely predicts the cash flow component of returns, implying that this variable may capture investors' biases in projecting aggregate future cash flows.

9.2.1 Motivation

To formally demonstrate the difference between these two sources of predictability, we can use the log-linearized present value identity proposed in Campbell and Shiller (1988) (Campbell (1991) and Campbell and Ammer (1993) later modify the log-linearization identity to apply to returns). They show that the unexpected return can be decomposed into discount rate and dividend growth components through log-linearization of the accounting identity that $R_t = \dfrac{P_t + D_t}{P_{t-1}}$:

$$
\begin{aligned}
e_{t+1} &= r_{t+1} - E_t r_{t+1} && (13)\\
&= (E_{t+1} - E_t)\sum_{j=0}^{\infty}\rho^j \Delta d_{t+1+j} - (E_{t+1} - E_t)\sum_{t=1}^{\infty}\rho^j r_{t+1+j} && (14)\\
&= e_{CF,t+1} - e_{DR,t+1}, && (15)
\end{aligned}
$$

where e is the total unexpected return, e_{CF} and e_{DR} are unexpected returns in cash flow and discount rate, d represents the log dividends, r is the return and ρ is a log-linearization constant. With this log-linearized identity, we can examine the sources of return predictability more clearly. For the avoidance of ambiguity, we use E to denote objective expectations, or expectation based on true distribution and $\tilde{E}$ to denote subjective expectations of the market participants in the rest of discussion in this section.

Time Varying Discount Rate The first source is time varying discount rate. The discount rate for the next period cash flow is a function of the variable based on certain state variables of today. The change in discount rate can be driven by both rational behaviors and behavioral motives. These theories assume that people can forecast future cash flow without bias. This view is consistent with much existing theoretical work that assumes agents are rational, such as ICAPM and the Lucas tree model (Merton 1973, Mehra and Prescott 1985), the long run risk model (Bansal and Yaron 2004) and time varying disaster risk (Gabaix 2008). On the other hand, models that includes bounded rationality can also generate time varying discount rates, such as the habit formation model (Campbell and Cochrane (1999)) and the prospect theory (Barberis, Huang, and Santos (2001)). Formally speaking, we can rearrange the equation (13) as

$$r_{t+1} = E_t r_{t+1} + e_{t+1}.$$

All the above mentioned theories focus on the expected return, $E_t r_{t+1}$, or discount rate. If $E_t r_{t+1}$ is a function of a variety of predictive variables, then naturally these variables contain information on the next period return. For example, Merton (1980) and French, Schwert, and Stambaugh (1987) consider whether conditional volatility can predict equity return. The motivation is that in ICAPM, holding all else constant, higher market volatility implies higher risk and therefore will lead to a higher discount rate next period.

Cash Flow Driven Predictability On the other hand, many practitioners believe that people over or underestimate the cash flow on the aggregate scale, which in turn generates predictability. In the classical framework, this result implies that people are irrational in their expectations. Few researchers formalize this setting. In a review work by Barberis et al. (2003), the authors summarize these models in the following words: “When they see a surge in dividends, they are too quickly to believe that mean dividend growth rate has increased. Their exuberance pushes prices up relative to dividends, adding to volatility”

(Barberis et al. (2003)). It follows that when investors observe certain public signals which they believe are related to fundamentals, they overreact to these signals so that the prices are pushed up or down too much. As a result, mean reversion in prices can be observed. Formally, if we assume that investors have subjective expectations (which may be different from the objective expectation implied by statistical distribution) about future cash flow (let the biased expectation be denoted as $\tilde{E}$), the return decomposition identity becomes

$$e_{t+1} = (\tilde{E}_{t+1} - \tilde{E}_t) \sum_{j=0}^{\infty} \rho^j \Delta d_{t+1+j} - (E_{t+1} - E_t) \sum_{t=1}^{\infty} \rho^j r_{t+1+j}.$$

Suppose the predictive variable captures biased belief regarding the future cash flow. Then we can write the difference between an investor's belief of future cash flow growth as a function of the predictive variable x_t: $E_t(\tilde{E}_{t+1} - \tilde{E}_t) \sum_{j=0}^{\infty} \rho^j \Delta d_{t+1+j} = f(x_t)$. In this case, the stock market return may become predictable, because price will adjust when fundamentals are revealed in the future.

The interpretation of cash flow driven predictability is in general inconsistent with Fama (1970) notion of informational market efficiency under classical assumptions. However, in the Bayesian learning framework (eg. Timmermann (1993), Lewellen and Shanken (2002)), predictability can still exist even if the agents are fully rational, the discount rate is constant and the conditional mean of dividends is constant. Predictability exists ex-post to researchers, but investors are only acting to the best of their knowledge.

9.2.2 Empirical Strategy

We use market prevailing forecasts for future cash flows (from IBES), since analyst earnings forecasts have been widely used in finance literature as a proxy for market earnings expectation.[21] Specifically, we adopt the framework in Chen, Da, and Zhao (2012) to

[21] We summarize a few papers that use analyst forecasts in asset pricing literature as follows. Pastor et al. (2008) use analyst forecasts to back out the market implied cost of capital and show that market volatility predicts future expected return. Chava and Purnanandam (2010) use analyst expectation to back out implied cost of capital for each individual stock and show that distressed stocks earn higher expected returns. Da and Warachka (2009b) use analyst forecast revisions as a proxy for expected cash

decompose returns into the cash flow return component and the discount rate return component. The first step of this procedure involves solving for the implied cost of capital (ICC) from the present value relationship. Following Pastor et al. (2008), we numerically solve the following equation using IBES consensus analyst forecasts on earnings,

$$P_t = \sum_{k=1}^{T} \frac{FE_{t+k}(1-b_{t+k})}{(1+r_e)^k} + \frac{FE_{t+T+1}}{r_e(1+r_e)},$$

where P_t is the price of the stock at the end of month t, FE_{t+k} is earnings forecast k years ahead, b_t is the plowback ratio at time t, and r_e is the implied cost of capital. For the first two years, the plowback rate is computed using the most recent net payout ratio for each firm. Plowback ratios b_{t+3} to b_{t+T} are calculated as

$$b_{t+k} = b_{t+k-1} - \frac{b_{t+2} - b}{T-1}$$

and b is the steady state plowback ratio and $b = g/r_e$, where g is equal to the the average historical GDP growth rate. The first three years' earnings forecasts are directly obtained from IBES. For earnings forecasts beyond three years (year $t+4$ to $t+T+1$), we project earnings using $FE_{t+k} = FE_{t+k-1} \times (1 + g_{t+k})$ and $g_{t+k} = g_{t+k-1} \times \exp[\log(g/g_{t+3})/(T-1)]$, where g is the mean long-term industry analyst forecast. T is set to 15 following Pastor et al (2008).

Our return decomposition methodology is based on Chen, Da, and Zhao (2012). A few minor changes are made to make the decomposition methodology more suitable for our purpose. Following Chen, Da, and Zhao (2012), we can then decompose the capital gain return into cash flow and discount rate components, using ICC calculated from the above procedure. The sample consists of firms at quarterly frequency from 1985Q1 to 2011Q4.

First, we notice that P_t is essentially a function of cash flow information (c, a vector of all the cash flow predictions) at time t and of $r_{e,t}$, the ICC at time t. We construct a

flow innovation. Chen, Da, and Zhao (2012) use analyst forecasts to back out cash flow and discount rate components of stock return.

counterfactual price P'_{t+j}. P'_{t+j} can be viewed as the "expected price" at $t+j$ estimated at t given the ICC of time $t+1$. Let c_t and c_{t+j} denote the cash flow information at time t and $t+j$. Cash flow c_t is a vector that can be represented as $[c_{t,t+j-1}, c'_{t+j}]$, where c'_{t+j} is the cash flow information from $t+j+1$ to infinite future projected at time t or $E_t[c_{t+j}]$. Let r_e denotes ICCs. Now we can represent every price as a function of c and r: $P_t = f(c_t, r_{e,t})$, $P_{t+1} = f(c_{t+j}, r_{e,t+j})$ and $P'_{t+j} = f(c'_{t+j}, r_{e,t+j})$. We define capital gain portion of return CG_j as the j period forward capital gain return (or ex-dividend return). Then

$$
\begin{aligned}
CG_j &= \frac{P_{t+j} - P_t}{P_t} && (16)\\
&= \frac{f(c_{t+j}, r_{e,t+j}) - f(c_t, r_{e,t})}{P_t} && (17)\\
&= \frac{f(c_{t+j}, r_{e,t+j}) - f(c'_{t+j}, r_{e,t+j})}{P_t} + \frac{f(c'_{t+j}, r_{e,t+j}) - f(c_t, r_{e,t+j})}{P_t} && (18)\\
&= \frac{P_{t+j} - P'_{t+j}}{P_t} + \frac{P'_{t+j} - P_t}{P_t}. && (19)
\end{aligned}
$$

Now, we have

$$CF_j = \frac{P_{t+j} - P'_{t+j}}{P_t}$$

and

$$DR_j = \frac{P'_{t+j} - P_t}{P_t},$$

where CF represents the cash flow component of returns and DR represents the discount rate component of returns. We argue that the difference between P_{t+j} and P'_{t+j} are driven by changes in expected cash flows, since discount rates are held at constant. Take the extreme case, for example, if there is no revision in cash flow expectation from time t and time $t+j$, then cash flow component of return is 0. The rest of the returns are identified as discount rate return, which includes expected return and return related to changes in future expected returns. Unlike Chen, Da, and Zhao (2012), our counterfactual price P' excludes the cash flow from time $t+1$ to $t+j$. This minor modification allows us to completely eliminate the expected return component from cash flow return[22].

This procedure is done for each individual firm. We then take the value-weighted average of the individual CF and DR return to obtain an aggregate level. The data is winsorized at 1% and 99%. We run three predictive regressions for each of the predictive variables:

$$CG_t = a_{CG} + b_{CG,t} AG_{t-1} + \epsilon_{CG,t} \tag{20}$$

$$CF_t = a_{CF} + b_{CF,t} AG_{t-1} + \epsilon_{CF,t} \tag{21}$$

$$DR_t = a_{DR} + b_{DR,t} AG_{t-1} + \epsilon_{DR,t} \tag{22}$$

where CG is the the capital gain portion of return, CF is the cash flow component and DR is the discount rate component of return, and x is the predictive variable. We also consider longer horizon predictability from 2 to 4 quarters ahead.

Since some of the predictive variables are highly persistence, the OLS estimates may be biased in the finite sample Stambaugh (2000). As a result, we report adjusted standard error suggested by Stambaugh (2000). We also impute the statistical significance of the bias-adjusted standard error using bootstrap procedure recommended by Nelson and Kim (1993) and Kothari and Shanken (1997). Results are reported in the following Table.

[22]Imagine a firm does not pay dividend and the expected return is r_e. In Chen and Zhao (2009b) decomposition, given there is no unexpected returns, the entire r_e will be counted towards cash flow return. Since Chen, Da, and Zhao (2012) focus on the unexpected component (or news) of returns, this concern is less important.

Appendix Table 1: Return Decomposition

The table reports the coefficients (β) and t-statistics from time series regressions of quarterly stock market returns (CG), cash flow components (CF), as well as discount rate components (DR) on the aggregate asset growth, at different time horizon τ, where τ=1, 2, 3, or 4 quarters

$$R_{t,t+\tau} = \alpha + \beta AG_t + u_t \quad \tau = 1, 2, 3, 4$$

t-statistics are computed using heteroskedasticity and auto-correlation consistent standard errors. The sample period is 1985Q1 to 2011Q4. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Returns	β in %	$t(\beta)$	Adj.R^2(%)
	Panel A: $R_{t,t+1} = \alpha + \beta AG_t + u_t$		
CG	-1.97***	-2.84	5.21
CF	-1.51***	-2.59	3.65
DR	-0.39	-1.35	0.26
	Panel B: $R_{t,t+2} = \alpha + \beta AG_t + u_t$		
CG	-3.41***	-3.85	8.03
CF	-1.64**	-2.72	4.60
DR	-1.62*	-2.02	1.72
	Panel C: $R_{t,t+3} = \alpha + \beta AG_t + u_t$		
CG	-4.83***	-4.81	11.68
CF	-2.02**	-2.29	4.77
DR	-2.59***	-2.59	3.29
	Panel D: $R_{t,t+4} = \alpha + \beta AG_t + u_t$		
CG	-4.58***	-3.53	8.29
CF	-2.96***	-2.81	10.27
DR	-1.32	-1.12	-0.07

References

Abarbanell, J., 1991, Do analysts' earnings forecasts incorporate information in prior stock price changes?, *Journal of Accounting and Economics* 14, 147–165.

Baker, Malcom, Ryan Taliaferro, and Jeffrey Wurgler, 2006, Predicting returns with managerial decision variables: Is there a small-sample bias?, *Journal of Finance* 4, 1711–1730.

Baker, M., and J. Wurgler, 2000, The equity share in new issues and aggregate stock returns, *Journal of Finance* 55, 2219–2257.

——— , 2006, Investor sentiment and the cross-section of stock returns, *Journal of Finance* 61, 1645–1680.

——— , 2007, Investor sentiment in the stock market, *Journal of Economic Perspectives* 21, 12–9–152.

Ball, R., 2011, Discussion of why do eps forecast error and dispersion not vary with scale? implications for analyst and managerial behavior, *Journal of Accounting Research* 49, 403–412.

Bansal, Ravi, and Amir Yaron, 2004, Risks for the long run: A potential resolution of asset pricing puzzles, *The Journal of Finance* 59, 1481–1509.

Barberis, Nicholas, Ming Huang, and Tano Santos, 2001, Prospect theory and asset prices, *The Quarterly Journal of Economics* 116, 1–53 ArticleType: research-article / Full publication date: Feb., 2001 / Copyright 2001 Oxford University Press.

Berk, J. B., R.C. Green, and V. Naik, 1999, Optimal investment, growth options, and security returns, *Journal of Finance* 54(5), 1553–1607.

——— , 2004, Valuation and return dynamics of new ventures, *Review of Financial Studies* 17, 1–35.

Bernard, V., and J. Thomas, 1990, Evidence that stock prices do not fully reflect the implications of current earnings for future earnings, *Journal of Accounting and Economics* 13, 305–340.

Bradshaw, M., and R. Sloan, 2002, Gaap versus the street: An empirical assessment of two alternative definitions of earnings, *Journal of Accounting Research* 40, 41–66.

Campbell, JY, and RJ Shiller, 1988, The dividend-price ratio and expectations of future dividends and discount factors, *Review of Financial Studies* 1, 195 –228.

Campbell, J. Y, 1991, A variance decomposition for stock returns, *The Economic Journal* 101, 157179.

Campbell, John Y., and John Ammer, 1993, What moves the stock and bond markets? a variance decomposition for long-term asset returns, *The Journal of Finance* 48, 3–37 ArticleType: research-article / Full publication date: Mar., 1993 / Copyright 1993 American Finance Association.

Campbell, John Y., and John H. Cochrane, 1999, By force of habit: A consumption-based explanation of aggregate stock market behavior, *Journal of Political Economy* 107, 205.

Campbell, John Y., Jens Hilscher, and Jan Szilagyi, 2008, In search of distress risk, *The Journal of Finance* 63, 2899–2939.

Campbell, John Y., and Samuel B. Thompson, 2008, Predicting excess stock returns out of sample: Can anything beat the historical average?, *The Review of Financial Studies* 21(4), 1509–1531.

Carhart, Mark M., 1997, On persistence in mutual fund performance, *The Journal of Finance* 52, 57–82.

Carlson, M., A. Fisher, and R. Giammarino, 2004, Corporate investment and asset price dynamics: implications for the cross-section of returns, *Journal of Finance* 59(6), 2577–2603.

Chan, Louis K.C., N. Jegadeesh, and J. Lakonishok, 1996, Momentum strategies, *Journal of Finance* 51, 1681–1713.

Chava, Sudheer, and Amiyatosh Purnanandam, 2010, Is default risk negatively related to stock returns?, *Review of Financial Studies* 23, 2523–2559.

Chen, Long, Zhi Da, and Xinlei Shelly Zhao, 2012, What drives stock price movement?, *SSRN eLibrary*.

Chen, L., R. Novy-Marx, and L. Zhang, 2010, An alternative three-factor model, *Unpublished working paper, University of Rochester*.

Chen, L., and X. Zhao, 2009a, Return decomposition, *Review of Financial Studies* 22, 22 (12) 5213–5249.

Chen, Long, and Xinlei Zhao, 2009b, Return decomposition, *Review of Financial Studies*.

Chen, N. F., R. Roll, and S. A. Ross, 1986, Economic forces and the stock market., *Journal of Business* 59(3), 383–403.

Cheong, F., and J. Thomas, 2011, Why do eps forecast error and dispersion not vary with scale? implications for analyst and managerial behavior, *Journal of Accounting Research* 49, 359–401.

Clark, Todd E, and Kenneth D. West, 2007, Approximately normal tests for equal predictive accuracy in nested models, *Journal of Econometrics* 138, 291–311.

Cochrane, J. H., 1991, Production-based asset pricing and the link between stock returns and economic fluctuations, *Journal of Finance* 46, 209–237.

Cochrane, John H., 1996, A cross-sectional test of an investment-based asset pricing, *Journal of Political Economy* 104, 572.

Cooper, I., 2006, Asset pricing implications of nonconvex adjustment costs and irreversibility of investment, *Journal of Finance* 61, 139–170.

Cooper, Ilan, and Richard Priestley, 2011, Real investment and risk dynamics, *Journal of Financial Economics* 101, 182–205.

Cooper, Michael J., Huseyin Gulen, and Michael J. Schill, 2008, Asset growth and the cross-section of stock returns, *Journal of Finance* 63, 1609 – 1651.

Da, Z., and M. Warachka, 2009a, Cashflow risk, systematic earnings revisions, and the cross-section of stock returns, *Journal of Financial Economics* 94, 448–468.

Da, Zhi, and Mitchell Craig Warachka, 2009b, Cashflow risk, systematic earnings revisions, and the cross-section of stock returns, *Journal of Financial Economics* 94, 448–468.

Daniel, K.D., and S. Titman, 2006, Market reactions to tangible and intangible information, *Journal of Finance* 61, 1605–1643.

DeLong, B., A. Shleifer, L.H. Summers, and R. Waldmann, 1990, Noise trader risk in financial market, *Journal of Political Economy* 90, 703–738.

Dichev, Ilia, 1998, Is the risk of bankruptcy a systematic risk?, *Journal of Finance* 53, 1131–1147.

Diether, K., C. Malloy, and A. Scherbina, 2002, Differences of opinion and the cross section of stock returns, *Journal of Finance* 57, 2113–2141.

Fama, E.F., and K.R. French, 2006, Profitability, investment and average returns, *Journal of Financial Economics* 82, 491–518.

Fama, Eugene F., 1970, Efficient capital markets: A review of theory and empirical work, *The Journal of Finance* 25, 383–417 ArticleType: research-article / Issue Title: Papers and Proceedings of the Twenty-Eighth Annual Meeting of the American Finance Association New York, N.Y. December, 28-30, 1969 / Full publication date: May, 1970 / Copyright 1970 American Finance Association.

French, Kenneth R., G.William Schwert, and Robert F. Stambaugh, 1987, Expected stock returns and volatility, *Journal of Financial Economics* 19, 3–29.

Gabaix, Xavier, 2008, Variable rare disasters: A tractable theory of ten puzzles in macro-finance, *The American Economic Review* 98, 64–67 ArticleType: research-article / Issue Title: Papers and Proceedings of the One Hundred Twentieth Annual Meeting of the American Economic Association / Full publication date: May, 2008 / Copyright 2008 American Economic Association.

Giacomini, R., and H. White, 2006, Tests of conditional predictive ability, *Econometrica* 74, 1545–1578.

Givoly, D., and J. Lakonishok, 1979, The information content of financial analysts' forecasts of earnings: Some evidence on semi-strong inefficiency, *Journal of Accounting and Economics* 1, 165–185.

Goyal, Amit, and Ivo Welch, 2008, A comprehensive look at the empirical performance of equity premium prediction, *Review of Financial Studies* 21, 1455 –1508.

Hirshleifer, D., K. Hou, S.H. Teoh, and Y. Zhang, 2004, Do investors overvalue firms with bloated balance sheets, *Journal of Accounting and Economics* 38, 297–331.

Hirshleifer, David, Kewei Hou, and Siew Hong Teoh, 2009, Accruals, cash flows, and aggregate stock returns, *Journal of Financial Economics* 91, 389–406.

Hong, H., and M. Kacperczyk, 2010, Competition and bias, *The Quarterly Journal of Economics* 125, 1683–1725.

Hou, K., Mathijs A. Van Dijk, and M. Zhang, 2011, The implied cost of capital: A new approach, *Journal of Accounting and Economics* Forthcoming.

Ivkovic, Z., and N. Jegadeesh, 2004, The timing and value of forecast and recommendation revisions, *Journal of Financial Economics* 73, 433–463.

Jegadeesh, N., J. Kim, S. Krische, and C. S. Lee, 2004, Analyzing the analysts: When do recommendations add value?, *The Journal of Finance* 59, 1083–1124.

Jegadeesh, Narasimhan, and Sheridan Titman, 1993, Returns to buying winners and selling losers: Implications for stock market effciency, *Journal of Finance* 48, 65–91.

Kirk, M., 2011, Research for sale: Determinants and consequences of paid-for analyst research, *Journal of Financial Economics* 100, 182–200.

Kothari, S.P., Jonathan W. Lewellen, and Jerold B. Warner, 2006, Stock returns, aggregate earnings surprises, and behavioral finance, *Journal of Financial Economics* 79, 537–568.

Kothari, S., and Jay Shanken, 1997, Book-to-market, dividend yield, and expected market returns: a time-series analysis, *Journal of Financial Economics* 44, 169–203.

La Porta, R., 1996, Expectations and the cross-section of stock returns, *The Journal of Finance* 51, 1715–1742.

Lam, F. E. C., and K.J. Wei, 2011, Limits-to-arbitrage, investment frictions, and the asset growth anomaly, *Journal of Financial Economics* 102(1), 127–149.

Lewellen, Jonathan, and Jay Shanken, 2002, Learning, asset-pricing tests, and market efficiency, *The Journal of Finance* 57, 1113–1145 ArticleType: research-article / Full publication date: Jun., 2002 / Copyright 2002 American Finance Association.

Li, D., and L. Zhang, 2010, Does q-theory with investment frictions explain anomalies in the cross section of returns?, *Journal of Financial Economics* 98(2), 297–314.

Li, E. X. N., D. Livdan, and L. Zhang, 2009, Anomalies, *Review of Financial Studies* 22(11), 4301–4334.

Lin, H., and M. McNichols, 1998, Underwriting relationships, analysts' earnings forecasts and investment recommendations, *Journal of Accounting and Economics* 25, 101–127.

Lipson, Marc L., Sandra Mortal, and Michael J. Schill, 2011, On the scope and drivers of the asset growth effect, *Journal of Financial and Quantitative Analysis* 46, 1651–1682.

Liu, L. X., T.M. Whited, and L. Zhang, 2009, Investment-based expected stock returns, *Journal of Political Economy* 117, 1105–1139.

Loughran, Tim, and Jay R. Ritter, 1995, The new issues puzzle, *Journal of Finance* 1995, 23–51.

Lys, T., and S. Sohn, 1990, The association between revisions of nancial analysts' earnings forecasts and security-price changes, *Journal of Accounting and Economics* 13, 341–363.

Mankiw, N.G., and M.D Shapiro, 1986, Do we reject too often? small sample properties of tests of rational expectation models, *Economics Letters* 20, 139–145.

Mehra, Rajnish, and Edward C. Prescott, 1985, The equity premium: A puzzle, *Journal of Monetary Economics* 15, 145–161.

Merton, Robert C., 1973, An intertemporal capital asset pricing model, *Econometrica* 41, 867–887 ArticleType: research-article / Full publication date: Sep., 1973 / Copyright 1973 The Econometric Society.

———, 1980, On estimating the expected return on the market: An exploratory investigation, *Journal of Financial Economics* 8, 323–361.

Miller, E.M, 1977, Risk, uncertainty and divergence of opinion, *Journal of Finance* 32, 1151–1168.

Nelson, C, and M.J. Kim, 1993, Predictable stock returns: the role of small sample bias, *Journal of Finance* 48, 641–661.

Novy-Marx, R., 2013, The other side of value: The gross profitability premium, *Journal of Financial Economics* 108, 1–28.

Ohlson, James A., 1980, Financial ratios and the probabilistic prediction of bankruptcy, *Journal of Accounting Research* 18, 109–131.

Philbrick, D., and W. Ricks, 1991, Using value line and ibes analyst forecasts in accounting research, *Journal of Accounting Research* 29, 397–417.

Pontiff, Jeffrey, and Lawrence D. Schall, 1998, Book-to-market ratios as predictors of market returns, *Journal of Financial Economics* 49, 141–160.

Ritter, J.R, 1991, The long-run performance of initial public offerings, *Journal of Finance* 46, 3–27.

Sloan, R.G, 1996, Do stock prices fully reflect information in accruals and cash flows about future earnings?, *Accounting Review* 71, 289–315.

So, Eric, 2013, A new approach to predicting analyst forecast errors: Do investors overweight analyst forecasts, *Journal of Financial Economics* 108, 615–640.

Stambaugh, R, 1986, Bias in regressions with lagged stochastic regressors, *Unpublished working paper,University of Chicago*.

——— , 2000, Predictive regressions, *Journal of Financial Economics* 54, 375–421.

——— , Jianfeng Yu, and Yu Yuan, 2012, The short of it: Investor sentiment and anomalies, *Journal of Financial Economics* 104, 288–302.

Timmermann, Allan G., 1993, How learning in financial markets generates excess volatility and predictability in stock prices, *The Quarterly Journal of Economics* 108, 1135 –1145.

Titman, S., K.C. Wei, and F. Xie, 2004, Capital investment and stock returns, *Journal of Financial and Quantitative Analysis* 39, 677–701.

Titman, Sheridan, K.C. John Wei, and Feixue Xie, 2012, Market development and the asset growth effect: International evidence, *Journal of Financial and Quantitative Analysis, forthcoming.*

Watanabe, Akiko, Yan Xu, Tong Yao, and Tong Yu, 2013, The asset growth effect: Insights from international equity markets, *Journal of Financial Economics* 108, 529–563.

Wen, Quan, and Dexin Zhou, 2013, What drives market return predictability?, *Working Paper, Emory University.*

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			p(ADF)
						1	2	3	
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 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. 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: 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 in Stambaugh, Yu, and Yuan (2012), and returns on a strategy that equally combines all the strategies (Combination). Panel A reports coefficient estimates of excess returns on the Baker and Wurgler 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 aggregate asset growth in previous four quarters.

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

$\perp$ denotes orthogonalization with respect to the following macrovariables: the growth in industrial production, growth in consumer durables, non-durables, and services, growth in employment, and a dummy variable for NBER recessions. Panel C reports coefficient estimates of excess returns on both Baker and Wurgler sentiment index and aggregate asset growth index,

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

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

Table 9–*Continued*

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

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

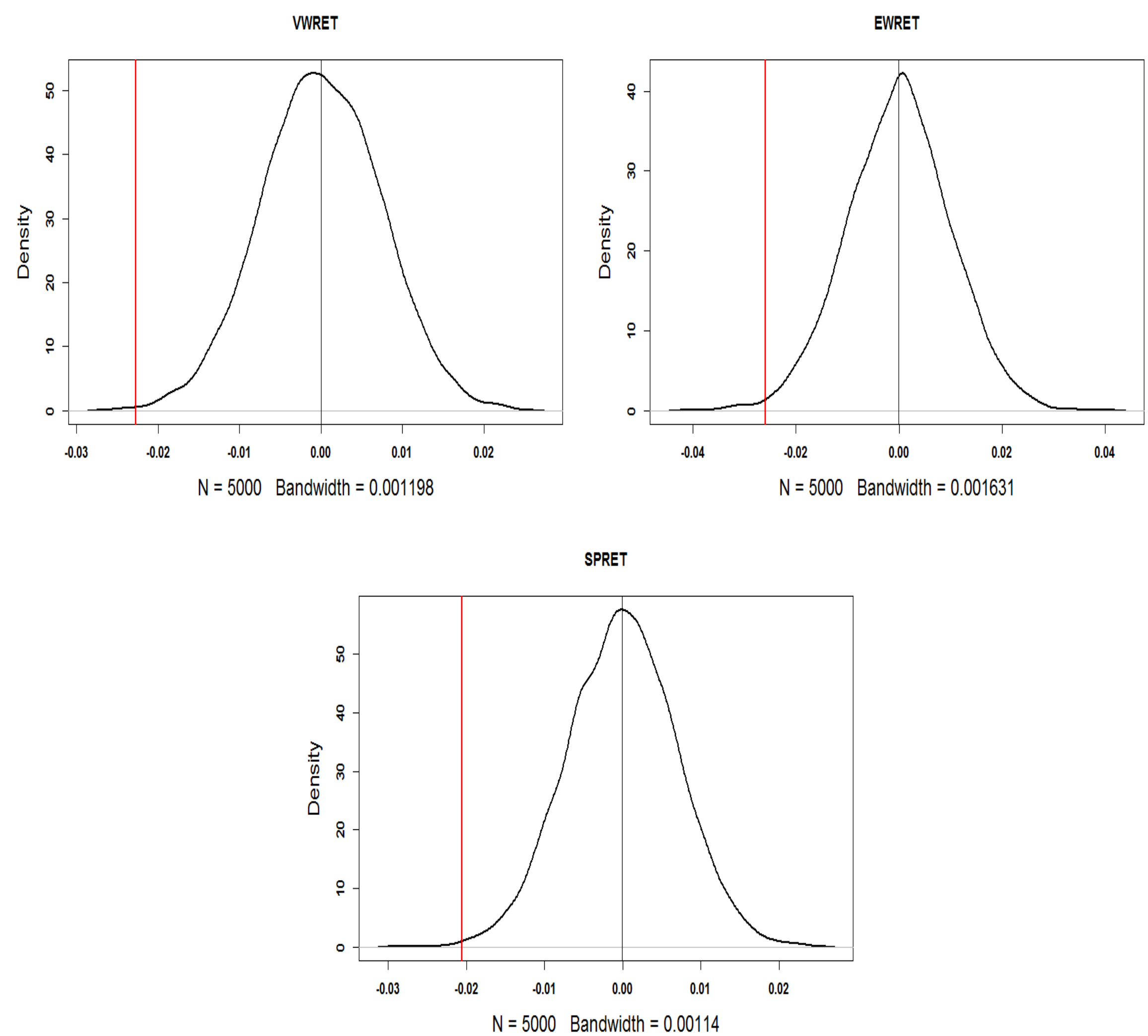
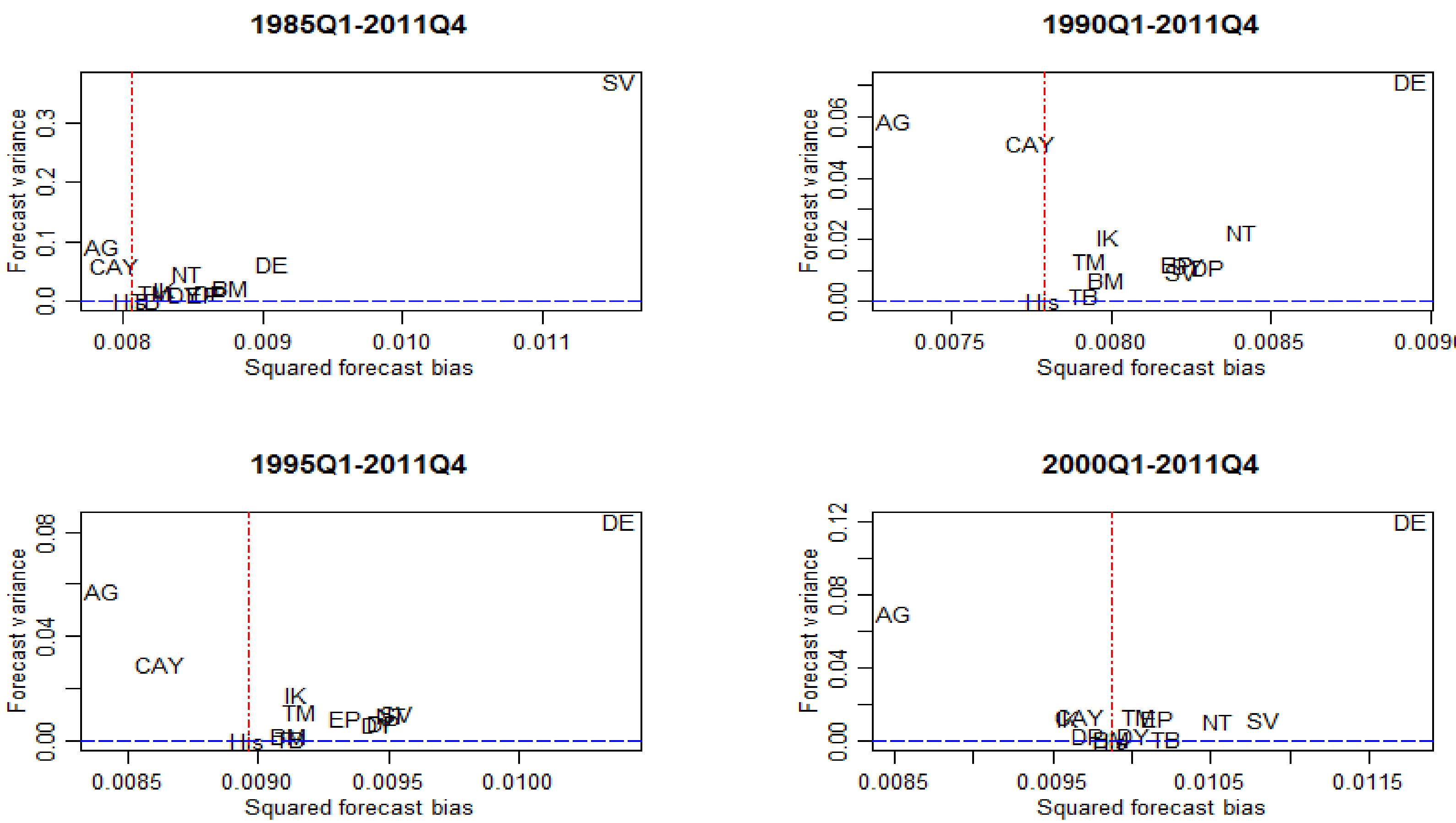


Figure 2

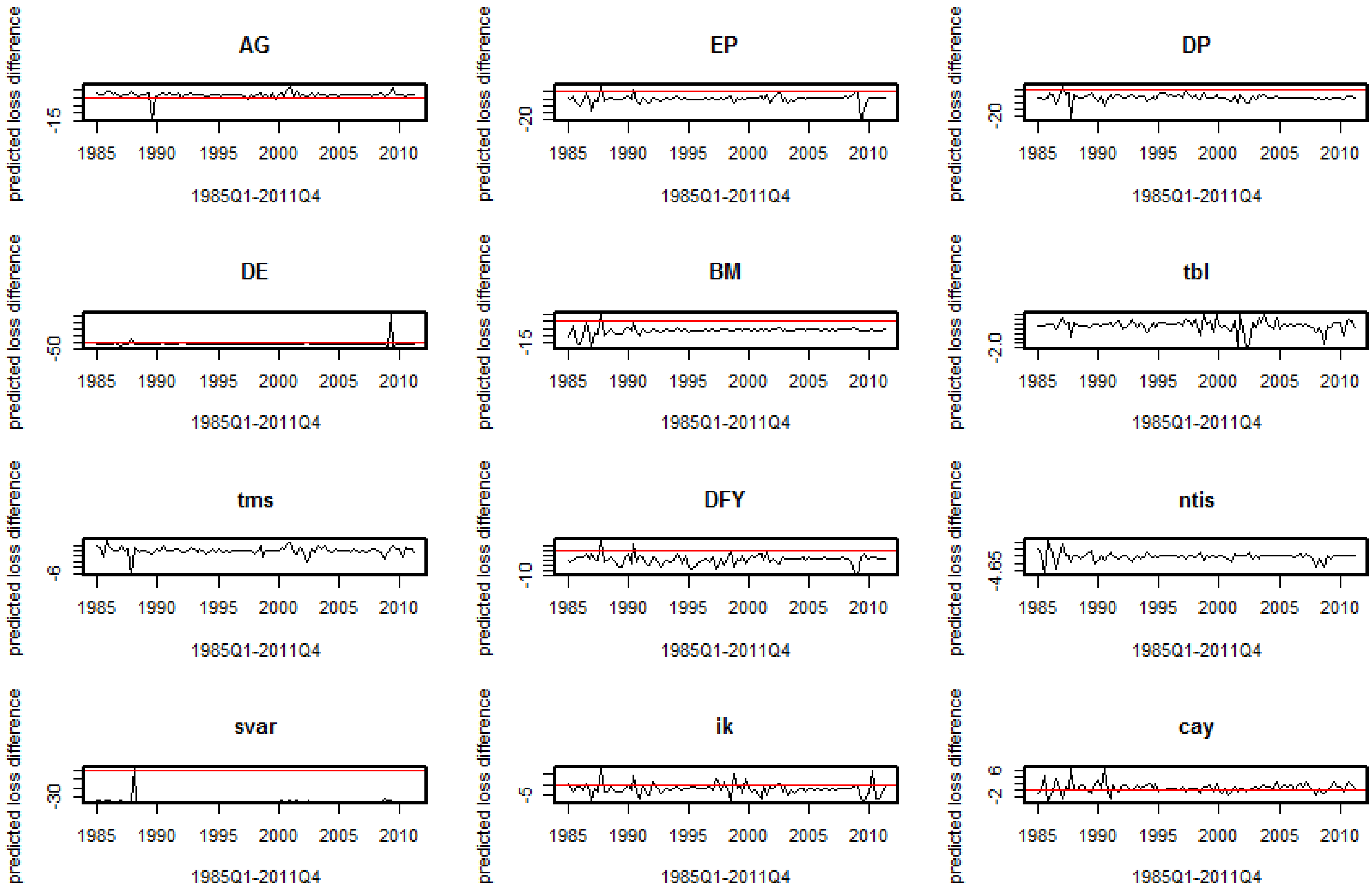
Scatterplots of Forecast Variance and Squared Forecast Bias



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

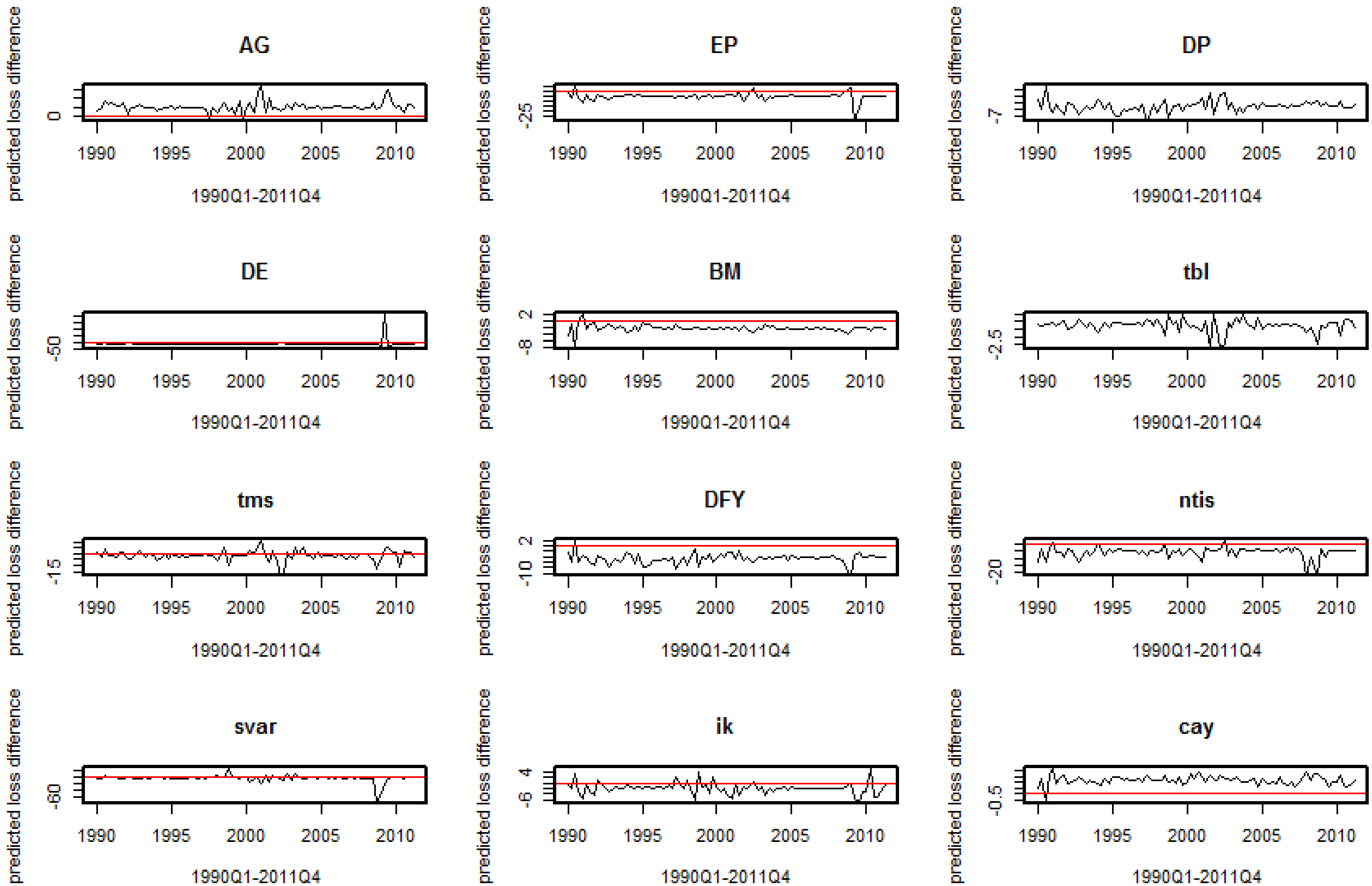
Time Path of Forecasting Performance: 1985Q1-2011Q4



This figure plots the time path of forecasting performance of asset growth (AG) and other predictive variables, following Giacomini and White (2006). The solid line represents the zero levels. The positive values in Figure 3 indicates the time periods in which the predictive variables perform better out-of-sample than the benchmark, and vice versa.

Figure 4

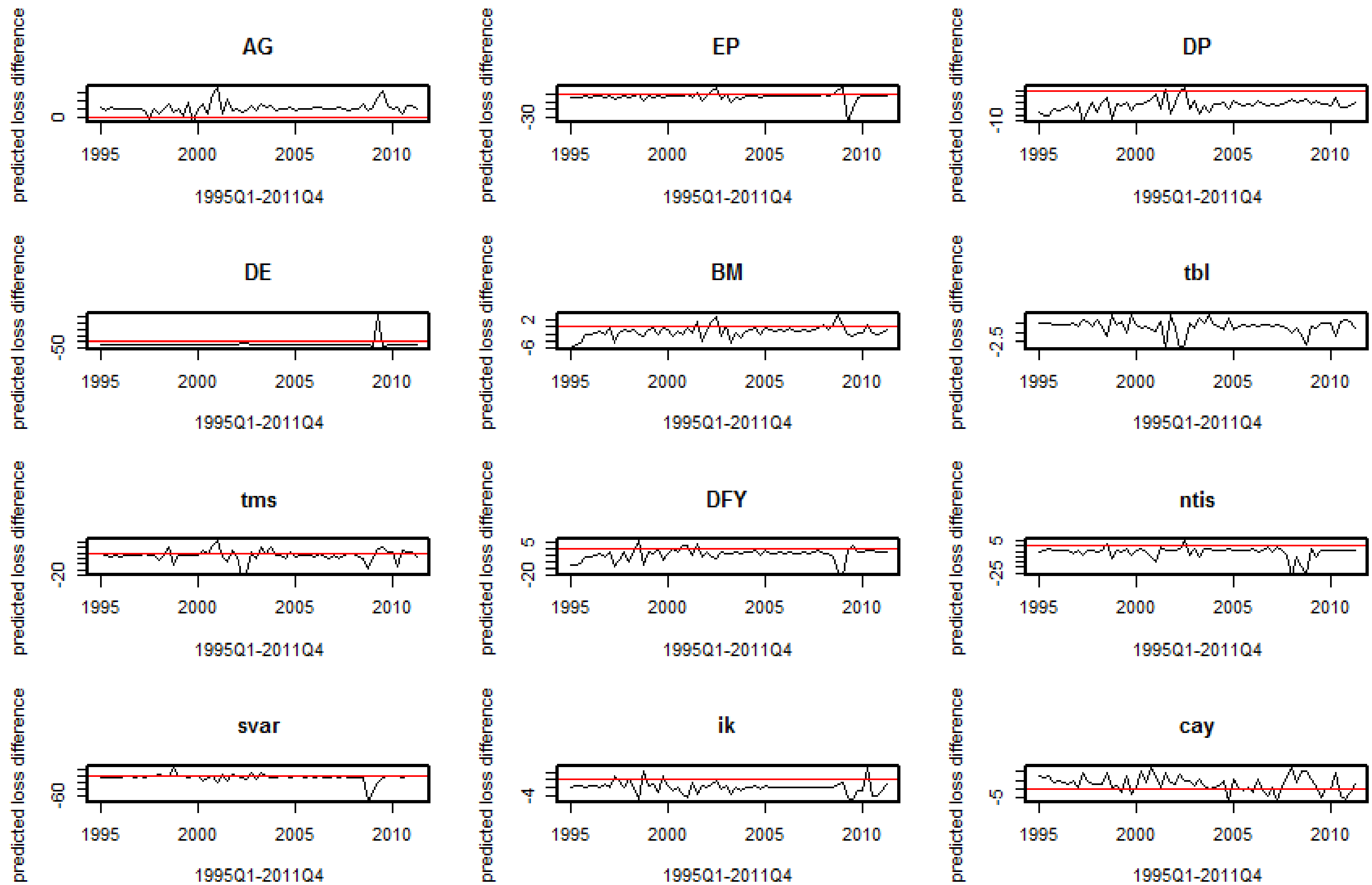
Time Path of Forecasting Performance: 1990Q1-2011Q4



This figure plots the time path of forecasting performance of asset growth (AG) and other predictive variables, following Giacomini and White (2006). The solid lines represent the zero levels. The positive values in Figure 4 indicates the time periods in which the predictive variables perform better out-of-sample than the benchmark, and vice versa.

Figure 5

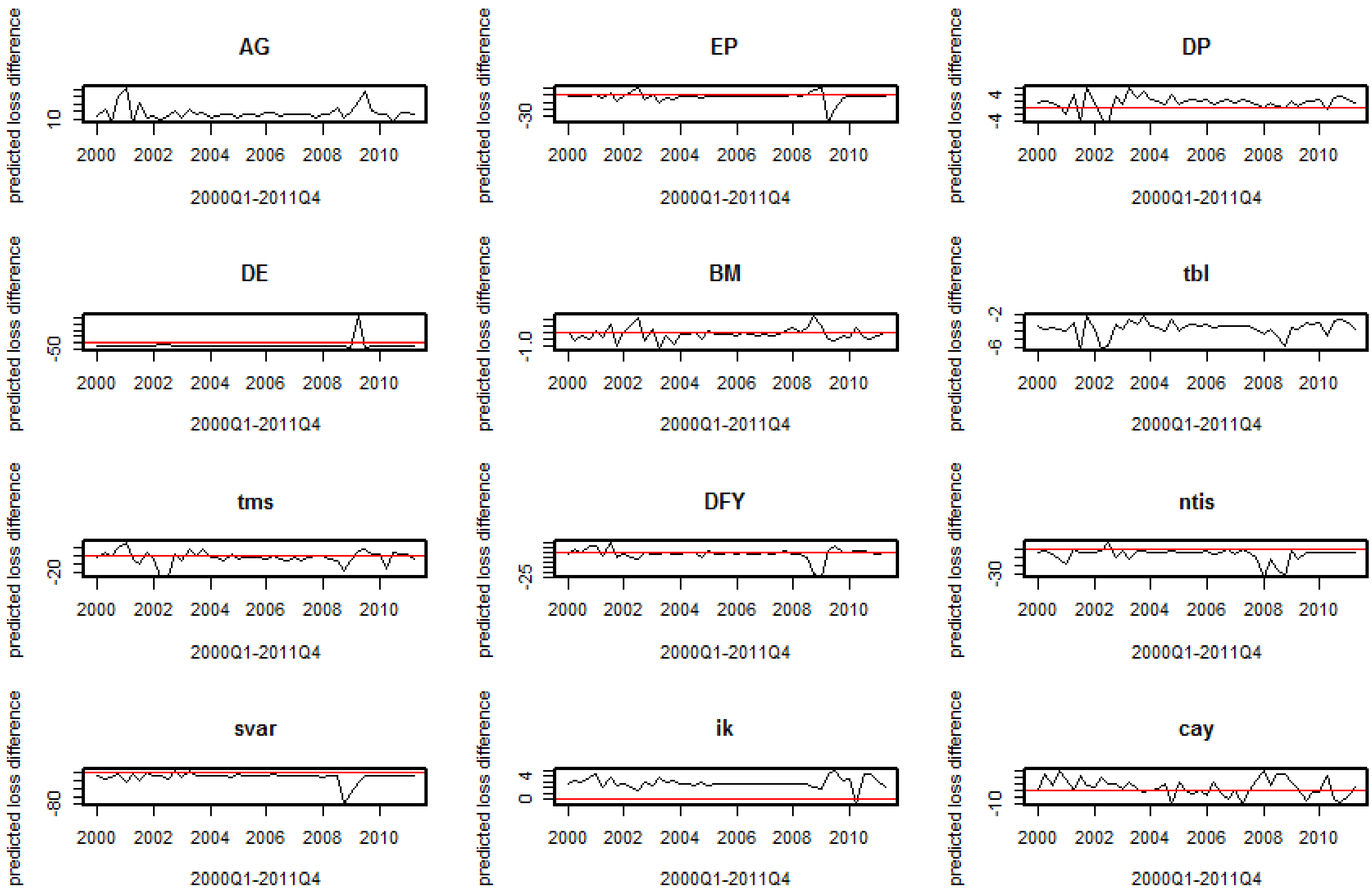
Time Path of Forecasting Performance: 1995Q1-2011Q4



This figure plots the time path of forecasting performance of asset growth (AG) and other predictive variables, following Giacomini and White (2006). The solid lines represent the zero levels. The positive values in Figure 5 indicates the time periods in which the predictive variables perform better out-of-sample than the benchmark, and vice versa.

Figure 6

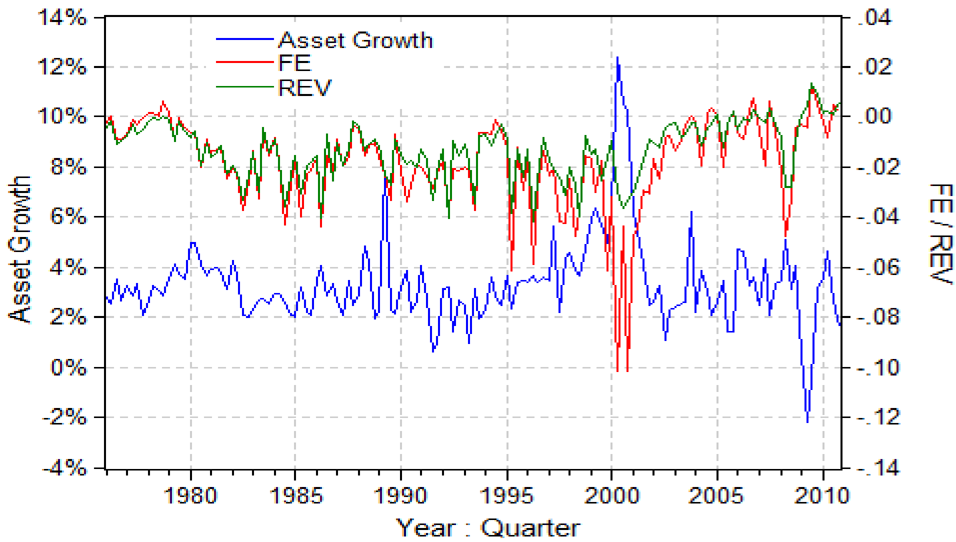
Time Path of Forecasting Performance: 2000Q1-2011Q4



This figure plots the time path of forecasting performance of asset growth (AG) and other predictive variables, following Giacomini and White (2006). The solid lines represent the zero levels. The positive values in Figure 6 indicates the time periods the predictive variables perform better out-of-sample than the benchmark, and vice versa.

Figure 7

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.