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Profitability, Asset Investment, and Aggregate Stock Returns

Timothy K. Chue
School of Accounting and Finance
Hong Kong Polytechnic University
Kowloon, Hong Kong
E-mail: timothy.chue@polyu.edu.hk

Jin (Karen) Xu*
School of Business and Management
Shanghai International Studies University
Shanghai, China
E-mail: jin.xu@shisu.edu.cn

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* Corresponding author.

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Abstract

We find that aggregate profitability and asset investment exhibit robust joint predictive power for aggregate excess stock returns, consistent with the investment model of Hou, Xue, and Zhang (henceforth HXZ, 2015). These results provide out-of-sample empirical support for HXZ, as the same mechanisms that HXZ use to explain firm-specific variation in stock returns can also be used to explain variation that is market-wide in nature. Also consistent with the HXZ investment model, we find that the growth rate of short-term (long-term) assets exhibits a stronger predictive power for one-year-ahead (two-year-ahead) stock returns.

Keywords: Profitability; Asset growth; Discount rates; Aggregate stock return forecasts.

JEL Classifications: G12, G17.

1. Introduction

Many recent studies document that one particular group of stocks with certain characteristics earns higher average returns than another. The return patterns that these studies uncover are often referred to as "anomalies," as they cannot be explained by the CAPM or the Fama and French (henceforth FF, 1993) three-factor model. Motivated by the investment model, Hou, Xue, and Zhang (henceforth HXZ, 2015, 2020), and Hou, Mo, Xue, and Zhang (henceforth HMXZ, 2019, 2021) show that firms' profitability and investment go a long way in accounting for these anomalies: much of the anomalies' positive (negative) alphas are associated with profitable (unprofitable) firms investing conservatively (aggressively). However, the success of these models also raises concerns that this may be the result of data-snooping. Lewellen, Nagel, and Shanken (2010) suggest examining the explanatory power of a model for other test assets. Fama (1998, p. 291) advises that a "model should be judged on how it explains the big picture." In this article, we examine whether the same mechanism that HXZ use to explain the firm-specific component of stock returns (as shown below in equation (1)) carries over to the market-wide component—that is, whether common variation in profitability and investment can also explain common variation in future stock returns. Just as profitable firms that invest conservatively are associated with high expected returns in the cross section, do high aggregate profits and low asset growth also precede high aggregate stock returns in the time series? After all, it is conceivable that cross-sectional variation in profitability and investment is related to the extent of mispricing across firms (Stambaugh and Yuan 2017), but is not driven by the theoretical mechanism proposed by HXZ. Because a firm-level variable's predictive power in the cross section does not need to translate into predictive power for its aggregate counterpart in the time series, our analysis serves as an out-of-sample (OOS) test of HXZ.[1]

[1] Both Kothari, Lewellen, and Warner (2006) and Hirshleifer, Hou, and Teoh (2009) study the aggregate counterpart of a cross-sectional predictive relationship and interpret their analyses as OOS tests. Kothari, Lewellen, and Warner (2006, p. 538) motivate their study as "a simple out-of-sample test of recent behavioral theories … [that] cite PEAD as a prime example of the type of irrational price behavior predicted by their models." In relation to Sloan's (1996) accruals anomaly, Hirshleifer, Hou, and Teoh (2009, p. 392) interpret their results as providing "out-of-sample evidence about the extent to which the behavioral theory used to explain the firm-level findings explains a broader range of stylized facts."

HXZ (2015) show how the predictive power of profitability and investment for future stock returns can arise in a q-theory-based model:

$$E_t\left[r_{i,t+1}\right] = \frac{E_t\left[\Pi_{i,t+1}\right]}{1 + a\left(I_{i,t}/A_{i,t}\right)}\,, \tag{1}$$

where $E_t\left[r_{i,t+1}\right]$ is the expected date t+1 stock return of firm i at date t; $E_t\left[\Pi_{i,t+1}\right]$ is the expected date t+1 profitability of firm i at date t, and can be viewed as the marginal benefit of investment; $A_{i,t}$ and $I_{i,t}$ are the assets and investment of firm i at date t, respectively; a is the adjustment cost parameter; and $1 + a\left(I_{i,t}/A_{i,t}\right)$ is the marginal cost of investment. Equation (1) implies that the investment return (the ratio between the date t+1 marginal benefit and date t marginal cost of investment) should equal the discount rate—a relationship that is also examined by Cochrane (1991), Liu, Whited, and Zhang (2009), Li and Zhang (2010), and Lin and Zhang (2013).

Following FF (2015) and HXZ (2015), we use the growth rate of total assets as our investment measure. To measure profits, we use Ball, Gerakos, Linnainmaa, and Nikolaev's (henceforth BGLN, 2016) cash-based operating profitability (OpCash/B), as BGLN show that an OpCash-based investment strategy generates superior Sharpe ratios relative to strategies that rely on other profitability measures, and Zhang (2017) shows that a q-factor model that uses an OpCash-based profitability factor can explain the accrual anomaly. Our results are robust to the use of ROE (HXZ 2015), operating profitability (FF 2015), or gross profitability (Novy-Marx 2013) as alternative profitability measures.

Even though we find that profitability has a negative OOS R^2 as a standalone predictor, HXZ (2015) emphasize that the cross-sectional predictive power of these variables is conditional in nature: "The negative relation between investment and the cost of capital is conditional on a given level of ROE. Investment and the cost of capital could be positively correlated unconditionally, if large investment delivers disproportionately high ROE. Analogously, the positive relation between ROE and the cost of capital is conditional on a given level of investment. ROE and the cost of capital could be negatively correlated unconditionally, if high ROE comes with disproportionately large investment. Sorting on investment and ROE jointly controls for these conditional relations" (HXZ 2015, pp. 662–63). We show that this insight carries over to the time series. In sharp contrast to the results from univariate regressions, all measures of aggregate profitability have highly significant predictive power when they are used jointly with aggregate investment in multivariate regressions. In annual forecasts, the predictive coefficients on (standardized) OpCash/B and asset growth are 0.054 and -0.068, with wild-bootstrapped p-values of 0.005 and 0.001, respectively. Economically, these coefficient estimates suggest that a one-standard-deviation increase in profitability and investment—conditional on the other variable—leads to changes in the one-year-ahead expected excess stock return by 5.4% and -6.8%. The OOS R^2 values are 5%, 12%, and 15%, respectively, in one-quarter-, one-year-, and two-year-ahead forecasts. This performance is neither driven by an isolated episode in the OOS forecast period, nor sensitive to the choice of sample split year. Using Clark and McCracken's (2001) ENC-NEW statistic, we show that these OOS forecasts are associated with statistically significant improvements in forecast accuracy relative to the historical mean.

To evaluate the implications of our results for portfolio choice, we calculate the certainty equivalent return (CER) gain from using OpCash/B and asset growth as predictors, relative to the case where the historical mean equity premium is used. We find that depending on the value of the risk aversion parameter, the CER gain ranges from 1.54% to 4.42% when one-year-ahead aggregate stock return forecasts are used for portfolio allocation, and from 0.64% to 2.89% when two-year-average aggregate stock return forecasts are used.

Although FF (2006, 2015, 2016) include the book-to-market ratio (B/M) as an additional predictor and motivate it with a valuation model, HMXZ (2019) show theoretically and FF (2015) show empirically that B/M becomes redundant once profitability and investment have been controlled for. We document a similar finding at the aggregate level. Using Harvey, Leybourne, and Newbold's (1998) encompassing test, we cannot reject the hypothesis that the predictive content of the two-variable model (profitability + investment) already subsumes that of the three-variable model (B/M + profitability + investment).

To gain a deeper understanding of the source of the predictive power of aggregate asset growth for future aggregate stock returns, we follow Cooper, Gulen, and Schill (2008) and decompose total assets into its major components. We find that the predictive power of total asset growth for future stock returns is more robust across different investment horizons than its individual components. Growth in cash and short-term assets has a stronger predictive power for one-year-ahead than for two-year-ahead stock returns, while the opposite is true for growth in longer-term assets. By incorporating the predictive power of all of its individual components, total asset growth can forecast future stock returns at both investment horizons. This is why, by focusing on only certain components of asset investment, Arif and Lee's (2014) investment measure is not as robust a predictor of aggregate stock returns as total asset growth across different time horizons.

We also find that the growth rate of short-term (long-term) assets exhibits a stronger predictive power for one-year-ahead (two-year-ahead) stock returns. This finding is consistent with the investment model's interpretation: that is, expected stock returns are a measure of the discount rate that firms use in their investment decisions, and firms' investment decisions are more responsive to variation in the discount rate that corresponds to the investment's time horizon. While this finding can also be driven by horizon-dependent biased beliefs (Cassella, Golez, Gulen, and Kelly 2021), the fact that we already control for profitability in our predictive regressions alleviates this concern. If systematic biases in managers' earnings expectations and investment decisions are caused by firms' recent performance and managers' subsequent over-extrapolation (Greenwood and Shleifer 2014; Hirshleifer, Li, and Yu 2015), then by holding recent earnings constant in a multivariate regression, we increase the likelihood that any marginal variation in asset growth is due to discount rate movements, rather than extrapolative expectation biases.

We also investigate whether the predictive power of profitability and asset investment comes from their correlation with other known predictors of aggregate excess stock returns. In particular, we control for earnings yield, term spread, default spread, T-bill rate (Ang and Bekaert 2007), CAY (the consumption–wealth ratio constructed by Lettau and Ludvigson 2001), investment-to-capital ratio (Cochrane 1991), equity issuance (Baker and Wurgler 2000), aggregate operating accruals (Hirshleifer, Hou, and Teoh 2009), and the investor sentiment measures proposed by Baker and Wurgler (2006, 2007) and Huang, Jiang, Tu, and Zhou (henceforth HJTZ, 2015). We find that even in the presence of these control variables, the predictive power of profitability and asset investment remains relatively unchanged. We also examine the performance of expected change in asset growth as an additional predictor (HMXZ 2021).

Our analysis emphasizes the evaluation of OOS return predictability, which is more relevant for investors in real time and is less subject to the Stambaugh (1999) small-sample bias (see Busetti and Marcucci 2013). To alleviate the concern that our in-sample inferences are distorted, we rely on *p*-values obtained from a wild bootstrap procedure, explained in detail by HJTZ (2015), to carry out inferences on all of our in-sample predictive regression estimates.

A number of studies have separately examined the predictive power of profitability and investment for aggregate stock returns. Vuolteenaho (2002) and Kelly and Pruitt (2013) have examined the joint predictive power of B/M and profitability, whereas Cochrane (1991), Lamont (2000), Arif and Lee (2014), and Wen (2019) have examined the predictive power of different measures of investment. However, no previous studies have jointly examined the time-series predictive power of aggregate profitability and investment.

The rest of the paper proceeds as follows. Section 2 documents the data and sample construction. Section 3.1 reports our aggregate excess stock return forecasts and their statistical significance. Section 3.2 evaluates their economic significance. Section 3.3 decomposes aggregate asset growth into its individual components and evaluates their predictive power over different forecast horizons. Section 3.4 makes use of this horizon-specific predictive power of different asset growth components to understand the performance of Arif and Lee's (2014) investment measure. Section 4 carries out a series of robustness checks. Section 5 concludes the paper.

2. Data and Sample Construction

We obtain U.S. financial statement data from the CRSP/Compustat merged annual and quarterly data files, and stock returns data from the CRSP monthly stock file. We include all common shares (share codes 10 and 11) listed on the NYSE/AMEX/Nasdaq (exchange codes 1, 2, and 3), but exclude all financial firms (SIC codes 6000–6999) from our analysis. We also exclude firm-years (or firm-quarters) with book assets of less than \$25 million or book equity of less than \$12.5 million. Our annual (quarterly) accounting data cover the period 1962–2019 (1975Q1–2020Q4), and stock returns data spanning July 1963–June 2021 (August 1975–July 2021).

Our main predictors are the log book-to-market ratio, profitability, and asset growth. The book-to-market ratio B_{it}/M_{it} of firm *i* in year *t* equals firm *i*'s book equity in year *t* divided by its market equity at the end of year *t*. Book equity equals total assets (Compustat item *AT*), minus total liabilities (Compustat item *LT*), plus balance sheet deferred taxes and investment tax credit (Compustat item *TXDITC*), if available, minus the book value of preferred stock. We use liquidation value (Compustat item *PSTKL*), if available, or redemption value (Compustat item *PSTKRV*), if available, or carrying value (Compustat item *PSTK*), if available, for the book value of preferred stock. We use BGLN's cash-based operating profitability, $OpCash_{it}/B_{it-1}$, which is computed as operating profitability, minus the change in accounts receivable (Compustat item *RECT*), minus the change in inventory (Compustat item *INVT*), minus the change in prepaid expenses (Compustat item *XPP*), plus the change in deferred revenue (Compustat item (*DRC*+*DRLT*)), plus the change in trade accounts payable (Compustat item *AP*), plus the change in accrued expenses (Compustat item *XACC*), scaled by lagged book equity. Operating profitability is defined as revenue (Compustat item *REVT*), minus cost of goods sold (Compustat item *COGS*), minus reported sales, general, and administrative expenses (Compustat item (*XSGA*-*XRD*)). As in BGLN (2015), we subtract expenditures on research and development (*XRD*) from reported sales, general, and administrative expenses (*XSGA*) to undo an adjustment that Standard & Poor's makes to firms' accounting statements. Asset growth in year *t*, dA_{it}/A_{it-1}, is given by $(A_{it} - A_{it-1})/A_{it-1}$, where A_{it} is firm *i*'s total assets (Compustat item *AT*) in year *t*.

In our quarterly analyses, we use quarterly-updated annual variables. Specifically, we compute *OpCash* as cash-based profits over the latest four quarters scaled by four-quarter-lagged book equity—rather than just using cash profits from the most recent quarter—to avoid confounding profitability with PEAD (see Novy-Marx 2015) and to reduce the impact of seasonalities. Similarly, quarterly updated annual asset growth is computed as the change in total assets over the latest four quarters scaled by four-quarter-lagged total assets. Further details on the construction of our variables are given in Appendix A. All firm-level accounting variables are winsorized at the 0.5th and 99.5th percentiles every year/quarter. A year/quarter *t* aggregate accounting ratio is then computed as a weighted average of its firm-level counterpart, using the market capitalizations at the end of year/quarter *t* as weights.

In annual analyses, we use accounting variables with fiscal year-ends in year *t* to forecast aggregate stock returns (in excess of the risk-free rate) from July of year *t*+1 to June of year *t*+2—thus allowing a gap of at least six months for accounting information to become publicly available after fiscal year end. Firm-level annual stock returns are obtained by compounding monthly stock returns (adjusted for delisting returns) from July in *t*+1 to June in *t*+2. If a firm's delisting return is missing and the delisting is performance-related, we assume a -30% delisting return. Otherwise, we set the missing returns to zero.[2] In quarterly analyses, we impose a four-month gap for quarterly accounting variables to become publicly available. Such a convention implies that the accounting variables in the first quarter of year *t* are used to forecast the August-to-October stock return in year *t*.

After subtracting the compounded one-month Treasury bill rates over the same 12 months to obtain excess returns, we compute aggregate excess stock returns in year *t*+1 (R^e_{t+1}) by aggregating firm-level excess returns using the market capitalizations at the end of year *t* as weights. The two-year average excess return $R^e_{(t+1,t+2)}$ is defined as the geometric average of annual total stock returns R_{t+1} and R_{t+2} minus the geometric average of annual risk-free rates RF_{t+1} and RF_{t+2}. We compute quarterly aggregate stock returns in a similar way—using market capitalizations at the end of quarter *t* as weights for firm-level quarterly excess returns four months ahead. Our annual sample contains 106,662 firm-years of accounting data over the period 1962–2019. The corresponding return prediction period spans July 1963–June 2021. Our quarterly sample contains 351,657 firm-quarters of accounting data over the period 1975Q1–2020Q4. The corresponding return prediction period spans August 1975–July 2021.

[2] This treatment of missing delisting returns follows the suggestion of Shumway (1997).

3. Empirical Results

This section reports our main empirical results. Section 3.1 evaluates the statistical significance of our aggregate excess stock return forecasts, by examining wild-bootstrapped-based p-values of our predictive coefficients and the OOS R^2 values of our predictive regressions. Section 3.2 compares our forecasts with those that only use the historical mean return or B/M as predictor, and quantifies the economic significance of the difference by calculating the CER gains. Section 3.3 explores the source of the predictive power of asset growth by decomposing it into various components, and Section 3.4 uses these results to understand why the predictive power of Arif and Lee's (2014) investment measure is less robust than total asset growth across different forecast horizons.

3.1 Statistical Significance of the Aggregate Excess Stock Return Forecasts

Because the investment model applies to all firms in period t, firms that are only listed after period t should not be included in our calculation of expected future aggregate variables. For this reason, we construct market returns (in periods t+1 and t+2) to be forecasted by including only those firms that are already in our sample in period t when the aggregate excess stock return forecast is made.[3] In addition to profitability and asset investment, which we discussed in Section 2 above, we also control for other predictors of aggregate excess stock returns. These variables are discussed in detail in Appendix A. Table 1 reports the summary statistics and the correlation matrices among the main variables.

To compute OOS R^2 values in the annual analysis, we use a training window that runs from 1962 to June 1992, which includes accounting data up to 1990 and stock returns data up to June 1992. The first OOS aggregate excess stock return forecast is for the period from July 1992 to June 1993, using values of the explanatory variables in 1991 and coefficient estimates of the predictive regression obtained from the training period. Coefficient estimates of the predictive regression are

[3] However, our main results remain robust even if the CRSP value-weighted index returns are used instead.

updated at the end of June every year, incorporating data in real time as they become available. For example, the OOS forecast made in June 1993 for the period July 1993–June 1994 is based on the predictive regression estimated using accounting data from 1962 to 1991 and stock returns data through June 1993. For one-year-ahead return forecasts, the OOS forecast period is July 1992–June 2021. For two-year-average return forecasts, the OOS forecast period covers July 1993–June 2021. In the quarterly analysis, the training window covers accounting data from 1975Q1 to 1990Q4 and stock returns data up to July 1991. The OOS forecast period is from August 1991 to July 2021. Section 3.1.2 below shows that our OOS analysis is robust to alternative choices of sample split year/quarter.

As in Kelly and Pruitt (2013), we compute the OOS R^2 as

$$R^2_{OOS} = 1 - \frac{\sum_t (y_t - \hat{y}_t)^2}{\sum_t (y_t - \bar{y}_t)^2}, \tag{2}$$

where y_t is the actual stock return in period t, $\hat{y}_t$ is the fitted value from a predictive regression estimated through period t-1, and $\bar{y}_t$ is the historical average return estimated through period t-1.

To compare the OOS forecast accuracy of a predictive model with that of the historical mean return, we apply Clark and McCracken's (2001) statistic ENC-NEW. The null hypothesis is that there is no improvement in forecast accuracy by using the predictive model under consideration, relative to using just the historical mean. The ENC-NEW statistic is given by:

$$\mathrm{ENC-NEW} = P\,\frac{P^{-1}\sum_t(\hat{u}^2_{1,t+1} - \hat{u}_{1,t+1}\hat{u}_{2,t+1})}{P^{-1}\sum_t \hat{u}^2_{2,t+1}}, \tag{3}$$

where P is the number of return forecasts, $\hat{u}_{1,t+1}$ is the forecast error from using the historical mean, and $\hat{u}_{2,t+1}$ is the forecast error from using the predictive model. The OOS R^2 and ENC-NEW statistics that we report are based on OOS aggregate excess stock return forecasts, with Campbell and Thompson's (2008) sign restrictions imposed. We find no material effects on our inference even if these restrictions are not imposed. To conserve space, we do not report these results.

3.1.1 Forecasting Aggregate Excess Stock Returns

We first use variables observed in period t as predictors to forecast one-year-ahead excess stock returns (R^e_{t+1}) and the two-year average excess stock returns over t+1 and t+2 ($R^e_{(t+1,t+2)}$). We then use these variables to predict quarterly aggregate stock returns. Table 2, Panel A reports our baseline one-year-ahead return prediction results, using profitability and asset growth as predictors. All right-hand-side (RHS) variables are standardized by their own time-series mean and standard deviation. A coefficient estimate can thus be interpreted as the change in annual stock return that is associated with a one-standard-deviation move in the corresponding predictor. The t-statistics in parentheses are computed using Newey-West (1987) standard errors with three lags. Inferences on their statistical significance are based on p-values obtained from the wild bootstrap procedure of HJTZ (2015), and are reported in square brackets below the t-statistics.[4]

Following FF (2015) and HXZ (2015), we use the growth rate of total assets as our investment measure. We use BGLN's (2016) cash-based operating profitability (OpCash/B) as our main profitability measure, as both BGLN (2016) and Zhang (2017) show that this measure exhibits superior explanatory power in the cross section. We also examine the robustness of our results to the use of ROE (HXZ 2015), operating profitability (FF 2015), or gross profitability (Novy-Marx 2013) as alternative measures.[5]

Regardless of which specific measure is used, we find that profitability has a negative OOS R^2 as a standalone predictor. Asset growth by itself is a strong predictor of future stock returns—a one-standard-deviation increase in asset growth lowers one-year-ahead stock returns by 4.7%, with the impact being statistically significant at the 1% level. Its OOS R^2 is 10%, with an

[4] For the predictive coefficient on profitability, we conduct one-sided tests of H_1: $\beta > 0$ against the null of H_0: $\beta \leq 0$. In contrast, for the predictive coefficient on asset growth, we conduct one-sided tests of H_1: $\beta < 0$ against the null of H_0: $\beta \geq 0$.

[5] Even though BGLN (2016) scale operating profits by lagged assets, we follow HXZ (2015) and FF (2015) and scale profits by lagged book equity. The reason behind this choice is to avoid the confounding effects between asset growth and OpCash/A (cash-based operating profits scaled by lagged assets). In untabulated results, we find that the correlation between OpCash/A and asset growth is 0.72 (p-value < 0.0001) and the marginal predictive power of OpCash/A for future stock returns becomes considerably weaker than that of OpCash/B.

improvement in forecast accuracy relative to the historical mean that is statistically significant at the 1% level, as indicated by the ENC-NEW statistic.

Because profitability and asset growth are positively correlated (correlation coefficient of 0.39, with p-value = 0.002) yet predict aggregate stock returns in opposite directions, their predictive powers for aggregate stock returns could cancel each other out in univariate regressions when only one of the two variables has been controlled for. Indeed, in Table 2, Panel A, Columns (6) to (9) show that profitability becomes a positive and significant (at the 1% or 5% level) predictor of one-year-ahead aggregate excess stock returns once asset growth has been controlled for, regardless of the specific profitability measure used. The (standardized) coefficient estimates range from 0.041 to 0.054, implying that a one-standard-deviation increase in profitability would raise the one-year-ahead aggregate excess stock return by 4.1%–5.4%. The magnitude and significance level of the asset growth coefficient also increase, with coefficient estimates ranging from -0.072 to -0.058, implying that a one-standard-deviation increase in asset growth is expected to lower the one-year-ahead aggregate excess stock return by 5.8%–7.2%. The OOS R^2 of 6%–15% is associated with forecast accuracy improvement (relative to the historical mean) that is statistically significant at the 1% level.

A similar picture emerges when one forecasts two-year-average (Table 2, Panel B) and one-quarter-ahead (Table 2, Panel C) aggregate excess stock returns. After controlling for asset growth, profitability becomes positive and significant. The OOS R^2 values of the two-variable models (asset growth + profitability) are all associated with forecast accuracy improvement (relative to the historical mean) that is statistically significant at the 1% level.

3.1.2 Cumulative Squared Forecast Errors

To investigate how the OOS forecast performance of different predictive models evolves over time, we examine their cumulative squared forecast errors (CSFE). In each year of the OOS forecast period, we compute the squared forecast error of the historical mean and then subtract from it a predictive model's squared forecast errors. All OOS forecasts are computed after imposing the sign restrictions of Campbell and Thompson (2008). We then add up these differences cumulatively at each point in time over the entire OOS forecast period, and scale the value by the sum of squared forecast errors of the historical mean over the full sample period. This scaling implies that the last observation will equal the OOS R^2 of the specification. If a predictive model outperforms the historical mean over a certain time period, the model will display a positively sloped CSFE difference curve over this period.

Figure 1, Panels A and B plot these differences in CSFE for our annual and quarterly analyses. Both panels show that the slope for B/M is predominantly flat (or negative), suggesting that B/M does not outperform the historical mean as a predictor. By contrast, the slope for the two-variable specification is predominantly positive. The main exception is the model's underperformance around 2000, when negative market returns were preceded by high profitability.

All of our OOS analyses carried out so far use the year 1990 (which is roughly the midpoint of our full sample) to divide the whole sample into a training sample and a test sample. We examine whether the OOS R^2 values obtained earlier are sensitive to the choice of sample split year. In our one-year-ahead forecasts, using 1990 as the split year, we obtain an OOS R^2 of 0.12. If we use any other year within 1982–1992 as the alternative split year, the OOS R^2 ranges from 0.10 to 0.13, with a mean of 0.11. In our one-quarter-ahead forecasts, using 1990Q4 as the split point, we obtain an OOS R^2 of 0.05. If we use any other quarter within 1982Q4–1992Q4 as the alternative split point, the OOS R^2 ranges from 0.02 to 0.06, with a mean of 0.04. This analysis shows that our results are not sensitive to the choice of OOS split point.

3.2 Economic Significance of the Aggregate Stock Return Forecasts

To illustrate the difference made by jointly using aggregate profitability and investment as predictors, we compare their most recent aggregate stock return forecasts with those that we obtain from using B/M alone as a predictor. Next, we evaluate the implication of our results for portfolio choice more systematically by computing the CER gains for different predictive models.

3.2.1 Recent Aggregate Excess Stock Return Forecasts

We compare the aggregate excess stock return forecasts—made as at June 2020 (2019) for one-year-ahead (two-year-average) aggregate excess stock return—to see whether the joint use of profitability and asset investment as predictors leads to substantially different forecasts, relative to when the historical mean or the B/M is used.

Table 3, Panel A1 (B1) reports the means, standard deviations, and the year 2019 (2018) values of the predictors. The last column computes the deviation of the 2019 (2018) values from their sample means, measured in standardized units (i.e., the deviations from means are scaled by their standard deviations). Panels A2 and B2 report the annual aggregate excess stock return forecasts over July 2020–June 2021, and the average annual aggregate excess stock return forecasts over July 2019–June 2021, respectively.

In June 2020, the aggregate stock market already appeared expensive from a pure valuation perspective—B/M was about 1.7 standard deviations below its sample mean. As a result, when only B/M is used as a predictor, the aggregate excess stock return forecast over July 2020–June 2021 is equal to 2.4%, which is 4.4% lower than the historical average of 6.8%.

However, profitability was high in 2019 relative to its historical average, even though asset growth was also high relative to its historical average. Thus, when we use both profitability and asset growth as predictors, the aggregate excess stock return forecast increases to 12.7%. We now know that, *ex post*, this last forecast is closest to the actual equity premium of 44.3% over this time period.

When forecasting the geometric average of aggregate excess stock returns over July 2019–June 2021, B/M generates a forecast of 3.8%, which is 2.2% lower than the forecast using the historical mean. In 2018, profitability was about 2.3 standard deviations above its sample mean and asset growth was about 0.8 standard deviation below its sample mean; therefore, the forecast yielded by jointly using the two variables is 23.2%, which is the closest to the realized equity premium of 26.1% during this period.

Of course, a single superior forecast does not validate a predictive model. The main point of this exercise is to show that the difference that our approach makes can be large and highly relevant in practice. To demonstrate the economic significance of our model for portfolio allocation more systematically, we compute its CER gains below.

3.2.2 CER Gains in Portfolio Allocation

This subsection reports the CER gains from jointly using profitability and asset investment—instead of the historical mean return—as aggregate stock return predictors in portfolio allocation. This CER gain represents the value to an investor in her portfolio allocation by switching from a historical mean-based OOS predictive model to one based on profitability and asset investment. The % CER gain can be interpreted as an annual fee that the investor would be willing to pay to switch from a historical mean-based forecast to our profitability/investment-based forecasts.

To obtain the CER of a predictive model, we examine the portfolio choice of a mean-variance investor who optimally allocates her wealth between the value-weighted market portfolio and the risk-free asset, using the OOS forecasts of the predictive model. At the end of period *t*, the investor allocates the weight w_t to the equity portfolio and $1 - w_t$ to the riskless asset. The weight w_t is given by

$$w_t = \frac{1}{\gamma} \frac{\hat{R}^e_{t+1}}{\hat{\sigma}^2_{t+1}} , \tag{4}$$

where γ is the risk aversion coefficient, $\hat{R}^e_{t+1}$ is the OOS aggregate excess stock return forecast obtained from the predictive model (with Campbell and Thompson's (2008) sign restrictions imposed), and $\hat{\sigma}^2_{t+1}$ is the variance forecast for aggregate excess stock returns, estimated using all available data prior to period *t*+1 (Ferreira and Santa-Clara 2011; HJTZ 2015).

The realized portfolio return R^P_{t+1} in period *t*+1 is

$$R^P_{t+1} = w_t R^e_{t+1} + R^f_{t+1} , \tag{5}$$

where R^e_{t+1} is the realized excess market return in period t+1, and R^f_{t+1} is the gross risk-free return in period t+1. w_t is winsorized at 0 and 1.5, to exclude short sales and leverage that exceeds 50%.

The CER of the portfolio is given by

$$CER_P = \hat{\mu}_P - 0.5\gamma\hat{\sigma}^2_P \,, \tag{6}$$

where $\hat{\mu}_P$ and $\hat{\sigma}^2_P$ are the sample mean and variance of the portfolio returns. The CER gain of a predictive model relative to the B/M-based model is the difference between the CER obtained from the predictive model and the CER obtained from using B/M alone as a predictor.

The CER gains for the two-year-average aggregate excess stock return forecasts are computed analogously. At the end of period t, the investor allocates the weight w_t to equities, based on a predictive model's two-year-average forecast for periods t+1 and t+2:

$$w_t = \frac{1}{\gamma}\frac{\hat{R}^e_{(t+1,t+2)}}{\hat{\sigma}^2_{(t+1,t+2)}} \,, \tag{7}$$

where $\hat{R}^e_{(t+1,t+2)}$ is the OOS forecast for the geometric average of the excess market returns over periods t+1 and t+2, and $\hat{\sigma}^2_{(t+1,t+2)}$ is the variance forecast for two-year average returns, estimated from historical average returns as at the end of period t.

The realized average portfolio return over periods t+1 and t+2 is the geometric average $\sqrt{w_t[(R^e_{t+1} + R^f_{t+1})(R^e_{t+2} + R^f_{t+2}) - R^f_{t+1}R^f_{t+2}] + R^f_{t+1}R^f_{t+2}}$, where R^e_{t+i} is the excess market return in period t+i (i=1,2). The CER for the average portfolio return is computed as in equation (6), with $\hat{\mu}_P$ and $\hat{\sigma}^2_P$ being the sample mean and variance of the average portfolio returns.

To examine whether the CER gain is statistically significant, we carry out the test introduced by DeMiguel, Garlappi, and Uppal (2009). (μ_i, σ^2_i) and (μ_n, σ^2_n), respectively, are the sample means and variances of the realized portfolio returns under forecast strategies i and n. $\sigma_{i,n}$ is the covariance between the portfolio returns of strategies i and n. We use υ to denote the vector, $\upsilon = (\mu_i, \mu_n, \sigma^2_i, \sigma^2_n)$, and $\hat{\upsilon}$ its empirical counterpart. The function $f(\upsilon) = \left(\mu_i - \frac{\gamma}{2}\sigma^2_i\right) - \left(\mu_n -\right.$

$\frac{\gamma}{2}\sigma_n^2\Big)$ calculates the difference in CER between strategies i and n. The asymptotic distribution of $f(\upsilon)$ is given by $\sqrt{T}(f(\hat{\upsilon}) - f(\upsilon)) \rightarrow N(0, \frac{\partial f}{\partial \upsilon}^{\mathrm{T}} \Theta \frac{\partial f}{\partial \upsilon})$, where $\Theta = \begin{pmatrix} \sigma_i^2 & \sigma_{i,n} & 0 & 0 \\ \sigma_{i,n} & \sigma_n^2 & 0 & 0 \\ 0 & 0 & 2\sigma_i^4 & 2\sigma_{i,n}^2 \\ 0 & 0 & 2\sigma_{i,n}^2 & 2\sigma_n^4 \end{pmatrix}$, and T is the number of observations in the full sample. The null hypothesis is that there is no difference in the CER between the two forecast strategies, i.e., $f(\upsilon) = 0$. The alternative hypothesis is that $f(\upsilon) \neq 0$. The test statistic $\frac{\sqrt{T}f(\hat{\upsilon})}{\sqrt{\left(\frac{\partial f}{\partial \upsilon}^{T} \Theta \frac{\partial f}{\partial \upsilon}\right)}}$ follows a standard normal distribution.

Table 4 reports the CER gains of the OpCash-plus-asset-growth model relative to the CER of the historical mean return. We consider three different values of risk aversion coefficients ($\gamma = 1, 3,$ or 5). Table 4, Panel A reports CER gains based on one-year-ahead aggregate stock return forecasts. When $\gamma = 1$, the two-variable specification generates a positive CER gain of 1.54%, but the gain is not statistically significantly different from zero. When γ equals 3, the two-variable specification produces a CER gain of 4.42%, which is significant at the 1% level. The CER gain at $\gamma = 5$ is equal to 3.05%, with a significance level of 5%. Table 4, Panel B reports CER gains based on two-year-average aggregate stock return forecasts. Here, when γ equals 1, the two-variable specification yields a positive but statistically insignificant CER gain. When γ equals 3 or 5, the two-variable specification yields positive and statistically significant CER gains (at the 5% level) that range from 1.75% to 2.89%.

Overall, our results suggest that the benefit to a mean-variance investor in using profitability and asset growth instead of the historical mean return for portfolio allocation is both statistically and economically significant.

3.3 Decomposing Asset Growth

In this section, we investigate the source of the predictive power of asset growth by decomposing it into its individual components. Following Cooper, Gulen, and Schill (2008), we decompose asset growth from the investment side and the financing side. From the investment side, we decompose asset growth into short-term asset growth (ChgSTAsst), other current asset growth (ChgCurAsst), property, plant, and equipment growth (ChgPPE), and other asset growth (ChgOthAsst). The short-term asset component corresponds to Compustat item *CHE*. As discussed in detail by Duchin, Gilbert, Harford, and Hrdlicka (2017), this item represents the sum of the balance sheet accounts "cash and cash equivalents" and "short-term investments," which include, respectively, financial assets with a maturity of up to 90 days at issuance and financial assets that the firm intends to liquidate within a year. From the financing side, asset growth is decomposed into operating liabilities growth (ChgOpLiab), retained earnings growth (ChgRE), stock financing growth (ChgStock), and debt financing growth (ChgDebt).

Table 5 reports the predictive power of the individual components of asset growth for future excess stock returns. Table 5, Panels A and B respectively report the one-year- and two-year- ahead return forecasts. Overall, we find that the predictive power of total asset growth for future stock returns is more robust across the two investment horizons than its individual components.

At the one-year horizon, growth in cash and short-term assets is the only component with significant predictive power. The growth rates in longer-term assets are all insignificant. These results contrast with those reported by Cooper et al. (2008), who find that the cash component of asset growth has the weakest predictive power for cross-sectional variations in one-year-ahead returns. At the two-year horizon, the growth in longer-term assets—property, plant, and equipment (PPE)—becomes a significant predictor of stock returns. In contrast, the predictive power of growth in cash and short-term assets—the component of total assets with the shortest duration—becomes weaker than its predictive power at the one-year horizon.[6]

[6] We also examine three-year-ahead forecasts of stock returns, but our results indicate that neither total asset growth nor its individual components have significant predictive power at the three-year horizon.

In untabulated results, we see that the positive correlation between asset growth and profitability is primarily driven by the cash and short-term assets component of asset growth (i.e., ChgSTAsst); the correlation coefficient between ChgSTAsst and OpCash/B is estimated at 0.49 (*p*-value < 0.0001). Consistent with this observation, the predictive power of OpCash/B is strongest when ChgSTAsst has been controlled for. We also examine the first-order serial correlation of the different components of asset growth, and find that it is PPE growth (i.e., ChgPPE) that exhibits the highest persistence (with an AC(1) of 0.71). This slow-moving nature of PPE is consistent with ChgPPE exhibiting a stronger predictive power for stock returns at longer horizons.

Our finding is consistent with firms' investment decisions being more responsive to changes in discount rates that correspond to the investment's time horizon. However, recent work by Cassella, Golez, Gulen, and Kelly (2021) suggests that this finding can also be driven by horizon-dependent biased beliefs. While more work is needed to distinguish between these two alternative interpretations, the fact that we already control for profitability in our predictive regressions at least alleviates concerns that our finding is driven by one particular source of biased earnings expectations. Greenwood and Shleifer (2014) and Hirshleifer, Li, and Yu (2015) identify firms' recent performance and managers' subsequent over-extrapolation as an important cause of managerial earnings expectation biases. By holding recent earnings constant in a multivariate regression, we alleviate the concern that any marginal variation in asset growth is driven by such extrapolative biases.[7]

3.4 Arif and Lee's (2014) Investment Measure

Arif and Lee (henceforth AL, 2014) also construct a measure of aggregate investment from firm-level data, and use it to forecast aggregate stock returns. As shown by AL (2014), and reproduced in Table 6, their investment measure has significant predictive power for aggregate

[7] Even when investor sentiment does move stock prices (Baker and Wurgler 2006, 2007; Huang, Jiang, Tu, and Zhou 2015), mispricing in the stock market may still not affect corporate investment (Bakke and Whited 2010; Warusawitharana and Whited 2016).

stock returns at the two-year horizon (Table 6, Panel B). Its ability to forecast one-year-ahead stock returns is only marginally significant (Table 6, Panel A). This finding can be understood in light of our results obtained earlier in this section—that long-term asset growth only forecasts long-term (but not short-term) stock returns—and the fact that AL's investment measure contains only the longer-term components of total assets.

To see this, we decompose AL's investment measure, denoted $Invest_{AL}$, into its components:

$$Invest_{AL,t} = ChgNOA_t + RND_t = ChgAT_t - ChgSTAsst_t - ChgNonDebt_t + RND_t, \quad (8)$$

where $ChgNOA_t$ is the change in net operating assets, RND_t is capitalized R&D expense, $ChgAT_t$ is the change in total assets, $ChgSTAsst_t$ is the change in short-term assets (i.e., the change in cash and short-term investments), and $ChgNonDebt_t$ is the change in non-debt liabilities. All of these variables, including $Invest_{AL,t}$, are scaled by average assets over t and t-1. The difference between asset growth (dA_t/A_{t-1}) and change in total assets ($ChgAT_t$) is minor, with the former being scaled by total assets at t-1, whereas the latter is scaled by average total assets over t and t-1.

We then use the components of $Invest_{AL,t}$ to predict aggregate stock returns over different time horizons. Table 6, Panels C and D report these results. Breaking down $Invest_{AL,t}$ into two components—$ChgNOA_t$ and RND_t—we find that $ChgNOA_t$, analogous to what is observed for $Invest_{AL,t}$, is not significantly related to stock returns at t+1, but exhibits strong predictive power for the returns at t+2. RND_t displays significant predictive power for the stock returns in both year t+1 and t+2. After breaking $ChgNOA_t$ down further into $ChgAT_t$, $ChgSTAsst_t$, and $ChgNonDebt_t$, it becomes clear that the difference in predictive power between asset growth and $Invest_{AL}$ comes from two sources—$ChgSTAsst_t$ and $ChgNonDebt_t$. Because both $ChgSTAsst_t$ and $ChgNonDebt_t$ predict one-year-ahead stock returns in the same direction as $ChgAT_t$, but both $ChgSTAsst_t$ and $ChgNonDebt_t$ are being *subtracted* from $ChgAT_t$ to obtain $Invest_{AL,t}$, the predictive power of $ChgSTAsst_t$ and $ChgNonDebt_t$ cancels out the predictive power of $ChgAT_t$, leaving $Invest_{AL,t}$ nearly insignificant when predicting one-year-ahead stock returns. In contrast, because only $ChgSTAsst_t$ can predict the stock returns in year t+2 with a weakened predictive power and $ChgNonDebt_t$ loses its predictive ability altogether at this horizon, $Invest_{AL,t}$ inherits the predictive power of $ChgAT_t$ at the two-year horizon.

4. Robustness Checks

We carry out a number of robustness checks on our main results. First, we control for other known predictors of aggregate stock returns. Second, we examine the predictive power of expected change in aggregate asset growth. Third, we use our predictors to forecast total stock returns, rather than just excess stock returns. Finally, we examine the effect of an alternative method of aggregating firm-level ratios to the aggregate level: by summing the numerator and denominator separately across all firms first before taking the ratio.

4.1 Controlling for Other Predictors

In this section, we investigate whether the predictive power of profitability and asset investment comes from their correlations with other known predictors of aggregate stock returns. In particular, we control for earnings yield, term spread, default spread, T-bill rate (Ang and Bekaert 2007), Baker and Wurgler's (2006, 2007) sentiment index, HJTZ's (2015) partial-least-squares-based sentiment index, CAY, aggregate operating accruals (Hirshleifer, Hou, and Teoh 2009), equity share in new issuance (Baker and Wurgler 2000), and investment-to-capital ratio (Cochrane 1991).

Table 7, Panels A to C respectively report one-year-ahead, two-year-average, and one-quarter-ahead aggregate excess stock return forecasts. When forecasting one-year-ahead aggregate stock returns, only the term spread and the HJTZ sentiment index exhibit statistically significant predictive power. The term spread by itself positively predicts one-year-ahead stock returns at the 5% level. This finding is consistent with Campbell and Vuolteenaho (2004) and Campbell, Polk, and Vuolteenaho (2010), among others. After controlling for profitability and asset growth, term spread becomes insignificant and its magnitude drops from .033 to .009. A similar picture emerges at the two-year horizon as well.

Consistent with HJTZ (2015), the HJTZ sentiment index exhibits strong predictive power for aggregate stock returns at the one-year and one-quarter horizons. By itself, the sentiment index is statistically significant at the 5% level. In the presence of profitability and asset growth, its forecast power remains largely unaffected. From a comparison with Table 2, we also see that the predictive power of profitability and asset growth remains unchanged even after the HJTZ index has been controlled for. These results indicate that the predictive power of these two sets of predictors comes from distinct sources.

Aggregate operating accruals by itself has no significant predictive power at all forecast horizons. At the one-year horizon, this variable becomes significant at the 5% level, after profitability and asset growth have been controlled for. CAY also becomes significant at all horizons after profitability and asset growth have been controlled for.

The equity share in new issuance is found to negatively predict one-quarter-ahead aggregate stock returns at the 5% level. This result is consistent with the findings of Baker and Wurgler (2000), who suggest that firms time the market when issuing securities. The significance level of this variable decreases to 10% after controlling for our predictors, and profitability becomes marginally significant—suggesting that the equity share and profitability have similar predictive content at the quarterly horizon.

The investment-to-capital ratio displays statistically significant predictive power for two-year-average and one-quarter-ahead aggregate stock returns (at either the 10% or 5% level), although its predictive power is subsumed by the inclusion of profitability and asset growth.

The earnings yield has no standalone predictive power for future returns at any horizon. At the quarterly forecasting horizon, it becomes positive and significant at the 5% level after profitability and asset growth have been controlled for.

In sum, even after controlling for all these predictors, asset growth remains statistically significant at the 1% level in all 27 specifications considered, while profitability is significant at the 5% level or above in 25 out of 27 specifications. These results imply that profitability and asset growth have predictive power for aggregate stock returns that is not subsumed by other known predictors.

4.2 Expected Change in Asset Growth

HMXZ (2021) show that expected investment growth predicts stock returns positively in the cross section, consistent with a dynamic investment model. We examine whether this predictive power carries over to the aggregate level. Following HMXZ, we use the change in asset growth to measure investment growth. Expected change in aggregate asset growth, $E_t[d^1(dA/A)]$, is obtained by value-weighting its firm-level counterparts, which are computed by running cross-sectional weighted least squares regressions (using each firm's market value as the weight) of the change in asset growth on lagged Tobin's q, operating cash flows, and the change in return on equity.

Table 8 reports the predictive regression results for aggregate stock returns when expected change in aggregate asset growth is used as a predictor. For one-year-ahead forecasts, we see that $E_t[d^1(dA/A)]$ does exhibit positive and significant predictive power for aggregate stock returns, consistent with HMXZ. This predictive power weakens slightly after controlling for profitability and asset growth.[8] At the two-year horizon, $E_t[d^1(dA/A)]$ is no longer significant, suggesting that firms' one-year ahead investment plans are more sensitive to discount rates at the one-year horizon.

4.3 Predicting Total Returns

So far, aggregate excess stock returns have been the object of our forecasts (i.e., the dependent variable of our predictive regressions). Because the risk-free rate is also part of the cost of capital, we examine whether aggregate profitability and investment can forecast total market

[8] The fact that the predictive power weakens once profitability has been controlled for is also consistent with HMXZ, who show that cash-based operating profits are a key driver of expected asset growth.

returns, which is inclusive of the risk-free rate. Table 9 reports these results. Overall, OpCash/B (asset growth) still forecasts total market returns positively (negatively). From a comparison with Table 2, we see that the predictive power for total returns seems slightly weaker than that for excess stock returns. Across the three forecast horizons, it is the two-year horizon that appears to be the most robust. This result indicates that aggregate investment is more sensitive to variations in two-year (rather than one-year or one-quarter) interest rates.

4.4 Alternative Aggregation

So far, we have formed all aggregate accounting ratios by taking a weighted average of their firm-level counterparts, using each firm's market capitalization as weights. Here, we aggregate the firm-level ratios using an alternative method: by summing the numerator and denominator separately across all firms first before taking the ratio. For example, aggregate OpCash/B is calculated by the sum of cash profits over all firms, divided by the sum of lagged book equity over all firms. Table 10 reports these results. We find that the predictive power of asset growth remains robust but that of the profitability measures has weakened. Summing the numerator and denominator separately before taking the ratio for these profitability measures is equivalent to taking a book-value-weighted average of the firm-level profitability measures. Because the object of our forecast is aggregate excess stock returns—a market-value-weighted average of firm-level excess stock returns—the use of book-value-weighted averages of firm-level profitability as predictors is expected to generate a weaker predictive power.

5. Conclusion

Profitability and asset investment play a special role in cross-sectional asset pricing. Not only are these variables themselves associated with significant return premiums, but HXZ (2015) and HMXZ (2019) show that they can also account for a wide range of other anomalies that the CAPM and FF's (1993) three-factor model fail to capture. Given this unique role played by profitability and investment, it is important to show the robustness of the underlying mechanism that generates their explanatory power.

While HXZ focus on cross-sectional, firm-specific variation in profitability and investment, we find that variation in profitability and investment that is common across firms can also explain common variation in future stock returns. Our results serve as OOS empirical support for HXZ.

At the same time, a long tradition in finance examines the predictability of aggregate stock returns. These studies not only affect how academics model the variation of the equity premium, but also how investors make use of different state variables for their portfolio allocation. We contribute to this literature by showing that the relationships between profitability, investment, and stock returns, as motivated by HXZ's (2015) investment model, capture significant variations in the equity premium.

Although our finding that the growth rate of short-term (long-term) assets exhibits a stronger predictive power for short-term (long-term) stock returns is consistent with the investment model, the recent work of Cassella, Golez, Gulen, and Kelly (2021) suggests that this finding can also be driven by horizon-dependent biased beliefs. By holding recent earnings constant in a multivariate regression, we alleviate the concern that any marginal variation in asset growth is driven by extrapolative biases. Future work should investigate whether other sources of earnings expectation biases can explain the predictive power of different asset growth components for the term structure of future stock returns.

Appendix A. Variable Descriptions

1. Firm-level variables

OpCash/B. $OpCash_{it}/B_{it-1}$ is firm *i*'s cash-based operating profitability in year t, divided by its book equity in year *t*-1. The construction of cash-based operating profitability follows the definition of Ball, Gerakos, Linnainmaa, and Nikolaev (2016). It equals operating profitability minus the change in accounts receivable (Compustat item *RECT*), minus the change in inventory (Compustat item *INVT*), minus the change in prepaid expenses (Compustat item *XPP*), plus the change in deferred revenue (Compustat item (*DRC*+*DRLT*)), plus the change in trade accounts payable (Compustat item *AP*), and plus the change in accrued expenses (Compustat item *XACC*). Operating profitability is defined as revenue (Compustat item *REVT*), minus cost of goods sold (Compustat item *COGS*), and minus reported sales, general, and administrative expenses (Compustat item (*XSGA*-*XRD*)). All of the balance sheet items in the computation of cash-based operating profitability are replaced by zero if missing.

ROE. ROE_{it} is defined as firm *i*'s income before extraordinary items (Compustat item *IB*) in year *t* divided by its book equity in year *t*-1.

GP/B. GP_{it}/B_{it-1} is firm *i*'s profitability in year *t*, defined as its gross profits in year *t* divided by its book equity in year *t*-1. Gross profits is defined as revenues (Compustat item *REVT*) minus cost of goods sold (Compustat item *COGS*).

OP_{FF}/B. $OP_{FF\,it}/B_{it-1}$ is Fama and French's (2015) operating profitability, defined as revenue (Compustat item *REVT*), minus cost of goods sold (Compustat item *COGS*), minus sales, general, and administrative expenses (Compustat item *XSGA*), minus interest expense (Compustat item *XINT*), divided by lagged book equity.

dA/A. dA_{it}/A_{it-1} is firm *i*'s asset growth in year *t*. In annual analyses, A_{it} is firm *i*'s total assets (Compustat item *AT*) in year *t*. dA_{it}/A_{it-1} equals $(A_{it} - A_{it-1})$ divided by A_{it-1}. Quarterly asset growth, $dA_{it}/A_{it-} \;\; = (A_{it} - A_{it-4})/A_{it-4}$, is defined as the change in total assets (Compustat item *ATQ*) between quarters *t* and *t*-4, divided by total assets in quarter *t*-4.

Invest_AL. *Invest_AL* is an investment measure constructed by Arif and Lee (2014). $Invest_{AL,it}$ is the change in net operating assets (ΔNOA_{it}) plus the capitalized R&D expenditures ($R\&D_{it} - RA_{it}$), scaled by average assets:

$$Invest_{AL,it} = \frac{\Delta NOA_{it} + R\&D_{it} - RA_{it}}{(TA_{it-1} + R\&DC_{it-1} + TA_{it} + R\&DC_{it})/2}\,, \qquad (A1)$$

where ΔNOA_{it} is defined as the change in non-cash assets minus the change in non-debt liabilities. Non-cash assets equal total assets (Compustat item *AT*) minus cash and short-term investments (Compustat item *CHE*). Non-debt liabilities equals total liabilities (Compustat item *LT*) plus minority interest (Compustat item *MIB*) minus debt (Compustat item *DLTT* plus Compustat item *DLC*). TA_{it} is total assets. $R\&D_{it}$ is R&D expenditures (Compustat item *XRD*). RA_{it} is R&D amortization, defined as the amortized portion of the historical R&D expenditures. $R\&DC_{it}$ is R&D capital, defined as the unamortized portion of the historical R&D expenditures. Both RA_{it} and $R\&DC_{it}$ are computed following Lev and Sougiannis (1996) by using the industry-specific amortization rates estimated by the authors. If the Compustat items *XRD* and *DLC* are missing, we set them to zero.

ln(B/M). The annual log book-to-market ratio ($ln\ (B_{it}/M_{it})$) equals the log of firm *i*'s book equity in year *t* divided by its market equity at the end of year *t*. Annual book equity equals total assets (Compustat item *AT*), minus total liabilities (Compustat item *LT*), plus balance sheet deferred taxes and investment tax credit (Compustat item *TXDITC*) if available, minus the book value of preferred stocks. We use liquidation value (Compustat item *PSTKL*) if available, or redemption value (Compustat item *PSTKRV*) if available, or carrying value (Compustat item *PSTK*) if available for the book value of preferred stocks. The quarterly book-to-market ratio equals firm *i*'s book equity in quarter *t* divided by its market equity at the end of quarter *t*. We compute quarterly book equity following Hou, Xue, and Zhang (2015) as shareholders' equity, plus balance sheet deferred taxes and investment tax credit (Compustat item *TXDITCQ*) if available, minus the book value of preferred stock. We use stockholders' equity (Compustat item *SEQQ*) if available, or common equity (Compustat item *CEQQ*) plus the carrying value of preferred stock (Compustat item *PSTKQ*) if available, or total assets (Compustat item *ATQ*) minus total liabilities (Compustat item *LTQ*) as shareholders' equity. We use redemption value (Compustat item *PSTKRQ*) if available, or carrying value for the book value of preferred stock.

2. Market-level variables

R^e^. The annual excess aggregate stock return in t+1, R_{t+1}^{e}, is computed by aggregating firm-level stock returns using the market capitalizations at the end of year t as weights, and subtracting the corresponding compounded one-month Treasury bill rates. Firm-level annual stock returns are obtained by compounding monthly stock returns (adjusted for delisting returns) from July in t+1 to June in t+2. If a firm's delisting return is missing and the delisting is performance-related, we assume a -30% delisting return. Otherwise, we set the missing returns to zero. $R_{(t+1,t+2)}^{e}$ is defined as the geometric average of annual excess stock returns over years t+1 and t+2.

Term. Term spread ($Term_t$) is the difference between the ten- and one-year Treasury constant maturity rates, measured as at the end of June in year t+1 in annual analyses (Table 7, Panels A and B), and as at the end of month 4 after calendar quarter t in quarterly analyses (Table 7, Panel C). The data are obtained from the Federal Reserve Economic Database maintained by the Federal Reserve Bank of St. Louis.

Def. Default rate (Def_t) is the difference between the Moody's BAA and AAA bond yields, measured as at the end of June in year t+1 in annual analyses (Table 7, Panels A and B), and as at the end of month 4 after calendar quarter t in quarterly analyses (Table 7, Panel C). The data are obtained from the Saint Louis Federal Reserve Economic Database.

Tbill. $Tbill_t$ is the 30-day Treasury bill rate, measured as at the end of June in year t+1 in annual analyses (Table 7, Panels A and B), and as at the end of month 4 after calendar quarter t in quarterly analyses (Table 7, Panel C). The data are obtained from Warton Research Data Services (WRDS).

Sent^BW^. $Sent_t^{BW}$ is Baker and Wurgler (2006)'s orthogonalized investor sentiment index. We use the value of the index in June of year *t*+1 in annual analyses (Table 7, Panels A and B), and the value in month 4 after calendar quarter *t* in quarterly analyses (Table 7, Panel C). The monthly index is obtained from Jeffrey Wurgler's website.

Sent^HJTZ^. $Sent_t^{HJTZ}$ is Huang, Jiang, Tu, and Zhou's (2015) partial-least-squares-based investor sentiment index. We use the value of the index in June of year *t*+1 in annual analyses (Table 7, Panels A and B), and the value in month 4 after calendar quarter *t* in quarterly analyses (Table 7, Panel C). The monthly index is obtained from Guofu Zhou's website.

CAY. CAY_t is the consumption–wealth ratio constructed by Lettau and Ludvigson (2001). We use the value of the ratio in the second quarter of year *t*+1 in annual analyses (Table 7, Panels A and B), and the value in calendar quarter *t*+1 in quarterly analyses (Table 7, Panel C). The series is obtained from Martin Lettau's website.

OpAcc. Aggregate operating accruals, $OpAcc_t$, is defined as in Hirshleifer, Hou, and Teoh (2009). It is aggregated from firm-level operating accruals, which equals the change in non-cash current assets (Compustat item *ACT* minus Compustat item *CHE*), minus the change in current liabilities (Compustat item *LCT*) excluding the change in short-term debt (Compustat item *DLC*) and the change in taxes payable (Compustat item *TXP*), minus depreciation and amortization expense (Compustat item *DP*), and scaled by lagged total assets. Quarterly operating accruals is computed as the change in value of each numerator component between the current and fourth-lagged quarters, scaled by four-quarter-lagged total assets.

EquityShare. $EquityShare_t$ is the equity share in new issues constructed by Baker and Wurgler (2000). We use the annual value in year *t* in annual analyses (Table 7, Panels A and B), and the monthly value one month prior to the return prediction period in quarterly analyses (Table 7, Panel C). The annual series over 1962–2007 and monthly series over July 1975–April 2008 are obtained from Jeffrey Wurgler's website, and are extended to 2019 and December 2020, respectively, using data from the Federal Reserve Bulletin.

IK. IK_t is the investment-to-capital ratio constructed by Cochrane (1991). We use its annual value in year *t* in annual analyses (Table 7, Panels A and B), and its latest available quarterly value in quarterly analyses (Table 7, Panel C). Both the annual and quarterly series are obtained from Amit Goyal's website.

E/P. $(E/P)_t$ is the earnings-to-price ratio, as defined in Arif and Lee (2014). It is aggregated from the firm-level earnings-to-price ratio, which is computed as a firm's operating income after depreciation (Compustat item *OIADP*) in year *t* divided by its market equity at the end of year *t.* Quarterly earnings-to-price ratio is computed as the sum of earnings in the latest four quarters scaled by the market equity at the end of quarter *t*, thus removing the seasonal effects in quarterly earnings.

$E_t[d^1(dA/A)]$. $E_t[d^1(dA/A)]$ is expected one-year-ahead change in aggregate asset growth, constructed as the aggregate counterpart to the firm-level measure of HMXZ (2021). It is obtained by value-weighting expected one-year-ahead change in firm-level asset growth, which is computed by running cross-sectional weighted least squares (with firms' market values as weights) of one-year-ahead changes in asset growth (one-year-ahead asset growth minus current-year asset growth) on Tobin's q, operating cash flows (Cop), and the change in return on equity (dROE). Tobin's q is computed as the market equity at the end of June, plus long-term debt (Compustat item *DLTT*), plus short-term debt (Compustat item *DLC*), scaled by total assets. Cop is constructed as total revenue (Compustat item *REVT*) minus cost of goods sold (Compustat item *COGS*), minus selling, general, and administrative expenses (Compustat item *XSGA*), plus research and development expenditures (Compustat item *XRD*), minus the change in accounts receivable (Compustat item *RECT*), minus the change in inventory (Compustat item *INVT*), minus the change in prepaid expenses (Compustat item *XPP*), plus the change in deferred revenue (Compustat item *DRC* plus *DRLT*), plus the change in trade accounts payable (Compustat item *AP*), and plus the change in accrued expenses (Compustat item *XACC*), scaled by total assets. dROE is computed as the change in income before extraordinary items (Compustat item *IB*) divided by lagged book equity. Aggregate $E_t[d^1(dA/A)]$ is then calculated as the market-value-weighted average of firm-level $E_t[d^1(dA/A)]$.

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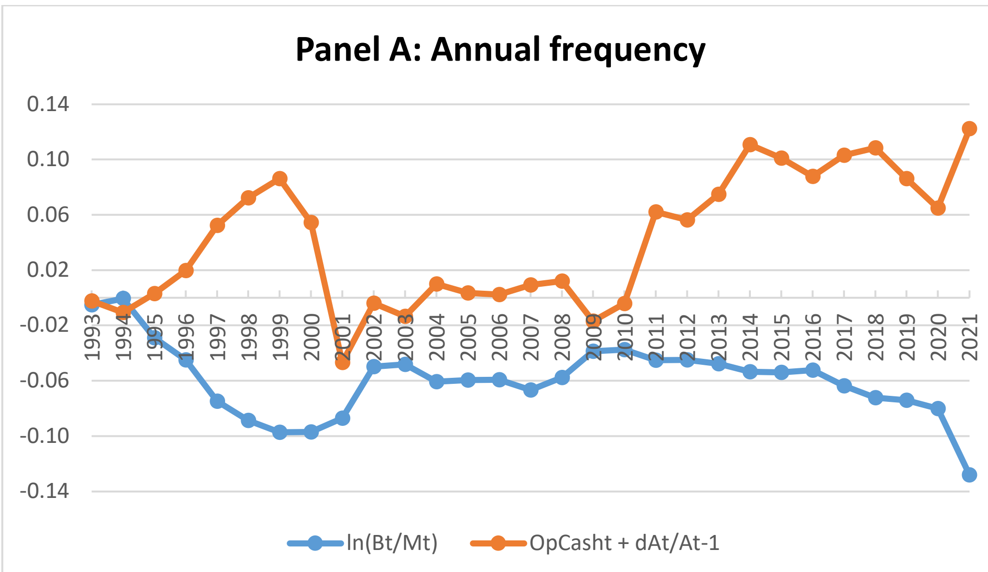
Figure 1. The difference in cumulative squared forecast errors

This figure displays the difference in cumulative squared forecast errors (CSFE) between the historical mean and different forecast models in one-year-ahead (Panel A) and one-quarter-ahead (Panel B) stock return forecasts. In each year/quarter of the OOS forecast period, we compute the difference between the squared forecast error of the historical mean and the squared forecast error of a forecast model. We then add up these differences cumulatively at each point in time over the entire OOS forecast period and scale this value by the sum of squared forecast errors of the historical mean over the full sample period. The OOS aggregate stock return forecasts are computed by imposing Campbell and Thompson's (2008) sign restrictions. In Panel A (Panel B), the training period uses accounting data from 1962-1990 (1975Q1-1990Q4), and corresponding stock returns data from July 1963-June 1992 (August 1975-July 1991). The out-of-sample forecast period for one-year-ahead stock returns is July 1992-June 2021 (August 1991-July 2021). The forecast models used are specifications with B/M only and cash-based profitability plus asset growth.



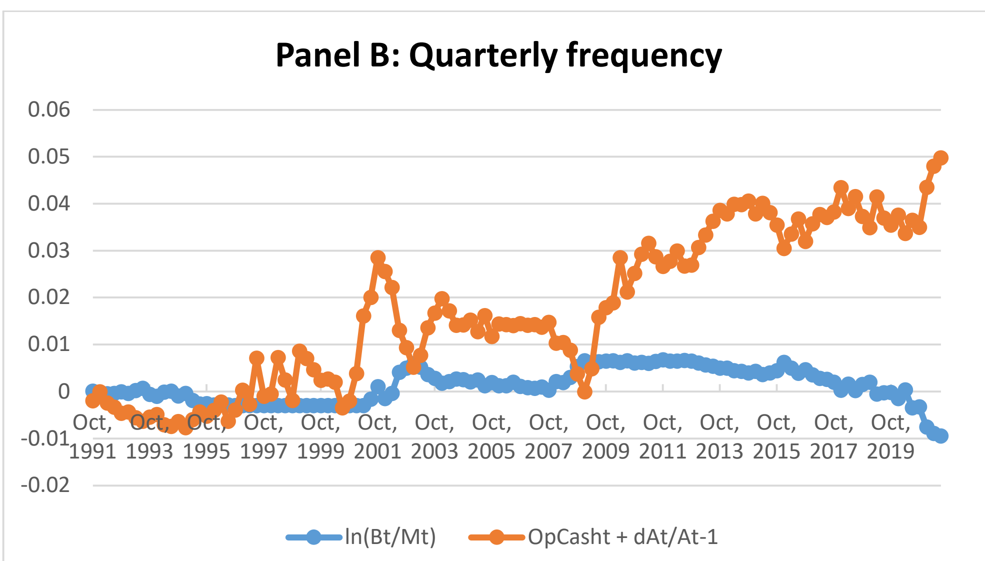


Table 1. Summary statistics of aggregate variables

This table reports the summary statistics and correlation matrix for various aggregate variables. Annual (Quarterly) aggregate variables are obtained by weighting firm-level variables by each firm's end-of-year (end-of-quarter) market capitalization. Firm-level variables (except for stock returns) are first winsorized at the 0.5 and 99.5 percentiles for each year (quarter) before being aggregated. Panel A reports summary statistics and the first-order autocorrelation coefficient of the aggregate variables measured at annual frequencies. $OpCash_t/B_{t-1}$ is aggregate cash-based operating profitability. ROE_t is aggregate return on equity. GP_t/B_{t-1} is aggregate gross profitability. ${OP_{FF}}_t/B_{t-1}$ is Fama-French's (2015) operating profitability. dA_t/A_{t-1} is aggregate asset growth. $Invest_{AL,t}$ is the investment measure proposed by Arif and Lee (2014). $ln(B_t/M_t)$ is the aggregate log book-to-market ratio. $Term_t$ is the term spread measured as of the end of June in year *t*+1, defined as the difference between the ten- and the one-year Treasury constant maturity rates. Def_t is the default spread measured as of the end of June in year *t*+1, defined as the difference between the Moody's BAA and AAA bond yields. $Tbill_t$ is the thirty-day Treasury bill rate measured as of the end of June in year *t*+1. $Sent_t^{BW}$ is Baker and Wurgler's (2006) orthogonalized investor sentiment index measured in June of year *t*+1. $Sent_t^{HJTZ}$ is Huang, Jiang, Tu, and Zhou's (2015) investor sentiment index in June of year *t*+1. CAY_t is the consumption-wealth ratio constructed by Lettau and Ludvigson (2001), measured at the second quarter of year *t*+1. $OpAcc_t$ is aggregate operating accruals, as defined by Hirshleifer, Hou, and Teoh (2009), and aggregated from firm-level operating accruals at the end of year *t*. $EquityShare_t$ is the equity share in new issues in year *t*, as proposed by Baker and Wurgler (2000). IK_t is Cochrane's (1991) investment-to-capital ratio in year *t*. $(E/P)_t$ is the earnings-to-price ratio. $E_t[d^1(dA/A)]$ is expected one-year-ahead change in asset growth. R^e_{t+1} is the annual excess stock return in *t*+1, computed by aggregating firm-level stock returns and subtracting the corresponding compounded one-month Treasury bill rates. $R^e_{(t+1,t+2)}$ is the two-year-average excess stock return over *t*+1 and *t*+2, computed as the geometric average of annual total stock returns R_{t+1} and R_{t+2} minus the geometric average of annual risk free rates RF_{t+1} and RF_{t+2}. Appendix A contains detailed definitions of these variables. In annual analyses, the sample period is July 1963-June 2021 for stock returns. For other variables, with the exceptions of Sent^{BW}, $\text{Sent}^{\text{HJTZ}}$, and CAY, the sample period (based on the time subscript *t*) is 1962-2019. For Sent^{BW} the sample period is 1965-2017. For $\text{Sent}^{\text{HJTZ}}$, the sample period is 1965-2019. For CAY, the sample period is 1962-2018. Panels B and C report annual and quarterly Pearson correlation coefficients between aggregate variables, with *p*-values in parentheses. In Panels C, $ln(B_t/M_t)$ is quarterly log book-to-market ratio. $\sum Profitability_{it}/B_{it-4}$ is quarterly-updated annual profitability, defined as the sum of gross profits over quarters *t*, *t*-1, *t*-2, and *t*-3, divided by book equity in quarter *t*-4. dA_t/A_{t-4} is quarterly-updated annual asset growth, defined as the change in total assets between quarters *t* and *t*-4, divided by total assets in quarter *t*-4. R^e_{t+1} is quarterly excess stock return in *t*+1. In quarterly analyses, the sample period is August 1975-July 2021 for stock returns. For accounting variables, the sample period (based on the time subscript *t*) is 1975Q1-2020Q4.

Table 1. Summary statistics of aggregate variables (continued)

Panel A: Summary Statistics of Aggregate Variables (Annual Frequency)							
	No. of Obs.	Mean	Std Dev	Q1	Median	Q3	AC(1)
$OpCash_t/B_{t-1}$	58	0.487	0.104	0.415	0.466	0.553	0.894
ROE_t	58	0.178	0.031	0.158	0.168	0.199	0.857
GP_t/B_{t-1}	58	0.909	0.148	0.822	0.882	0.983	0.903
OP_{FFt}/B_{t-1}	58	0.402	0.052	0.366	0.393	0.418	0.807
dA_t/A_{t-1}	58	0.152	0.077	0.111	0.144	0.169	0.682
$InvestAL_t$	58	0.075	0.031	0.052	0.070	0.090	0.585
$\ln(B_t/M_t)$	58	-0.978	0.435	-1.235	-1.012	-0.651	0.940
$Term_t$	58	0.010	0.011	0.002	0.010	0.017	0.555
Def_t	58	0.010	0.004	0.008	0.009	0.012	0.672
$Tbill_t$	58	0.004	0.003	0.002	0.004	0.005	0.816
$Sent^{BW}_t$	53	0.019	0.984	-0.453	0.044	0.551	0.571
$Sent^{HJTZ}_t$	55	0.003	1.000	-0.617	-0.324	0.310	0.409
CAY_t	57	-0.003	0.020	-0.017	-0.002	0.012	0.846
$OpAcc_t$	58	-0.043	0.012	-0.049	-0.043	-0.038	0.459
$EquityShare_t$	58	0.165	0.084	0.109	0.142	0.209	0.737
Ik_t	58	0.036	0.003	0.034	0.036	0.039	0.708
$(E/P)_t$	58	0.123	0.057	0.083	0.103	0.150	0.872
$E_t[d^1(dA/A)]$	58	-0.021	0.068	-0.044	-0.012	0.011	0.185
R^e_{t+1}	58	0.074	0.171	0.006	0.070	0.173	-0.090
$R^e_{(t+1,t+2)}$	57	0.064	0.111	0.009	0.069	0.119	0.385

Table 1. Summary statistics of aggregate variables (continued)

Panel B: Pearson Correlation Coefficients between Aggregate Variables (Annual Frequency)

	$OpCash_t/B_{t-1}$	ROE_t	GP_t/B_{t-1}	OP_{FFt}/B_{t-1}	dA_t/A_{t-1}	$InvestAL_t$	$\ln(B_t/M_t)$	$E_t[d^1(dA/A)]$	R^e_{t+1}	$R^e_{(t+1,t+2)}$
$OpCash_t/B_{t-1}$	1	0.77	0.92	0.82	0.39	0.08	-0.71	-0.23	0.16	0.22
		(<.0001)	(<.0001)	(<.0001)	(0.002)	(0.555)	(<.0001)	(0.084)	(0.232)	(0.094)
ROE_t		1	0.71	0.83	0.29	0.12	-0.60	0.10	0.14	0.17
			(<.0001)	(<.0001)	(0.029)	(0.377)	(<.0001)	(0.455)	(0.284)	(0.208)
GP_t/B_{t-1}			1	0.85	0.52	0.28	-0.67	-0.13	0.09	0.14
				(<.0001)	(<.0001)	(0.030)	(<.0001)	(0.325)	(0.504)	(0.308)
OP_{FFt}/B_{t-1}				1	0.54	0.38	-0.65	-0.08	0.05	0.10
					(<.0001)	(0.004)	(<.0001)	(0.568)	(0.694)	(0.440)
dA_t/A_{t-1}					1	0.83	-0.43	-0.11	-0.28	-0.42
						(<.0001)	(0.001)	(0.402)	(0.036)	(0.001)
$InvestAL_t$						1	-0.15	0.06	-0.20	-0.44
							(0.269)	(0.666)	(0.124)	(0.001)
$\ln(B_t/M_t)$							1	0.22	0.08	0.09
								(0.098)	(0.535)	(0.484)
$E_t[d^1(dA/A)]$								1	0.17	-0.03
									(0.210)	(0.809)
R^e_{t+1}									1	0.70
										(<.0001)
$R^e_{(t+1,t+2)}$										1

Table 1. Summary statistics of aggregate variables (continued)

Panel C: Pearson Correlation Coefficients between Aggregate Variables (Quarterly Frequency)

	$\sum$ OpCash$_t$/B$_{t-4}$	ROE$_t$	$\sum$ GP$_t$/B$_{t-4}$	$\sum$ OP$_{FFt}$/B$_{t-4}$	dA$_t$/A$_{t-4}$	ln(B$_t$/M$_t$)	R$^e_{t+1}$
$\sum$ OpCash$_t$/B$_{t-4}$	1	0.79	0.86	0.88	0.21	-0.87	0.11
		(<.0001)	(<.0001)	(<.0001)	(0.005)	(<.0001)	(0.155)
ROE$_t$		1	0.71	0.80	0.20	-0.64	0.08
			(<.0001)	(<.0001)	(0.006)	(<.0001)	(0.265)
$\sum$ GP$_t$/B$_{t-4}$			1	0.86	0.45	-0.84	0.06
				(<.0001)	(<.0001)	(<.0001)	(0.454)
$\sum$ OP$_{FFt}$/B$_{t-4}$				1	0.35	-0.72	0.05
					(<.0001)	(<.0001)	(0.520)
dA$_t$/A$_{t-4}$					1	-0.38	-0.22
						(<.0001)	(0.003)
ln(B$_t$/M$_t$)						1	0.02
							(0.820)
R$^e_{t+1}$							1

Table 2. Predicting aggregate stock returns

This table reports time-series predictive regression results that use profitability and asset growth as predictors. All RHS variables are standardized by their own means and standard deviations. Panel A predicts one-year-ahead excess stock returns over the risk-free rate. Panel B predicts average excess stock returns over years t+1 and t+2. Panel C predicts one-quarter-ahead excess stock returns. The t-statistics in parentheses are computed using Newey-West (1987) standard errors with three lags in Panels A and B, and with four lags in Panel C. Inferences on their statistical significance are based on wild-bootstrapped p-values of one-sided hypothesis tests, which are reported in brackets. For the predictive coefficient on profitability, the one-sided tests are H_1: $\beta > 0$ against the null of H_0: $\beta \leq 0$. For the predictive coefficient on asset growth, the one-sided tests are H_1: $\beta < 0$ against the null of H_0: $\beta \geq 0$. Our full sample of annual (quarterly) accounting data covers the period 1962-2019 (1975Q1-2020Q4), and the corresponding stock returns data spans July 1963-June 2021 (August 1975-July 2021). For OOS analyses, in Panels A and B, the training window uses accounting data from 1962-1990, and corresponding stock returns data from July 1963-June 1992 (for one-year-ahead return forecasts) and July 1963-June 1993 (for two-year-average return forecasts). The out-of-sample forecast period is July 1992-June 2021 (for one-year-ahead return forecasts) and July 1993-June 2021 (for two-year-average return forecasts). For Panel C, the training window uses accounting data from 1975Q1-1990Q4, and corresponding stock returns data from August 1975-July 1991. The out-of-sample forecast period is August 1991-July 2021. The Clark and McCracken's (2001) ENC-NEW statistic is used to test whether the forecast accuracy improvement of a model relative to the historical mean is significantly positive. The OOS R^2s and the ENC-NEW statistics are computed by imposing Campbell and Thompson's (2008) sign restrictions. Statistical significance at 10%, 5%, and 1% are indicated as *, **, and ***, respectively.

Table 2. Predicting aggregate stock returns (continued)

Panel A: Predicting one-year-ahead stock returns R^e_{t+1}	1	2	3	4	5	6	7	8	9
$OpCash_t/B_{t-1}$	0.027					0.054***			
	(1.03)					(3.01)			
	[0.193]					[0.005]			
ROE_t		0.025					0.041***		
		(1.28)					(2.76)		
		[0.160]					[0.010]		
GP_t/B_{t-1}			0.016					0.052***	
			(0.66)					(3.19)	
			[0.300]					[0.004]	
OP_{FFt}/B_{t-1}				0.009					0.047**
				(0.38)					(2.20)
				[0.400]					[0.024]
dA_t/A_{t-1}					-0.047***	-0.068***	-0.058***	-0.072***	-0.069***
					(-3.18)	(-3.86)	(-4.42)	(-4.50)	(-3.44)
					[0.008]	[0.001]	[0.000]	[0.000]	[0.003]
No. of Obs.	58	58	58	58	58	58	58	58	58
Prob>F	0.307	0.207	0.512	0.707	0.002	0.001	0.000	0.000	0.005
IS R^2	0.03	0.02	0.01	0.00	0.08	0.16	0.13	0.15	0.12
IS adj. R^2	0.01	0.00	-0.01	-0.01	0.06	0.13	0.10	0.12	0.09
					OOS forecast with the sign restrictions				
OOS R^2	-0.04	-0.02	-0.03	-0.04	0.10	0.12	0.06	0.15	0.13
ENC-NEW	0.97*	0.20	0.13	-0.27	2.06***	7.05***	4.27***	5.32***	4.81***

Table 2. Predicting aggregate stock returns (continued)

Panel B: Predicting two-year-average stock returns $R^e_{(t+1,t+2)}$	1	2	3	4	5	6	7	8	9
$OpCash_t/B_{t-1}$	0.025					0.051***			
	(1.08)					(4.26)			
	[0.261]					[0.000]			
ROE_t		0.019					0.035***		
		(0.99)					(3.05)		
		[0.270]					[0.006]		
GP_t/B_{t-1}			0.016					0.052***	
			(0.68)					(4.68)	
			[0.320]					[0.000]	
OP_{FFt}/B_{t-1}				0.012					0.052***
				(0.50)					(3.21)
				[0.360]					[0.010]
dA_t/A_{t-1}					-0.047***	-0.067***	-0.055***	-0.071***	-0.074***
					(-5.16)	(-6.61)	(-7.67)	(-7.09)	(-7.03)
					[0.002]	[0.000]	[0.000]	[0.000]	[0.000]
No. of Obs.	57	57	57	57	57	57	57	57	57
Prob>F	0.285	0.325	0.498	0.618	0.000	0.000	0.000	0.000	0.000
IS R^2	0.05	0.03	0.02	0.01	0.18	0.36	0.27	0.35	0.33
IS adj. R^2	0.03	0.01	0.00	-0.01	0.16	0.33	0.24	0.32	0.31
					OOS forecast with the sign restrictions				
OOS R^2	-0.20	-0.17	-0.17	-0.16	0.12	0.15	0.20	0.32	0.27
ENC-NEW	0.31	-1.25	-0.59	-1.38	2.22***	10.86***	8.00***	11.95***	10.68***

Table 2. Predicting aggregate stock returns (continued)

Panel C: Predicting one-quarter-ahead stock returns R^e_{t+1}

	1	2	3	4	5	6	7	8	9
$\sum OpCash_t/B_{t-4}$	0.008*					0.012***			
	(1.47)					(2.48)			
	[0.074]					[0.010]			
ROE_t		0.006					0.010**		
		(1.23)					(1.99)		
		[0.130]					[0.036]		
$\sum GP_t/B_{t-4}$			0.004					0.013***	
			(0.68)					(2.82)	
			[0.270]					[0.003]	
$\sum OP_{FFt}/B_{t-4}$				0.004					0.011**
				(0.63)					(2.32)
				[0.290]					[0.014]
dA_t/A_{t-4}					-0.016***	-0.019***	-0.018***	-0.021***	-0.024***
					(-3.48)	(-4.29)	(-6.08)	(-5.92)	(-4.75)
					[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
No. of Obs.	184	184	184	184	184	184	184	184	184
Prob>F	0.14	0.22	0.50	0.53	0.00	0.00	0.00	0.00	0.00
IS R^2	0.01	0.01	0.00	0.00	0.05	0.07	0.07	0.07	0.09
IS adj. R^2	0.01	0.00	0.00	0.00	0.04	0.06	0.06	0.06	0.08
					OOS forecast with the sign restrictions				
OOS R^2	-0.01	-0.01	-0.01	-0.01	0.05	0.05	0.04	0.06	0.05
ENC-NEW	1.06*	0.16	0.61	-0.07	3.78***	8.15***	6.30***	8.60***	8.20***

Table 3. Forecasting aggregate stock returns

This table reports the aggregate stock return forecasts—made as at June 2020 (2019) for one-year-ahead (two-year-average) aggregate stock returns—by using the historical mean return, B/M, cash-based profitability, and asset growth as predictors. Panel A1 (B1) reports the means, standard deviations, and the year 2019 (2018) values of the predictors. The last column computes the deviation of the 2019 (2018) values from their sample means, measured in standardized units. Panel A2 reports the annual aggregate stock return forecasts over July 2020-June 2021, and Panel B2 reports the average annual aggregate stock return forecasts over July 2019-June 2021. The predictive coefficients reported on these panels are estimated from standardized variables.

Panel A1: Summary statistics of the predictors

Predictors	Mean	Std Dev	Value in 2019	Deviation of the value in 2019 from the mean (in standardized unit)
$\ln(B_t/M_t)$	-0.978	0.435	-1.703	-1.668
$OpCash_t/B_{t-1}$	0.487	0.104	0.680	1.859
dA_t/A_{t-1}	0.152	0.077	0.174	0.278

Panel A2: Forecasting the return premium of 2020 (July 2020- June 2021)

Predictor(s)	Estimated intercept	Value of the first predictor in 2019	Coefficient estimate of the first predictor	Value of the second predictor in 2019	Coefficient estimate of the second predictor	Forecasted return premium of 2020
Historical Mean			-			0.068
$\ln(B_t/M_t)$	0.068	-1.668	0.026	-	-	0.024
$OpCash_t/B_{t-1}$ dA_t/A_{t-1}	0.068	1.859	0.042	0.278	-0.066	0.127

Panel B1: Summary statistics of the predictors

Predictors	Mean	Std Dev	Value in 2018	Deviation of the value in 2018 from the mean (in standardized unit)
$\ln(B_t/M_t)$	-0.966	0.427	-1.543	-1.350
$OpCash_t/B_{t-1}$	0.483	0.102	0.715	2.276
dA_t/A_{t-1}	0.152	0.077	0.090	-0.802

Panel B2: Forecasting the geometric average of the return premia over 2019-2020 (July 2019 - June 2021)

Predictor(s)	Estimated intercept	Value of the first predictor in 2018	Coefficient estimate of the first predictor	Value of the second predictor in 2018	Coefficient estimate of the second predictor	Forecasted geometric average of the return premia over 2019-2020
Historical Mean			-			0.060
$\ln(B_t/M_t)$	0.060	-1.350	0.017	-	-	0.038
$OpCash_t/B_{t-1}$ dA_t/A_{t-1}	0.060	2.276	0.051	-0.802	-0.069	0.232

Table 4. Certainty equivalent return (CER) gains

This table reports the certainty equivalent return (CER) gains from jointly using cash-based profitability and asset investment instead of only using the historical mean return as aggregate stock return predictors in portfolio allocation. This CER gain represents the value to an investor in her portfolio allocation by switching from a historical mean-based OOS predictive model to one that is based on cash-based profitability plus asset investment. The % CER gain can be interpreted as an annual fee that the investor would be willing to pay to switch from a historical mean-based to a profitability/investment-based forecast. The CER gains reported here are computed by imposing Campbell and Thompson's (2008) sign restrictions on all OOS aggregate stock return forecasts. Panel A reports CER gains based on one-year-ahead aggregate stock return forecasts, and Panel B reports CER gains based on two-year-average aggregate stock return forecasts. In each panel, the risk aversion coefficient γ can take on values of 1, 3, or 5. The training window of the OOS analysis uses accounting data from 1962-1990, and corresponding stock returns data from July 1963-June 1992 (for one-year-ahead return forecasts) and July 1963-June 1993 (for two-year-average return forecasts). The OOS forecast period is July 1992-June 2021 (for one-year-ahead return forecasts) and July 1993-June 2021 (for two-year-average return forecasts). Statistical significance at 10%, 5%, and 1% are indicated as *, **, and ***, respectively.

Panel A: Portfolio allocation considering one-year-ahead stock returns				
Predictor(s)		**CER (%)**	**CER gain (%)**	**Test statistic for CER gain**
		Panel A1: Risk aversion coefficient γ = 1		
Historical Mean	-	14.22	-	-
$OpCash_t/B_{t-1}$	dA_t/A_{t-1}	15.76	1.54	1.34
		Panel A2: Risk aversion coefficient γ = 3		
Historical Mean	-	6.95	-	-
$OpCash_t/B_{t-1}$	dA_t/A_{t-1}	11.37	4.42***	2.63
		Panel A3: Risk aversion coefficient γ = 5		
Historical Mean	-	5.08	-	-
$OpCash_t/B_{t-1}$	dA_t/A_{t-1}	8.13	3.05**	2.29
Panel B: Portfolio allocation considering two-year average stock returns				
Predictor(s)		**CER (%)**	**CER gain (%)**	**Test statistic for CER gain**
		Panel B1: Risk aversion coefficient γ = 1		
Historical Mean	-	13.70	-	-
$OpCash_t/B_{t-1}$	dA_t/A_{t-1}	14.34	0.64	0.87
		Panel B2: Risk aversion coefficient γ = 3		
Historical Mean	-	9.87	-	-
$OpCash_t/B_{t-1}$	dA_t/A_{t-1}	11.62	1.75**	2.15
		Panel B3: Risk aversion coefficient γ = 5		
Historical Mean	-	6.60	-	-
$OpCash_t/B_{t-1}$	dA_t/A_{t-1}	9.49	2.89**	2.46

Table 5. Predictive power of individual components of asset growth

This table reports the predictive power of individual components of asset growth. We decompose asset growth from the investment side and the financing side. From the investment side, asset growth is decomposed into short-term asset growth (ChgSTAsst), other current asset growth (ChgCurAsst), property, plant and equipment growth (ChgPPE), and other asset growth (ChgOthAsst). From the financing side, asset growth is decomposed into operating liabilities growth (ChgOpLiab), retained earnings growth (ChgRE), stock financing growth (ChgStock), and debt financing growth (ChgDebt). Panel A reports one-year-ahead excess return forecasts, and Panel B reports two-year-ahead excess return forecasts. This analysis uses accounting data from 1962-2019 and stock returns data from July 1963-June 2021. All RHS variables are standardized by their own means and standard deviations. The *t*-statistics in parentheses are computed using Newey-West (1987) standard errors with three lags. Inferences on their statistical significance are based on wild-bootstrapped *p*-values of one-sided hypothesis tests, which are reported in brackets. Statistical significance at 10%, 5%, and 1% are indicated as *, **, and ***, respectively.

Table 5. Predictive power of individual components of asset growth (continued)

Panel A: Predicting one-year-ahead stock returns R^e_{t+1}

	1	2	3	4	5	6	7	8	9	10	11
dA_t/A_{t-1}	-0.060***										
	(-3.39)										
	[0.000]										
$ChgSTAsst_t$		-0.083***				-0.115***					
		(-4.71)				(-2.98)					
		[0.000]				[0.005]					
$ChgCurAsst_t$			-0.030			-0.005					
			(-1.13)			(-0.17)					
			[0.182]			[0.452]					
$ChgPPE_t$				-0.024		-0.017					
				(-0.90)		(-0.54)					
				[0.235]		[0.327]					
$ChgOthAsst_t$					-0.041	0.044					
					(-1.04)	(1.31)					
					[0.198]	[0.893]					
$ChgOpLiab_t$							-0.063***				-0.014
							(-2.93)				(-0.55)
							[0.003]				[0.262]
$ChgRE_t$								-0.051***			-0.022
								(-3.05)			(-1.18)
								[0.003]			[0.184]
$ChgStock_t$									-0.064***		-0.063***
									(-5.35)		(-2.95)
									[0.000]		[0.008]
$ChgDebt_t$										0.017	0.035
										(0.61)	(1.76)
										[0.715]	[0.951]
$OpCash_t/B_{t-1}$	0.041*	0.060**	0.016	0.015	0.038	0.052**	0.047**	0.019	0.044*	0.019	0.049**
	(1.66)	(2.15)	(0.66)	(0.54)	(1.04)	(2.09)	(2.16)	(0.88)	(1.87)	(0.70)	(1.95)
	[0.063]	[0.035]	[0.294]	[0.308]	[0.219]	[0.037]	[0.025]	[0.242]	[0.051]	[0.278]	[0.049]
No. of Obs.	58	58	58	58	58	58	58	58	58	58	58
R^2	0.12	0.19	0.04	0.03	0.06	0.22	0.12	0.10	0.13	0.02	0.21
Adj. R^2	0.09	0.16	0.01	-0.01	0.02	0.15	0.09	0.07	0.10	-0.01	0.13

Table 5. Predictive power of individual components of asset growth (continued)

Panel B: Predicting two-year-ahead stock returns R^e_{t+2}

	1	2	3	4	5	6	7	8	9	10	11
dA_t/A_{t-1}	-0.047**										
	(-2.40)										
	[0.014]										
$ChgSTAsst_t$		-0.046**				-0.081***					
		(-2.20)				(-2.57)					
		[0.029]				[0.010]					
$ChgCurAsst_t$			-0.037**			0.019					
			(-1.96)			(0.81)					
			[0.032]			[0.738]					
$ChgPPE_t$				-0.058***		-0.070**					
				(-2.71)		(-2.35)					
				[0.010]		[0.021]					
$ChgOthAsst_t$					-0.013	0.046					
					(-0.32)	(1.28)					
					[0.376]	[0.874]					
$ChgOpLiab_t$							-0.046*				0.014
							(-1.78)				(0.32)
							[0.052]				[0.603]
$ChgRE_t$								-0.057***			-0.056***
								(-3.05)			(-2.56)
								[0.005]			[0.010]
$ChgStock_t$									-0.038**		-0.034
									(-1.81)		(-1.11)
									[0.049]		[0.183]
$ChgDebt_t$										0.005	0.007
										(0.14)	(0.22)
										[0.502]	[0.542]
$OpCash_t/B_{t-1}$	0.019	0.025	-0.001	-0.010	0.007	0.010	0.023	0.004	0.017	0.002	0.012
	(0.55)	(0.71)	(-0.03)	(-0.39)	(0.16)	(0.44)	(0.88)	(0.18)	(0.48)	(0.05)	(0.52)
	[0.330]	[0.292]	[0.535]	[0.636]	[0.446]	[0.347]	[0.254]	[0.449]	[0.352]	[0.456]	[0.322]
No. of Obs.	57	57	57	57	57	57	57	57	57	57	57
R^2	0.06	0.05	0.05	0.11	0.00	0.18	0.06	0.11	0.04	0.00	0.13
Adj. R^2	0.03	0.02	0.01	0.07	-0.03	0.10	0.02	0.08	0.01	-0.04	0.04

Table 6 The predictive power of $Invest_{AL}$

This table reports time-series predictive regression results that use Arif and Lee's (2014) investment measure, $Invest_{AL}$, and its individual components, as predictors. Panels A and B report results using $Invest_{AL}$ as the predictor, with controlling for cash-based profitability. Panel A predicts one-year-ahead excess stock returns over the risk-free rate; Panel B predicts the average excess stock returns over years *t*+1 and *t*+2. Panels C and D use $Invest_{AL}$'s individual components as predictors. $Invest_{AL,t}$ is decomposed into: $Invest_{AL,t} = ChgNOA_t + RND_t = ChgAT_t - ChgSTAsst_t - ChgNonDebt_t + RND_t$, where $ChgNOA_t$ is change in net operating assets, RND_t is capitalized R&D expense, $ChgAT_t$ is change in total assets, $ChgSTAsst_t$ is change in short-term asset (change in cash and short-term investments), and $ChgNonDebt_t$ is change in non-debt liabilities. Panels C and D predict one-year-ahead and two-year-ahead excess stock returns respectively. Our full sample of annual accounting data covers the period 1962-2019, and the corresponding stock returns data spans July 1963-June 2021. All RHS variables are standardized by their own means and standard deviations. The *t*-statistics in parentheses are computed using Newey-West (1987) standard errors with three lags. Inferences on their statistical significance are based on wild-bootstrapped *p*-values of one-sided hypothesis tests, which are reported in brackets. Statistical significance at 10%, 5%, and 1% are indicated as *, **, and ***, respectively.

Panel A: Predicting one-year-ahead stock returns R^e_{t+1}

	1	2	3
$OpCash_t/B_{t-1}$	0.030		0.032**
	(1.25)		(1.79)
	[0.129]		[0.049]
$InvestAL_t$		-0.036*	-0.037
		(-1.47)	(-1.29)
		[0.091]	[0.133]
No. of Obs.	58	58	58
Prob>F	0.217	0.148	0.006
IS R^2	0.03	0.04	0.08
IS adj. R^2	0.01	0.03	0.04

Panel B: Predicting two-year-average stock returns $R^e_{(t+1,t+2)}$

	1	2	3
$OpCash_t/B_{t-1}$	0.026		0.029**
	(1.21)		(2.34)
	[0.122]		[0.011]
$InvestAL_t$		-0.049***	-0.051***
		(-3.61)	(-2.96)
		[0.002]	[0.007]
No. of Obs.	57	57	57
Prob>F	0.230	0.001	0.000
IS R^2	0.06	0.19	0.26
IS adj. R^2	0.04	0.18	0.23

Table 6 The predictive power of $Invest_{AL}$ (continued)

Panel C: Predicting one-year-ahead stock returns R^e_{t+1}

	1	2	3	4	5	6
$InvestAL_t$	-0.037					
	(-1.29)					
	[0.133]					
$ChgNOA_t$		-0.033				
		(-1.06)				
		[0.179]				
RND_t			-0.067***			
			(-2.97)			
			[0.005]			
$ChgAT_t$				-0.060***		
				(-3.09)		
				[0.002]		
$ChgSTAsst_t$					-0.078***	
					(-3.16)	
					[0.002]	
$ChgNonDebt_t$						-0.048**
						(-2.43)
						[0.013]
$OpCash_t/B_{t-1}$	0.032**	0.029*	0.069***	0.040**	0.064***	0.038**
	(1.79)	(1.42)	(3.76)	(2.48)	(2.76)	(1.98)
	[0.049]	[0.097]	[0.000]	[0.020]	[0.009]	[0.034]
No. of Obs.	58	58	58	58	58	58
Prob>F	0.006	0.008	0.001	0.002	0.008	0.010
IS R^2	0.08	0.07	0.13	0.14	0.20	0.10
IS adj. R^2	0.04	0.03	0.10	0.11	0.17	0.07

Table 6 The predictive power of $Invest_{AL}$ (continued)

Panel D: Predicting two-year-ahead stock returns R^e_{t+2}

	1	2	3	4	5	6
$InvestAL_t$	-0.057***					
	(-3.34)					
	[0.002]					
$ChgNOA_t$		-0.055***				
		(-3.06)				
		[0.005]				
RND_t			-0.059***			
			(-2.91)			
			[0.007]			
$ChgAT_t$				-0.058***		
				(-3.50)		
				[0.002]		
$ChgSTAsst_t$					-0.045**	
					(-1.79)	
					[0.046]	
$ChgNonDebt_t$						-0.020
						(-0.69)
						[0.271]
$OpCash_t/B_{t-1}$	0.036**	0.031*	0.068***	0.044***	0.054***	0.037**
	(2.35)	(1.88)	(4.20)	(3.23)	(3.21)	(1.98)
	[0.020]	[0.052]	[0.000]	[0.001]	[0.004]	[0.038]
No. of Obs.	57	57	57	57	57	57
Prob>F	0.000	0.000	0.000	0.000	0.005	0.031
IS R^2	0.16	0.15	0.12	0.16	0.10	0.05
IS adj. R^2	0.13	0.12	0.09	0.13	0.06	0.02

Table 7. Controlling for other predictors

This table reports results of predictive regressions that include other predictors as controls. Panels A to C, respectively, report one-year-ahead, two-year-average, and one-quarter-ahead aggregate stock return forecasts. The control variables include the term spread (Term), default spread (Def), Treasury bill rate (Tbill), the Baker and Wurgler's sentiment index ($Sent^{BW}$), the Huang, Jiang, Tu, and Zhou's (2015) sentiment index ($Sent^{HJTZ}$), Lettau and Ludvigson's (2001) consumption-wealth ratio (CAY), aggregate operating accruals (OpAcc), equity share in new issuance (EquityShare), the Cochrane's (1991) investment-to-capital ratio (IK), and the earnings-to-price ratio (E/P). All RHS variables are standardized by their own means and standard deviations. The *t*-statistics in parentheses are computed using Newey-West (1987) standard errors with three lags in Panels A and B, and with four lags in Panel C. Inferences on their statistical significance are based on wild-bootstrapped *p*-values of one-sided hypothesis tests, which are reported in brackets. In Panels A and B, the sample period is July 1963-June 2021 for stock returns, and 1962-2019 for other variables. In Panel C, the sample period is August 1975-July 2021 for stock returns, and 1975Q1-2020Q4 for other variables. The following variables are available only during part of these sample periods. $Sent^{BW}$ is available from 1965-2017 (up to 2018Q2 in quarterly analyses). $Sent^{HJTZ}$ is available from 1965-2019 (up to 2020Q2 in quarterly analyses). CAY is available from 1962-2018 (up to 2019Q2 in quarterly analyses). IK is available up to 2020Q3 in quarterly analyses. Appendix A contains a more detailed description of these variables. Statistical significance at 10%, 5%, and 1% are indicated as *, **, and ***, respectively.

Table 7. Controlling for other predictors (continued)

Panel A: Predicting one-year-ahead stock returns R^e_{t+1}

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
$Term_t$	0.033**										0.009									
	(2.23)										(0.55)									
	[0.043]										[0.364]									
Def_t		0.018										0.017								
		(0.98)										(0.98)								
		[0.218]										[0.291]								
$Tbill_t$			-0.028										0.006							
			(-1.47)										(0.25)							
			[0.125]										[0.523]							
$Sent^{BW}_t$				-0.012										0.005						
				(-0.40)										(0.18)						
				[0.370]										[0.561]						
$Sent^{HJTZ}_t$					-0.064**										-0.045**					
					(-3.03)										(-2.33)					
					[0.011]										[0.020]					
CAY_t						0.011										0.027*				
						(0.59)										(1.74)				
						[0.310]										[0.080]				
$OpAcc_t$							0.031										0.032**			
							(1.37)										(2.18)			
							[0.164]										[0.042]			
$EquityShare_t$								0.003										0.018		
								(0.17)										(0.91)		
								[0.556]										[0.731]		
Ik_t									-0.032										0.020	
									(-1.30)										(0.71)	
									[0.146]										[0.698]	
$(E/P)_t$										0.010										0.034
										(0.50)										(1.61)
										[0.358]										[0.102]
$OpCash_t/B_{t-1}$											0.051***	0.055***	0.057**	0.052**	0.049***	0.042**	0.060***	0.061***	0.060***	0.072***
											(2.62)	(3.03)	(2.42)	(2.09)	(2.79)	(2.78)	(3.24)	(3.00)	(2.93)	(3.41)
											[0.010]	[0.004]	[0.021]	[0.034]	[0.006]	[0.015]	[0.005]	[0.004]	[0.004]	[0.003]
dA_t/A_{t-1}											-0.066***	-0.068***	-0.071***	-0.071***	-0.048***	-0.073***	-0.065***	-0.069***	-0.083***	-0.070***
											(-3.33)	(-4.09)	(-3.39)	(-4.50)	(-2.68)	(-4.40)	(-4.57)	(-3.79)	(-3.16)	(-4.53)
											[0.003]	[0.000]	[0.003]	[0.001]	[0.007]	[0.000]	[0.000]	[0.001]	[0.002]	[0.000]
No. of Obs.	58	58	58	53	55	57	58	58	58	58	58	58	58	53	55	57	58	58	58	58
Prob>F	0.030	0.332	0.147	0.692	0.004	0.556	0.177	0.869	0.198	0.622	0.001	0.000	0.002	0.001	0.000	0.001	0.000	0.002	0.002	0.000
IS R^2	0.04	0.01	0.03	0.01	0.13	0.00	0.03	0.00	0.04	0.00	0.16	0.17	0.16	0.15	0.22	0.17	0.19	0.17	0.17	0.19
IS adj. R^2	0.02	-0.01	0.01	-0.01	0.12	-0.01	0.01	-0.02	0.02	-0.01	0.12	0.12	0.11	0.10	0.17	0.12	0.15	0.12	0.12	0.15

Table 7. Controlling for other predictors (continued)

Panel B: Predicting two-year-average stock returns $R^e_{(t+1,t+2)}$

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
$Term_t$	0.029*										0.005									
	(2.32)										(0.39)									
	[0.074]										[0.378]									
Def_t		0.010										0.010								
		(0.61)										(0.88)								
		[0.352]										[0.353]								
$Tbill_t$			-0.015										0.021							
			(-1.02)										(1.85)							
			[0.255]										[0.940]							
$Sent^{BW}_t$				0.008										0.027						
				(0.39)										(1.96)						
				[0.598]										[0.951]						
$Sent^{HJTZ}_t$					-0.023										0.003					
					(-1.27)										(0.23)					
					[0.213]										[0.525]					
CAY_t						0.018										0.034***				
						(0.96)										(3.77)				
						[0.274]										[0.000]				
$OpAcc_t$							0.020										0.020**			
							(1.17)										(2.64)			
							[0.226]										[0.011]			
$EquityShare_t$								0.007										0.021		
								(0.47)										(1.56)		
								[0.613]										[0.886]		
Ik_t									-0.035*										0.013	
									(-2.25)										(0.87)	
									[0.084]										[0.740]	
$(E/P)_t$										0.003										0.021
										(0.16)										(1.39)
										[0.483]										[0.142]
$OpCash_t/B_{t-1}$											0.049***	0.052***	0.062***	0.047***	0.053***	0.051***	0.054***	0.059***	0.055***	0.062***
											(3.68)	(4.34)	(4.54)	(2.77)	(3.89)	(6.32)	(4.59)	(4.42)	(4.14)	(4.38)
											[0.000]	[0.000]	[0.000]	[0.006]	[0.002]	[0.000]	[0.000]	[0.001]	[0.001]	[0.000]
dA_t/A_{t-1}											-0.065***	-0.067***	-0.075***	-0.075***	-0.068***	-0.076***	-0.065***	-0.068***	-0.076***	-0.068***
											(-6.98)	(-7.01)	(-7.28)	(-6.08)	(-5.35)	(-7.38)	(-7.61)	(-6.52)	(-5.51)	(-7.37)
											[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
No. of Obs.	57	57	57	53	54	57	57	57	57	57	57	57	57	53	54	57	57	57	57	57
Prob>F	0.024	0.542	0.312	0.699	0.211	0.340	0.246	0.643	0.029	0.875	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
IS R^2	0.07	0.01	0.02	0.00	0.04	0.03	0.03	0.00	0.10	0.00	0.36	0.37	0.38	0.37	0.36	0.44	0.39	0.39	0.36	0.39
IS adj. R^2	0.05	-0.01	0.00	-0.01	0.03	0.01	0.02	-0.01	0.08	-0.02	0.32	0.33	0.35	0.33	0.32	0.41	0.35	0.35	0.33	0.35

Table 7. Controlling for other predictors (continued)

Panel C: Predicting one-quarter-ahead stock returns R^e_{t+1}

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
$Term_t$	0.003										-0.003									
	(0.64)										(-0.63)									
	[0.281]										[0.726]									
Def_t		0.005										0.007								
		(0.75)										(1.14)								
		[0.239]										[0.150]								
$Tbill_t$			-0.006										0.010							
			(-0.98)										(1.04)							
			[0.193]										[0.840]							
$Sent^{BW}_t$				-0.009										-0.003						
				(-0.92)										(-0.42)						
				[0.178]										[0.377]						
$Sent^{HJTZ}_t$					-0.020***										-0.013**					
					(-3.32)										(-2.37)					
					[0.001]										[0.011]					
CAY_t						0.003										0.010**				
						(0.51)										(1.99)				
						[0.330]										[0.023]				
$OpAcc_t$							-0.001										-0.004			
							(-0.15)										(-0.64)			
							[0.553]										[0.717]			
$EquityShare_t$								-0.013**										-0.010*		
								(-1.92)										(-1.50)		
								[0.031]										[0.093]		
Ik_t									-0.012**										-0.000	
									(-1.78)										(-0.08)	
									[0.043]										[0.474]	
$(E/P)_t$										0.000										0.018**
										(0.06)										(1.99)
										[0.432]										[0.030]
$\sum OpCash_t/B_{t-4}$											0.012***	0.014***	0.019***	0.010**	0.009*	0.013**	0.011**	0.009*	0.012**	0.026***
											(2.52)	(3.04)	(2.65)	(1.81)	(1.75)	(2.43)	(2.16)	(1.67)	(2.34)	(3.27)
											[0.010]	[0.003]	[0.005]	[0.050]	[0.064]	[0.013]	[0.015]	[0.057]	[0.014]	[0.001]
dA_t/A_{t-4}											-0.020***	-0.019***	-0.022***	-0.018***	-0.013***	-0.021***	-0.020***	-0.018***	-0.019***	-0.019***
											(-4.25)	(-4.25)	(-4.44)	(-4.37)	(-2.95)	(-5.01)	(-4.13)	(-3.60)	(-3.11)	(-4.69)
											[0.000]	[0.000]	[0.000]	[0.000]	[0.003]	[0.000]	[0.000]	[0.000]	[0.003]	[0.000]
No. of Obs.	184	184	184	174	182	178	184	184	183	184	184	184	184	174	182	178	184	184	183	184
Prob>F	0.524	0.456	0.327	0.357	0.001	0.613	0.877	0.056	0.077	0.950	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
IS R^2	0.00	0.00	0.01	0.01	0.06	0.00	0.00	0.03	0.02	0.00	0.07	0.08	0.08	0.07	0.09	0.08	0.07	0.09	0.07	0.09
IS adj. R^2	0.00	0.00	0.00	0.00	0.06	0.00	-0.01	0.02	0.02	-0.01	0.06	0.06	0.06	0.05	0.07	0.07	0.06	0.07	0.05	0.08

Table 8. The predictive power of expected change in aggregate asset growth

This table reports predictive regression results for aggregate excess stock returns when expected change in aggregate asset growth is used as a predictor. Expected change in aggregate asset growth, $E_t[d^1(dA/A)]$ is obtained by value-weighting its firm-level counterparts, which are computed by running cross-sectional weighted least squares of the change in asset growth on lagged Tobin's q, operating cash flows, and the change in return on equity, using each firm's market value as weights. The accounting data spans 1962-2019. The stock returns data spans July 1963-June 2021. All RHS variables are standardized by their own means and standard deviations. Panel A predicts one-year-ahead excess stock returns. Panel B predicts average excess stock returns over years *t*+1 and *t*+2. The *t*-statistics in parentheses are computed using Newey-West (1987) standard errors with three lags. Inferences on their statistical significance are based on wild-bootstrapped *p*-values of one-sided hypothesis tests, which are reported in brackets. Statistical significance at 10%, 5%, and 1% are indicated as *, **, and ***, respectively.

Panel A: Predicting one-year-ahead stock returns R^e_{t+1}		
	1	2
$OpCash_t/B_{t-1}$		0.065***
		(3.37)
		[0.002]
dA_t/A_{t-1}		-0.071***
		(-4.07)
		[0.000]
$E_t[d^1(dA/A)]$	0.028**	0.036**
	(2.21)	(1.90)
	[0.050]	[0.034]
No. of Obs.	58	58
Prob>F	0.031	0.000
IS R^2	0.03	0.20
IS adj. R^2	0.01	0.16
Panel B: Predicting two-year-average stock returns $R^e_{(t+1,t+2)}$		
	1	2
$OpCash_t/B_{t-1}$		0.053***
		(3.72)
		[0.000]
dA_t/A_{t-1}		-0.071***
		(-6.47)
		[0.000]
$E_t[d^1(dA/A)]$	-0.004	0.003
	(-0.54)	(0.25)
	[0.650]	[0.399]
No. of Obs.	57	57
Prob>F	0.592	0.000
IS R^2	0.00	0.36
IS adj. R^2	-0.02	0.33

Table 9. Predicting total stock returns

This table reports time-series predictive regression results for aggregate total stock returns. All RHS variables are standardized by their own means and standard deviations. Panel A predicts one-year-ahead stock returns. Panel B predicts average stock returns over years *t*+1 and *t*+2. Panel C predicts one-quarter-ahead stock returns. The *t*-statistics in parentheses are computed using Newey-West (1987) standard errors with three lags in Panels A and B, and with four lags in Panel C. Inferences on their statistical significance are based on wild-bootstrapped *p*-values of one-sided hypothesis tests, which are reported in brackets. Our full sample of annual (quarterly) accounting data covers the period 1962-2019 (1975Q1-2020Q4), and the corresponding stock returns data spans July 1963-June 2021 (August 1975-July 2021). Statistical significance at 10%, 5%, and 1% are indicated as *, **, and ***, respectively.

Panel A: Predicting one-year-ahead stock returns R_{t+1}			
	1	2	3
$OpCash_t/B_{t-1}$	0.012		0.035*
	(0.49)		(1.82)
	[0.352]		[0.056]
dA_t/A_{t-1}		-0.043**	-0.057***
		(-2.46)	(-2.81)
		[0.024]	[0.007]
No. of Obs.	58	58	58
Prob>F	0.627	0.017	0.021
IS R^2	0.01	0.07	0.10
IS adj. R^2	-0.01	0.05	0.0705
Panel B: Predicting two-year-average stock returns $R_{(t+1,t+2)}$			
	1	2	3
$OpCash_t/B_{t-1}$	0.010		0.033**
	(0.45)		(2.43)
	[0.397]		[0.025]
dA_t/A_{t-1}		-0.045***	-0.058***
		(-4.51)	(-5.00)
		[0.006]	[0.001]
No. of Obs.	57	57	57
Prob>F	0.654	0.000	0.000
IS R^2	0.01	0.17	0.25
IS adj. R^2	-0.01	0.16	0.22

Table 9. Predicting total stock returns (continued)

Panel C: Predicting one-quarter-ahead stock returns R_{t+1}

	1	2	3
$\sum$ $OpCash_t/B_{t-4}$	0.002		0.006
	(0.42)		(1.13)
	[0.356]		[0.145]
dA_t/A_{t-4}		-0.015***	-0.016***
		(-2.94)	(-3.27)
		[0.005]	[0.001]
No. of Obs.	184	184	184
Prob>F	0.68	0.00	0.00
IS R^2	0.00	0.04	0.05
IS adj. R^2	0.00	0.04	0.04

Table 10. Alternative aggregation

This table reports time-series predictive regression results for aggregate excess stock returns. All aggregate predictors are computed by summing up the denominator and numerator of the firm-level variables separately before taking the ratio. All RHS variables are standardized by their own means and standard deviations. Panel A predicts one-year-ahead excess stock returns. Panel B predicts average excess stock returns over years t+1 and t+2. Panel C predicts one-quarter-ahead excess stock returns. The t-statistics in parentheses are computed using Newey-West (1987) standard errors with three lags in Panels A and B, and with four lags in Panel C. Inferences on their statistical significance are based on wild-bootstrapped p-values of one-sided hypothesis tests, which are reported in brackets. Our full sample of annual (quarterly) accounting data covers the period 1962-2019 (1975Q1-2020Q4), and the corresponding stock returns data spans July 1963-June 2021 (August 1975-July 2021). Statistical significance at 10%, 5%, and 1% are indicated as *, **, and ***, respectively.

Panel A: Predicting one-year-ahead stock returns R^e_{t+1}

	1	2	3	4
$OpCash_t/B_{t-1}$	0.025			
	(1.27)			
	[0.151]			
ROE_t		0.022*		
		(1.72)		
		[0.087]		
OP_{FFt}/B_{t-1}			0.032**	
			(2.25)	
			[0.031]	
GP_t/B_{t-1}				0.019
				(1.34)
				[0.138]
dA_t/A_{t-1}	-0.052**	-0.060***	-0.071***	-0.057**
	(-2.36)	(-3.04)	(-3.29)	(-2.69)
	[0.023]	[0.002]	[0.002]	[0.011]
No. of Obs.	58	58	58	58
Prob>F	0.026	0.011	0.006	0.031
IS R^2	0.12	0.10	0.12	0.10
IS adj. R^2	0.09	0.07	0.09	0.07

Table 10. Alternative aggregation (continued)

Panel B: Predicting two-year-average stock returns $R^e_{(t+1,t+2)}$				
	1	2	3	4
$OpCash_t/B_{t-1}$	0.024*			
	(1.65)			
	[0.073]			
ROE_t		0.013		
		(1.05)		
		[0.183]		
OP_{FFt}/B_{t-1}			0.038***	
			(3.12)	
			[0.005]	
GP_t/B_{t-1}				0.025**
				(2.41)
				[0.015]
dA_t/A_{t-1}	-0.055***	-0.059***	-0.076***	-0.063***
	(-3.38)	(-4.13)	(-4.81)	(-4.18)
	[0.002]	[0.001]	[0.000]	[0.000]
No. of Obs.	57	57	57	57
Prob>F	0.001	0.000	0.000	0.000
IS R^2	0.31	0.25	0.34	0.29
IS adj. R^2	0.29	0.23	0.32	0.26

Panel C: Predicting one-quarter-ahead stock returns R^e_{t+1}				
	1	2	3	4
$\sum OpCash_t/B_{t-4}$	0.010**			
	(2.04)			
	[0.026]			
ROE_t		0.009*		
		(1.37)		
		[0.098]		
$\sum OP_{FFt}/B_{t-4}$			0.011**	
			(1.80)	
			[0.041]	
$\sum GP_t/B_{t-4}$				0.009*
				(1.70)
				[0.068]
dA_t/A_{t-4}	-0.013**	-0.019***	-0.026***	-0.018***
	(-1.97)	(-3.02)	(-4.29)	(-2.71)
	[0.024]	[0.003]	[0.000]	[0.006]
No. of Obs.	184	184	184	184
Prob>F	0.00	0.01	0.00	0.03
IS R^2	0.05	0.06	0.08	0.05
IS adj. R^2	0.04	0.04	0.07	0.03