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Profitability, Asset Investment, and Aggregate Stock Returns

Abstract

The book-to-market ratio (B/M), profitability, and asset investment exhibit robust joint predictive power for the equity premium, generating out-of-sample R^2s of 7%, 20%, and 29%, respectively, in one-quarter-, one-year-, and two-year-ahead forecasts. Since profitability and investment are positively correlated with each other yet predict future returns in opposite directions, while B/M and profitability are negatively correlated with each other yet predict future returns in the same direction, the variables' joint predictive power is much higher than the sum of their standalone counterparts. Just as Fama and French (2006, 2015, 2016) and Hou, Xue, and Zhang (2014, 2015, 2017) show that profitable firms who invest conservatively are associated with high future alphas in the *cross section*, we find that high aggregate profits and low asset growth precede high aggregate stock returns in the *time series*. We also find that short-term (long-term) asset growth predicts one-year-ahead (two-year-ahead) stock returns—consistent with firms' investment decisions being more responsive to changes in discount rates that correspond to the investment's time horizon. To explain this pattern from a behavioral perspective requires two types of sentiment—one that primarily influences short-term investment and another that affects long-term investment only.

Keywords: Profitability; Asset growth; Book-to-market ratio; Equity premium forecasts.

JEL Classifications: G12, G17.

1. Introduction

Many recent studies document that one group of stocks with certain characteristics earn higher average returns than another. The return patterns that these studies uncover have often been referred to as "anomalies"—as they cannot be explained by the CAPM or the Fama and French (henceforth FF, 1993) three-factor model. FF (2006, 2015, 2016) and Hou, Xue, and Zhang (henceforth HXZ, 2014, 2015, 2017) 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). Yet, the success of these models also brings concerns 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". We follow these advices, and examine if the same mechanisms that FF and HXZ use to explain the firm-specific component of stock returns (as shown below in equations (1) and (2)) carry over to the market-wide component that is common across firms—whether common variations in profitability and investment can also explain common variations in future stock returns. After all, if cross-sectional variations in profitability and investment only happen to correlate, *ex post*, with the extent of mispricing across firms (Stambaugh and Yuan 2017)—rather than driven by the theoretical mechanisms proposed by FF and HXZ *ex ante*—it is unclear if their time-series variations would also predict aggregate stock returns.[1]

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 should make use of different state variables for their portfolio allocation. Welch and Goyal (2008) show that most predictors previously proposed have poor in-sample (IS) and out-of-sample (OOS) performance, and conclude that "the profession has yet to find some variable that has meaningful and robust empirical equity premium forecasting power, both IS and OOS." (p. 1505) We examine if the relationships between B/M, profitability, investment, and stock returns, as motivated by FF and HXZ, can fill this void—by generating robust forecasts of the equity premium. In fact, among the variables considered by Welch and Goyal (2008) is the B/M. Despite being shown by Kothari and Shanken (1997), Pontiff and

[1] Indeed, cross-sectional anomalies need not extend to the time series. For example, although Sloan (1996) finds that firm-level accruals negatively predicts stock returns in the cross section, Hirshleifer, Hou, and Teoh (2009) show that aggregate accruals is a *positive* time-series predictor of aggregate stock returns. Kothari, Lewellen, and Warner (2006) also find that the firm-level post-earnings announcement drift effect (PEAD), as documented by Bernard and Thomas (1990), becomes much weaker at the aggregate level.

Schall (1998), and Lewellen (1999) in earlier works that the B/M has significant time-series predictive power for stock returns, Welch and Goyal (2008) find that this predictive power is not robust. Motivated by FF's and HXZ's findings that profitability and investment can account for *cross-sectional* variations in stock returns that the B/M fails to explain, we investigate if profitability and investment can also help explain *time-series* variations in stock returns that cannot be accounted for by the B/M. Just as profitable firms investing conservatively are associated with high future alphas in the cross section, do high aggregate profits and low asset growth also precede high aggregate stock returns in the time series?

Since a firm-level variable's predictive power in the cross section needs not translate into predictive power for its aggregate counterpart in the time series, our analysis serves as an out-of-sample test of FF and HXZ. 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 out-of-sample 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."

Our analysis examines if FF and HXZ's mechanisms that tie B/M, profitability, investment, and stock returns together only hold for firm-specific deviations from market averages, or if they also hold for time-series variations in the market averages themselves. Specifically, does the valuation model in FF hold not only for firm-specific, but also for market-wide, components of its variables? Do firms in HXZ's model consider not only firm-specific, but also market-wide, components of their costs and benefits when making investment decisions?

FF use the valuation model of Miller and Modigliani (1961, MM hereafter) to motivate the link between profitability, investment, and stock returns, and can be written as:

$$\frac{M_t}{B_t} = \frac{\sum_{\tau=1}^{\infty} E(Y_{t+\tau} - dB_{t+\tau})/(1+r_t)^{\tau}}{B_t}, \tag{1}$$

where M_t is a firm's market value of equity at the end of period *t*, B_t is the book value of equity at the end of period *t*, $Y_{t+\tau}$ is the earnings to be received at the end of period *t*+*τ*, $dB_{t+\tau}$ is the change in book equity in period $t+\tau$, defined as $(B_{t+\tau} - B_{t+\tau-1})$, and r_t is expected stock return.[2] FF (2006, 2015, 2016) and Aharoni, Grundy, and Zeng (2013) examine if this relationship that links B/M, profitability, investment, and stock returns together holds for firm-specific deviations from market averages. For instance, with a firm's market-adjusted B/M being held constant, they evaluate if the firm's expected stock returns would be higher than the market average when its market-adjusted profitability is high or its market-adjusted investment is low.

HXZ (2014, 2015) motivate the importance of profitability and investment with a q-theory-based model:

$$E_t\left[r_{i,t+1}\right] = \frac{E_t\left[\Pi_{i,t+1}\right]}{1 + a\left(I_{i,t}/A_{i,t}\right)}, \tag{2}$$

where $E_t\left[r_{i,t+1}\right]$ is the expected date t+1 stock return of firm i as of date t; $E_t\left[\Pi_{i,t+1}\right]$ is the expected date t+1 profitability of firm i as 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 a constant parameter; and $1 + a\left(I_{i,t}/A_{i,t}\right)$ is the marginal cost of investment. Equation (2) 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). The empirical analysis of HXZ (2014, 2015) examines the cross-sectional relationship between profitability, asset investment, and expected stock returns—effectively focusing on variations of these variables relative to their market averages.[3]

Our initial findings suggest that the time-series predictive power of B/M and profitability for aggregate stock returns is weak. As standalone predictors, both B/M and

[2] r_t is the internal rate of return (IRR) calculated as of time t. MM's valuation model, written as in equation (1), does not imply that the IRR r_t necessarily has to take on the same value for different t. What it does imply, however, is the term structure of discount rates when applied to $(Y_{t+\tau} - dB_{t+\tau})$ with the same t but different τ, is flat. This restriction is analogous to that imposed by the "implied cost of capital" methodology—which backs out the IRR (with a flat term structure) conditional on current analyst earnings forecasts. Pastor, Sinha, and Swaminathan (2008) and Li, Ng, and Swaminathan (2013) use this methodology to back out the IRR on the aggregate stock market.

[3] Consistent with equations (1) and (2), in our empirical analyses below, the computation of expected future aggregate stock returns as of period t excludes firms that only get listed after period t.

profitability have negative OOS R^2s. Only asset investment has IS and OOS R^2s that are both positive.[4]

Yet, in evaluating the predictive power of B/M, profitability, and investment, it is important to go beyond univariate, simple regressions. Both FF and HXZ emphasize the cross-sectional predictive power of these variables is *conditional* in nature.[5] We show that these insights carry over to the time series. In sharp contrast to the results from simple regressions, all three predictors become significant when they are used jointly in multiple regressions. In annual forecasts, the predictive coefficients on (standardized) B/M, profitability, and investment are 0.038, 0.062, and -0.062, with wild-bootstrapped *p*-values of 0.907, 0.981, and 0.001, respectively. Economically, these coefficient estimates suggest that a one-standard-deviation increase in B/M, profitability, and investment—conditional on the other two variables—will lead to changes in one-year-ahead expected equity premium by 3.8%, 6.2%, and -6.2%.[6] The OOS R^2s are 7%, 20%, and 29%, respectively, in one-quarter-, one-year-, and two-year-ahead forecasts. 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. By contrast, when B/M or profitability is used as standalone predictors, the OOS R^2s are all negative. Using the Harvey, Leybourne, and Newbold's (1998) encompassing test, we find that the predictive content of the three-variable model cannot be subsumed by a model that uses investment only, or by a model that includes only B/M and profitability.[7] In sum, we find strong evidence that *the whole is more than the*

[4] The poor performance of B/M and various measures of scaled earnings as predictors of aggregate stock returns has been documented by Welch and Goyal (2008), Kothari, Lewellen, and Warner (2006), and Bali, Demirtas, and Tehranian (2008).

[5] "Cleanly identifying the book-to-market, profitability, or investment effects in expected returns requires controls for the other two variables, which are often missing in earlier tests." (FF 2006, p.493) "Controlling for profitability and investment, B/M is positively related to average return, and there are similar conditional predictions for the relations between average return and profitability or investment… Fama and French (1995) show that the three variables are correlated. High B/M value stocks tend to have low profitability and investment, and low B/M growth stocks – especially large low B/M stocks – tend to be profitable and invest aggressively." (FF 2015, p.4) "The negative investment-return relation is conditional on a given level of ROE. The correlation could be positive unconditionally if large investment delivers exceptionally high ROE. Similarly, the positive ROE-return relation is conditional on a given level of investment. The correlation could be negative unconditionally if high ROE comes with exceptionally large investment. A joint sort on investment and ROE controls for these conditional relations." (HXZ 2014, p.12)

[6] In simple regressions, the coefficient estimates on B/M, profitability, and investment are, respectively, 0.031, 0.011, and -0.046, and only investment is statistically significant.

[7] Vuolteenaho (2002) and Kelly and Pruitt (2013) have examined the joint predictive power of B/M and profitability for stock returns, but have not studied investment. Cochrane (1991), Lamont (2000), and Arif and Lee (2014) have examined the predictive power of certain measures of investment for aggregate stock returns, but have not jointly considered B/M and profitability.

sum of its parts—the B/M, profitability, and investment have joint predictive power that is substantially higher than the sum of their standalone predictive power.

Next, we analyze how this improvement comes about. At both the aggregate-market and 48-industry levels, profitability and investment are positively correlated with each other over time yet predict future returns in opposite directions—profitability positively forecasts while investment negatively forecasts stock returns. At the same time, B/M and profitability are negatively correlated with each other yet both predict future returns positively. This correlation structure "masks" the predictive power of an individual variable in univariate regressions. In annual aggregate data, the correlation between profitability and investment is 0.50 (p-value = 0.0001) and the correlation between profitability and B/M is -0.52 (p-value < 0.0001). When computed at quarterly frequencies, the corresponding correlation coefficients are 0.29 (p-value = 0.0002) and -0.77 (p-value < 0.0001). Similar patterns are also found at the 48-industry level, with the time-series correlation between profitability and investment being significant and positive, and that between profitability and B/M being significant and negative.

To measure profitability, we follow Novy-Marx (2013) in using gross profits (revenue minus cost of goods sold) rather than earnings. Gross profits better capture expensed investments (such as R&D and advertising), which directly reduce earnings without increasing book equity, but are associated with higher future economic profits. In this sense, gross profits are considered "the cleanest accounting measure of true economic profitability." (Novy-Marx 2013, p. 2) However, we do not follow Novy-Marx (2013) in scaling gross profits by total assets, to avoid confounding profitability with asset growth (see Zhang 2017). Instead, we follow FF (2015) and HXZ (2015) and scale profits by book equity. At the same time, to avoid confounding profitability with PEAD (see Novy-Marx 2015), we always examine *annual* gross profits. Even in quarterly analyses, we compute profitability based on total gross profits in the previous four quarters.[8] In Section 5.2 below, we use Ball, Gerakos, Linnainmaa, and Nikolaev's (2016) cash-based operating profits as an alternative earnings measure and find that our results are robust to this change.[9]

[8] FF's (2015, 2016) profitability factor is also formed using annual gross profits.

[9] In contrast to the results in the cross section, we find that cash-based operating profits do not display stronger forecast power than gross profits for aggregate stock returns. This result is due to firm-level accruals display negative predictive power for cross-sectional stock returns but aggregate operating accruals display positive forecast power for aggregate stock returns (see Hirshleifer, Hou, and Teoh 2009 and Table 8 below). As such, including accruals in aggregate profitability does not hurt its forecast power for future stock returns.

With respect to investment, although equation (1) refers to equity investment, $dB_{t+\tau}/B_t$, we follow FF (2006, 2015, 2016) and HXZ (2015) to measure investment as total asset growth, $dA_{t+\tau}/A_t$, which the authors judge to give a better picture of investment.[10] Cochrane (1991) constructs an aggregate investment measure from macroeconomic data that negatively predicts subsequent stock returns, but the predictive power is subsumed by the dividend yield. Lamont (2000) reports a stronger predictive relationship between investment and stock returns, but the investment measure is based on survey data on managers' *expected* (rather than actual) investment. Arif and Lee (2014) construct an aggregate investment measure that focuses on certain components of total asset growth. Their investment measure displays strong predictive power for two-year-ahead (but not one-year-ahead) aggregate stock returns. By contrast, total asset growth, the investment measure used by FF and HXZ and examined here, exhibits predictive power for aggregate stock returns that is robust across both the one- and two-year horizons.

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—from both an investment perspective (left-hand side of the balance sheet) and a financing perspective (right-hand side of the balance sheet). From the investment perspective, total assets are decomposed into cash and short-term assets,[11] other current assets, property, plant, and equipment (PPE), and other assets. From the financing perspective, total assets are decomposed into operating liabilities, retained earnings, equity financing, and debt financing. 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. The growth in cash and short-term assets can only predict one-year-ahead (but not two-year-ahead) stock returns while the growth in longer-term assets can only predict two-year-ahead (but not one-year-ahead) stock returns. By incorporating the predictive power of all its individual components, total asset growth can forecast future stock returns at *both*

[10] We obtain qualitatively similar results when $dB_{t+\tau}/B_t$ is used to measure investment instead. $dB_{t+\tau}/B_t$ is highly correlated with $dA_{t+\tau}/A_t$, with a correlation of 0.86 (p-value < .0001). The predictive power of $dB_{t+\tau}/B_t$ for future stock returns is somewhat weaker, but remains significantly negative. In addition, $dB_{t+\tau}/B_t$ is still significantly negatively correlated with B/M and significantly positively correlated with profitability. As a result, the conditional predictive power of B/M and profitability—whether conditional on $dA_{t+\tau}/A_t$ or $dB_{t+\tau}/B_t$—is unaffected.

[11] This 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 maturity of up to 90 days at issuance and financial assets that the firm intends to liquidate within a year.

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 the equity premium as total asset growth across different time horizons.[12]

Although equation (1) by itself does not tell us if valuations are driven by rational or behavioral factors, our finding that short-term (long-term) asset growth forecasts short-term (long-term) stock returns is consistent with firms' investment decisions being more responsive to changes in discount rates that correspond to the investment's time horizon. By contrast, to explain this pattern from a behavioral perspective requires two types of sentiment—one that primarily influences short-term investment and another that affects long-term investment only. Such a characterization of investor sentiment, while not inconceivable, has yet to receive any empirical support elsewhere.[13]

At the same time, since we already control for profitability in our predictive regressions, marginal variations in asset growth are more likely to pick up discount rate movements—rather than biased earnings expectations. If systematic biases in managers' earnings expectations are caused by firms' recent performance and managers' subsequent over-extrapolation (Greenwood and Shleifer 2014; Hirshleifer, Li, and Yu 2015), by holding recent earnings constant in a multiple regression, we alleviate the concern that any marginal variation in asset growth is driven by such extrapolative expectations biases.

To show that jointly using aggregate B/M, profitability, and investment as predictors does make an economically significant impact on equity premium forecasts, we begin with what an investor observed in mid-2016. At that time, purely from a valuation standpoint, the stock market already appeared "expensive"—B/M was more than one standard deviation (s.d.) below its historical mean. As a result, the one-year-ahead equity premium forecast—based on B/M alone—was 2.5%. Yet, at the same time, since aggregate profitability was 1.2 s.d. above its mean and investment .38 s.d. below its mean, the forecasted equity premium became 11.3% when all three variables were used as predictors instead.[14] To evaluate the implication of our results for portfolio choice more systematically, we calculate the certainty equivalent return (CER) gain from using aggregate B/M, profitability, and investment as predictors—relative to

[12] Appendix B below examines the predictive power of Arif and Lee's (2014) investment measure in detail.
[13] Even though investor sentiment can 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).
[14] With the benefit of hindsight, we now know that the actual equity premium from June 2016 to June 2017 is 14.7%.

the case where only the B/M is used. We find that, depending on the value of the risk aversion parameter, the CER gain ranges from 2.23% to 3.61% when one-year-ahead equity premium forecasts are used, and ranges from 2.97% to 6.88% when two-year-average equity premium forecasts are used for portfolio allocation.

We also investigate if the predictive power of profitability and asset investment comes from their correlation with other known predictors of the equity premium. In particular, we control for the T-bill rate, term spread, default spread, CAY (the consumption-wealth ratio constructed by Lettau and Ludvigson 2001), the cross-sectional beta premium (Polk, Thompson, and Vuolteenaho 2006), 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 (2015). We find that, even in the presence of these control variables, the predictive power of profitability and asset investment remains relatively unchanged.

As we discuss in Footnote 3 above, to use equations (1) and (2) for an aggregate-level analysis, we should only include those firms that are already in existence in period t when calculating the aggregate market return to be forecasted in period t+1 or t+2. To examine how sensitive our results are to this restriction, we replace our market return measures by the CRSP value-weighted returns—which include new firms that get listed between period t and period t+1 or t+2. Not surprisingly, we find that the results become weaker—but only slightly so. All our main conclusions remain unchanged.

Our analysis emphasizes the evaluation of out-of-sample 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). Relative to typical predictive regressions that only use valuation ratios as predictors, our concern for this small-sample bias is further reduced by profitability and investment being less persistent than the valuation ratios,[15] and the correlations between aggregate stock returns and contemporaneous asset investment and profitability both being insignificantly different from zero. To further alleviate the concern that our in-sample inferences are distorted, we rely on p-values obtained from a wild bootstrap

[15] The first-order autocorrelations of asset investment and profitability are equal to 0.6 and 0.8, respectively, whereas those for the valuation ratios are in the neighborhood of 0.9.

procedure, explained in detail by Huang, Jiang, Tu, and Zhou (2015), to carry out inferences on our main in-sample predictive regression estimates.[16]

The rest of the paper proceeds as follows. Section 2 provides a brief review of studies that are related to ours. Section 3 documents data and sample construction. Section 4.1 reports our equity premium forecasts and their statistical significance. Section 4.2 evaluates economic significance. Section 4.3 decomposes asset growth into its individual components and evaluates their predictive power over different forecast horizons. Section 4.4 examines if the predictive power of profitability and investment is related to aggregate stock market volatility. Section 5 carries out a series of robustness checks. Section 6 concludes.

2. Literature Review

Our study builds on the literature that uses various investment and profitability measures to explain the *cross section* of expected stock returns. FF (2006, 2015, 2016), Aharoni, Grundy, and Zeng (2013), and HXZ (2015) control for both the profitability and investment factors, while Novy-Marx (2013) and Ball, Gerakos, Linnainmaa, and Nikolaev (2015, 2016) focus on the explanatory power of profitability. Titman, Wei, and Xie (2004) find that firms with higher capital investment tend to have lower subsequent stock returns. Using a variance decomposition approach, Mao and Wei (2016) further demonstrate that investors' cash flow expectations for high-investment firms tend to be overoptimistic. Cooper, Gulen, and Schill (2008) find that total asset growth negatively predicts future abnormal stock returns. Lipson, Mortal, and Schill (2011) further show that total asset growth subsumes the predictive power of other investment measures, and that the asset growth effect is concentrated in firms that are relatively costly to arbitrage.

The investment effect can also be understood from a rational perspective. Based on the *q*-theory of investment, Lin and Zhang (2013) and HXZ (2015) propose a two-period model, as displayed in equation (2) above, in which firms invest until the marginal cost of date t investment equals its expected date t+1 marginal benefit. This *q*-theory-based model has

[16] When generating the pseudo samples, this procedure makes use of Nicholls and Pope's (1988) results to obtain reduced-bias estimates for the AR(1) parameters of the predictors—as suggested by Stambaugh (1999) and Amihud, Hurvich, and Wang (2009)—so as to capture the persistence of the predictors more accurately. Correlations between the predictors and contemporaneous stock returns as well as conditional heteroscedasticity in the variables are also built into the generation of pseudo samples.

received empirical support from HXZ (2015), who find that a four-factor model that combines the market, size, profitability, and investment factors can account for many anomalies in the cross section of stock returns. Xing (2008) finds that the value effect disappears once an investment growth factor has been controlled for, where the investment growth factor is defined as the difference in returns between low-investment and high-investment stocks. Li and Zhang (2010) and Lam and Wei (2011) compare the relative explanatory power of *q*-theory-based versus mispricing-based variables for the investment effect. Li and Zhang (2010) find that mispricing-based variables tend to be stronger, while Lam and Wei (2011) show that both sets of variables receive similar degrees of empirical support. Bakke and Whited (2010) show that private investor information affects corporate investment but stock market mispricing does not. Warusawitharana and Whited (2016) find that stock misevaluation affects firms' financing rather than their investment decisions. Using an international sample, Watanabe, Xu, Yao, and Yu (2013) further show that the negative cross-sectional relationship between asset growth and subsequent stock returns is stronger in markets with more efficient stock prices, suggesting that the relationship is more likely due to an optimal investment effect rather than mispricing. Kogan and Papanikolanou (2013) show that the investment anomaly is related to investment-specific technology (IST) shocks. Specifically, they find that firms' investment rates are associated with future IST risk exposures, even after other risks have been controlled for. They find that heterogeneity in IST shocks account for a large fraction of the average return variations that are associated with investment rates.

A long literature examines the predictive power of various valuation ratios for future stock returns. FF (1988) study the predictive relationship between the dividend-price ratio and subsequent aggregate stock returns, and find that this predictive power tends to strengthen at longer forecast horizons. Campbell and Shiller (1988a, 1988b) use a vector-autoregressive (VAR) framework to examine how this predictive relationship is linked to the variation in the dividend-price ratio over time. Vuolteenaho (2002) extends this framework and relates variations in the book-to-market ratio to movements in future stock returns and profitability.

Recent empirical evidence on the predictive power of valuation ratios is more mixed. Ang and Bekaert (2007) find that the dividend yield can only predict aggregate stock returns at short (but not long) horizons. Henkel, Martin, and Nardari (2011) further show that the dividend yield exhibits short-horizon forecast power for stock returns only during business cycle contractions (but not expansions). Welch and Goyal (2008) find that the OOS forecast performance of valuation ratios is much poorer than their IS counterparts. On the other hand, Campbell and Thompson (2008) show that, after imposing sign restrictions on coefficient estimates and return forecasts, valuation ratios beat the historical mean in their out-of-sample forecast accuracy.[17] Cochrane (2008) finds that the evidence for the absence of dividend growth predictability is more compelling than the presence of stock return predictability. Given that either future stock returns or future dividend growth rates must be predictable to justify the variation in the dividend-price ratio, Cochrane interprets the lack of dividend growth predictability as supportive evidence for return predictability.

To account for the weak empirical relationship between the dividend-price ratio and subsequent stock returns, Menzly, Santos, and Veronesi (2004) propose a general equilibrium model that exhibits time-varying expected dividend growth rates. These time-varying expectations induce a negative relationship between the dividend yield and expected returns, offsetting the positive relationship that would be present if expected dividend growth rates were constant. Lettau and Van Nieuwerburgh (2008) examine the effects of possible shifts in the steady-state means of the valuation ratios. Jank (2015) further examines how such shifts occurred when a large number of low-dividend-paying firms entered the stock market since the 1970s, resulting in a decline of the aggregate dividend-price ratio.

Other recent studies exploit disaggregate information in making aggregate-level forecasts. To predict the aggregate stock return, Ferreira and Santa-Clara (2011) forecast its three components—the dividend-price ratio, earnings growth, and the price-earnings ratio growth. Kelly and Pruitt (2013) extract a single factor from the cross section of firm-level book-to-market ratios. Both methods achieve considerable improvements in OOS forecast accuracy.

3. 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) with December fiscal year-ends, but exclude all financial firms (SIC codes 6000-6999). We also exclude firm-years (or firm-quarters) with book assets less than \$25 million or book equity less than \$12.5 million. Our annual (quarterly) accounting data covers the period

[17] All our OOS equity premium forecasts below also impose the Campbell and Thompson's (2008) sign restrictions.

1962-2014 (1975Q1-2016Q4), and the corresponding stock returns data spans July 1963-June 2016 (August 1975-July 2017).

Our main predictors include 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 liquidating 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. Firm *i*'s profitability in year *t*, GP_{it}/B_{it-1}, is defined as the firm's gross profits in year *t* divided by its book equity in year *t*-1, where gross profits is computed as revenues (Compustat item REVT) minus cost of goods sold (Compustat item COGS). Gross profits better capture expensed investments (such as R&D and advertising), which directly reduce earnings without increasing book equity, but are associated with higher future economic profits. In this sense, gross profits are considered "the cleanest accounting measure of true economic profitability." (Novy-Marx 2013, p. 2) However, we do not follow Novy-Marx (2013) in scaling gross profits by total assets, to avoid confounding profitability with asset growth (see Zhang 2017). Instead, we follow FF (2015) and HXZ (2015) and scale profits by book equity.[18] 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 quarterly analyses, we use quarterly-updated annual variables. Specifically, we compute profitability as total gross profits over the latest four quarters scaled by four-quarter-lagged book equity—rather than just using gross 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 described in Appendix A. All firm-level accounting variables are winsorized at the 0.5 and 99.5 percentiles every year/quarter.

Aharoni, Grundy, and Zeng (2013) point out that the valuation model (1) holds at the firm rather than per-share level. We follow their suggestion and measure all variables at the

[18] In Section 5.2 below, we use Ball, Gerakos, Linnainmaa, and Nikolaev's (2016) cash-based operating profits as an alternative earnings measure and find that our results are robust to this change.

firm level, without scaling them by the number of shares outstanding. We then aggregate each firm-level variable together by using firms' end-of-period market capitalizations as the weights.

Since we only include firms with December year-ends in our sample, in the annual analysis, we use accounting variables 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 six-month gap for accounting information to become publicly available after a fiscal year ends. 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.[19] In the quarterly analysis, 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* would be 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_{t+1}^{e}) by aggregating firm-level excess returns using the market capitalizations at the end of year *t* as weights. The two-year average return $R_{(t+1,t+2)}^{e}$ is defined as the geometric average of annual excess stock returns R_{t+1}^{e} and R_{t+2}^{e}. 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 70,970 firm-years of accounting data over the period 1962-2014. The corresponding return prediction period spans July 1963-June 2016. Our quarterly sample contains 241,071 firm-quarters of accounting data over the period 1975Q1-2016Q4. The corresponding return prediction period spans August 1975-July 2017.

4. Empirical Results

This section reports our main empirical results. Section 4.1 uses OOS R^2s to compare the forecast accuracy of our predictors relative to the historical mean and tests the statistical significance of the difference. Section 4.2 compares our forecasts with those that only use B/M as predictor, and quantifies the economic significance of the difference by calculating the

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

certainty equivalent return (CER) gains. We then explore the source of the predictive power of asset growth by decomposing it into various components, and use these results to understand why the predictive power of the investment measure constructed by Arif and Lee (2014) is less robust than total asset growth across different time horizons. Last, we examine if higher B/M, higher aggregate profitability and lower asset growth—predictors of higher equity premium—also predict higher aggregate stock market volatility.

4.1 Statistical Significance of the Equity Premium Forecasts

MM's valuation model, which motivates our analysis, implies that equation (1) holds for all firms in period *t*. But since this relationship applies to all firms in period *t*, firms that only get 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 equity premium forecast is made—instead of using the returns on a stock market index, which allows new firms to enter after period *t*.[20] In addition to B/M, profitability, and asset investment, which we already discuss in Section 3 above, we also control for other predictors for the equity premium. These variables are discussed in detail in Appendix A. Table 1 reports their summary statistics, as well as the correlation matrices among the main variables.

To compute OOS R^2s 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 equity premium forecast is for the period 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 updated at the end of June every year, incorporating data that just become available in real time. 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 2016. For two-year-average return forecasts, the OOS forecast period covers July 1993-June 2016. In the quarterly analysis, the training window covers accounting data

[20] In Section 5.3 below, we show that our main results become only slightly weaker at annual frequency when the CRSP value-weighted index is used instead to measure aggregate market returns.

from 1975Q1 to 1990Q4 and stock returns data up to July 1991. The OOS forecast period is from August 1991 to July 2017.

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

$$R^2_{OOS} = 1 - \frac{\sum_t (y_t - \hat{y}_t)^2}{\sum_t (y_t - \bar{y}_t)^2}, \tag{3}$$

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 (2001)'s 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:

$$\mathrm{ENC-NEW} = P \frac{P^{-1}\sum_t \left(\hat{u}^2_{1,t+1} - \hat{u}_{1,t+1}\hat{u}_{2,t+1}\right)}{P^{-1}\sum_t \hat{u}^2_{2,t+1}}, \tag{4}$$

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 equity premium 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.

4.1.1 Forecasting Aggregate 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 geometric average of 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 B/M, 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 Huang, Jiang, Tu, and Zhou's (2015) wild bootstrap procedure.

Both B/M and profitability exhibit weak predictive power when they enter as standalone predictors—with negative OOS R^2s and only B/M is significant in sample (at the 10% level). Asset growth by itself is a strong predictor for future stock returns—a one-standard-deviation increase in asset growth would lower one-year-ahead stock returns by 4.6%, with the impact being statistically significant at the 1% level. Its OOS R^2 is 12%, with a forecast accuracy improvement relative to the historical mean that is statistically significantly at the 5% level, as indicated by the ENC-NEW statistic.

Due to the correlation structure among the predictors, we go beyond simple regressions and examine their joint predictive power. Since B/M and profitability are negatively correlated with each other (correlation coefficient of -0.52, with *p*-value < 0.0001, as shown in Table 1, Panel B) yet both of them positively forecast future stock returns, their predictive power offsets each other when they enter the regression separately. At the same time, since profitability and asset growth are positively correlated (correlation coefficient of 0.50, with *p*-value = 0.0001) yet predict aggregate stock returns in opposite directions, their predictive power for aggregate stock returns could cancel each other out in univariate, simple regressions.

Table 2, Panel A, Column (4) shows that, jointly controlling for both B/M and profitability moves the OOS R^2 into positive territory (1%), although still not enough to generate a statistically significant forecast accuracy improvement relative to the historical mean (the ENC-NEW statistic is insignificantly different from zero). The magnitudes of the predictive coefficients also increase—from 0.031 to 0.050 for B/M, and from 0.011 to 0.036 for profitability.

The improvement in predictive power is more apparent when we control for asset growth as well. These results are reported in Table 2, Panel A, Column (6). The OOS R^2 of 20% is associated with a forecast accuracy improvement (relative to the historical mean) that is statistically significant at the 5% level.[21] All three variables' coefficient estimates and *t*-statistics increase in magnitude relative to their standalone counterparts. Profitability exhibits the most substantial increase—from 0.011 (*t*-stat = 0.40) to 0.062 (*t*-stat = 3.01). The coefficient

[21] Using different approaches to obtain annual equity premium forecasts, Ferreira and Santa-Clara (2011) and Kelly and Pruitt (2013) report OOS R^2 of 13.4% and 13%, respectively.

estimate of 0.062 implies that a one-standard-deviation increase in profitability would raise aggregate stock return by 6.2%. For B/M and asset growth, their coefficient estimates of 0.038 and -0.062 indicate that a respective one-standard-deviation increase in these variables would increase aggregate stock returns by 3.8% and depress aggregate stock returns by 6.2%.

In results reported on Table 2, Panels B and C, we show that our findings carry over to the forecasts of two-year-average and one-quarter-ahead stock returns. In the quarterly analysis reported on Table 2, Panel C, B/M, profitability, and asset growth are all computed using quarterly accounting data. To avoid confounding profitability with PEAD (see Novy-Marx 2015) and to reduce the impact of seasonalities, we compute profitability as total gross profits over the latest four quarters (scaled by four-quarter-lagged book equity), rather than just using gross profits from the most recent quarter. In other words, we are still measuring firms' annual profitability—only now we update them quarterly (rather than annually). In line with this convention, we also compute quarterly updated annual asset growth—as the change in total assets over the latest four quarters scaled by four-quarter-lagged total assets.

Finally, using the encompassing tests of Harvey, Leybourne, and Newbold (1998) and Rapach, Strauss, and Zhou (2010), we find that the predictive content of the three-variable model cannot be subsumed by a model that uses asset investment only, or by a model that includes only B/M and profitability.[22] These alternative models are of interest because Vuolteenaho (2002) and Kelly and Pruitt (2013) have examined the joint predictive power of B/M and profitability, whereas Cochrane (1991), Lamont (2000), and Arif and Lee (2014) have examined the predictive power of certain measures of investment for aggregate stock returns—but no prior studies have jointly examined the time-series predictive power of all three variables together.

In sum, our results in this section constitute strong evidence that *the whole is more than the sum of its parts*—the B/M, profitability, and investment have joint predictive power that is substantially higher than the sum of their standalone predictive power.

[22]An encompassing test compares the OOS forecast performance between two models *i* and *j*. The null hypothesis is that model *i*'s forecast encompasses model *j*'s forecast, i.e., model *j*'s forecast does not contain any useful information beyond model *i*'s forecast. Our (untabulated) results show that we cannot reject the null hypothesis that the three-predictor model encompasses models with only asset growth (*p*-value = 0.71) or with B/M plus profitability (*p*-value = 0.96).

4.1.2 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. If a predictive model outperforms the historical mean over a certain time period, the model would display a positively-sloped CSFE difference curve over this period. Figures 1 and 2, respectively, plot these differences in CSFE for our annual and quarterly analyses.

Figure 1, Panel A displays the CSFE difference for the B/M. Its slope throughout the forecast period is predominantly negative—suggesting that B/M consistently underperforms the historical mean as a predictor. The specifications that add either profitability or asset growth to B/M fare slightly better—especially since the financial crisis of 2008. Panel D displays the model with standalone asset growth, and Panel E the model with all three predictors. These CSFE difference curves display an overall positive slope—suggesting that their superior OOS performance is not driven by an isolated episode. Figure 2 displays a similar pattern using quarterly data. Both Figures 1 and 2 show that the three-variable model displays the most pronounced positive slope.

4.1.3 Forecasting Industry-Level Stock Returns

To see whether the time-series predictive relationship between B/M, profitability, asset growth, and future stock returns is robust, we carry out an analysis at the industry level. We aggregate firm-level B/M, profitability, and asset growth to the industry level and use them to forecast industry-level stock returns. At the end of each year/quarter, we group firms by the Fama-French 48-industry classification, weighting firm-level variables by each firm's end-of-year/end-of-quarter market capitalization. Since we have excluded all financial firms from our sample, there are no observations in Industries 44-47.

We run panel regressions with industry fixed effects. These regressions allow us to examine whether time-series variations in industry-level B/M, profitability, and asset growth predict industry-level stock returns. To make our results here more comparable with the aggregate-level results reported earlier, all independent variables are standardized by their industry-specific mean and aggregate standard deviation—so a unit change is equivalent to a one-aggregate-standard-deviation move of the variable in question. We run panel regressions that either equal-weight or value-weight industries every period. Since the two approaches generate similar results, we only report those that we obtain based on value weights, in Table 3. The *t*-statistics in parentheses are computed by using two-way clustered standard errors.

Table 3, Panels A to C, respectively, reports one-year-ahead, two-year-average, and one-quarter-ahead industry-level stock returns. Consistent with the aggregate-level analysis examined above, asset growth remains to be the predictor that exhibits the strongest standalone predictive power. The predictive power of B/M seems stronger at the industry than at the aggregate level. Comparing across all specifications, the three-predictor model continues to be the one with the highest adjusted R^2.

4.2 Economic Significance of the Equity Premium Forecasts

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

4.2.1 Recent Equity Premium Forecasts

We compare the equity premium forecasts—made as at June 2016—to see if the joint use of B/M, profitability, and asset investment as predictors leads to substantially different forecasts, relative to when only the B/M is used.

Table 4, Panel A reports the means, standard deviations, and the year 2015 values of the predictors. The last column computes the deviation of the 2015 values from their sample means, measured in standardized units (i.e. the deviations from means are scaled by their standard deviations). Panels B1 and B2 report the annual equity premium forecasts over July

2016-June 2017, and the average annual equity premium forecasts over July 2016-June 2018, respectively.[23]

In June 2016, the aggregate stock market already appeared expensive from a pure valuation perspective—B/M was more than one standard deviation below its sample mean. As a result, when only the B/M is used as predictor, the equity premium forecast over July 2016-June 2017 is given by 2.5%, which is 3.7% lower than the historical average of 6.2%.

Yet, profitability was high in 2015 relative to its historical average, and asset growth was low relative to its historical average. Thus, when profitability is added to the specification with B/M only, the forecasted equity premium for July 2016-June 2017 increases to 4.6%. When we use B/M, profitability, and asset growth as predictors, the equity premium forecast increases to 11.3%. We now know that, *ex post*, this last forecast is closest to the actual equity premium of 14.7% over this time 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 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 certainty equivalent return (CER) gains below.

4.2.2 CER Gains in Portfolio Allocation

This subsection reports the certainty equivalent return (CER) gains from jointly using the B/M, profitability, and asset investment—instead of the B/M only—as equity premium predictors in portfolio allocation. This CER gain represents the value to an investor in her portfolio allocation by switching from a B/M-based OOS predictive model to one that is based on the B/M, 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 B/M-based to our B/M-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

[23] Since the predictive coefficients reported on these panels are estimated from non-standardized variables, their magnitudes are different from those displayed in Table 2 above.

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:

$$w_t = \frac{1}{\gamma} \frac{\hat{R}^e_{t+1}}{\hat{\sigma}^2_{t+1}} , \tag{5}$$

where γ is the risk aversion coefficient, $\hat{R}^e_{t+1}$ is the out-of-sample equity premium 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 the equity premium, estimated using all available data prior to period *t*+1 (Ferreira and Santa-Clara 2011; Huang, Jiang, Tu, and Zhou 2015).

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

$$R^P_{t+1} = w_t R^e_{t+1} + R^f_{t+1} , \tag{6}$$

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, in order to exclude short sales and leverage that exceeds 50%.

The CER of the portfolio is given by

$$CER_P = \hat{\mu}_P - 0.5\gamma\hat{\sigma}^2_P , \tag{7}$$

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 the B/M alone as predictor.

The CER gains for the two-year-average equity premium forecasts are computed analogously. At the end of period *t*, the investor allocates the weight w_t to equities that is based on a predictive model’s two-year-average forecast for periods *t*+1 and *t*+2:

$$w_t = \frac{1}{\gamma} \frac{\hat{R}^e_{(t+1,t+2)}}{\hat{\sigma}^2_{(t+1,t+2)}} , \tag{8}$$

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 $R^P_{(t+1,t+2)} = \sqrt{(w_t {R^e}_{t+1} + R^f_{t+1})(w_t {R^e}_{t+2} + R^f_{t+2})}$,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 (5), 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_i^2) and (μ_n, σ_n^2), 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, $\upsilon = (\mu_i, \mu_n, \sigma_i^2, \sigma_n^2)$, and $\hat{\upsilon}$ its empirical counterpart. The function $f(\upsilon)$, $f(\upsilon) = \left(\mu_i - \frac{\gamma}{2}\sigma_i^2\right) - \left(\mu_n - \frac{\gamma}{2}\sigma_n^2\right)$, 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 5 reports the CER gains of other predictive models relative to the CER of B/M. We examine models that use B/M a profitability, or B/M plus profitability plus asset growth as predictors. We consider three different values of risk aversion coefficients ($\gamma = 1, 3,$ or 5).

Table 5, Panel A reports CER gains based on one-year-ahead equity premium forecasts. When $\gamma = 1$, the specification that includes all three predictors generates a positive CER gain of 3.23%, with a significance level of 5%. The CER gain for the specification with B/M plus profitability is negative but insignificant. When γ equals 3 or 5, the specification that includes all three predictors produces CER gains of 3.61% and 2.23%, respectively, which are both statistically significant at the 1% level. The specification with B/M plus profitability yields positive but statistically insignificant CER gains.

Table 5, Panel B reports CER gains based on two-year-average equity premium forecasts. As before, the specification of B/M plus profitability does not generate any statistically significant CER gain, regardless of the value of the risk aversion coefficient used. By contrast, the specification that includes all three predictors always yields positive and statistically significant CER gains, which range from 2.97% to 6.88%.

Overall, our results suggest that the benefit to a mean-variance investor in adding profitability and asset growth to a B/M-only model for portfolio allocation is both statistically and economically significant.

4.3 Decomposing Asset Growth

In this section, we investigate the source of the predictive power of asset growth by decomposing it into 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 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 6 reports the predictive power of individual components of asset growth for future excess stock returns. Table 6, Panels A and B, respectively, report the one-year-ahead and two-year-average return forecasts. 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, the growth in cash and short-term assets has the strongest predictive power by far. The predictive power of the growth rates in longer-term assets is relatively weak. At the two-year horizon, by contrast, the growth in cash and short-term assets—the component of total assets that has the shortest duration—is no longer significant. It is now the growth in longer-term assets that drive the predictive power of total assets.

Our finding that short-term (long-term) asset growth forecasts short-term (long-term) stock returns is consistent with firms' investment decisions being more responsive to changes in discount rates that correspond to the investment's time horizon—lending support to a rational interpretation of our results. By contrast, to explain this pattern from a behavioral perspective requires two types of sentiment—one that primarily influences short-term investment and another that affects long-term investment only. Such a characterization of investor sentiment, while not inconceivable, has yet to receive any empirical support elsewhere.

Arif and Lee (2014) also construct a measure of aggregate investment from firm-level data, and use it to forecast aggregate stock returns. As shown by Arif and Lee (2014), and reproduced in Appendix B below, their investment measure has significant predictive power for aggregate stock returns at the two-year horizon only. Its ability to forecast one-year-ahead stock return is not statistically significant. This finding can be understood in light of our results from this section—that long-term asset growth only forecasts long-term (but not short-term) stock returns—and the fact that Arif and Lee's investment measure contains only the longer-term components of total assets. Appendix B presents the details of this analysis.

4.4 Predicting Market Volatility

We find that higher B/M, higher profitability, and lower asset investment predict higher future stock returns. In this section, we investigate if this predictive power is related to market volatility risks. Following Huang et al. (2015), we estimate aggregate stock market variance in a time period by the sum of the squared daily returns on the CRSP value-weighted index during the period. We use the same timing convention as before. In annual analyses, $LVOL_{t+1}$ denotes aggregate stock market volatility over the period from July, year *t*+1 to June, year *t*+2. In quarterly analyses, $LVOL_{t+1}$represents aggregate stock market volatility over the three-month period that begins four months subsequent to calendar quarter *t*. Appendix A contains a more detailed discussion of this variable.

We examine if aggregate B/M, profitability, and asset growth in period *t* can predict $LVOL_{t+1}$, after controlling for $LVOL_t$. Table 7 reports these results, at both annual and quarterly frequencies. The predictive power of profitability is relatively weak and not robust across the two forecast horizons. B/M and asset growth have significant predictive power for *LVOL*—but with the "wrong" signs. Higher B/M predicts lower rather than higher future *LVOL*, while higher asset growth predicts higher rather than lower future *LVOL*. Since a higher B/M (asset growth rate) forecasts a higher (lower) equity premium, the variables' predictive power for the equity premium cannot be explained by time-varying market volatility risks. By contrast, since periods with high predicted equity premium are associated with low predicted market volatility, our predictors appear to pick up variations in the price (rather than the quantity) of market risks.

5. Robustness Checks

We carry out a number of robustness checks on our main results. First, we control for other known predictors of the equity premium. Second, we use Ball, Gerakos, Linnainmaa, and Nikolaev's (2016) cash-based operating profitability to construct an alternative measure of aggregate profitability. Third, we use our predictors to forecast the CRSP value-weighted index, thereby relaxing the requirement that we only forecast the returns of those firms that are already in our sample when the equity premium forecast is made. Fourth, we forecast non-overlapping two-year-average stock returns. Finally, we examine how the OOS predictive performance of B/M, profitability, and asset growth varies with the sample split year of the training sample.

5.1 Controlling for Other Predictors

In this section, we investigate if the predictive power of B/M, profitability, and asset investment comes from their correlations with other known predictors of the equity premium. In particular, we control for the term spread, default spread, T-bill rate, the Baker and Wurgler's (2006, 2007) sentiment index, the Huang, Jiang, Tu, and Zhou's (2015, HJTZ hereafter) partial-least-squares-based sentiment index, CAY (the consumption-wealth ratio constructed by Lettau and Ludvigson 2001), aggregate operating accruals (Hirshleifer, Hou, and Teoh 2009), the equity share in new issuance (Baker and Wurgler 2000), the cross-sectional beta premium (Polk, Thompson, and Vuolteenaho 2006), and the investment-to-capital ratio (Cochrane 1991).

Table 8, Panels A to C, respectively, report one-year-ahead, two-year-average, and one-quarter-ahead equity premium forecasts. When forecasting one-year-ahead aggregate stock returns, only the term spread, the HJTZ sentiment index, CAY, aggregate operating accruals, and the cross-sectional beta premium are statistically significant. The term spread by itself positively predicts one-year-ahead stock returns at the 1% level. This finding is consistent with Campbell and Vuolteenaho (2004) and Campbell, Polk, and Vuolteenaho (2010), among others. After controlling for B/M, profitability, and asset growth, term spread becomes insignificant and its magnitude drops from .039 to .017. A similar picture emerges at the two-year horizon as well. The term spread by itself significantly predicts two-year-average stock returns—but the predictive power weakens after B/M, profitability, and asset growth have been controlled for.

Consistent with the results presented in Huang, Jiang, Tu, and Zhou (2015), the HJTZ sentiment index significantly predicts future stock returns at the one-year and one-quarter (but not two-year) horizons. At the one-year and one-quarter horizons, the sentiment index by itself is statistically significant at the 5% and 1% levels, respectively. In the presence of B/M, profitability, and asset growth, its forecast power remains largely unaffected. After controlling for the HJTZ sentiment index, the explanatory power of B/M and profitability strengthens, but that of asset growth weakens, especially at the one-quarter horizon—for which the significance level of asset growth decreases from 1% to 10%.

CAY is another significant predictor for future stock returns. By itself, CAY is positively associated with one-year-ahead returns at the 5% level. This positive relationship between CAY and expected stock returns is explained by Lettau and Ludvigson (2001)—investors who desire smooth consumption over time will cut current consumption in response to forecasts of poor future stock returns. As a result, the consumption-to-wealth ratio positively forecasts future stock returns. We find that the predictive power of CAY becomes stronger as the forecast horizon lengthens—CAY becomes statistically significant at the 1% level and its magnitude rises from .029 to .047—when it is used to predict the two-year-average market returns. Moreover, the B/M, profitability, and asset growth subsume CAY's predictive power for one-year-ahead stock returns but not for two-year-average returns. By contrast, CAY's predictive power at the quarterly horizon is weak.

Aggregate operating accruals by itself positive forecasts one-year-ahead aggregate stock returns at the 10% level, but has no predictive power at the other forecast horizons. Even at the one-year horizon, its forecast power is subsumed by the inclusion of B/M, profitability, and asset growth,

The equity share in new issuance is found to positively predict one-quarter-ahead aggregate stock returns at the 10% 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 increases to 5% after controlling for our predictors.

The investment-to-capital ratio only has statistically significant predictive power for two-year-average aggregate stock returns, although its predictive power is subsumed by the inclusion of B/M, profitability, and asset growth.

The cross-sectional beta premium measures the association between a firm's expected stock return and its own beta—and is expected to positively forecast future market returns. Yet, we find that this variable predicts future aggregate stock returns with a *negative* sign—opposite to what it is supposed to be. Polk, Thompson, and Vuolteenaho (2006) also find that the cross-sectional beta premium does not significantly predict the equity premium in the second half of their sample period (1965-2002). They attribute the poor performance to the failure of the CAPM in recent years in capturing cross-sectional stock return variations.

In sum, even after controlling for all these predictors, profitability remains statistically significant at the 5% level in all 30 specifications considered while asset growth is significant at the 5% level in 28 out of 30 specifications. The result for B/M is somewhat weaker, but it is still significant at the 10% level (or stronger) in 17 of the 30 specifications. These results imply that the B/M, profitability, and asset growth contain predictive power for the equity premium that is not subsumed by other known predictors.

5.2 Using Cash-Based Operating Profitability

In this section, we use cash-based operating profitability as an alternative measure of aggregate profitability. Ball, Gerakos, Linnainmaa, and Nikolaev (2016) find that, by excluding accruals from profitability, cash-based operating profitability subsumes accruals in explaining the variations in cross-sectional stock returns. We find that cash-based operating profitability is highly correlated with the gross-profits-based profitability measure that we have been using—the correlation coefficient equals 0.89 and is significant at the 1% level. Like gross-profits-based profitability, cash-based operating profitability is also negatively correlated with B/M and positively correlated with asset growth.

Table 9 reports the results of using B/M, cash-based operating profitability, and asset growth to predict one-year-ahead and two-year-average stock returns. Because of its correlation structure with B/M and asset growth, we see that cash-based operating profitability, like the gross-profits-based measure we use before, is not a significant standalone predictor for future aggregate stock returns. But after B/M and asset growth have been controlled for, it becomes highly significant—both statistically and economically. A one-standard-deviation increase in cash-based operating profitability would raise both the one-year-ahead and two-year-average expected stock returns by 5.8%.

By comparing Table 9 with Table 2, we see that, unlike Ball, Gerakos, Linnainmaa, and Nikolaev's (2016) findings for the cross section, cash-based operating profitability does not display stronger forecast power than gross-profits-based profitability for the time series of aggregate stock returns. This result is due to firm-level accruals display negative predictive power for cross-sectional stock returns but aggregate operating accruals display *positive* forecast power for aggregate stock returns (see Hirshleifer, Hou, and Teoh 2009 and Table 8 above). As such, including accruals in aggregate profitability does not hurt its forecast power for future stock returns.

5.3 Predicting the CRSP Index Returns

As we discuss above, the relationship implied by equation (1) applies to all firms in period t, and firms that only get listed after period t should not be included in the calculation of expected future aggregate variables. For this reason, in all our analyses so far, the market returns (in periods t+1 and t+2) to be forecasted only include those firms that are already in our sample in period t when the equity premium forecast is made. Here, we examine the robustness of our results when we use the CRSP value-weighted index instead to measure aggregate market returns.

Table 10 reports these results. Panels A, B, and C of Table 10 examines the predictive regressions for one-year-ahead, two-year-average, and one-quarter-ahead stock returns, respectively. Comparing Table 10 with Table 2, we see that the overall predictive power of all three variables remains robust—with a deterioration in performance only at the quarterly horizon.

5.4 Non-Overlapping Two-Year-Average Stock Returns

So far, all our forecasts for two-year-average returns are made annually. Since the annual observations for two-year-average returns are overlapping, this approach induces serial correlations across different observations over time. To mitigate the concern that our results are driven by the overlapping observations, we redo our analysis for two-year-average returns—but using non-overlapping, two-year-average returns—with equity premium forecasts made only every other year.

Table 11 reports the return forecast results. Despite the sample size being cut in half, we see that the *t*-statistics and the levels of statistical significance of the three predictors decline only slightly—relative to those results reported in Table 2, Panel B. Table 12 reports results for the CER gains relative to the standalone B/M specification. Here, the impact of the sample size reduction is more apparent. Relative to results reported on Table 5, the drop in statistical significance is more substantial. The CER gain of the three-predictor model becomes insignificant when $\gamma = 1$, but remains statistically significant at the 10% level when $\gamma = 3$ and at the 1% level when $\gamma = 5$. In terms of magnitude, the CER gains still range from 2.30% to 5.68%, which are economically significant.

5.5 OOS R^2 with Different Sample Split Years

All our OOS analyses carried out so far use the year 1990 to divide the whole sample into a training sample and a test sample. This section examines if the OOS R^2s obtained before are sensitive to the choice of sample split year.

Figure 3 plots the OOS R^2s as a function of the sample split for a variety of predictive specifications—with the standalone B/M, B/M plus profitability, B/M plus asset growth, standalone asset growth, or all three variables used as predictors. Panels A and B, respectively, reports results from annual and quarterly analyses. We impose Campbell and Thompson's (2008) sign restrictions throughout. The sample split year ranges from 1982 to 1998.

Regardless of the sample split year chosen, and whether annual or quarterly analyses are carried out, the OOS R^2s of the three-variable specification are uniformly higher than those of other specifications. In annual analyses, the specification yields OOS R^2s of 20%-30%. The next best OOS forecast performance is achieved by standalone asset growth, which generates high and stable OOS R^2s of 10%-15%. Most of the OOS R^2s generated by standalone B/M are negative. The specification with B/M plus profitability outperforms standalone B/M prior to year 1996 and underperforms subsequently. In quarterly analyses, the three-variable specification generates OOS R^2s of 4%-8%, while standalone asset growth yields 3%-7%.

6. Conclusion

Profitability and asset investment play a special role in cross-sectional asset pricing. Not only are these variables themselves associated with significant return premia, HXZ (2015, 2017) and FF (2016) show that they also help account for a wide range of other anomalies that the CAPM and the FF's (1993) three-factor model fail to capture. Given this unique role played by profitability and investment, showing the robustness of the underlying mechanism that generates their explanatory power is of paramount importance.

While FF and HXZ focus on cross-sectional, firm-specific variations in profitability and investment, we find that variations in profitability and investment that are common across firms can also explain common variations in future stock returns. These results provide out-of-sample empirical support for FF and HXZ—as the same mechanisms that FF and HXZ use to explain firm-specific variations in stock returns can also be used to explain variations that are market-wide in nature.

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 should make use of different state variables for their portfolio allocation. However, Welch and Goyal (2008) argue that the finance profession has yet to identify predictors of the equity premium that are robust, both IS and OOS. We show that the relationships between B/M, profitability, investment, and stock returns, as motivated by FF and HXZ, can fill this void.

Also consistent with the insights of FF and HXZ for the cross section, we find strong time-series evidence that *the whole is more than the sum of its parts*—the B/M, profitability, and investment have joint predictive power that is substantially higher than the sum of their standalone predictive power. This result follows from the correlation structure between these variables. At both the aggregate-market and 48-industry levels, B/M and profitability are negatively correlated with each other but both variables positively forecast future stock returns; asset growth and profitability are positively correlated with each other yet predict future stock returns in opposite directions. As a result, the predictive power of these variables—as standalone predictors—tends to offset each other and becomes much weaker than their joint predictive power when all three variables are controlled for.

Although equation (1) by itself does not tell us if valuations are driven by rational or behavioral factors, our finding that short-term (long-term) asset growth forecasts short-term (long-term) stock returns is consistent with firms' investment decisions being more responsive to changes in discount rates that correspond to the investment's time horizon. By contrast, to explain this pattern from a behavioral perspective requires two types of sentiment—one that primarily influences short-term investment and another that affects long-term investment only. Such a characterization of investor sentiment, while not inconceivable, has yet to receive any empirical support elsewhere. At the same time, since we already control for profitability in our predictive regressions, marginal variations in asset growth are more likely to pick up discount rate movements—rather than biased earnings expectations. If systematic biases in managers' earnings expectations are caused by firms' recent performance and managers' subsequent over-extrapolation (Greenwood and Shleifer 2014; Hirshleifer, Li, and Yu 2015), by holding recent earnings constant in a multiple regression, we alleviate the concern that any marginal variation in asset growth is driven by such extrapolative expectations biases. However, we also show that the higher equity premium associated with higher B/M, higher profitability, and lower asset investment is not simply a compensation for higher market volatility risk. Whether it is other sources of risk, changes in the price of risk, or other behavioral factors that drive such variations in the equity premium is left for future research.

Appendix A. Variable Descriptions

1. Firm-level variables

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 liquidating 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 by following Hou, Xue, and Zhang (2015)—it equals 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.

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*). $\sum GP_{it}\,/B_{it-4}$ is firm *i*'s profitability in quarter *t*, defined as the sum of its gross profits in quarters *t*, *t*-1, *t*-2, *t*-3 divided by its book equity in quarter *t*-4. Quarterly gross profits is defined as revenues (Compustat item *REVTQ*) minus cost of goods sold (Compustat item *COGSQ*).

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 the balance sheet items in the computation of cash-based operating profitability are replaced by zero if missing.

dA/A. dA_{it}/A_{it-1} is firm *i*'s asset growth in *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, $dA_{it}/A_{it-4} = (A_{it} - A_{it-4})/A_{it-4}$, 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*) less cash and short-term investments (Compustat item *CHE*). Non-debt liabilities equals total liabilities (Compustat item *LT*) plus minority interest (Compustat item *MIB*) less 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.

2. Market-level variables

R^e. The annual excess aggregate stock return in *t*+1, R^e_{t+1}, 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. $R^e_{(t+1,t+2)}$ 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 the one-year Treasury constant maturity rates, measured as at the end of June in year *t*+1 in annual analyses (Table 8, Panels A and B), and as at the end of month 4 after calendar quarter *t* in quarterly analyses (Table 8, Panel C). The data are obtained from the Saint Louis Federal Reserve Economic Database.

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 8, Panels A and B), and as at the end of month 4 after calendar quarter *t* in quarterly analyses (Table 8, Panel C). The data are obtained from the Saint Louis Federal Reserve Economic Database.

Tbill. $Tbill_t$ is the thirty-day Treasury bill rate, measured as at the end of June in year *t*+1 in annual analyses (Table 8, Panels A and B), and as at the end of month 4 after calendar quarter *t* in quarterly analyses (Table 8, Panel C). The data are obtained from Warton Research Data Services (WRDS).

Sent^BW. $Sent^{BW}_t$ 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 8, Panels A and B), and the value in month 4 after calendar quarter *t* in quarterly analyses (Table 8, Panel C). The monthly index is obtained from Guofu Zhou's website.

Sent^HJTZ. $Sent^{HJTZ}_t$ is Huang, Jiang, Tu, and Zhou (2015)'s partial-least-squares-based investor sentiment index. We use the value of the index in June of year *t*+1 in annual analyses (Table 8, Panels A and B), and the value in month 4 after calendar quarter *t* in quarterly analyses (Table 8, 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 8, Panels A and B), and the value in calendar quarter *t*+1 in quarterly analyses (Table 8, 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 values of each numerator components 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 8, Panels A and B), and the monthly value one month prior to the return prediction period in quarterly analyses (Table 8, Panel C). The annual series over 1962-2007 and monthly series over July 1975-April 2008 are obtained from Jeffery Wurgler's website, and are extended to 2014 and April 2017, respectively, using data from the Federal Reserve Bulletin.

CSP. CSP_t is cross-sectional beta premium proposed by Polk, Thompson, and Vuolteenaho (2006). We use its annual value in year *t* in annual analyses (Table 8, Panels A and B), and its latest available quarterly value in quarterly analyses (Table 8, Panel C). Both the annual and quarterly series are obtained from Amit Goyal's website.

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 8, Panels A and B), and its latest available quarterly value in quarterly analyses (Table 8, Panel C). Both the annual and quarterly series are obtained from Amit Goyal's website.

LVOL. Annual $LVOL_t$ is the aggregate stock market volatility from July of year *t* to June of year *t*+1. It is equal to $\log(\sqrt{SVAR_t})$, where $SVAR_t$ is the annual aggregate stock market variance, defined as the sum of squared daily returns on the CRSP value-weighted index during the period,

$$SVAR_t = \sum_{i=1}^{N_t} R_{i,t}^2\,, \qquad (A3)$$

where N_t is the total number of trading days in the measurement period, and $R_{i,t}$ is the excess return of the CRSP value-weighted index on the i^{th} trading day of the measurement period. Quarterly aggregate stock market volatility is computed analogously, over the three months prior to the return prediction period.

Appendix B. Arif and Lee's (2014) Investment Measure

In this appendix, we examine the predictive power of the investment measure proposed by Arif and Lee (2014, AL hereafter), which we denote as $Invest_{AL}$. AL document that $Invest_{AL}$ has predictive power for two-year-ahead (but not one-year-ahead) aggregate stock returns. We obtain the same results, as shown in Table B.1. From Table B.1, Panel A, we see that $Invest_{AL}$'s forecast power for one-year-ahead stock returns is weak, with or without controlling for B/M and profitability. However, it is significantly associated with two-year-average returns over years t+1 and t+2—a one-standard-deviation increase in $Invest_{AL}$ depresses the average return by 5.2%. The corresponding OOS R^2 is 32%, with a forecast accuracy improvement over the historical mean that is statistically significant at the 1% level. When B/M, profitability, and $Invest_{AL}$ are controlled for, all predictors are significantly associated with the two-year-average returns, with an IS adjusted R^2 of 29% and OOS R^2 of 30%.

To understand why the predictive power of asset growth is robust across investment horizons but $Invest_{AL}$ is not, we decompose $Invest_{AL}$ into its components:

$$Invest_{AL,t} = ChgNOA_t + RND_t = ChgAT_t - ChgSTAsst_t - ChgNonDebt_t + RND_t, \quad \text{(D1)}$$

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 asset (i.e., the change in cash and short-term investments), $ChgNonDebt_t$ is the change in non-debt liabilities. All 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 in 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 B.2 reports 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 the stock returns in t+1, but exhibits strong predictive power for the returns in t+2. RND_t displays marginal predictive power for the stock returns in t+1 only and has no significant predictive power for the stock returns in year t+2. After breaking $ChgNOA_t$ down further into $ChgAT_t$, $ChgSTAsst_t$, and $ChgNonDebt_t$, it becomes clear that the difference in the predictive power between asset growth and $Invest_{AL}$ comes from two sources—$ChgSTAsst_t$ and $ChgNonDebt_t$. Since 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 $Invest_{AL,t}$ insignificant when predicting one-year-ahead stock returns. In contrast, since neither $ChgSTAsst_t$ nor $ChgNonDebt_t$ can predict the stock returns in year t+2, $Invest_{AL,t}$ inherits the predictive power of $ChgAT_t$ at the two-year horizon.

Table B.1 The predictive power of *$Invest_{AL}$*

This table reports time-series predictive regression results that use Arif and Lee's (2014) investment measure, *$Invest_{AL}$*, as predictor. 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. Panel A predicts one-year-ahead stock returns; Panel B predicts the average stock returns over years *t*+1 and *t*+2. Our full sample of annual accounting data covers the period 1962-2014, and the corresponding stock returns data spans July 1963-June 2016. For OOS analyses, 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 2016 (for one-year-ahead return forecasts) and July 1993-June 2016 (for two-year-average return forecasts). The Clark and McCracken (2001)'s 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 B.1 The predictive power of *Invest$_{AL}$* (continued)

Panel A: Predicting one-year-ahead stock returns R^e_{t+1}						
	1	2	3	4	5	6
Constant	0.064***	0.064***	0.064***	0.064***	0.064***	0.064***
	(3.13)	(3.25)	(3.77)	(3.22)	(3.50)	(3.78)
$\ln(B_t/M_t)$	0.034			0.045*	0.029	0.044**
	(1.63)			(1.95)	(1.57)	(2.26)
GP_t/B_{t-1}		0.004		0.025		0.035
		(0.17)		(1.00)		(1.63)
$InvestAL_t$			-0.033		-0.028	-0.036
			(-1.53)		(-1.43)	(-1.63)
No. of Obs.	53	53	53	53	53	53
IS R^2	0.04	0.00	0.04	0.06	0.07	0.11
IS adj. R^2	0.02	-0.02	0.02	0.02	0.04	0.05
			OOS forecasts			
OOS R^2	-0.03	-0.02	0.08	0.00	0.04	0.10
ENC-NEW	0.20	-0.14	1.29*	0.50	0.93	1.90*

Panel B: Predicting two-year-average stock returns $R^e_{(t+1,t+2)}$						
	1	2	3	4	5	6
Constant	0.056***	0.057***	0.058***	0.056***	0.057***	0.057***
	(3.08)	(3.19)	(4.21)	(3.23)	(3.98)	(4.69)
$\ln(B_t/M_t)$	0.024			0.035	0.014	0.031**
	(1.29)			(1.67)	(1.12)	(2.29)
GP_t/B_{t-1}		0.006		0.023		0.037**
		(0.31)		(1.11)		(2.59)
$InvestAL_t$			-0.052***		-0.050***	-0.057***
			(-3.38)		(-3.44)	(-3.59)
No. of Obs.	52	52	52	52	52	52
IS R^2	0.05	0.00	0.23	0.08	0.25	0.33
IS adj. R^2	0.03	-0.02	0.21	0.04	0.22	0.29
			OOS forecasts			
OOS R^2	-0.09	-0.11	0.32	-0.11	0.26	0.30
ENC-NEW	-0.65	-0.81	6.43***	-0.75	5.33***	6.25***

Table B.2 The predictive power of individual components of *Invest*$_{AL}$

This table reports the predictive power of individual components of $Invest_{AL}$ for aggregate stock returns. $Invest_{AL,t}$ 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. 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. Statistical significance at 10%, 5%, and 1% are indicated as *, **, and ***, respectively. Panels A and B predict one-year-ahead and two-year-ahead stock returns respectively. Accounting data are from 1962-2014 and stock returns data are from July 1963-June 2016.

Table B.2 The predictive power of individual components of $Invest_{AL}$ (continued)

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

	1	2	3	4	5	6
Constant	0.064***	0.064***	0.064***	0.064***	0.064***	0.064***
	(3.77)	(3.68)	(3.35)	(3.87)	(3.18)	(3.41)
$InvestAL_t$	-0.033					
	(-1.53)					
$ChgNOA_t$		-0.029				
		(-1.29)				
RND_t			-0.039*			
			(-1.92)			
$ChgAT_t$				-0.051***		
				(-3.57)		
$ChgCash_t$					-0.051**	
					(-2.31)	
$ChgNonDebt_t$						-0.039**
						(-2.08)
No. of Obs.	53	53	53	53	53	53
IS R^2	0.04	0.03	0.06	0.10	0.10	0.06
IS adj. R^2	0.02	0.01	0.04	0.08	0.08	0.04

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

	1	2	3	4	5	6
Constant	0.064***	0.064***	0.063***	0.064***	0.063***	0.063***
	(4.11)	(4.09)	(3.39)	(3.98)	(3.37)	(3.37)
$InvestAL_t$	-0.065***					
	(-3.90)					
$ChgNOA_t$		-0.064***				
		(-3.61)				
RND_t			-0.030			
			(-1.55)			
$ChgAT_t$				-0.053***		
				(-3.84)		
$ChgCash_t$					-0.011	
					(-0.45)	
$ChgNonDebt_t$						-0.005
						(-0.20)
No. of Obs.	52	52	52	52	52	52
IS R^2	0.17	0.16	0.04	0.11	0.00	0.00
IS adj. R^2	0.15	0.14	0.02	0.09	-0.01	-0.02

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Figure 1. The difference in cumulative squared forecast errors—Annual frequency

This figure displays the difference in cumulative squared forecast errors (CSFE) between the historical mean and different forecast models in one-year-ahead stock return forecasts. In each year 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. The OOS equity premium forecasts are computed by imposing Campbell and Thompson's (2008) sign restrictions. The training period uses accounting data from 1962-1990, and corresponding stock returns data from July 1963-June 1992. The out-of-sample forecast period for one-year-ahead stock returns is July 1992-June 2016. The forecast models used are specifications with B/M only (Panel A), B/M plus profitability (Panel B), B/M plus asset growth (Panel C), asset growth (Panel D), and B/M plus profitability plus asset growth (Panel E).

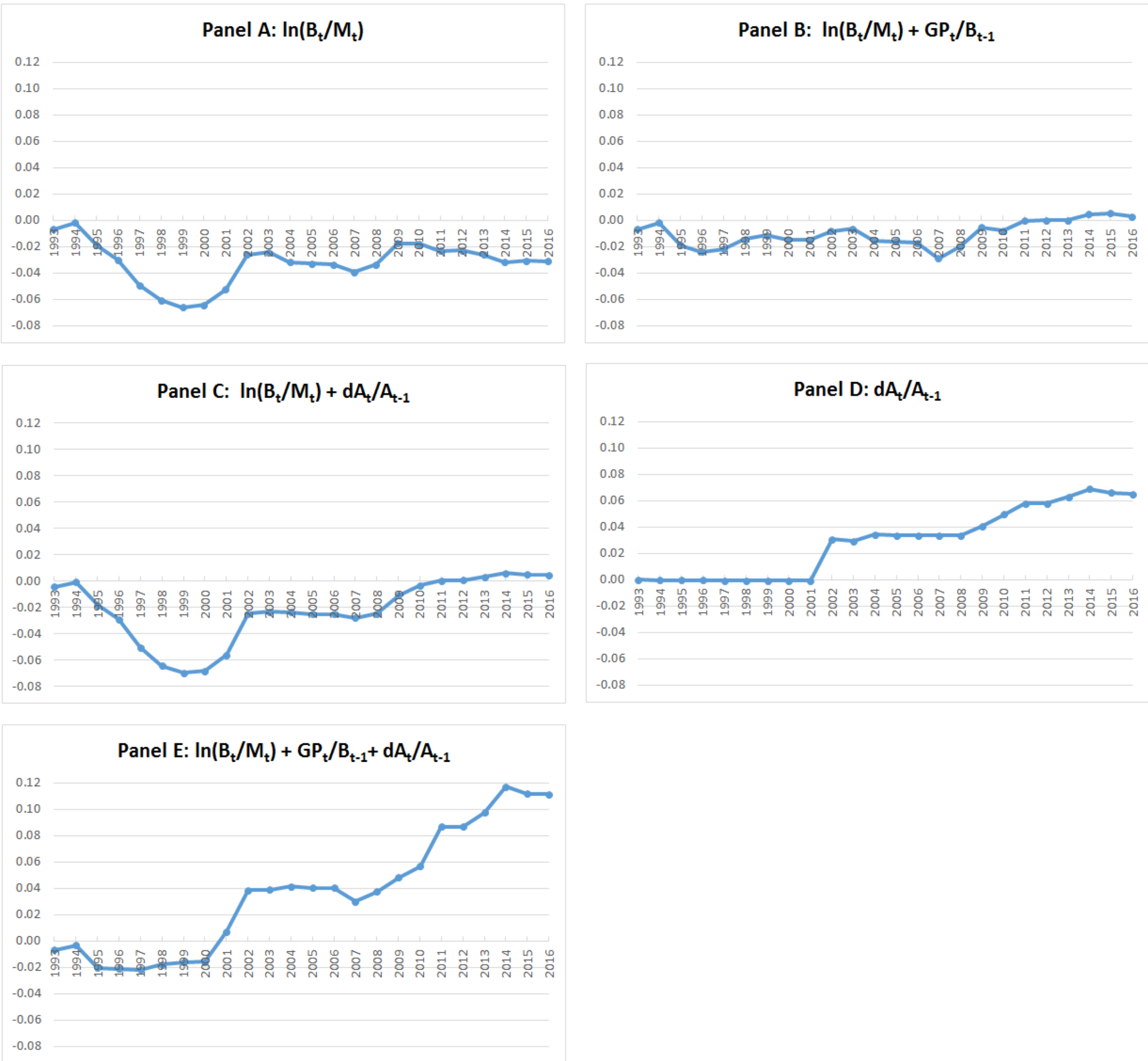

Figure 2. The difference in cumulative squared forecast errors—Quarterly frequency

This figure displays the difference in cumulative squared forecast errors (CSFE) between the historical mean and different forecast models in one-quarter-ahead stock return forecasts. In each 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. The OOS equity premium forecasts are computed by imposing Campbell and Thompson's (2008) sign restrictions. The training period uses accounting data from 1975Q1-1990Q4, and corresponding stock returns data from August 1975-July 1991. The out-of-sample forecast period for one-quarter-ahead stock returns is August 1991-July 2017. The forecast models used are specifications with B/M only (Panel A), B/M plus profitability (Panel B), B/M plus asset growth (Panel C), asset growth (Panel D), and B/M plus profitability plus asset growth (Panel E).

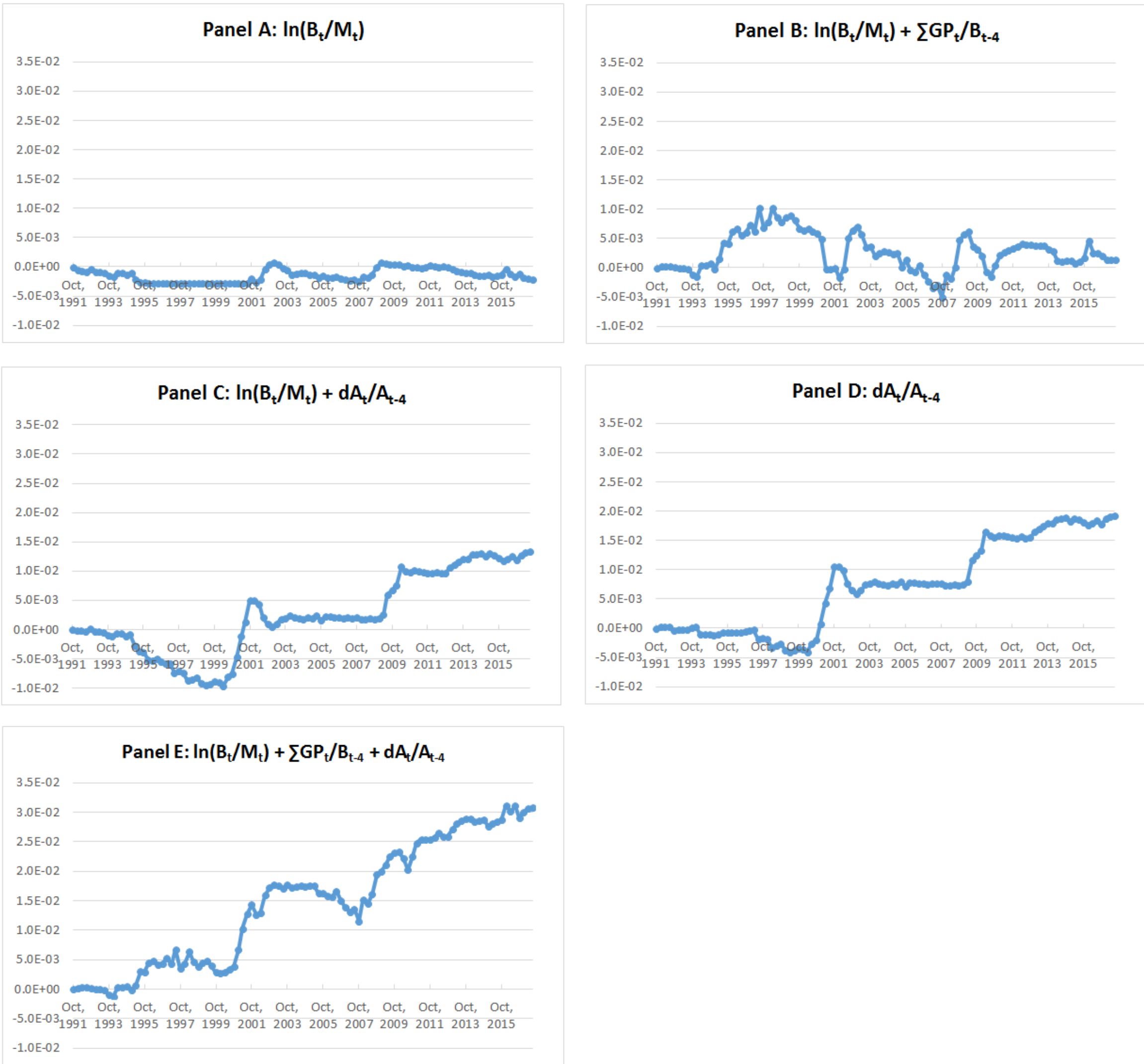

Figure 3. OOS R^2 by sample split year/quarter

This figure displays OOS R^2s as a function of sample split year/quarter, with Panels A and B applied to the annual and quarterly analyses, respectively. The sample split year/quarter is used to divide the whole sample (1962-2014, or, 1975Q1-2016Q4, based on the timing of the accounting variables) into a training sample and a test sample. The OOS R^2s are computed by imposing Campbell and Thompson's (2008) sign restrictions on the equity premium forecasts. The specifications examined include those that use the standalone B/M, B/M plus profitability, B/M plus asset growth, standalone asset growth, or B/M plus profitability plus asset growth as predictors.

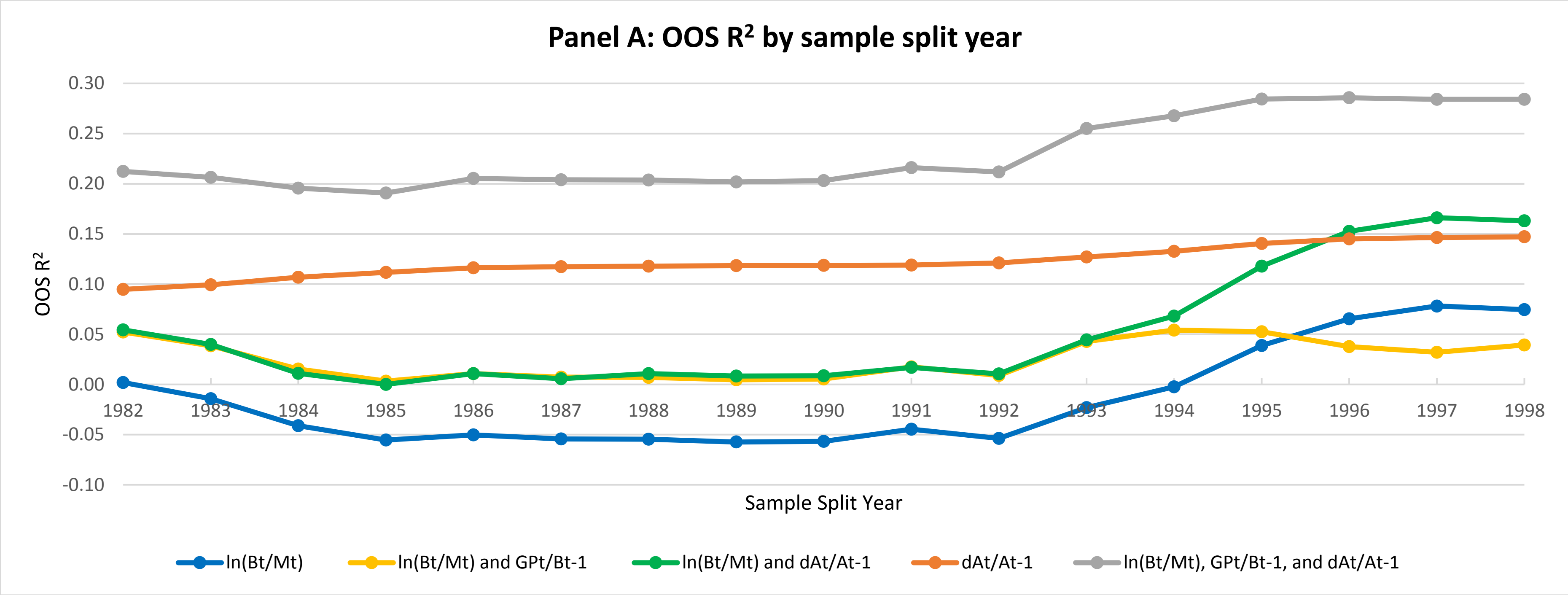

Figure 3. OOS R^2 by sample split year/quarter (continued)

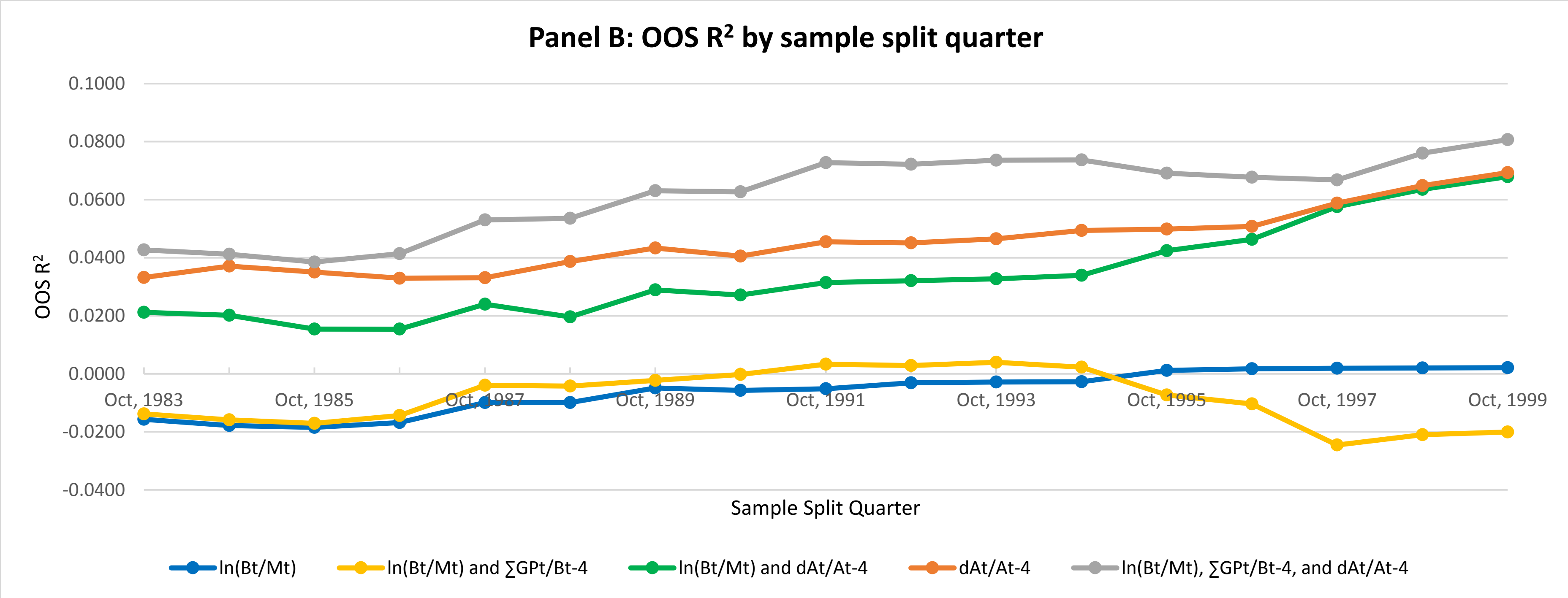

Table 1. Summary statistics of aggregate/industry-level variables

This table reports the summary statistics and correlation matrices for various aggregate/industry-level 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. $ln(B_t/M_t)$ is the aggregate log book-to-market ratio. GP_t/B_{t-1} is aggregate profitability. $OpCash_t/B_{t-1}$ is aggregate cash-based operating profitability. dA_t/A_{t-1} is aggregate asset growth. $Invest_{AL,t}$ is the investment measure proposed by Arif and Lee (2014). $Term_t$ 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). CSP_t is Polk, Thompson, and Vuolteenaho's (2006) cross-sectional beta premium in year *t*. IK_t is Cochrane's (1991) investment-to-capital ratio in year *t*. $LVOL_t$ is the annual aggregate stock market volatility from July of year *t* to June of year *t*+1, computed by using daily returns on the CRSP value-weighted index. R_{t+1}^e 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. $R_{(t+1,t+2)}^e$ is the geometric average of annual excess stock returns over years *t*+1 and *t*+2. Appendix A contains detailed definitions of these variables. In annual analyses, the sample period is July 1963-June 2016 for stock returns. For other variables, with the exceptions of $Sent^{BW}$, $Sent^{HJTZ}$, and CSP, the sample period (based on the time subscript *t*) is 1962-2014. For $Sent^{BW}$ and $Sent^{HJTZ}$, the sample period is 1965-2013. For CSP, the sample period is 1962-2002. Panels B and C (D and E) report annual and quarterly Pearson correlation coefficients between aggregate (industry-level) variables, with *p*-values in parentheses. In Panels D and E, firm-level variables are aggregated to the industry level at the end of each year/quarter, by weighting firm-level variables by each firm's end-of-year/end-of-quarter market capitalization, and using the Fama-French 48-industry definitions. $ln(B_t/M_t)$ is quarterly log book-to-market ratio. $\sum GP_{it}/B_{it-4}$ 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_{t+1}^e is quarterly excess stock return in *t*+1. In quarterly analyses, the sample period is August 1975-July 2017 for stock returns. For accounting variables, the sample period (based on the time subscript *t*) is 1975Q1-2016Q4.

Table 1. Summary statistics of aggregate/industry-level variables (continued)

Panel A: Summary Statistics of Aggregate Variables (Annual Frequency)							
	No. of Obs.	Mean	Std Dev	Q1	Median	Q3	AR(1)
$\ln(B_t/M_t)$	53	-0.780	0.395	-1.036	-0.850	-0.438	0.933
GP_t/B_{t-1}	53	0.822	0.122	0.748	0.798	0.891	0.845
$OpCash_t/B_{t-1}$	53	0.480	0.087	0.420	0.467	0.545	0.769
dA_t/A_{t-1}	53	0.138	0.069	0.106	0.120	0.148	0.569
$InvestAL_t$	53	0.069	0.029	0.051	0.061	0.091	0.476
$Term_t$	53	0.010	0.011	0.002	0.010	0.018	0.560
Def_t	53	0.010	0.004	0.008	0.009	0.012	0.676
$Tbill_t$	53	0.004	0.003	0.003	0.004	0.005	0.798
$Sent^{BW}_t$	49	-0.011	0.964	-0.381	-0.081	0.394	0.677
$Sent^{HJTZ}_t$	49	0.117	0.963	-0.456	-0.153	0.274	0.420
CAY_t	53	-0.003	0.020	-0.013	-0.003	0.012	0.829
$OpAcc_t$	53	-0.048	0.012	-0.053	-0.047	-0.043	0.367
$EquityShare_t$	53	0.172	0.085	0.116	0.150	0.217	0.714
CSP_t	41	-0.001	0.001	-0.002	-0.001	0.000	0.734
Ik_t	53	0.036	0.004	0.034	0.036	0.039	0.741
$LVOL_{t+1}$	53	-2.038	0.391	-2.280	-2.124	-1.828	0.499
R^e_t	53	0.102	0.168	0.013	0.101	0.230	-0.089
R^e_{t+1}	53	0.062	0.160	-0.013	0.061	0.179	-0.086
$R^e_{(t+1,t+2)}$	52	0.056	0.107	0.008	0.049	0.118	0.397

Panel B: Pearson Correlation Coefficients between Aggregate Variables (Annual Frequency)								
	$\ln(B_t/M_t)$	GP_t/B_{t-1}	$OpCash_t/B_{t-1}$	dA_t/A_{t-1}	$InvestAL_t$	R^e_t	R^e_{t+1}	$R^e_{(t+1,t+2)}$
$\ln(B_t/M_t)$	1	-0.52	-0.52	-0.40	-0.15	-0.06	0.19	0.19
		(<.0001)	(<.0001)	(0.0032)	(0.2683)	(0.6458)	(0.1635)	(0.1675)
GP_t/B_{t-1}		1	0.89	0.50	0.23	0.10	0.07	0.13
			(<.0001)	(0.0001)	(0.0973)	(0.4876)	(0.6404)	(0.3659)
$OpCash_t/B_{t-1}$			1	0.31	-0.03	0.03	0.13	0.24
				(0.0217)	(0.8289)	(0.8039)	(0.3424)	(0.0856)
dA_t/A_{t-1}				1	0.76	0.04	-0.29	-0.44
					(<.0001)	(0.7793)	(0.0371)	(0.0010)
$InvestAL_t$					1	0.01	-0.21	-0.48
						(0.9410)	(0.1390)	(0.0003)
R^e_t						1	-0.10	-0.16
							(0.4614)	(0.2669)
R^e_{t+1}							1	0.72
								(<.0001)
$R^e_{(t+1,t+2)}$								1

Table 1. Summary statistics of aggregate/industry-level variables (continued)

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

	$\ln(B_t/M_t)$	$\sum GP_t/B_{t-4}$	dA_t/A_{t-4}	R^e_t	R^e_{t+1}
$\ln(B_t/M_t)$	1	-0.77	-0.29	0.08	0.06
		(<.0001)	(0.0001)	(0.2797)	(0.4684)
$\sum GP_t/B_{t-4}$		1	0.29	-0.04	0.06
			(0.0002)	(0.5799)	(0.473)
dA_t/A_{t-4}			1	-0.14	-0.21
				(0.0647)	(0.0075)
R^e_t				1	-0.06
					(0.4545)
R^e_{t+1}					1

Panel D: Pearson Correlation Coefficients between Industry-level Variables (Annual Frequency)

	$\ln(B_t/M_t)$	GP_t/B_{t-1}	dA_t/A_{t-1}	R^e_t	R^e_{t+1}	$R^e_{(t+1,t+2)}$
$\ln(B_t/M_t)$	1	-0.36	-0.10	-0.11	0.11	0.12
		(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
GP_t/B_{t-1}		1	0.19	0.07	0.02	0.04
			(<.0001)	(0.0004)	(0.3543)	(0.0674)
dA_t/A_{t-1}			1	-0.03	-0.15	-0.19
				(0.2017)	(<.0001)	(<.0001)
R^e_t				1	-0.07	-0.11
					(0.0011)	(<.0001)
R^e_{t+1}					1	0.70
						(<.0001)
$R^e_{(t+1,t+2)}$						1

Panel E: Pearson Correlation Coefficients between Industry-level Variables (Quarterly Frequency)

	$\ln(B_t/M_t)$	$\sum GP_t/B_{t-4}$	dA_t/A_{t-4}	R^e_t	R^e_{t+1}
$\ln(B_t/M_t)$	1	-0.45	-0.11	0.06	0.05
		(<.0001)	(<.0001)	(<.0001)	(<.0001)
$\sum GP_t/B_{t-4}$		1	0.15	0.01	0.02
			(<.0001)	(0.5127)	(0.1053)
dA_t/A_{t-4}			1	-0.08	-0.10
				(<.0001)	(<.0001)
R^e_t				1	-0.01
					(0.2894)
R^e_{t+1}					1

Table 2. Predicting aggregate stock returns

This table reports time-series predictive regression results that use B/M, profitability, and asset growth as predictors. 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. Our full sample of annual (quarterly) accounting data covers the period 1962-2014 (1975Q1-2016Q4), and the corresponding stock returns data spans July 1963-June 2016 (August 1975-July 2017). 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 2016 (for one-year-ahead return forecasts) and July 1993-June 2016 (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 2017. 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
Constant	0.062	0.062	0.062	0.062**	0.062	0.062***
	(3.11)	(3.24)	(3.58)	(3.26)	(3.41)	(4.13)
$\ln(B_t/M_t)$	0.031*			0.050*	0.015	0.038*
	(1.56)			(2.13)	(0.82)	(1.98)
GP_t/B_{t-1}		0.011		0.036		0.062**
		(0.40)		(1.42)		(3.01)
dA_t/A_{t-1}			-0.046***		-0.040***	-0.062***
			(-3.99)		(-3.09)	(-4.46)
No. of Obs.	53	53	53	53	53	53
Prob>F	0.125	0.689	0.000	0.095	0.001	0.000
IS R^2	0.04	0.00	0.08	0.08	0.09	0.18
IS adj. R^2	0.02	-0.02	0.06	0.04	0.05	0.13
OOS forecasts						
OOS R^2	-0.06	-0.04	0.12	0.01	0.01	0.20
ENC-NEW	-0.09	0.08	1.90**	0.60	0.61	4.00**

Panel B: Predicting two-year-average stock returns $R^e_{(t+1,t+2)}$	1	2	3	4	5	6
Constant	0.056	0.056	0.056	0.056	0.056	0.056*
	(3.09)	(3.20)	(3.49)	(3.37)	(3.45)	(4.87)
$\ln(B_t/M_t)$	0.021			0.039*	0.001	0.025*
	(1.19)			(1.82)	(0.10)	(1.69)
GP_t/B_{t-1}		0.014		0.035		0.061***
		(0.61)		(1.65)		(4.45)
dA_t/A_{t-1}			-0.047***		-0.047***	-0.068***
			(-5.83)		(-4.55)	(-6.41)
No. of Obs.	52	52	52	52	52	52
Prob>F	0.241	0.547	0.000	0.124	0.000	0.000
IS R^2	0.04	0.02	0.20	0.11	0.20	0.40
IS adj. R^2	0.02	0.00	0.18	0.08	0.16	0.36
OOS forecasts						
OOS R^2	-0.13	-0.15	0.21	-0.15	0.06	0.29
ENC-NEW	-1.04	-0.52	3.63***	-0.86	1.46*	5.97***

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
Constant	0.017	0.017	0.017	0.017***	0.017	0.017***
	(3.00)	(3.00)	(3.28)	(3.11)	(3.27)	(3.47)
$\ln(B_t/M_t)$	0.004			0.017**	-0.000	0.014*
	(0.60)			(2.07)	(-0.05)	(1.71)
$\sum GP_t/B_{t-4}$		0.004		0.017**		0.020***
		(0.60)		(2.31)		(2.78)
dA_t/A_{t-4}			-0.015***		-0.015***	-0.016***
			(-4.11)		(-3.67)	(-3.35)
No. of Obs.	168	168	168	168	168	168
Prob>F	0.546	0.550	0.000	0.053	0.000	0.001
IS R^2	0.00	0.00	0.04	0.03	0.04	0.07
IS adj. R^2	0.00	0.00	0.04	0.02	0.03	0.06
OOS forecasts						
OOS R^2	-0.01	-0.02	0.05	0.00	0.03	0.07
ENC-NEW	-0.05	1.03	3.33**	1.94*	2.55*	5.73***

Table 3. Predicting industry-level stock returns

This table reports industry-level panel predictive regression results. Firm-level variables are aggregated to the industry level at the end of each year/quarter, by weighting firm-level variables by each firm's end-of-year/end-of-quarter market capitalization. The Fama-French 48-industry definitions (with financial industries 44-47 excluded) are used. Panel A predicts one-year-ahead industry-level stock returns. Panel B predicts two-year average industry-level stock returns. Panel C predicts one-quarter-ahead stock returns. We run panel regressions that value-weight industries every period, and with industry fixed effects. All the RHS variables are standardized by their industry-specific mean and aggregate standard deviation. The sample periods for the accounting variables span 1962-2014 for Panel A, 1962-2013 for Panel B, and 1975Q1-2016Q4 for Panel C. The corresponding sample periods for stock returns are July 1963-June 2016 (Panels A and B), and August 1975-July 2017 (Panel C). The *t*-statistics in parentheses are computed based on two-way clustered standard errors. 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	5	6
$\ln(B_t/M_t)$	0.036**			0.042***	0.029*	0.037**
	(-2.31)			(2.62)	(1.95)	(2.41)
GP_t/B_{t-1}		0.003		0.010***		0.013***
		(-0.80)		(2.63)		(3.21)
dA_t/A_{t-1}			-0.026***		-0.022***	-0.024***
			(-3.57)		(-3.54)	(-3.99)
No. of Obs.	2,315	2,315	2,315	2,315	2,315	2,315
R^2	0.03	0.00	0.04	0.04	0.07	0.08
Adj. R^2	0.03	0.00	0.04	0.04	0.06	0.08
Industry Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes

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

	1	2	3	4	5	6
$\ln(B_t/M_t)$	0.028**			0.035***	0.021**	0.029***
	(2.43)			(2.82)	(2.21)	(2.84)
GP_t/B_{t-1}		0.004		0.010***		0.013***
		(1.24)		(2.95)		(3.42)
dA_t/A_{t-1}			-0.023***		-0.021***	-0.022***
			(-4.48)		(-4.78)	(-5.39)
No. of Obs.	2,271	2,271	2,271	2,271	2,271	2,271
R^2	0.04	0.00	0.08	0.06	0.10	0.13
Adj. R^2	0.04	0.00	0.08	0.06	0.10	0.13
Industry Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes

Table 3. Predicting industry-level stock returns (continued)

Panel C: Predicting one-quarter-ahead stock returns R^e_{t+1}						
	1	2	3	4	5	6
$\ln(B_t/M_t)$	0.007			0.010*	0.004	0.008
	(1.62)			(1.94)	(1.00)	(1.63)
$\sum GP_t/B_{t-4}$		0.001		0.003**		0.004***
		(1.04)		(2.23)		(2.93)
dA_t/A_{t-4}			-0.009***		-0.009***	-0.009***
			(-4.86)		(-4.41)	(-4.71)
No. of Obs.	7,235	7,235	7,235	7,235	7,235	7,235
R^2	0.01	0.00	0.03	0.01	0.03	0.03
Adj. R^2	0.01	0.00	0.03	0.01	0.03	0.03
Industry Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes

Table 4. Forecasting the equity premium as at June 2016

This table reports the equity premium forecasts—made as at June 2016—by using the B/M, profitability, and asset growth as predictors. Panel A reports the means, standard deviations, and the year 2015 values of the predictors. The last column computes the deviation of the 2015 values from their sample means, measured in standardized units. Panel B1 reports the annual equity premium forecasts over July 2016-June 2017, and Panel B2 reports the average annual equity premium forecasts over July 2016-June 2018. The predictive coefficients reported on these panels are estimated from non-standardized variables.

Panel A: Summary statistics of the predictors

Predictors	Mean	Std Dev	Value in 2015	Deviation of the value in 2015 from the mean (in standardized unit)
$\ln(B_t/M_t)$	-0.789	0.396	-1.254	-1.174
GP_t/B_{t-1}	0.825	0.123	0.967	1.164
dA_t/A_{t-1}	0.137	0.069	0.111	-0.378

Panel B1: Forecasting the return premium of 2016 (July 2016 - June 2017)

Predictor(s)			Estimated intercept	Value of the first predictor in 2015	Coefficient estimate of the first predictor	Value of the second predictor in 2015	Coefficient estimate of the second predictor	Value of the third predictor in 2015	Coefficient estimate of the third predictor	Forecasted return premium of 2016
$\ln(B_t/M_t)$	-	-	0.124	-1.254	0.079	-	-	-	-	0.025
$\ln(B_t/M_t)$	GP_t/B_{t-1}	-	-0.084	-1.254	0.127	0.967	0.298	-	-	0.046
$\ln(B_t/M_t)$	dA_t/A_{t-1}	GP_t/B_{t-1}	-0.153	-1.254	0.098	0.111	-0.888	0.967	0.504	0.113

Panel B2: Forecasting the geometric average of the return premia over 2016-2017 (July 2016 - June 2018)

Predictor(s)			Estimated intercept	Value of the first predictor in 2015	Coefficient estimate of the first predictor	Value of the second predictor in 2015	Coefficient estimate of the second predictor	Value of the third predictor in 2015	Coefficient estimate of the third predictor	Forecasted geometric average of the return premia over 2016-2017
$\ln(B_t/M_t)$	-	-	0.097	-1.254	0.053	-	-	-	-	0.031
$\ln(B_t/M_t)$	GP_t/B_{t-1}	-	-0.098	-1.254	0.100	0.967	0.280	-	-	0.049
$\ln(B_t/M_t)$	dA_t/A_{t-1}	GP_t/B_{t-1}	-0.169	-1.254	0.064	0.111	-0.966	0.967	0.496	0.123

Table 5. Certainty equivalent return (CER) gains

This table reports the certainty equivalent return (CER) gains from jointly using B/M, profitability, and asset investment instead of only using the B/M only as equity premium predictors in portfolio allocation. This CER gain represents the value to an investor in her portfolio allocation by switching from a B/M-based OOS predictive model to one that is based on B/M, 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 B/M-based to a B/M/profitability/investment-based forecast. The CER gains reported here are computed by imposing Campbell and Thompson's (2008) sign restrictions on all OOS equity premium forecasts. Panel A reports CER gains based on one-year-ahead equity premium forecasts, and Panel B reports CER gains based on two-year-average equity premium 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 2016 (for one-year-ahead return forecasts) and July 1993-June 2016 (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					
$\ln(B_t/M_t)$	-	-	9.32	-	-
$\ln(B_t/M_t)$	GP_t/B_{t-1}	-	9.10	-0.22	-0.14
$\ln(B_t/M_t)$	dA_t/A_{t-1}	GP_t/B_{t-1}	12.55	3.23	2.35**
Panel A2: Risk aversion coefficient γ = 3					
$\ln(B_t/M_t)$	-	-	5.05	-	-
$\ln(B_t/M_t)$	GP_t/B_{t-1}	-	5.66	0.61	0.62
$\ln(B_t/M_t)$	dA_t/A_{t-1}	GP_t/B_{t-1}	8.66	3.61	2.91***
Panel A3: Risk aversion coefficient γ = 5					
$\ln(B_t/M_t)$	-	-	4.04	-	-
$\ln(B_t/M_t)$	GP_t/B_{t-1}	-	4.38	0.34	0.56
$\ln(B_t/M_t)$	dA_t/A_{t-1}	GP_t/B_{t-1}	6.27	2.23	2.91***
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					
$\ln(B_t/M_t)$	-	-	10.78	-	-
$\ln(B_t/M_t)$	GP_t/B_{t-1}	-	10.85	0.07	0.08
$\ln(B_t/M_t)$	dA_t/A_{t-1}	GP_t/B_{t-1}	13.76	2.97	2.49**
Panel B2: Risk aversion coefficient γ = 3					
$\ln(B_t/M_t)$	-	-	5.30	-	-
$\ln(B_t/M_t)$	GP_t/B_{t-1}	-	6.79	1.49	1.35
$\ln(B_t/M_t)$	dA_t/A_{t-1}	GP_t/B_{t-1}	12.18	6.88	5.33***
Panel B3: Risk aversion coefficient γ = 5					
$\ln(B_t/M_t)$	-	-	4.02	-	-
$\ln(B_t/M_t)$	GP_t/B_{t-1}	-	3.67	-0.35	-0.28
$\ln(B_t/M_t)$	dA_t/A_{t-1}	GP_t/B_{t-1}	9.94	5.92	4.95***

Table 6. 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 return forecasts, and Panel B reports two-year-average return forecasts. 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. Statistical significance at 10%, 5%, and 1% are indicated as *, **, and ***, respectively. This analysis uses accounting data from 1962-2014 and stock returns data from July 1963-June 2016.

Table 6. 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
Constant	0.063***	0.063***	0.063***	0.063***	0.063***	0.063***	0.063***	0.063***	0.063***	0.063***	0.063***
	(3.75)	(3.33)	(3.67)	(3.78)	(3.31)	(3.90)	(3.31)	(3.30)	(3.49)	(3.57)	(3.53)
dA_t/A_{t-1}	-0.048***										
	(-4.89)										
$ChgCash_t$		-0.051***				-0.081**					
		(-3.57)				(-2.02)					
$ChgCurAsst_t$			-0.023			0.005					
			(-1.09)			(0.29)					
$ChgPPE_t$				-0.033		-0.045*					
				(-1.46)		(-1.86)					
$ChgOthAsst_t$					-0.033*	0.033					
					(-1.72)	(0.91)					
$ChgOpLiab_t$							-0.014				-0.001
							(-1.08)				(-0.05)
$ChgRE_t$								-0.003			0.004
								(-0.24)			(0.25)
$ChgStock_t$									-0.028		-0.019
									(-1.32)		(-0.55)
$ChgDebt_t$										-0.032	-0.025
										(-1.54)	(-1.14)
No. of Obs.	53	53	53	53	53	53	53	53	53	53	53
R^2	0.09	0.10	0.02	0.04	0.04	0.17	0.01	0.00	0.03	0.04	0.05
Adj. R^2	0.07	0.09	0.00	0.03	0.02	0.11	-0.01	-0.02	0.01	0.02	-0.03

Table 6. 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
Constant	0.063***	0.063***	0.063***	0.063***	0.063***	0.063***	0.063***	0.063***	0.063***	0.063***	0.063***
	(3.75)	(3.51)	(4.06)	(3.76)	(3.40)	(3.73)	(3.46)	(3.42)	(3.62)	(3.64)	(3.61)
dA_t/A_{t-1}	-0.043***										
	(-3.33)										
$ChgCash_t$		-0.015				0.002					
		(-0.78)				(0.08)					
$ChgCurAsst_t$			-0.035**			-0.002					
			(-2.25)			(-0.07)					
$ChgPPE_t$				-0.045**		-0.042					
				(-2.22)		(-1.33)					
$ChgOthAsst_t$					-0.028*	-0.026					
					(-1.75)	(-0.83)					
$ChgOpLiab_t$							-0.014				-0.004
							(-0.91)				(-0.12)
$ChgRE_t$								-0.004			0.005
								(-0.33)			(0.24)
$ChgStock_t$									-0.029**		-0.014
									(-2.22)		(-0.53)
$ChgDebt_t$										-0.043***	-0.038*
										(-2.89)	(-2.01)
No. of Obs.	52	52	52	52	52	52	52	52	52	52	52
R^2	0.08	0.01	0.05	0.09	0.03	0.11	0.01	0.00	0.04	0.08	0.09
Adj. R^2	0.06	-0.01	0.03	0.07	0.01	0.04	-0.01	-0.02	0.02	0.06	0.01

Table 7. Predicting market volatility

This table reports the predictability of market volatility ($LVOL_{t+1}$), as measured by the sum of the squared daily returns on the CRSP value-weighted index over a year (Panel A) or a quarter (Panel B). In Panel A, $LVOL_{t+1}$ denotes aggregate stock market volatility over the period from July, year t+1 to June, year t+2. In Panel B, $LVOL_{t+1}$represents aggregate stock market volatility over the three-month period that begins four months subsequent to calendar quarter t. 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 Panel A, and four lags in Panel B. Statistical significance at 10%, 5%, and 1% are indicated as *, **, and ***, respectively. Panel A (Panel B) uses accounting data from 1962-2014 (1975Q1-2016Q4) and stock returns data from July 1963-June 2016 (August 1975-July 2017).

Panel A: Predicting one-year-ahead market volatility $LVOL_{t+1}$

	1	2	3	4	5	6	7	8	9
Constant	-2.038***	-2.038***	-2.038***	-2.038***	-2.038***	-2.038***	-2.038***	-2.038***	-2.038***
	(-44.78)	(-28.22)	(-44.86)	(-30.60)	(-46.31)	(-32.46)	(-48.56)	(-32.57)	(-47.06)
$LVOL_t$	0.200***		0.191***		0.175***		0.170***		0.166***
	(4.34)		(4.35)		(3.68)		(4.52)		(4.18)
$\ln(B_t/M_t)$		-0.104*	-0.084**					-0.025	-0.042
		(-1.75)	(-2.08)					(-0.44)	(-0.89)
GP_t/B_{t-1}				0.136*	0.083*			0.066	0.022
				(1.89)	(1.78)			(0.71)	(0.37)
dA_t/A_{t-1}						0.155***	0.109***	0.112*	0.083
						(3.82)	(2.93)	(1.74)	(1.63)
No. of Obs.	53	53	53	53	53	53	53	53	53
R^2	0.26	0.07	0.31	0.12	0.30	0.16	0.33	0.19	0.35
Adj. R^2	0.25	0.05	0.28	0.10	0.27	0.14	0.31	0.14	0.30

Table 7. Predicting market volatility (continued)

Panel B: Predicting one-quarter-ahead market volatility $LVOL_{t+1}$	1	2	3	4	5	6	7	8	9
Constant	-2.724***	-2.724***	-2.724***	-2.724***	-2.724***	-2.724***	-2.724***	-2.724***	-2.724***
	(-117.56)	(-50.94)	(-117.63)	(-49.17)	(-117.58)	(-52.02)	(-118.37)	(-53.65)	(-117.72)
$LVOL_t$	0.276***		0.265***		0.272***		0.260***		0.254***
	(10.79)		(10.22)		(10.36)		(9.04)		(8.89)
$\ln(B_t/M_t)$		-0.110***	-0.042**					-0.116*	-0.046
		(-2.62)	(-2.11)					(-1.68)	(-1.32)
$\sum GP_t/B_{t-4}$				0.071	0.027			-0.049	-0.019
				(1.61)	(1.42)			(-0.71)	(-0.53)
dA_t/A_{t-4}						0.129***	0.054***	0.109***	0.048***
						(4.68)	(3.86)	(3.49)	(3.03)
No. of Obs.	168	168	168	168	168	168	168	168	168
R^2	0.45	0.07	0.46	0.03	0.45	0.10	0.46	0.14	0.47
Adj. R^2	0.45	0.07	0.45	0.02	0.45	0.09	0.46	0.12	0.46

Table 8. 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 equity premium 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), Polk, Thompson, and Vuolteenaho's (2006) cross-sectional beta premium (CSP), and Cochrane's (1991) investment-to-capital ratio (IK). 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. Statistical significance at 10%, 5%, and 1% are indicated as *, **, and ***, respectively. In Panels A and B, the sample period is July 1963-June 2016 for stock returns, and 1962-2014 for other variables. In Panel C, the sample period is August 1975-July 2017 for stock returns, and 1975Q1-2016Q4 for other variables. The following variables are available only during part of these sample periods. $Sent^{BW}$ and $Sent^{HJTZ}$ are available from 1965-2013 (up to 2014Q2 in quarterly analyses), CSP is available only up to 2002Q3, CAY up to 2016Q2, and IK up to 2016Q3. Appendix A contains a more detailed description of these variables.

Table 8. 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
Constant	0.062***	0.062***	0.062***	0.062***	0.062***	0.062***	0.062***	0.062***	0.055**	0.062***	0.062***	0.062***	0.062***	0.054***	0.053***	0.062***	0.062***	0.062***	0.055***	0.062***
	(3.61)	(3.18)	(3.21)	(2.88)	(2.84)	(3.49)	(3.22)	(3.16)	(2.53)	(3.68)	(4.19)	(4.08)	(4.03)	(3.35)	(2.96)	(4.25)	(3.94)	(4.09)	(3.07)	(4.08)
$Term_t$	0.039***										0.017									
	(2.82)										(0.93)									
Def_t		0.017										-0.002								
		(0.92)										(-0.09)								
$Tbill_t$			-0.016										-0.035							
			(-0.82)										(-1.44)							
$Sent^{BW}_t$				-0.015										-0.000						
				(-0.52)										(-0.01)						
$Sent^{HJTZ}_t$					-0.060**										-0.045**					
					(-2.54)										(-2.12)					
CAY_t						0.029**										0.011				
						(2.02)										(0.81)				
$OpAcc_t$							0.037*										0.016			
							(2.00)										(0.90)			
$EquityShare_t$								0.015										0.009		
								(0.80)										(0.41)		
CSP_t									-0.053***										-0.041**	
									(-3.18)										(-2.35)	
Ik_t										-0.034										0.001
										(-1.53)										(0.06)
$\ln(B_t/M_t)$											0.039**	0.040*	0.064**	0.054**	0.056**	0.034*	0.030	0.034	0.031	0.039*
											(2.06)	(1.80)	(2.31)	(2.40)	(2.36)	(1.73)	(1.29)	(1.62)	(1.58)	(1.96)
GP_t/B_{t-1}											0.054**	0.062***	0.060***	0.085***	0.076***	0.056**	0.056**	0.063***	0.053**	0.062***
											(2.28)	(3.09)	(2.74)	(3.96)	(3.45)	(2.56)	(2.64)	(2.92)	(2.48)	(3.05)
dA_t/A_{t-1}											-0.054***	-0.061***	-0.046**	-0.059***	-0.041**	-0.061***	-0.060***	-0.063***	-0.051***	-0.063***
											(-3.17)	(-4.36)	(-2.66)	(-3.95)	(-2.41)	(-4.24)	(-4.38)	(-4.23)	(-2.77)	(-3.88)
No. of Obs.	53	53	53	49	49	53	53	53	41	53	53	53	53	49	49	53	53	53	41	53
R^2	0.06	0.01	0.01	0.01	0.13	0.03	0.05	0.01	0.11	0.05	0.19	0.18	0.21	0.21	0.27	0.19	0.19	0.18	0.22	0.18
Adj. R^2	0.04	-0.01	-0.01	-0.01	0.11	0.01	0.04	-0.01	0.08	0.03	0.12	0.11	0.14	0.14	0.21	0.12	0.12	0.12	0.14	0.11

Table 8. 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
Constant	0.057***	0.056***	0.056***	0.057***	0.057***	0.054***	0.056***	0.056***	0.049**	0.057***	0.056***	0.056***	0.056***	0.051***	0.050***	0.055***	0.056***	0.056***	0.049***	0.056***
	(3.81)	(3.13)	(3.14)	(2.98)	(3.02)	(3.48)	(3.16)	(3.02)	(2.60)	(3.87)	(5.02)	(4.83)	(4.83)	(4.63)	(4.06)	(5.27)	(4.78)	(4.68)	(3.97)	(4.79)
$Term_t$	0.035***										0.009									
	(2.81)										(0.76)									
Def_t		0.014										0.005								
		(0.82)										(0.37)								
$Tbill_t$			-0.010										-0.005							
			(-0.58)										(-0.33)							
$Sent^{BW}_t$				0.002										0.020*						
				(0.10)										(1.71)						
$Sent^{HJTZ}_t$					-0.027										-0.006					
					(-1.52)										(-0.48)					
CAY_t						0.047***										0.034***				
						(3.70)										(3.75)				
$OpAcc_t$							0.022										0.001			
							(1.41)										(0.07)			
$EquityShare_t$								0.016										0.017		
								(1.01)										(1.07)		
CSP_t									-0.041***										-0.030***	
									(-3.92)										(-3.04)	
Ik_t										-0.037***										-0.001
										(-2.74)										(-0.07)
$\ln(B_t/M_t)$											0.025*	0.022	0.029	0.034**	0.035**	0.014	0.025	0.017	0.019	0.025
											(1.74)	(1.34)	(1.46)	(2.06)	(2.09)	(1.23)	(1.29)	(0.95)	(1.39)	(1.66)
GP_t/B_{t-1}											0.056***	0.060***	0.060***	0.075***	0.074***	0.044***	0.060***	0.063***	0.057***	0.060***
											(3.99)	(4.24)	(4.39)	(4.92)	(5.56)	(4.01)	(3.85)	(4.40)	(3.96)	(4.37)
dA_t/A_{t-1}											-0.063***	-0.068***	-0.065***	-0.073***	-0.064***	-0.064***	-0.067***	-0.069***	-0.061***	-0.066***
											(-6.44)	(-6.26)	(-6.02)	(-6.21)	(-4.75)	(-5.91)	(-6.17)	(-6.01)	(-5.33)	(-6.59)
No. of Obs.	52	52	52	49	49	52	52	52	41	52	52	52	52	49	49	52	52	52	41	52
R^2	0.11	0.02	0.01	0.00	0.06	0.18	0.04	0.02	0.16	0.12	0.40	0.40	0.40	0.46	0.43	0.48	0.40	0.42	0.47	0.40
Adj. R^2	0.09	0.00	-0.01	-0.02	0.04	0.16	0.02	0.00	0.14	0.11	0.35	0.35	0.35	0.41	0.38	0.43	0.35	0.37	0.41	0.35

Table 8. 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
Constant	0.017***	0.017***	0.017***	0.017***	0.017***	0.017***	0.017***	0.017***	0.013*	0.017***	0.017***	0.017***	0.017***	0.017***	0.017***	0.017***	0.017***	0.017***	0.013**	0.017***
	(3.01)	(2.98)	(3.01)	(2.78)	(2.93)	(2.92)	(2.97)	(3.00)	(1.75)	(3.04)	(3.46)	(3.43)	(3.52)	(3.21)	(3.34)	(3.34)	(3.45)	(3.58)	(2.06)	(3.44)
$Term_t$	0.004										0.002									
	(0.74)										(0.35)									
Def_t		0.001										0.002								
		(0.12)										(0.29)								
$Tbill_t$			-0.003										-0.008							
			(-0.58)										(-0.91)							
$Sent^{BW}_t$				-0.004										-0.004						
				(-0.51)										(-0.68)						
$Sent^{HJTZ}_t$					-0.015***										-0.014***					
					(-2.97)										(-2.65)					
CAY_t						0.009										0.005				
						(1.55)										(0.94)				
$OpAcc_t$							-0.004										-0.008			
							(-0.47)										(-1.16)			
$EquityShare_t$								-0.011*										-0.016**		
								(-1.69)										(-2.28)		
CSP_t									-0.009										-0.011*	
									(-1.48)										(-1.97)	
Ik_t										-0.009										-0.005
										(-1.59)										(-0.99)
$\ln(B_t/M_t)$											0.016*	0.014	0.022**	0.015	0.019**	0.012	0.019**	0.025**	0.027**	0.016*
											(1.88)	(1.51)	(2.06)	(1.65)	(2.04)	(1.23)	(2.10)	(2.44)	(2.04)	(1.86)
$\sum GP_t/B_{t-4}$											0.020***	0.020***	0.022***	0.021***	0.023***	0.018**	0.022***	0.024***	0.032**	0.022***
											(2.95)	(2.83)	(3.21)	(2.87)	(3.24)	(2.22)	(3.12)	(3.04)	(2.56)	(3.13)
dA_t/A_{t-4}											-0.015***	-0.016***	-0.013**	-0.016***	-0.011*	-0.016***	-0.015***	-0.014**	-0.011	-0.013**
											(-2.74)	(-3.37)	(-2.28)	(-3.13)	(-1.96)	(-3.15)	(-2.77)	(-2.57)	(-1.46)	(-2.28)
No. of Obs.	168	168	168	158	158	166	168	168	111	167	168	168	168	158	158	166	168	168	111	167
R^2	0.00	0.00	0.00	0.00	0.04	0.01	0.00	0.03	0.01	0.01	0.07	0.07	0.08	0.07	0.11	0.08	0.08	0.12	0.10	0.08
Adj. R^2	0.00	-0.01	0.00	0.00	0.04	0.01	0.00	0.02	0.00	0.01	0.05	0.05	0.06	0.05	0.08	0.05	0.06	0.09	0.06	0.05

Table 9. Cash-based operating profitability

This table reports time-series predictive regression results that use B/M, cash-based operating profitability, and asset growth as predictors. 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. The t-statistics in parentheses are computed using Newey-West (1987) standard errors with three lags. Our full sample of annual (quarterly) accounting data covers the period 1962-2014 (1975Q1-2016Q4), and the corresponding stock returns data spans July 1963-June 2016 (August 1975-July 2017). For OOS analyses, 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 OOS forecast period is July 1992-June 2016 (for one-year-ahead return forecasts) and July 1993-June 2016 (for two-year-average return forecasts). 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 9. Cash-based operating profitability (continued)

Panel A: Predicting one-year-ahead stock returns R^e_{t+1}	1	2	3	4	5	6
Constant	0.063***	0.063***	0.063***	0.063***	0.063***	0.063***
	(3.05)	(3.24)	(3.57)	(3.23)	(3.37)	(3.93)
$\ln(B_t/M_t)$	0.031			0.060**	0.014	0.045*
	(1.48)			(2.14)	(0.72)	(1.84)
$OpCash_t/B_{t-1}$		0.018		0.052*		0.058**
		(0.67)		(1.87)		(2.38)
dA_t/A_{t-1}			-0.046***		-0.040***	-0.047***
			(-3.68)		(-2.75)	(-3.07)
No. of Obs.	53	53	53	53	53	53
Prob>F	0.146	0.505	0.001	0.082	0.001	0.001
IS R^2	0.04	0.01	0.08	0.10	0.08	0.17
IS adj. R^2	0.02	-0.01	0.06	0.07	0.05	0.12
			OOS forecasts			
OOS R^2	-0.05	-0.04	0.12	0.07	0.01	0.19
ENC-NEW	-0.12	0.36	1.84**	1.51**	0.68	3.86**

Panel B: Predicting two-year-average stock returns $R^e_{(t+1,t+2)}$	1	2	3	4	5	6
Constant	0.056***	0.056***	0.056***	0.056***	0.056***	0.056***
	(3.02)	(3.22)	(3.46)	(3.39)	(3.47)	(4.81)
$\ln(B_t/M_t)$	0.018			0.047*	-0.004	0.026
	(0.96)			(1.79)	(-0.28)	(1.47)
$OpCash_t/B_{t-1}$		0.025		0.051**		0.058***
		(1.19)		(2.47)		(3.54)
dA_t/A_{t-1}			-0.049***		-0.051***	-0.057***
			(-5.81)		(-4.73)	(-5.25)
No. of Obs.	52	52	52	52	52	52
Prob>F	0.341	0.238	0.000	0.051	0.000	0.000
IS R^2	0.03	0.05	0.20	0.17	0.20	0.38
IS adj. R^2	0.01	0.03	0.18	0.14	0.16	0.34
			OOS forecasts			
OOS R^2	-0.13	-0.06	0.20	0.00	0.05	0.31
ENC-NEW	-1.07	0.95*	3.26***	1.18	1.25	7.57***

Table 10. Predicting the CRSP index returns

Panels A, B, and C of this table predict, respectively, one-year-ahead, two-year-average, and one-quarter-ahead value-weighted returns on the CRSP index. 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. Statistical significance at 10%, 5%, and 1% are indicated as *, **, and ***, respectively. This analysis uses accounting data from 1962-2014 (1975Q1-2016Q4) and stock returns data from July 1963-June 2016 (August 1975-July 2017) in Panels A and B (Panel C).

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

	1	2	3	4	5	6
Constant	0.063***	0.063***	0.063***	0.063***	0.063***	0.063***
	(3.02)	(3.17)	(3.42)	(3.18)	(3.25)	(3.87)
$\ln(B_t/M_t)$	0.034			0.055**	0.018	0.043**
	(1.64)			(2.27)	(0.85)	(2.04)
GP_t/B_{t-1}		0.012		0.041		0.067***
		(0.46)		(1.47)		(2.87)
dA_t/A_{t-1}			-0.048***		-0.041***	-0.065***
			(-3.99)		(-3.00)	(-4.82)
No. of Obs.	53	53	53	53	53	53
R^2	0.04	0.01	0.08	0.08	0.09	0.18
Adj. R^2	0.02	-0.01	0.06	0.04	0.05	0.13

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

	1	2	3	4	5	6
Constant	0.055***	0.055***	0.055***	0.055***	0.055***	0.055***
	(2.85)	(2.94)	(3.22)	(3.09)	(3.18)	(4.40)
$\ln(B_t/M_t)$	0.022			0.042*	0.001	0.027
	(1.22)			(1.80)	(0.09)	(1.67)
GP_t/B_{t-1}		0.014		0.036		0.065***
		(0.56)		(1.40)		(3.48)
dA_t/A_{t-1}			-0.051***		-0.051***	-0.073***
			(-6.54)		(-5.11)	(-7.03)
No. of Obs.	52	52	52	52	52	52
R^2	0.04	0.01	0.19	0.10	0.19	0.38
Adj. R^2	0.02	-0.01	0.17	0.07	0.16	0.34

Table 10. Predicting the CRSP index returns (continued)

Panel C: Predicting one-quarter-ahead stock returns R^e_{t+1}						
	1	2	3	4	5	6
Constant	0.019***	0.019***	0.019***	0.019***	0.019***	0.019***
	(3.18)	(3.17)	(3.36)	(3.26)	(3.33)	(3.45)
$\ln(B_t/M_t)$	0.007			0.017**	0.004	0.015*
	(1.08)			(1.98)	(0.60)	(1.73)
$\sum GP_t/B_{t-4}$		0.000		0.014*		0.016*
		(0.08)		(1.69)		(1.74)
dA_t/A_{t-4}			-0.012**		-0.011**	-0.012*
			(-2.31)		(-2.07)	(-1.76)
No. of Obs.	168	168	168	168	168	168
R^2	0.01	0.00	0.03	0.02	0.03	0.05
Adj. R^2	0.00	-0.01	0.02	0.01	0.02	0.03

Table 11. Non-overlapping two-year-average stock returns: predictive regressions

This table reports predictive regression results for non-overlapping, two-year-average stock returns. In OOS analyses, the training sample contains only the even years in 1962-1990, and the OOS period contains only the even years in 1992-2016. 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. 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.

Predicting two-year-average stock returns $R^e_{(t+1,t+2)}$						
	1	2	3	4	5	6
Constant	0.057***	0.057***	0.057***	0.057***	0.057***	0.057***
	(3.04)	(3.45)	(3.18)	(3.32)	(3.08)	(4.67)
$\ln(B_t/M_t)$	0.021			0.034*	0.003	0.022*
	(1.57)			(1.87)	(0.19)	(1.74)
GP_t/B_{t-1}		0.011		0.028		0.059***
		(0.58)		(1.41)		(3.72)
dA_t/A_{t-1}			-0.046***		-0.045***	-0.069***
			(-4.59)		(-3.86)	(-5.22)
No. of Obs.	26	26	26	26	26	26
IS R^2	0.05	0.01	0.23	0.11	0.23	0.47
IS adj. R^2	0.01	-0.03	0.20	0.04	0.17	0.40
			OOS forecasts			
OOS R^2	-0.09	-0.11	0.23	-0.12	0.09	0.32
ENC-NEW	-0.31	-0.15	2.05**	-0.32	0.96	3.36**

Table 12. Non-overlapping two-year-average stock returns: CER gains

This table reports the certainty equivalent return (CER) gains from jointly using B/M, profitability, and asset investment instead of the B/M only as equity premium predictors for portfolio allocation, based on non-overlapping, two-year-average equity premium forecasts. The training sample contains only the even years in 1962-1990, and the OOS period contains only the even years in 1992-2016. Statistical significance at 10%, 5%, and 1% are indicated as *, **, and ***, respectively.

Predictor(s)			CER (%)	CER gain (%)	Test statistic for CER gain
			Panel A: Risk aversion coefficient γ = 1		
$\ln(B_t/M_t)$	-	-	12.33	-	-
$\ln(B_t/M_t)$	GP_t/B_{t-1}	-	12.33	0.00	0.00
$\ln(B_t/M_t)$	dA_t/A_{t-1}	GP_t/B_{t-1}	14.62	2.30	1.28
			Panel B: Risk aversion coefficient γ = 3		
$\ln(B_t/M_t)$	-	-	8.18	-	-
$\ln(B_t/M_t)$	GP_t/B_{t-1}	-	8.48	0.30	0.17
$\ln(B_t/M_t)$	dA_t/A_{t-1}	GP_t/B_{t-1}	11.85	3.67	1.80*
			Panel C: Risk aversion coefficient γ = 5		
$\ln(B_t/M_t)$	-	-	4.96	-	-
$\ln(B_t/M_t)$	GP_t/B_{t-1}	-	5.47	0.51	0.31
$\ln(B_t/M_t)$	dA_t/A_{t-1}	GP_t/B_{t-1}	10.64	5.68	3.29***