Aggregate Expected Investment Growth and Stock Market Returns*

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Abstract

Consistent with neoclassical models with investment lags, we find that a bottom-up measure of aggregate investment plans, namely, aggregate expected investment growth (AEIG), negatively predicts future stock market returns, with an adjusted in-sample R^2 of 18.5% and an out-of-sample R^2 of 16.3% at the one-year horizon. The return predictive power is robust after controlling for popular macroeconomic return predictors, in subsample periods, as well as in other G7 countries. Further analyses suggest that the predictive ability of AEIG is more likely to be driven by the time-varying risk premium than by behavioral biases such as extrapolative expectations.

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1 Introduction

A basic idea in economics (e.g., Cochrane (1991)) states that capital expenditure decreases with the cost of capital, so corporate investment should negatively predict future stock returns. However, the existing literature finds mixed evidence on the relation between investment and future market returns. While some papers (e.g., Arif and Lee (2014)) document a strong negative relation, others (e.g., Lamont (2000) and Baker and Wurgler (2000)) find this return predictability to be quite weak. Lamont (2000) attributes this weak correlation to the friction of investment lags. Using plant and equipment expenditure survey data from the US Department of Commerce, Lamont (2000) finds that firms' investment plans, rather than actual capital expenditures, have substantial forecasting power for future market returns.

In this paper, we propose a bottom-up measure of aggregate investment plans, referred to as the aggregate expected investment growth (AEIG), by aggregating the firm-level expected investment growth (EIG). Consistent with the prediction of neoclassical models with investment lags, we show that AEIG is a strong and negative predictor for future stock market returns from one-month to 5-year horizons. At the one-month horizon, the coefficient on AEIG is negative and more than 3.1 standard errors below zero. At the one-year horizon, AEIG predicts future stock market returns with an adjusted in-sample R^2 of 18.5% and an out-of-sample R^2 of 16.3%. This predictive power is remarkably strong compared with most existing well-known predictors.[1] It peaks at about two years and gradually decays afterwards, consistent with the relatively low persistence of AEIG.

The predictive ability of AEIG is robust to controlling for other popular predictive variables, including the Treasury bill rate, term spread, default spread, and market return variance, as well as variables in more recent papers, such as the aggregate investment rate (Arif and Lee (2014)) and the ratio of new orders to shipments (Jones and Tuzel (2013)). We further test the robustness of the predictive ability of AEIG in several ways. First, we split the full sample period in half and find similar results in both subsamples. Second, to minimize the effect of autocorrelation of errors on the statistical inferences due to the overlapping sample in cumulative returns, we repeat the predictive regressions using a non-overlapping sample. Again, we find very similar results

[1] For example, in their abstract, Rapach, Ringgenberg, and Zhou (2016) state that "we show that short interest is arguably *the* strongest known predictor of aggregate stock returns. It outperforms a host of popular return predictors both in and out of sample with annual R^2 statistics of 12.89% and 13.24%, respectively".

as in the benchmark overlapping sample. Third, we control for small sample bias (Stambaugh (1999)) using Monte Carlo simulations. We consider a case in which AEIG and market returns are independent of each other, and another case in which lag market returns and AEIG are correlated. In both cases, the empirically estimated AEIG coefficients are statistically significant at almost all horizons. Lastly, we extend the analysis to the international data and find qualitatively similar patterns among all other G7 countries.

AEIG predicts not only future market returns but also macroeconomic activities. We find hump-shaped dynamics of aggregate investment growth, gross domestic product (GDP) growth, consumption growth, and industrial production growth following periods of high AEIG. In particular, the economic growth tends to be positive in the first two quarters, followed by recessions in the subsequent two to three years. In the predictive regressions for future non-residential investment growth, a one percentage point increase in AEIG is associated with a 0.45% (t-statistic = 3.09) increase in the actual non-residential investment growth in the subsequent year. However, the effect becomes -0.03% (t-statistic = -0.2) in the second year and -0.38% (t-statistic = -3.24) in the third year. A similar pattern exists for GDP and aggregate consumption growth. Although high AEIG is associated with strong GDP and consumption growth in the subsequent year, the coefficients on AEIG become strongly negative in the second year. Therefore, high AEIG leads both stock market declines and business cycle peaks.

Our main finding that AEIG negatively predicts stock returns can be consistent with both rational and behavioral explanations. On the rational side, when the aggregate cost of capital falls due to either a lower price of risk or a lower quantity of risk, firms initiate more investment plans and AEIG increases. This is followed by lower stock returns on average, corresponding to a risk-based explanation for the predictive ability of AEIG. On the behavioral side, investors can be overly optimistic about the aggregate economy and overvalue the stock market, while managers initiate too many investment plans either because they share this sentiment with investors or because they take advantage of this overvaluation by issuing more equity. This mispricing is then corrected by disappointing future economic fundamentals when investors realize their prior expectation errors, giving rise to the negative predictive ability of AEIG for market returns.

To examine these two alternative interpretations, we first investigate the relation between AEIG and various measures of economic uncertainty. For all six uncertainty measures we consider, including the survey-based and market-based measures, we find strong negative correlations with AEIG. For example, a one-standard-deviation increase in the forecast dispersion in business fixed investment growth is associated with a 28% decrease in AEIG. Similarly, a one-standard-deviation increase in the market return variance is associated with a 21% decrease in AEIG. The negative relation between economic uncertainty and investment plans can be consistent with neoclassical models of investment: when the aggregate uncertainty is high, the cost of capital is high and the aggregate investment plan is low. It can also be consistent with the standard real option theory of investment: when uncertainty is high, firms tend to postpone investment decisions because the option value of waiting is high (e.g., Dixit and Pindyck (1994), Bloom (2009)). Thus, the lower risk premium due to the lower aggregate quantity of risk following periods of high AEIG can contribute to the return predictive ability of AEIG.

We then examine how AEIG relates to investor sentiment. Of the five investor sentiment measures we consider, namely, the Baker and Wurgler (2006) investor sentiment index, the aligned investor sentiment index from Huang, Jiang, Tu, and Zhou (2015), the University of Michigan consumer sentiment index, the aggregate investment rate from Arif and Lee (2014), and the percent equity issuance from Baker and Wurgler (2000), we find AEIG is positively correlated with all these five measures, with a correlation coefficient of 0.41, 0.52, 0.27, 0.47, and 0.01, respectively. However, in the return predictive regressions, the coefficient on AEIG remains negative and significant after controlling for each of these sentiment measures. Moreover, we test whether AEIG is able to predict future earnings announcement returns and analyst forecast errors, as would be predicted by a sentiment-based explanation. Again, we only find some weak evidence that AEIG is positively related to long-term forecast errors. Even controlling for these ex post earnings surprises and forecast errors measures, AEIG is still able to significantly predict market returns, suggesting that the return predictive power of AEIG is unlikely to be completely driven by investor sentiment.

As an alternative test, we compare the performance of the industry-level EIG and AEIG in predicting industry-level returns. If investor sentiment is the driving force behind the AEIG's predictive ability, we expect that the industry-level EIG would dominate because it captures industry-level sentiment better than AEIG. In the univariate regressions, the coefficients on industry-level EIG and AEIG are both negative. However, when we run horse races between the industry-level and aggregate expected investment growths, AEIG completely drives out the predictive ability of industry-level EIG. This result holds in all three industry classifications we consider: the Global Industry Classification Standard (GICS), the Fama and French 5 industries, and the Fama and French 30 industries, suggesting that investor sentiment is unlikely to be the main driver for the return predictive ability of AEIG.

This paper contributes to the large literature that links financial markets with firms' investment decisions. Cochrane (1996) finds that aggregate investment growth is a risk factor that helps to price the cross section of stock returns. Liu, Whited, and Zhang (2009) extend Cochrane (1991) and find that the Euler equation implied from a firm's optimization problem could capture the average stock returns of earnings surprises, book-to-market equity, and capital investment. Hou, Xue, and Zhang (2015) propose a four-factor asset-pricing model based on the q theory of investment and find that this empirical factor model can well capture a broad cross section of stock returns.[2]

The closest papers to ours are Lamont (2000) and Jones and Tuzel (2013). Lamont (2000) tests the effect of investment lags on neoclassical models of investment using the plant and equipment expenditure survey from the US Department of Commerce and documents a negative relation between investment plans and future market returns. Compared to this survey-based investment plans measure, our AEIG measure has several advantages. First, AEIG is available at higher frequencies and has more comprehensive coverage of public firms, which allows us to more closely examine the relation between investment lags, aggregate stock returns, and business cycle variables. It also provides more timely information about the aggregate risk premium for investors to time the market. In contrast, the survey-based measure of investment plans is only available at an annual frequency. In addition, the AEIG measure is based on firm-level stock return and accounting data and is easy to construct, whereas the survey-based measure in Lamont (2000) has been discontinued since 1994. Moreover, our approach avoids the look-ahead bias that affects many of Lamont's results.[3] Therefore, AEIG can be considered as an alternative, more timely measure of aggregate investment plans that is available at higher frequencies.

The more recent paper by Jones and Tuzel (2013) studies the return predictive power of the ratio

[2]Other papers that study the implications of investment-based asset-pricing models on asset prices include Belo (2010), Jermann (2010), Kogan and Papanikolaou (2013), Kogan and Papanikolaou (2014), and Li (2016). Cochrane (2005) and Zhang (2015) provide excellent reviews on this literature.

[3]The investment plans series is usually not collected until February or March of the year. However, the investment plan variable is used to predict calendar-year returns and investment in many of Lamont's analyses. This approach leads to look-ahead bias.

of new orders and shipment of durable goods (NO/S). To the extent that new orders capture future investment, NO/S can be interpreted as another measure of aggregate investment plans. Indeed, high values of both AEIG and NO/S follow economic expansions and stock market rallies, and both measures negatively predict future market returns. However, compared to NO/S in Jones and Tuzel (2013), AEIG is a bottom-up measure from the aggregation of firm-level expected investment growths. When firms' managers have unique information and perspectives about the macroeconomy and investors' required rates of returns, the aggregation of firm-level investment plans (AEIG) can contain valuable information about the market risk premium that is absent in aggregate measures such as NO/S. Moreover, the new orders and shipments data only cover manufacture industries, whereas our AEIG is more representative for the whole market. Indeed, the monthly correlation between AEIG and NO/S is only 0.05, and the return predictive power of AEIG remains strong after controlling for NO/S up to three years.

AEIG is also related to the bottom-up measure of aggregate investment (INV) from Arif and Lee (2014). A key difference between these two investment-related variables is that the former is a measure of the *expected* investment growth, whereas the latter is a measure of *realized* investment. Due to lags in investments, neoclassical theories of investment imply that expected or planned investment growth should capture the time variation in the cost of capital better than realized investment (see, e.g., Cochrane (1991), Lamont (2000), and Jones and Tuzel (2013)). Although the correlation between AEIG and INV of Arif and Lee (2014) is 0.47, controlling for INV does not substantially alter the predictive power of our AEIG. Moreover, INV and AEIG have very different economic interpretations. While Arif and Lee (2014) argue that their INV mainly captures the time variation in investor sentiment, our empirical analyses show that the predictive power of AEIG is more likely to be driven by the time variation of aggregate risk premium.

Lastly, this study is also related to an extensive literature on aggregate market return predictability, which is too vast to cite here (for a survey, see Lettau and Ludvigson (2010)). Unlike traditional macro predictors such as the dividend yield (Campbell and Shiller (1988)), the wealth-consumption ratio (Lettau and Ludvigson (2001)), and the consumption-surplus ratio (Campbell and Cochrane (1999)), whose 12-order autocorrelation coefficients are all 0.9 or above at the monthly frequency, the 12-order autocorrelation for AEIG is only 0.39. Thus, our findings indicate that the market risk premium has significant high-frequency movements. A few recent studies have also highlighted the high-frequency (i.e., low-persistence) fluctuations in the risk premium (see, e.g., Kelly and Pruitt (2013), Liu, Tao, Wu, and Yu (2016), and Martin (2017)), although earlier studies (e.g., Fama and French (1989)) tend to find highly persistent risk premia.

The paper proceeds as follows. Section 2 describes the data sources and variable construction for our empirical analysis. Section 3 discusses the main results. Specifically, we document a strong negative relation between AEIG and future stock returns, and perform several robustness checks on this finding. In Section 4, we perform extensive analyses on the sources of the predictive power of AEIG. The results suggest that the time variation in the quantity of risk, and hence the aggregate risk premium, is more likely to be responsible for the return predictive ability of AEIG, whereas investor sentiment plays a less important role. Section 5 concludes.

2 Data

The data used in our analyses come from several sources. Stock data are from the Center for Research in Security Prices (CRSP) database, and the firm-level accounting data are from the Compustat annual database. Macroeconomic return predictors, except for the surplus ratio and Jones and Tuzel's (2013) ratio of new orders to shipments, are from Amit Goyal's website. The aggregate earnings and dividends data are from Robert Shiller's website, and the growth rates of standard business cycle variables are from the national income and product accounts (NIPA) from the Bureau of Economic Analysis (BEA).[4] Industrial production data are from Federal Reserve Bank of St. Louis. The data on the Livingston Survey are from the Federal Reserve Bank of Philadelphia. Analyst forecast data come from I/B/E/S. Our full sample is monthly from June 1953 to December 2015.

Our main predictive variable, aggregate expected investment growth (AEIG), is a bottom-up measure from firm-level expected investment growth (EIG). Similar to Li and Wang (2017), we estimate firm-level EIG in two steps. In the first step, each year, we run a panel predictive regression of the investment growth in the subsequent year on momentum (prior 2-12 month stock returns), q, and cash flow, using the up-to-date data of all stocks (excluding ADR). In the second step, we calculate the monthly firm-level EIG as the out-of-sample predicted value of investment

[4] We thank Christopher Jones and Selale Tuzel for making their data and code publicly available. We thank Amit Goyal, Ivo Welch, and Robert Shiller for making their data publicly available.

growth based on the estimated coefficients to date and the current values of momentum, q, and cash flow.[5] AEIG is then defined as the value-weighted average of firm-level EIG (excluding ADR) with the market value of equity at the end of the previous month as the weight. In order to remove the monthly seasonality in stock returns, such as the January effect, we further smooth our AEIG measure using its prior 12-month moving average.

Panel A of Table 1 reports the mean, standard deviation (Std), 12th-order autocorrelation (AC(12)),[6] skewness (Skew), and kurtosis (Kurt) of the monthly predictive variables used in our analysis. These predictive variables include AEIG, log of dividend yield (DP), consumption-wealth ratio (CAY) from Lettau and Ludvigson (2001), term spread (TMS), stock variance (SVAR), default yield spread (DFY), inflation (INFL), detrended T-bill rate (TBL) detrended by the Hodrick-Prescott (HP) filter, surplus ratio (SPLUS) as in Wachter (2006), investment-to-capital ratio (I/K), and the ratio of new orders to shipments (NO/S) from Jones and Tuzel (2013).[7] The standard deviation of AEIG is about 5% per year, which is smaller than the 8.9% for the realized gross private domestic investment growth. More importantly, AEIG is not very persistent. Unlike predictive variables such as DP, CAY, and SPLUS, which are highly persistent over time, the 12th-order autocorrelation coefficient for AEIG is only 0.39. This low persistence implies that if AEIG captures some component of the market risk premium, this component tends to be relatively short-lived compared to those captured by DP, CAY, or SPLUS. As for the higher moments of the AEIG distribution, we observe a small positive skewness (0.57) with a kurtosis of 2.29.

[Insert Table 1 Here]

Panel B of Table 1 reports the correlation matrix of these predictive variables. The variable that has the highest correlation with AEIG is DP, with a correlation coefficient of −0.5. Since an important determinant of firm-level EIG is the prior 2- to 12-month stock returns, AEIG tends

[5] Specifically, investment growth is the growth rate of investment expenditure (Compustat data item CAPX), momentum is the (-12,-2) 11-month cumulative stock return from the fiscal year end, q is the market value of the firm (sum of market equity, long-term debt, and preferred stock minus inventories and deferred taxes) divided by capital (Compustat data item PPEGT), and cash flow (CF) is the sum of depreciation (Compustat data item DP) and income before extraordinary items (Compustat data item IB) divided by capital (Compustat data item PPEGT). By linking firm-level investment growth to the momentum, q, and cash flows, Li and Wang (2017) find that EIG is a very strong predictor of future investment growth.

[6] The moving average smoothing mechanically generates a high 1st autocorrelation at the monthly frequency. Therefore, we report the 12th-order autocorrelation, which is not affected by this procedure.

[7] Following Goyal and Welch (2008), we lag inflation data by one month since the data are only released to the public in the following month.

to be high when the past market return is high, which also corresponds to periods with a low DP ratio. However, given that these two variables have very different persistence, their return predictive powers work at different horizons, as we see in the next section. The other variables that comove strongly with AEIG is I/K, with a correlation coefficient of 0.43. Intuitively, when aggregate q and cash flow are high, the economy invests more and initiates greater investment plans. On the other hand, the negative correlation between AEIG and SPLUS (-0.1) is a bit surprising because both variables tend to be procyclical with respect to business cycles. Since SPLUS is a common proxy for the aggregate risk aversion (Campbell and Cochrane (1999)), this weak and negative correlation can be used to distinguish the roles of the price of risk and quantity of risk for a risk-based interpretation. We elaborate this discussion in Section 4.

Figure 1 plots the time series of normalized AEIG and the actual growth rate of gross private domestic investment from NIPA. Since AEIG in a certain year measures the expectation of the realized investment growth in the next year, we lag AEIG by one year to align with the timing of the realized investment growth to facilitate illustration. Figure 1 shows that AEIG predicts aggregate investment growth reasonably well. For instance, it captures the large variation in aggregate investment growth during the mid-1970s oil crisis, as well as the sharp decline in investment growth in the most recent 2008-2009 financial crisis. The correlation between AEIG and the one-year future realized aggregate investment growth is 0.48.

[Insert Figure 1 Here]

In untabulated analyses, we provide two additional justifications for our AEIG measure. First, we find that AEIG indeed captures the aggregate investment plans by corporate and noncorporate firms. The correlation between AEIG and the investment plans from the plant and equipment expenditure survey from the US Department of Commerce (Lamont (2000)) is 0.58 between 1953 and 1994.[8] However, the return predictive power of AEIG is not subsumed by these aggregate investment plans and remains highly significant in the same sample period. Specifically, the Newey-West t-statistic is -5.7 and the Hodrick t-statistic is -3.55 at a one-year predictive horizon after controlling for the aggregate investment plans in Lamont (2000). Second, we confirm that AEIG

[8]The survey was discontinued in September 1994. We are very grateful to Selale Tuzel for sharing these hand-collected data on aggregate investment plans with us.

is indeed expected by investors. Using the average forecasted one-year business fixed investment growth (`BFIX_B12M_Median`) from the Livingston Survey, we find that AEIG is positively associated with these forecasted investment growth measures, with a correlation coefficient of 0.42.

3 Stock return predictability

In this section, we explore the relation between AEIG and future stock market returns.

3.1 Main results

Table 2 reports the result of the return predictive regressions using the monthly overlapping sample. The monthly excess market return is calculated as the difference between the value-weighted market returns from CRSP and the risk-free rate. For each specification of the predictive regressions, we report the point estimate, the t-statistics estimated based on the Newey and West (1987) standard error and Hodrick (1992) standard error, and the in-sample adjusted R^2.

[Insert Table 2 Here]

Panel A of Table 2 presents the result from the univariate regressions of the log of cumulative excess market returns over the next one month, three months, one year, two years, three years, and five years on AEIG and other predictive variables that are described in Table 1. For all horizons considered here, the coefficient on AEIG is strongly negative, indicating that high AEIG predicts lower stock market returns. At the very short end of the spectrum (one-month), the coefficient on AEIG is -0.12 with a Newey-West t-statistic of -3.68 and a Hodrick t-statistic of -3.15, and the adjusted R^2 is 1.53%. The predictive power of AEIG exceeds all other predictive variables except the detrended T-bill rate, which has an adjusted R^2 of 2.17% at the one-month horizon. The magnitude of the AEIG coefficient and the associated adjusted R^2 from the predictive regressions increase with horizons. At the one-year horizon, the coefficient on AEIG becomes -1.54 with a Hodrick t-statistic of -3.59 and an adjusted R^2 of 18.53%. This R^2 is significantly greater than that of all other predictive variables, which ranges from 0.25% for market variance (SVAR) to 9.09% for the ratio of new orders to shipments (NO/S). Economically, AEIG captures a large time-series variation in expected excess market returns, with a one-standard-deviation increase in AEIG being associated with about a 7.7% decrease in annual expected market returns. The magnitude of AEIG coefficient continues to rise but at a much lower rate beyond the two-year horizon, suggesting that the expected return captured by AEIG is relatively short-lived.

Panel A of Table 2 also reports the return predictability of other macro variables. The previous literature documents that variables related to the business cycle can predict future stock market returns.[9] Consistent with the literature, we find that the dividend yield (DP), the consumption-wealth ratio (CAY), and the term premium (TMS) are positively associated with future market returns, whereas inflation (INFL), the detrended T-bill rate (TBL), and the surplus ratio (SPLUS) negatively predict market returns. The predictive variables in the last two specifications of Panel A are related to investment. I/K from Goyal and Welch (2008) measures the aggregate investment rate, and NO/S from Jones and Tuzel (2013) captures the ratio of new orders to shipments and can be considered as a measure of aggregate future investment growth. Across horizons from one month to five years, both investment-related measures predict market returns with a negative sign. However, the return predictive power of AEIG is not subsumed by these macro variables. Panel B reports the coefficients in the bivariate regressions, controlling for each one of the macro variables in Panel A. In all specifications, the coefficient on AEIG remains statistically significant at the 5% level for up to three-year horizons. Even at the five-year horizon, 8 out of 11 specifications still generate a significantly negative AEIG coefficient based on the Hodrick t-statistics. Lastly, when all variables from Panel B (except NO/S) are included in the regression, we find qualitatively similar patterns for AEIG coefficients in Panel C of Table 2.[10] In addition, the investment-to-capital ratio I/K becomes insignificant at most horizons once other macro variables are controlled for.

Since our AEIG is the aggregation of firm-level EIG which in turn is based on firm-level stock returns, q, and cash flow, one might be concerned that our results could be driven by the predictive power of the aggregate lagged market returns, aggregate market-to-book ratios, and aggregate earnings. Thus, in untabulated analysis, we control for additional predictors including cumulative market returns over the past one, three, or five years, aggregate book-to-market ratio, aggregate

[9]See, for example, Chen, Roll, and Ross (1986), Keim and Stambaugh (1986), Campbell and Shiller (1988), Fama and French (1988), Fama and French (1989), Fama (1990), Campbell (1991), Ferson and Harvey (1991), Lettau and Ludvigson (2001), and Lettau and Ludvigson (2005).

[10]We exclude NO/S in the pooling regressions due to its shorter sample period. Our results are similar if we include NO/S and start our sample in February 1958, the first month that NO/S is available. In an untabulated analysis, we use another specification, controlling for the first three principal components extracted from these macro variables, and find that AEIG is still significant.

earnings-price ratio from Goyal and Welch (2008), as well as more recently documented return predictors including the variance risk premium (Bollerslev, Tauchen, and Zhou (2009)), and the nearness to the Dow 52-week high and the nearness to the Dow historical high (Li and Yu (2012)), the government investment rate (Belo and Yu (2013)), short interests (Rapach, Ringgenberg, and Zhou (2016)), and the debt-to-GDP ratio (Liu (2017)).[11] The coefficient of AEIG remains significant at all horizons after controlling for these predictors. To save space, these results are omitted and available upon request.

As argued by Cochrane (1991) and Lamont (2000), when discount rates fall, current stock prices increase, and thus current stock returns are high. Meanwhile, investments should rise in response to a drop in discount rates. Thus, if investments can adjust *instantaneously* to the changes in discount rates, the contemporaneous correlation between investment growth and stock returns should be positive, and the correlation between investment growth and future stock returns should be negative. However, as shown by Lamont (2000) and confirmed with more recent data, the contemporaneous correlation between nonresidential investment growth and stock returns is negative (correlation $= -0.33$, t-stat $= -2.22$). In addition, nonresidential investment growth cannot significantly forecast future stock returns (correlation $= -0.08$, t-stat $= -0.82$).

On the other hand, aggregate expected future investment growth ($AEIG_t$) and current stock returns (r_t) positively covary over time (correlation $= 0.28$, t-stat $= 2.42$). This is consistent with the important role of investment lags: when discount rates fall, firms immediately increase planned investment, even though the actual capital expenditure does not realize until the subsequent years. Meanwhile, stock prices also rise instantly. Moreover, the negative correlation between expected investment growth and expected returns (Table 2) reduces the correlation between realized investment growth and realized returns and can even turn it negative. Taken together, these facts indicate that investment lags can break the immediate temporal link between investments and stock prices, as implied by standard q theory of investment. These facts also highlight the importance of using expected and planned investment growth, rather than realized investment growth, in predicting future stock returns.

Lastly, our results indicate that the time-series relation between AEIG and future aggregate stock returns is negative, although Li and Wang (2017) show that the cross-sectional relation

[11]We thank Yang Liu for sharing his data with us.

between firm-level expected investment growth and stock returns is positive. It is well-known that firm-level relations do not necessarily carry to the aggregate level. For example, Kothari, Lewellen, and Warner (2006) document a negative relation between aggregate earnings surprises and stock returns, opposite to the well-known positive firm-level relation. In addition, Hirshleifer, Hou, and Teoh (2009) find a positive accrual-return relation at the aggregate level and a negative relation at the firm level. These opposite patterns can be driven by the fact that news about individual firms and news about the aggregate economy have a different impact on the pricing kernel. Indeed, Yan (2011) argues that news about an individual stock typically has only a trivial impact on the aggregate economy, whereas news of the aggregate stock market may have a significant impact on the prospects of the economy, and hence has a large impact on the pricing kernel. Thus, while the cash flow effect may dominate at the firm level, whereas the discount effect can dominate at the aggregate level, potentially leading to the opposite relation in the time series and the cross section.

3.2 Robustness checks

In this subsection, we perform several robustness checks to the return predictability of AEIG. In Section 3.2.1, we repeat the same regressions in two subsamples and a non-overlapping full sample. Section 3.2.2 addresses the estimation bias due to the finite sample using Monte Carlo simulations. In Section 3.2.3, we examine the out-of-sample performance of AEIG in predicting market returns.

3.2.1 Subperiod and non-overlapping analysis

As the first robustness check, we perform subsample analyses. We divide the full sample into two subsamples and repeat the monthly overlapping regressions within each subsample. The early subsample is from June 1953 to December 1983 except for NO/S, which is from February 1958 to December 1983 due to the data availability of NO/S, and the late subsample is from January 1984 to December 2015. Table 3 reports the results for the early subsample (Panel A) and the late subsample (Panel B). In each panel, the first column reports the results for the univariate regressions with AEIG as the only return predictor. For all other columns, we run the bivariate regressions with AEIG and one of the macro control variables as the predictive variables, and report the coefficient and t-statistics of AEIG and the associated adjusted R^2.

[Insert Table 3 Here]

In the early subsample in Panel A, AEIG negatively predicts market returns in the univariate regressions, and its coefficient remains statistically significant. For the one-month market return predictive regression, the AEIG coefficient is -0.13 with a Hodrick t-statistic of -2.91, and its magnitude increases to -1.85 (Hodrick t-statistic = -3.79) at the one-year horizon. The one-year adjusted R^2 is 22.67%, suggesting a strong potential for market timing in this early sample period. The magnitude of the AEIG coefficient continues to rise with the horizon, although the adjusted R^2 peaks in about two years. At the five-year horizon, the adjusted R^2 becomes 29.30%. Moreover, controlling for other macro variables does not alter the results from the univariate regressions. The coefficient remains stable and significant at all horizons up to two years.

The result is largely consistent during the post-1984 sample, as reported in Panel B of Table 3. The statistical significance is slightly weaker compared to the early subsample and the full sample, but this is partly due to the smaller sample size. When we focus on the economic magnitude of the estimated AEIG coefficient and the adjusted R^2, the main finding remains strong in this late sample. Take the one-year return predictive regressions as an example. In the univariate regression, the AEIG coefficient is -1.60 with a Hodrick t-statistic of -2.24, and the adjusted R^2 is 19.05%, which is close to the full sample adjusted R^2 of 18.53%. When we control for other macro variables, the coefficient of AEIG ranges from -1.85 to -1.44, and the adjusted R^2 ranges from 18.85% to 21.51%. Therefore, our main results reported in Table 2 also hold in subperiods.

The analyses above all focus on the overlapping data, in which we have used both Newey and West (1987) and Hodrick (1992) standard errors to adjust for the autocorrelation and heteroscedasticity. Table 4 reports the results from the return predictive regressions using non-overlapping data. Because we do not have many non-overlapping observations at low frequencies, we focus our discussion only on the horizons up to two years. When AEIG is the only predictor (the first column in Table 4), the magnitude of its coefficient increases from -0.12 (t-statistic = -3.68) at the one-month horizon to -1.54 (t-statistic = -4.55) at the one-year horizon and -2.22 (t-statistic = -3.5) at the two-year horizon. The one-year adjusted R^2 is 18.71%. Controlling for other macro variables does not substantially affect this return predictability. The estimated AEIG coefficient is statistically significant for all specifications.

[Insert Table 4 Here]

3.2.2 Small sample bias

Stambaugh (1986) and Stambaugh (1999) have shown that the standard t-statistics based on asymptotic theory can have poor finite sample properties. When predictor variables are persistent and the innovations in the predictors are highly correlated with the variable being predicted, the small sample biases can be severe (see also Valkanov (2003) and Campbell and Yogo (2006)). To address this issue when predicting stock returns with AEIG, we perform two versions of Monte Carlo simulations to investigate whether the statistical inference based on the in-sample t-statistics is affected by size distortions.

In the first experiment, we assume that AEIG and stock returns are independent of each other. Specifically, we assume the data-generating processes for these two variables to be

$$r_t = r_0 + \epsilon_{0,t}, \tag{1}$$

$$AEIG_t = a_0 + \rho_1 AEIG_{t-1} + \eta_{0,t}, \tag{2}$$

where r_0 and a_0 are constant, ρ_1 captures the 1-month autocorrelation of AEIG, and $\epsilon_{0,t}$ and $\eta_{0,t}$ are independent and identically distributed (i.i.d.) and follow normal distributions. In the second experiment, we still assume no predictability under the null hypothesis. However, we take into account the fact that AEIG is positively correlated with the prior 2- to 12-month market returns ($r_{t-12,t-2}$) due to the way that AEIG is constructed, and allow for this correlation in the data-generating processes:

$$r_t = r_0 + \epsilon_{0,t}, \tag{3}$$

$$AEIG_t = a_0 + \rho_1 AEIG_{t-1} + b_0 r_{t-12,t-2} + \eta_{0,t}, \tag{4}$$

where $b_0 > 0$ captures the positive dependence of AEIG on prior market returns, ρ_1 measures the autocorrelation of AEIG, and $\epsilon_{0,t}$ and $\eta_{0,t}$ are again i.i.d..

For both models, we calibrate the parameter values using the empirical data for AEIG and excess market returns in our benchmark sample.[12] In each simulation, we simulate 850 months with the initial 100-month burn-in period, so that the simulated sample size is the same as its empirical counterpart. We then run the univariate return predictive regressions at various horizons ranging from one month to five years, as we did in Section 3.1. We repeat this procedure 10,000 times, which generates the distribution of the t-statistics (both Newey-West and Hodrick) of the estimated AEIG coefficient, along with the distribution of the adjusted R^2 from the return predictive regressions. To assess whether there are any size distortions with the t-statistics, we compare the empirical size generated from the Monte Carlo experiment against a 5% nominal size. The empirical size is defined as the percentage of times the relevant absolute t-statistics are greater than 1.96. If the empirical size is greater than 5%, the t-statistics tend to overreject the null hypotheses.

We report the results from the Monte Carlo simulations in Table 5. Panel A is for the specification that assumes independence between AEIG and market returns (i.e., Equations (1) and (2)). For one-month-ahead forecasting regressions, the Newey-West t-statistic has reasonable size properties. It is 6% for the null of no return predictability, as opposed to the nominal 5% value. Therefore, the size distortion is mild for the one-month horizon. However, when we increase the forecast horizon, the size distortion is stronger. At the one-year horizon, the size from the simulations is 13%, and it further increases to 17% at the five-year horizon. On the other hand, when we compute the t-statistics for the AEIG coefficient following Hodrick (1992), the empirical sizes are no more than 6% across all horizons we consider here. Hence, consistent with Ang and Bekaert (2007), we indeed find that Newey-West standard errors lead to severe overrejections of the null hypothesis of no predictability at longer horizons, whereas the standard errors in Hodrick (1992) retain the correct size in small samples.

[Insert Table 5 Here]

To evaluate the severity of the size distortions, we provide the 2.5% and 97.5% quantiles of the simulated t-statistics for AEIG. In the Monte Carlo simulations under the assumption of independence between AEIG and returns, the 2.5% quantiles for the Newey-West t-statistics are below the asymptotic value of -1.96 and decrease from -1.99 at the one-month horizon to -2.85 at the

[12] To be more precise, we calibrate the processes using the monthly data on the log of market returns and raw AEIG, simulate the model, and then use the 12-month moving average of the simulated AEIG to run the return predictive regressions.

five-year horizon. These results indicate that for the longer-horizon predictive regressions, we need a Newey-West t-statistic that is higher than standard critical value (in absolute value) to reject the null hypotheses. Comparing these thresholds with the Newey-West t-statistics in Panel A of Table 2, we find the significant predictive power of AEIG holds in all horizons. For example, the t-statistics for AEIG in Panel A of Table 2 are -3.68, -4.41, -6.19, and -5.49 at the 1-, 3-, 12-, and 24-month horizons, as opposed to the threshold t-statistics of -1.99, -2.21, -2.53, and -2.68, respectively, from the simulations reported in Panel A of Table 5. Even at the five-year horizon, the empirical t-statistic is still greater (in magnitude) than the 2.5% quantile from the Monte Carlo simulations. When we use the Hodrick (1992) standard errors, the 2.5% quantiles of the simulated t-statistics for AEIG are very close to the nominal size of -1.96, and the AEIG coefficients from Panel A of Table 2 are again statistically significant for all horizons.

Panel B reports the results from the model that takes into account the correlation between the AEIG and prior market returns (i.e., Equations (3) and (4)). Similar to the small sample properties of the dividend-price ratio in predicting market returns (e.g., Stambaugh (1999)), we find that the size distortions are in general stronger when this correlation is considered. For the Newey-West t-statistics, the empirical size increases from 5% for one month to 16% for five years. On the other hand, the empirical sizes are much closer to the nominal value of 5% for the Hodrick t-statistics. Table 5 also reports the 2.5% and 97.5% quantiles of the simulated adjusted R^2 for both Monte Carlo experiments. When compared to the empirical findings in Table 2, these threshold t-statistics and adjusted R^2 suggest that the return predictive power of AEIG remains statistically significant for all horizons. For example, at the one-year horizon, the 2.5% quantiles of Newey-West and Hodrick t-statistics and the adjusted R^2 are -2.65, -2.08, and 6.45%, while the empirical estimates are -6.19, -3.59, and 18.53%, respectively, from Panel A of Table 2. Collectively, the finite sample bias is unlikely to drive the return predictive ability of AEIG.

3.2.3 Out-of-sample return prediction

We now turn to the out-of-sample performance of AEIG. In a comprehensive study, Goyal and Welch (2008) show that many traditional return forecasting variables perform poorly out of sample. To examine the out-of-sample performance of a predictor, x_t, they first run a regression $r_{t+1} = a + bx_t + \epsilon_{t+1}$ using data up to time τ and use $\hat{r}_{t+1} \equiv \hat{a} + \hat{b}x_\tau$ to forecast the return at time $\tau + 1$.

They then compare the mean squared error of the forecast $\hat{r}_{t+1}$ with that of the other forecast, the sample mean return, $\bar{r}_\tau$, up to time τ. For all variables except CAY, we use $\tau = 120$ months (or 10 years) for our initial estimation. We add one month at a time and reestimate the coefficients $\hat{a}$ and $\hat{b}$ recursively. Since the standard CAY measure in Lettau and Ludvigson (2001) is constructed using full-sample regression coefficients and has look-ahead bias, we follow Lettau and Ludvigson (2001) and estimate an out-of-sample version of CAY, denoted as CAYA ("ante"), using an initial estimation sample period of pre-March 1968. The results are reported in Table 6.

We conduct two sets of out-of-sample tests for AEIG. The first set of tests, the out-of-sample R^2 in (I), is defined as

$$R^2_{oos} = 1 - \frac{\sum_{\tau=1}^{T}(r_\tau - \hat{r}_\tau)^2}{\sum_{\tau=1}^{T}(r_\tau - \bar{r}_\tau)^2}, \tag{5}$$

where $\sum_{\tau=1}^{T}(r_\tau - \hat{r}_\tau)^2$ is the mean squared forecast error (MSFE) of the predictive variable, and $\sum_{\tau=1}^{T}(r_\tau - \bar{r}_\tau)^2$ is the MSFE based on the historical mean of market returns. A positive R^2_{oos} indicates that the predictive variable allows better market timing than the naive investment strategy that is based on the historical average market returns. The second set of tests, the MSFE-adj statistic in (II), tests the null hypothesis that the MSFE based on the historical mean of market returns is greater than the MSFE of the predictive variable following Clark and West (2007). The null hypothesis is rejected at the 95% confidence interval if the resulting MSFE-adj statistic is larger than the critical value 1.645.

[Insert Table 6 Here]

Panel A reports results from the univariate predictive regression in which either AEIG or one of the macro variables is the only predictor. When we focus on the out-of-sample R^2, the return predictive ability of AEIG is the strongest most of the time. At the one-month horizon, the R^2_{oos} for AEIG is 1.08%, and it increases to 16.25% at one year, 21.73% at two years, and then gradually declines to 14.66% at five years. For the other macro variables, we find the R^2_{oos} is positive for INFL, I/K, and NO/S, but negative for DP, CAYA, TMS, SVAR, DFY, TBL, and SPLUS at the one-year horizon.[13] Except for AEIG, the variable with the strongest one-year predictive power is

[13]Alternatively, we follow Campbell and Thompson (2008) and impose the restriction that the equity premium forecast is non-negative to conduct out-of-sample tests. Imposing this restriction sometimes helps improve the out-of-sample performance of return predictors. For example, the R^2_{oos} for CAYA turns positive and becomes 3.5% at

NO/S from Jones and Tuzel (2013), with an associated R^2_{oos} of 7.29%. The result is qualitatively the same when we focus on the MSFE-adj statistic, and the out-of-sample predictive ability of AEIG remains statistically significant for all horizons.

Panel B reports the results from the bivariate return predictive regressions using AEIG and one other macro variable. Among all specifications we consider in Table 6, only five generate negative R^2_{oos}, and some of these specifications come from the long horizons in which we do not have many independent observations. At the one-year horizon, the R^2_{oos} ranges from 3.37% when the dividend-price ratio (DP) is included to 19.06% when NO/S is included. At the two-year horizon, the R^2_{oos} ranges from 0.55% to 30.89%. The reported MSFE-adj statistic implies that the predictive power in the bivariate regressions is statistically significant for all specifications up to two years, so AEIG can also be combined with other macro variables in timing the market.

3.3 Alternative AEIG measures

Our benchmark AEIG is a bottom-up measure of the expected economy-wide investment growth from the aggregation of the firm-level expected investment growth (EIG). To examine the importance of the bottom-up approach, we study two alternative aggregate expected investment growth measures in market return predictive regressions. The results are reported in Table 7.

[Insert Table 7 Here]

In Panel A, we use the median forecasted one-year business fixed investment growth from the Livingston Survey (`BFIX_B12M_Median` series). In the univariate return predictive regression using this forecasted investment growth, we only see some weak evidence of return predictive ability in the long run. In the one-year horizon, the BFIX coefficient is only -0.47 with Newey-West t-statistic of -0.68 and Hodrick t-statistic of -0.57. In the five-year horizon, the BFIX coefficient becomes -4.63 with Newey-West t-statistic of -5.72 and Hodrick t-statistic of -2.88. More importantly, AEIG dominates this survey-based aggregate investment growth forecast in the bivariate regressions including both variables. While the BFIX coefficient becomes insignificant after controlling for AEIG, the AEIG coefficient remains statistically significant for horizons up to three years.[14]

the one-year horizon with this restriction. However, the predictive power of AEIG is barely affected and the one-year R^2_{oos} is 14.30%.

[14]In untabulated analysis, we also use the mean forecasted one-year business fixed investment growth

In Panel B of Table 7, we create another AEIG measure (AEIG_{AG}) using aggregate variables. Specifically, we follow the same procedure as we did when estimating the firm-level EIG and directly construct aggregate expected investment growth by regressing aggregate investment growth on the prior 2- to 12-month market returns, aggregate q, and aggregate cash flows. The first column in Panel B shows that, unlike the benchmark AEIG, the predictive power of AEIG_{AG} for future market returns is quite weak. At the one-month horizon, the AEIG_{AG} coefficient is only -0.02 (with t_{HD} of -0.99). Even at the one-year horizon, the AEIG_{AG} coefficient is -0.18 (with t_{HD} of -0.64). When we run bivariate return predictive regressions using AEIG and AEIG_{AG}, the AEIG coefficient remains negative and statistically significant, and its magnitudes are close to the univariate coefficients reported in Panel A of Table 2. In contrast, the AEIG_{AG} coefficient turns positive after controlling for AEIG at all horizons.

This result in Table 7 suggests that our bottom-up AEIG measure better captures the aggregate investment plans, indicating that managers' perception of future economic conditions contains superior information about market-wide expected returns to aggregate variables such as prior market returns, aggregate q and cash flows, and survey-based aggregate forecasts.

3.4 International evidence

In this subsection, we provide empirical evidence of the return predictive ability of AEIG from the other G7 countries (Canada, Germany, France, UK, Italy, and Japan). For each country, we construct the monthly AEIG as the market value-weighted average of firm-level expected investment growth in the same way as what we do in our benchmark US sample. The international firm-level stock and accounting data come from Compustat Global database. Following Hou, Karolyi, and Kho (2011), we calculate the US dollar denominated market excess returns in excess of the US T-bill rate.[15] The results of the monthly overlapping regressions in these countries are reported in Table 8.

[Insert Table 8 Here]

Table 8 shows that AEIG negatively predicts future stock returns in all other G7 countries.

(`BFIX_B12M_Mean`) from the Livingston Survey and obtain very similar results. AEIG is still significant after controlling for the mean forecasted growth.

[15] We thank Kenneth French to make the data publicly available.

Since the sample sizes of these countries are substantially smaller than that of the US, the statistical significance is weaker and the result should be interpreted with cautions. With this concern in mind, we find the international evidence quite encouraging. At the one-month horizon, the adjusted R^2 is 1.17% in Germany and 2.76% in Japan. At the one-year horizon, the adjusted R^2 is 8.66% for Canada, 9.43% for Germany, 0.94% for France, 3.76% for UK, 7.37% for Italy, and 39.96% for Japan, and the associated Hodrick t-statistic is -1.09, -2.26, -0.91, -1.48, -1.48, and -3.44, respectively. In addition, the estimated coefficient ranges from -3.23 to -0.45, which is economically consistent with -1.54 estimated for our benchmark US sample (Table 2). Therefore, the return predictive ability of AEIG also finds empirical supports in other developed economies.

4 Interpretations

In the previous section, we document that AEIG has strong and robust predictive power for future stock market returns. This return predictability can be due to the time-varying risk premium, where the expected return rises with higher risk aversion (e.g., Campbell and Cochrane (1999)) or a larger aggregate quantity of risk (e.g., Bansal and Yaron (2004)). It can also be driven by investors' behavioral bias. High sentiment can drive up current stock prices and corporate investment plans, giving rise to a negative correlation between aggregate expected investment growth and future stock market returns when mispricing gets corrected by economic fundamentals. For instance, when investors have extrapolative expectations biases (e.g., Barberis, Greenwood, Jin, and Shleifer (2015), Hirshleifer, Li, and Yu (2015)), this negative return predictability naturally arises.

We perform several analyses in this section to differentiate these potential explanations. We explore the relation between AEIG and future economic activities in Section 4.1. Section 4.2 connects AEIG to several measures of economic uncertainty, providing strong empirical support for the interpretation based on the time-varying quantity of risk. Section 4.3 examines the relation between AEIG and investor sentiment. We find some evidence that AEIG is positively associated with investor sentiment. However, these analyses also suggest that the return predictive power of AEIG is unlikely to be completely driven by investor sentiment. Following Jones and Tuzel (2013), we test the relative performance of AEIG and industry-level EIG in predicting future industry returns in Section 4.4. Our finding that AEIG is a much better predictor than industry-level EIG for industry-level returns again supports the risk-based explanation.

4.1 AEIG and economic growth

According to its definition, AEIG captures one-year forecasted aggregate investment growth. Since business investment represents about 15% of GDP in the United States, AEIG should also be closely related to broader economic growth. We study these links in this section.

Table 9 reports the results from the predictive regressions of future fixed investment growth (FINVG) and non-residential investment growth (NRG), and broader economic growth measures in the subsequent first, second, third, and fourth quarter as well as in the next year, second year, third year, and fifth year on AEIG. The broader economic growth measures include GDP growth (GDPG), industrial production growth (IPG), consumption growth (CONG), aggregate earnings growth (EG), and aggregate dividend growth (DG). The estimated coefficients on AEIG are significantly positive in the next quarter for all economic growth measures except EG and DG. A one percentage point increase in AEIG is associated with a 0.62% increase in FINVG, 0.57% increase in NRG, 0.21% increase in GDPG, 0.11% increase in IPG, and 0.15% increase in CONG. These effects decrease over time, and in the second quarter, the AEIG coefficient is only significantly positive for FINVG and NRG. By the fourth quarter, the coefficients become negative for all but two specifications, and none of them are statistically significant. When we aggregate the growth from a quarterly to an annual frequency, AEIG strongly predicts the subsequent one-year investment and economic growth, with the associated adjusted R^2s of more than 10% for FINVG, NRG, GDPG, and CONG.

[Insert Table 9 Here]

The picture looks quite different when we focus on longer horizons. At the two-year horizon, the AEIG coefficient is significantly negative for GDPG, IPG, and EG. In the third year, the coefficient also becomes negative and statistically significant for FINVG, NRG, and DG.[16] This subsequent decline in economic activities is also consistent with the predictive power of AEIG for the future

[16]The delayed response of investment relative to GDP or consumption growth is consistent with the investment lags/investment plans friction that has been studied extensively in macroeconomic literature. See, for example, Christiano and Todd (1996), Koeva (2001), Basu and Kimball (2005), and Lamont (2000). Li (2016) examines the asset-pricing implications of this friction for momentum profits in the cross-sectional stock returns.

market returns, which is also a leading indicator for economic growth. At the five-year horizon, the coefficient on AEIG is insignificant for all economic growth proxies.

Taken together, the dynamics of macroeconomic growth following periods of high AEIG display a hump-shaped pattern. In the short run of one or two quarters, high AEIG is associated with strong economic booms, featuring positive growth rates in aggregate investment, GDP, and consumption, as well as in industrial production. In the longer run of subsequent two or three years, AEIG predicts a sharp decline in economic activities. In a recent paper, Jones and Tuzel (2013) document that the ratio of new orders to shipments (NO/S) is one type of "peak indicator" in that high NO/S foretells an imminent business cycle peak, with predicted output growth that is higher in the very short run but lower for longer horizons. From this perspective, AEIG is similar to NO/S. However, compared to NO/S, AEIG is a bottom-up measure that aggregates firm-level investment plans, and the monthly correlation between them is only 0.05, suggesting that these two variables contain very different information. Moreover, AEIG is able to strongly predict one-month market returns, whereas the return predictive power of NO/S is much weaker at the short horizon (0.15% adjusted R^2 for NO/S vs. 1.53% for AEIG).[17]

4.2 AEIG and economic uncertainty

If the return predictive ability of AEIG is due to the time-varying risk premium, AEIG should be negatively related to either the aggregate price of risk or the aggregate quantity of risk or both. Panel B of Table 1 shows that AEIG is slightly negatively correlated with the surplus ratio, with a correlation coefficient of -0.1. Because a high surplus ratio implies a low risk aversion (e.g., Campbell and Cochrane (1999)), this weak and negative correlation between AEIG and the surplus ratio suggests that the time-varying price of risk is unlikely to capture the negative AEIG coefficients in the predictive regressions in Section 3. Thus, we investigate the relation between AEIG and the quantity of aggregate risk below.

In Table 10, we examine the relation between AEIG and proxies of economic uncertainty. Panel A measures aggregate uncertainty using the forecast dispersions in GDP growth (GDPG), business fixed investment growth (BFIG), and industrial production growth (IPG) in the subsequent 12

[17]In their Table 7-A, Jones and Tuzel (2013) find that the univariate coefficient of NO/S is statistically significant at the one-month horizon in their sample ending in 2009. However, controlling for other macroeconomic variables, NO/S loses its predictive power.

months (i.e., from the base period to 12 months after the date when the survey is conducted) from the Livingston Survey.[18] We report the results from the regressions of the AEIG on forecast dispersions in BFIG, GDPG, or IPG. All variables are standardized to have a zero mean and a unit standard deviation. The results show that a one-standard-deviation increase in forecast dispersion in BFIX, GDPG, and IPG is associated with a 0.28-, 0.44-, and 0.27-standard-deviation decrease in AEIG, respectively. All three coefficients are significant from zero.

[Insert Table 10 Here]

Two potential concerns are associated with the survey-based measures of economic uncertainty. First, besides the actual uncertainty, forecast dispersions may capture behavioral biases such as sentiment. High sentiment can be related to less disagreement among survey respondents, so the negative correlation between AEIG and forecast dispersion may reflect the positive relation between AEIG and sentiment. We formally distinguish sentiment from AEIG in Section 4.3, but in Panel B of Table 10, we use two market-based uncertainty measures as a robustness check. The first measure is the market variance (SVAR), and the second measure is conditional market variance (CVAR) estimated from the GARCH(1,1) model using daily market returns. As reported in the first two columns of Panel B, a one-standard-deviation increase in SVAR (CVAR) is associated with a 0.21 (0.23) -standard-deviation decrease in AEIG, and these negative correlations are statistically significant at the 5% level.[19] Another concern about the forecast dispersion measures from Panel A is that the information sets and expectations of investors may be different from those of the survey respondents. Even though survey respondents feel ambiguous about future economic growth, investors may disagree. To alleviate this concern, we use the square of Chicago Board Options Exchange (CBOE) Volatility Index (VIX) as our last measure for economic uncertainty. The last column of Panel B shows that AEIG and VIX are still negatively correlated with an estimated coefficient of -0.19 (t-statistic $= -2.67$).

[18] To be specific, we use the "B12M" version of these data series from the Livingston Survey data available from the website of the Federal Reserve Bank of Philadelphia (https://www.philadelphiafed.org/research-and-data/real-time-center/livingston-survey). Since the Livingston Survey is conducted each June and December, we construct AEIG based on a subset of firms with a fiscal year end of December to align the timing of these variables.

[19] Note that the definition of SVAR here is different from that in Table 1, in which we find a slightly positive correlation. Because AEIG measures aggregate expected annual investment growth, we take the 12-month moving average of market variance here by removing its high-frequency movement to better capture the uncertainty of the business environment. Similarly, we use the 12-month moving average of CVAR and VIX in Table 10.

The negative relation between AEIG and economic uncertainty in Table 10 suggests that the return predictive power of AEIG is consistent with the time-varying risk premium due to the time-varying quantity of risk. Intuitively, when uncertainty falls, firms initiate more investment plans because the cost of capital is low and/or option value of waiting is low (e.g., Dixit and Pindyck (1994), Bloom (2009)). At the same time, the lower risk premium implies that the high aggregate expected investment growth predates lower future market returns.

4.3 AEIG and sentiment

In this subsection, we examine the relation between AEIG and investor sentiment in more detail. High sentiment can drive the stock market above its fundamental value and induce more investment plans. Therefore, the negative AEIG coefficient in the return predictive regressions in Section 3 may reflect the time variation in investor sentiment. We use five sentiment measures from the existing literature. The first three measures are the Baker and Wurgler sentiment index (S^{BW}), the aligned investor sentiment data (S^{PLS}) from Huang, Jiang, Tu, and Zhou (2015), and the index of consumer sentiment (ICS) from the University of Michigan Survey of Consumers.[20,21] Based on six proxies for investor sentiment — trading volume, dividend premium, close-end fund discount, the number of and first-day returns on IPOs, and equity share in the new issues — Baker and Wurgler (2006) find that the sentiment index is an important determinant of stock returns in the cross section. Huang, Jiang, Tu, and Zhou (2015) propose a refined version of Baker and Wurgler investor sentiment index that is aligned with the purpose of predicting stock returns by removing the common noise component in the sentiment proxies. The next two sentiment measures are the aggregate investment rate (INV) from Arif and Lee (2014) and the percent equity issuing measure (EQIS) from Baker and Wurgler (2000). Arif and Lee (2014) find that their bottom-up measure of aggregate corporate investments mirrors waves of investor optimism and pessimism and also predicts aggregate stock returns with a negative sign.[22]

[20] The Baker and Wurgler sentiment index data are from Jeffrey Wurgler's website. The aligned sentiment data are from Guofu Zhou's website. We thank Malcolm Baker, Jeffrey Wurgler, and Guofu Zhou for making their data publicly available.

[21] In an untabulated analysis, we also use an alternative sentiment measure based on the aggregate asset growth from Wen (2016) and find qualitatively similar results. We thank Quan Wen for sharing his data with us.

[22] Following Arif and Lee (2014), we define INV of year t as the arithmetic average of aggregate investment rates in year t and year $t-1$, and then we assign this value to all 12 months from June of year $t+1$ to May of year $t+2$ to get monthly INV. EQIS is calculated as the ratio of equity issues as a fraction of total issues of equity and bonds. To smooth out seasonality, we use the prior 12-month moving average of EQIS.

We report the correlation matrix among AEIG and these four sentiment measures in Panel A of Table 11. The correlation between AEIG and the Baker and Wurgler sentiment index (S^{BW}) and the aligned sentiment index (S^{PLS}) are 0.41 and 0.52, respectively, indicating that periods of high aggregate expected investment growth coincide with periods of high investor sentiment. Similarly, the correlation of AEIG is 0.27 with the University of Michigan consumer sentiment index (ICS), 0.47 with the Arif and Lee (2014) aggregate investment rate (INV), and 0.01 with equity issuance (EQIS) from Baker and Wurgler (2000). The positive correlation between AEIG and INV indicates that a high past investment rate is also associated with more investment plans.

[Insert Table 11 Here]

A natural question one may ask is the following: does the return predictive power of AEIG come from its positive correlation with investor sentiment? To answer this question, we report the results of the return predictive regressions using AEIG and these four sentiment measures in Panel B of Table 11. For each measure, we consider univariate regressions (Uni) with only one sentiment measure and bivariate regressions in which we also include AEIG. For the Baker and Wurgler sentiment index (S^{BW}), the coefficients are negative but statistically insignificant at all horizons up to five years. For example, the one-year S^{BW} coefficient is -0.03 with a Hodrick t-statistic of -1.24. This finding is consistent with Baker and Wurgler (2007), who also document that the BW index predicts returns better in the cross section than at the aggregate level. When AEIG is included, the S^{BW} coefficient becomes even weaker, whereas AEIG coefficient is negative and statistically significant. The next three columns report the result using the aligned investor sentiment index (S^{PLS}). Consistent with Huang, Jiang, Tu, and Zhou (2015), S^{PLS} shows much stronger return predictive power than S^{BW}, especially at the short horizons up to one year. Although the AEIG coefficient is weaker at the 1- and 3-month horizons after controlling for S^{PLS}, AEIG dominates S^{PLS} from one year and beyond. The estimated AEIG coefficient at the one year horizon is -1.26, only slightly lower than the estimate of -1.54 from the benchmark sample in Panel A of Table 2. Lastly, controlling for ICS index doesn't affect the predictive ability of AEIG either. When we use AEIG and ICS to predict future market returns in the bivariate regressions, the coefficient of AEIG is statistically negative at all horizons.

The next three columns in Panel B compare AEIG with INV. Consistent with Arif and Lee

(2014), we find that INV is a strong return predictor. In the univariate regression, the coefficient of INV increases from -0.18 (Hodrick t-statistic $= -2.51$) at one month to -1.63 (Hodrick t-statistic $= -2.07$) at one year and -3.23 (Hodrick t-statistic $= -1.75$) at three years. However, when we control for AEIG, the predictive power of INV becomes insignificant. The magnitude of the corresponding coefficient decreases to -0.09 (Hodrick t-statistic $= -1.16$), -0.34 (Hodrick t-statistic $= -0.41$), and -1.22 (Hodrick t-statistic $= -0.69$), respectively. In contrast, AEIG remains significant at all horizons. This result highlights an important difference between AEIG and INV: both being based on aggregate investment, INV is a measure of the past investment rate, whereas AEIG captures the expectation of future investment growth. Even though these two variables are positively correlated, our analysis suggests that AEIG contains more timely information about future market returns than INV, potentially because AEIG is more forward looking than INV. The last three columns report the results for the equity issuance (EQIS) measure. In the univariate regression, we find that EQIS has a strong return predictive power, especially at the short horizons of one month and three months. However, the low correlation between AEIG and EQIS indicates that the return predictive power of AEIG is barely affected by the inclusion of EQIS, as can be seen from the last two columns of Panel B.5.

The analyses above suggest that even though high AEIG coincides with periods of high sentiment, the return predictive power of AEIG is unlikely to be completely driven by the latter. In Table 12, we provide additional evidence by examining the relation between AEIG, forecast errors, and earnings surprises. If the time-varying risk premium is the primary channel through which AEIG predicts future market returns, AEIG should not be strongly associated with future earnings surprises and forecast errors. In contrast, if AEIG predicts future stock returns because it captures investor sentiment, we would expect to see earnings surprises and forecast errors following periods of high AEIG. Panel A reports the results of the predictive regressions of earnings announcement returns (EAR, Panel A.1), one-year-ahead analyst forecast errors ($\text{Error}_{\text{ROA}}$, Panel A.2), and long-term forecast errors ($\text{Error}_{\text{LTG}}$, Panel A.3) on the current value of AEIG, with and without controlling for other macro return predictive variables.[23] Panel A.1 shows that AEIG cannot pre-

[23] Following Arif and Lee (2014), we calculate EAR as the value-weighted average firm-level earnings announcement return in year $t+1$, with weights being the market cap at the end of December in year t. The firm-level earnings announcement return is the average cumulative stock return over the (-1,+1) three-day event window centered around the firm's quarterly earnings announcement dates in year $t+1$. We calculate $\text{Error}_{\text{ROA}}$ as the value-weighted difference between the forecasted one-year-ahead return on assets (ROA) at the end of December in year t and the actual realized

dict the average earnings announcement returns in the subsequent year, with the AEIG coefficients statistically insignificant from zero in both specifications. This result is in sharp contrast with Table 7 of Arif and Lee (2014), who find that high INV strongly predicts negative future earnings announcement returns, which again confirms the different information contained in AEIG and INV. In Panel A.2, we find that AEIG is not strongly associated with the one-year-ahead forecast errors either. In the univariate regression to predict long-term forecast errors (Panel A.3), we find that the AEIG coefficient is significantly positive at 0.53 (t-statistic = 5.04), suggesting that analysts are overoptimistic about long-term growth when AEIG is high. This is also consistent the positive correlation between AEIG and investor sentiment (Table 11). However, when we control for other macro variables, the coefficient on AEIG is reduced to 0.28 and becomes marginally significant.

[Insert Table 12 Here]

In Panel B of Table 12, we perform a related test that examines whether AEIG is still able to predict future stock returns controlling for ex post earnings surprises or forecast errors, as well as GDP growth. If the return predictive power of AEIG originates from the investment sentiment about firms' fundamentals, AEIG would be subsumed by these subsequent shocks about fundamentals. The results in the last three specifications of Panel B indicate that this is not the case. In all specifications, we find that the AEIG coefficient remains negative and statistically significant. Therefore, even though AEIG and investor sentiment are positively correlated, our analyses in this section suggest that this correlation is unlikely the primary driving force for the return predictive power of AEIG.

4.4 Horse race with industry-level EIG

To further differentiate the risk-based explanation from the behaviorial explanation based on investor sentiment, we follow Jones and Tuzel (2013) and perform a horse race analysis between AEIG and industry-level EIG in predicting the returns of the same industries. If investor sentiment drives the variation in expected investment growth and the return predictive ability of AEIG,

ROA in year $t+1$. The forecasted ROA is the median EPS forecast multiplied by shares outstanding and normalized by total assets as of December in year t. We calculate $\text{Error}_{\text{LTG}}$ as the value-weighted difference between the forecast long-term earnings and the actual realized ROA, which is the arithmetic average of actual ROA in year $t+2$ and year $t+3$. The analyst forecast data are from I/B/E/S.

industry-level EIG should have stronger forecasting power for industry-level returns than AEIG because the former is a more accurate measure of investor sentiment for that industry. Specifically, we run panel regressions of industry-level excess returns over the subsequent 1 month, 3 months, 1 year, 2 years, 3 years, and 5 years onto AEIG and industry-level EIG.[24] We consider three industry classifications: 11 sectors in the Global Industry Classification Standard (GICS) from Morgan Stanley Capital International (MSCI), the Fama and French 5 industries, and the Fama and French 30 industries. Table 13 reports the results.

[Insert Table 13 Here]

For each industry classification (i.e, each panel of Table 13), the first two columns report the coefficient of AEIG or industry-level EIG from the univariate return predictive regressions. Under all three industry classifications, both AEIG and industry-level EIG strongly predict industry-level returns with a negative sign, but the predictive power is greater for AEIG. For instance, when we use the GICS classification (Panel A), the t-statistic of the estimated AEIG coefficient at the one-year horizon is -4.94, compared to the industry-level EIG coefficient which has a t-statistic of -3.40. The adjusted R^2 using EIG_{GICS} is also much smaller than that using AEIG (5.15% vs 11.65%). The pattern is similar when we use the Fama and French 5 industries and the Fama and French 30 industries. The next two columns of each panel report the results from the horse race between AEIG and industry-level EIG in predicting the future returns of the same industries. In the bivariate regressions, the coefficients on AEIG remain significantly negative at all horizons, whereas the return predictive power of industry-level EIG is weakened substantially, with none of its coefficients being statistically significant.

Therefore, the results in this section show little support for the behavioral explanation based on investor sentiment. Instead, the stronger predictive power for industry-level returns by AEIG is more consistent with the mechanism from the time variation in the aggregate risk premium.

[24]Using the same coefficients from the first stage EIG estimation in Section 2, we define the EIG of an industry as the value-weighted firm-level expected investment growth of all firms in that industry. The industry-level excess returns are calculated as the value-weighted stock returns of the same industry in excess of the risk-free rate.

5 Conclusion

In this paper, we document that a new aggregate investment plans measure, aggregate expected investment growth (AEIG), is a strong predictor for future stock market returns. Consistent with neoclassical models of investment, we find that an increase in AEIG is associated with declines in the stock market, with an adjusted in-sample R^2 of 18.5% and an out-of-sample R^2 of 16.3% at the one-year horizon. Our measure differs from the investment plans measures from Lamont (2000) and Jones and Tuzel (2013) in that it is a bottom-up measure that aggregates firm-level expected investment growth. AEIG is easy to construct and is available at a monthly frequency, which allows investors to better time the market. More importantly, its return predictive power is not subsumed by other macroeconomic variables that are well-known for predicting market returns. The main result holds in several robustness checks, including subsample analysis, non-overlapping regressions, controlling for small sample biases, as well as in the other G7 countries.

Stock return predictability can be consistent with both a risk-based explanation and a behavioral explanation. Even though we cannot completely rule out all the potential behavioral forces underlying our results, further analysis shows more support for the time-varying risk premium interpretation. For example, AEIG is negatively correlated with several survey-based forecast dispersions and market-based uncertainty measures, consistent with the channel due to the time-varying aggregate quantity of risk. We also document that the return predictive power of AEIG remains even after controlling for ex post forecast errors, suggesting that biased cash flow forecasts, probably due to extrapolative expectations, cannot be the key driver of our findings.

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Table 1: Summary statistics

Panel A of this table reports the mean, standard deviation (Std), 12th-order autocorrelation (AC(12)), skewness (Skew), and kurtosis (Kurt) of monthly return predictive variables. These variables include aggregate expected investment growth (AEIG), log of dividend yield (DP), consumption-wealth ratio (CAY) from Lettau and Ludvigson (2001), term spread (TMS) defined as the difference between the long-term yield on government bonds and the T-bill, stock variance (SVAR) defined as the sum of squared daily returns on the S&P 500 index, default yield spread (DFY) defined as the yield spread between BAA- and AAA-rated corporate bonds, inflation (INFL) from monthly consumer price index for all urban consumers, detrended T-bill rate (TBL) using the Hodrick-Prescott filter, surplus ratio (SPLUS) computed as a smoothed average of the past 40-quarter consumption growth as in Wachter (2006), investment-to-capital ratio (I/K) defined as the ratio of aggregate investment to aggregate capital, and log of the ratio of new orders to shipments (NO/S) from Jones and Tuzel (2013). The means and standard deviations of CAY, TMS, SVAR, DFY, INFL, TBL, I/K, and NO/S are multiplied by 100. Panel B reports the pairwise correlation coefficients of these variables. The sample is monthly from June 1953 to December 2015, except for NO/S, which is from February 1958 to December 2015.

Panel A: Summary statistics											
Vars.	AEIG	DP	CAY	TMS	SVAR	DFY	INFL	TBL	SPLUS	I/K	NO/S
Mean	0.10	-3.54	0.02	1.73	0.20	0.98	0.29	0.00	0.12	3.57	1.48
Std	0.05	0.40	2.32	1.43	0.42	0.44	0.32	0.85	0.04	0.36	3.98
AC(12)	0.39	0.90	0.91	0.55	0.06	0.54	0.34	-0.02	0.98	0.76	0.08
Skew	0.57	-0.37	-0.25	-0.19	10.73	1.79	0.33	0.17	-0.89	0.27	-0.17
Kurt	2.29	-0.59	-0.59	-0.19	150.05	4.54	4.19	3.73	0.47	-0.52	3.18
Panel B: Correlation matrix											
Vars.	AEIG	DP	CAY	TMS	SVAR	DFY	INFL	TBL	SPLUS	I/K	NO/S
AEIG	1.00										
DP	-0.50	1.00									
CAY	-0.09	0.11	1.00								
TMS	-0.07	-0.23	0.23	1.00							
SVAR	0.07	-0.07	0.01	0.13	1.00						
DFY	0.02	0.26	-0.03	0.25	0.32	1.00					
INFL	0.06	0.31	-0.18	-0.30	-0.08	0.13	1.00				
TBL	0.12	0.00	-0.08	-0.59	-0.05	-0.16	0.26	1.00			
SPLUS	-0.10	0.41	0.03	-0.51	-0.15	-0.30	0.21	0.07	1.00		
I/K	0.43	-0.14	-0.17	-0.52	0.01	-0.12	0.30	0.26	0.36	1.00	
NO/S	0.05	-0.01	-0.15	-0.27	-0.15	-0.36	0.16	0.17	0.15	0.23	1.00

Table 2: Monthly overlapping regressions

Panel A of this table reports the coefficients of univariate predictive regressions of log of future cumulative excess market returns over 1-month (1M), 3-month (3M), 1-year (1Y), 2-year (2Y), 3-year (3Y), and 5-year (5Y) horizons onto aggregate expected investment growth (AEIG), log of dividend yield (DP), Lettau and Ludvigson (2001)'s consumption-wealth ratio (CAY), term spread (TMS), stock variance (SVAR), default yield spread (DFY), inflation (INFL), detrended T-bill rate (TBL), surplus ratio (SPLUS), investment-to-capital ratio (I/K), and Jones and Tuzel (2013)'s log of the ratio of new orders to shipments (NO/S), respectively. Panel B reports the coefficients from bivariate predictive regressions of future excess market returns on AEIG and each one of the macro controls. Panel C reports the coefficients from a pooling regression that includes all variables from Panel A except NO/S. To smooth out seasonality, we use the prior 12-month moving average of AEIG. The t-statistics based on Newey-West standard errors (t_{NW}) and Hodrick's (1992) standard errors (t_{HD}) are in parentheses. Adjusted R-squares (R^2_{Adj}) are reported in percentages. The sample is monthly from June 1953 to December 2015, except for the last specification (NO/S) which is from February 1958 to December 2015.

Panel A: Univariate return predictive regressions

Vars.	AEIG	DP	CAY	TMS	SVAR	DFY	INFL	TBL	SPLUS	I/K	NO/S
1M	-0.12	0.01	0.20	0.23	-1.14	0.32	-0.62	-0.78	-0.07	-1.35	-0.06
t_{NW}	(-3.68)	(1.63)	(3.09)	(1.93)	(-2.52)	(0.6)	(-0.92)	(-4.54)	(-1.78)	(-2.94)	(-1.12)
t_{HD}	(-3.15)	(1.6)	(3.13)	(1.95)	(-1.5)	(0.71)	(-0.97)	(-3.8)	(-1.83)	(-2.85)	(-1.2)
R^2_{Adj}	1.53	0.28	0.99	0.44	1.06	-0.03	0.06	2.17	0.29	1.11	0.15
3M	-0.38	0.02	0.60	0.64	-0.76	1.07	-2.62	-1.68	-0.22	-3.88	-0.31
t_{NW}	(-4.41)	(1.89)	(3.13)	(1.86)	(-0.51)	(0.74)	(-1.67)	(-3.46)	(-1.87)	(-3.06)	(-2.58)
t_{HD}	(-3.31)	(1.73)	(3.03)	(1.82)	(-0.53)	(0.82)	(-1.56)	(-2.97)	(-1.82)	(-2.73)	(-2.4)
R^2_{Adj}	4.81	1.15	2.86	1.20	0.02	0.22	0.95	3.13	0.99	2.95	2.24
1Y	-1.54	0.10	2.21	2.64	2.46	4.04	-10.13	-2.83	-0.92	-12.75	-1.26
t_{NW}	(-6.19)	(2.02)	(2.92)	(2.52)	(1.37)	(1.17)	(-2.23)	(-1.67)	(-2.35)	(-2.66)	(-3.5)
t_{HD}	(-3.59)	(1.84)	(2.55)	(2.07)	(0.75)	(0.98)	(-1.89)	(-1.61)	(-1.9)	(-2.28)	(-3.15)
R^2_{Adj}	18.53	4.99	8.64	5.06	0.25	1.04	3.52	2.00	4.35	7.54	9.09
2Y	-2.44	0.16	3.98	4.28	5.13	4.45	-10.96	-0.43	-1.89	-21.80	-1.39
t_{NW}	(-5.49)	(1.82)	(3.3)	(3.36)	(1.88)	(0.89)	(-2.42)	(-0.15)	(-3.14)	(-2.86)	(-2.51)
t_{HD}	(-3.31)	(1.54)	(2.15)	(1.97)	(1.1)	(0.63)	(-1.18)	(-0.17)	(-1.83)	(-2.09)	(-1.98)
R^2_{Adj}	26.02	7.53	14.92	7.45	0.80	0.66	2.25	-0.11	9.41	12.43	6.04
3Y	-2.56	0.18	5.56	6.28	3.75	5.48	-11.58	-1.08	-2.77	-32.27	-1.40
t_{NW}	(-5.82)	(1.8)	(4.29)	(4.56)	(0.92)	(0.94)	(-2.95)	(-0.33)	(-3.82)	(-4.63)	(-2.4)
t_{HD}	(-2.68)	(1.22)	(1.99)	(2.17)	(0.66)	(0.57)	(-0.95)	(-0.45)	(-1.67)	(-2.24)	(-1.6)
R^2_{Adj}	23.18	8.14	22.54	12.79	0.27	0.83	1.98	0.00	14.32	21.81	4.70
5Y	-2.95	0.28	7.41	8.13	9.24	15.56	-14.74	-1.09	-4.28	-49.09	-2.55
t_{NW}	(-4.97)	(3.59)	(4.67)	(2.6)	(1.44)	(1.83)	(-1.82)	(-0.39)	(-2.74)	(-6.08)	(-3.59)
t_{HD}	(-2.35)	(1.15)	(1.69)	(2.08)	(1.39)	(1.07)	(-0.83)	(-0.58)	(-1.31)	(-2.38)	(-2.79)
R^2_{Adj}	21.38	12.83	26.89	14.45	1.52	5.25	2.21	-0.04	17.85	33.36	10.99

	Panel B: Bivariate predictive regressions										
	Control	DP	CAY	TMS	SVAR	DFY	INFL	TBL	SPLUS	I/K	NO/S
1M	AEIG	-0.12	-0.11	-0.12	-0.12	-0.12	-0.12	-0.11	-0.13	-0.09	-0.13
	t_{NW}	(-3.47)	(-3.34)	(-3.58)	(-3.44)	(-3.7)	(-3.6)	(-3.36)	(-3.96)	(-2.51)	(-3.42)
	t_{HD}	(-2.99)	(-2.88)	(-3.04)	(-2.95)	(-3.15)	(-3.07)	(-2.75)	(-3.31)	(-2.28)	(-2.81)
	Control	0.00	0.18	0.21	-1.06	0.35	-0.51	-0.71	-0.09	-0.83	-0.05
	t_{NW}	(0)	(2.66)	(1.75)	(-2.2)	(0.67)	(-0.75)	(-4.09)	(-2.18)	(-1.63)	(-1)
	t_{HD}	(0)	(2.73)	(1.74)	(-1.38)	(0.78)	(-0.8)	(-3.47)	(-2.2)	(-1.67)	(-1.06)
	R^2_{Adj}	1.40	2.28	1.85	2.41	1.53	1.53	3.29	2.02	1.78	1.54
3M	AEIG	-0.38	-0.36	-0.37	-0.38	-0.38	-0.37	-0.35	-0.40	-0.31	-0.39
	t_{NW}	(-4.03)	(-4.02)	(-4.31)	(-4.32)	(-4.44)	(-4.28)	(-4.19)	(-4.82)	(-3)	(-4.27)
	t_{HD}	(-3.12)	(-3.04)	(-3.21)	(-3.26)	(-3.32)	(-3.21)	(-3.03)	(-3.48)	(-2.52)	(-2.88)
	Control	0.00	0.53	0.56	-0.47	1.17	-2.30	-1.46	-0.26	-2.16	-0.29
	t_{NW}	(0.05)	(2.66)	(1.67)	(-0.29)	(0.86)	(-1.44)	(-2.99)	(-2.37)	(-1.48)	(-2.47)
	t_{HD}	(0.05)	(2.62)	(1.59)	(-0.33)	(0.89)	(-1.36)	(-2.58)	(-2.21)	(-1.44)	(-2.23)
	R^2_{Adj}	4.69	7.01	5.70	4.75	5.11	5.51	7.11	6.36	5.47	6.43
1Y	AEIG	-1.52	-1.46	-1.49	-1.57	-1.55	-1.51	-1.50	-1.64	-1.37	-1.44
	t_{NW}	(-5.93)	(-6.03)	(-6.17)	(-6.35)	(-6.03)	(-6.39)	(-6.11)	(-6.93)	(-5.32)	(-5.87)
	t_{HD}	(-3.34)	(-3.33)	(-3.48)	(-3.64)	(-3.61)	(-3.47)	(-3.48)	(-3.78)	(-3.05)	(-2.9)
	Control	0.01	1.93	2.31	3.64	4.45	-8.72	-1.87	-1.12	-5.07	-1.18
	t_{NW}	(0.15)	(2.49)	(2.4)	(2.28)	(1.67)	(-2.04)	(-1.27)	(-3.21)	(-1.1)	(-3.31)
	t_{HD}	(0.11)	(2.19)	(1.81)	(1.11)	(1.08)	(-1.6)	(-1.06)	(-2.29)	(-0.87)	(-2.91)
	R^2_{Adj}	18.43	25.03	22.37	19.26	19.84	21.12	19.34	24.99	19.41	23.36
2Y	AEIG	-2.37	-2.30	-2.35	-2.48	-2.45	-2.40	-2.46	-2.58	-2.10	-2.15
	t_{NW}	(-4.83)	(-5.52)	(-5.49)	(-5.49)	(-5.48)	(-5.41)	(-5.52)	(-5.95)	(-5.42)	(-4.05)
	t_{HD}	(-3.12)	(-3.1)	(-3.19)	(-3.37)	(-3.33)	(-3.23)	(-3.33)	(-3.5)	(-2.92)	(-2.5)
	Control	0.02	3.58	3.70	7.05	5.24	-8.53	1.14	-2.17	-9.83	-1.28
	t_{NW}	(0.25)	(2.96)	(3.12)	(3.12)	(1.37)	(-2.22)	(0.51)	(-3.71)	(-1.83)	(-2.6)
	t_{HD}	(0.16)	(1.92)	(1.7)	(1.53)	(0.74)	(-0.91)	(0.46)	(-2.1)	(-0.94)	(-1.79)
	R^2_{Adj}	25.99	38.03	31.55	27.69	27.02	27.36	26.11	38.42	27.97	24.51
3Y	AEIG	-2.40	-2.37	-2.43	-2.60	-2.58	-2.52	-2.58	-2.77	-1.82	-2.37
	t_{NW}	(-4.44)	(-5.72)	(-5.97)	(-5.79)	(-6.13)	(-5.58)	(-5.73)	(-6.14)	(-5.22)	(-4.44)
	t_{HD}	(-2.44)	(-2.45)	(-2.54)	(-2.72)	(-2.69)	(-2.61)	(-2.69)	(-2.9)	(-2.09)	(-2.12)
	Control	0.04	5.14	5.66	5.78	6.32	-8.99	0.57	-3.11	-21.78	-1.27
	t_{NW}	(0.42)	(3.87)	(4.55)	(1.7)	(1.37)	(-2.33)	(0.21)	(-4.38)	(-4.31)	(-2.6)
	t_{HD}	(0.25)	(1.82)	(1.96)	(1.04)	(0.66)	(-0.72)	(0.24)	(-1.88)	(-1.57)	(-1.42)
	R^2_{Adj}	23.37	42.29	33.52	24.03	24.37	24.35	23.11	41.15	31.10	22.17
5Y	AEIG	-2.41	-2.68	-2.78	-3.02	-3.01	-2.90	-2.97	-3.30	-1.61	-2.51
	t_{NW}	(-3.09)	(-4.36)	(-4.91)	(-5.14)	(-5.11)	(-5.03)	(-5.16)	(-5.05)	(-2.97)	(-4.3)
	t_{HD}	(-1.72)	(-2.07)	(-2.19)	(-2.42)	(-2.39)	(-2.28)	(-2.34)	(-2.71)	(-1.39)	(-1.72)
	Control	0.13	6.89	7.40	11.62	16.62	-11.78	0.81	-4.87	-39.33	-2.41
	t_{NW}	(1.34)	(4.55)	(2.48)	(2.2)	(2.49)	(-1.56)	(0.34)	(-3.75)	(-5)	(-4.34)
	t_{HD}	(0.47)	(1.54)	(1.87)	(1.8)	(1.14)	(-0.66)	(0.41)	(-1.5)	(-1.92)	(-2.53)
	R^2_{Adj}	23.32	44.43	33.30	23.88	27.43	22.76	21.32	44.33	38.34	24.94

Panel C: Pooling predictive regressions										
	AEIG	DP	CAY	TMS	SVAR	DFY	INFL	TBL	SPLUS	I/K
1M	-0.10	0.00	0.23	-0.48	-1.31	0.35	0.17	-1.09	-0.17	-0.18
t_{NW}	(-2.48)	(0.02)	(3.58)	(-2.8)	(-2.75)	(0.71)	(0.24)	(-4.84)	(-3.14)	(-0.3)
t_{HD}	(-2.22)	(0.02)	(3.29)	(-2.49)	(-1.62)	(0.61)	(0.24)	(-4)	(-2.78)	(-0.3)
R^2_{Adj}										5.97
3M	-0.31	0.01	0.59	-0.99	-1.04	0.31	-0.91	-2.10	-0.45	0.05
t_{NW}	(-2.59)	(0.72)	(3.36)	(-2.22)	(-0.63)	(0.23)	(-0.6)	(-4.04)	(-3.13)	(0.03)
t_{HD}	(-2.32)	(0.66)	(2.83)	(-1.81)	(-0.77)	(0.2)	(-0.51)	(-2.84)	(-2.53)	(0.03)
R^2_{Adj}										11.47
1Y	-1.34	0.11	1.53	0.59	1.64	-1.77	-7.92	-0.77	-1.53	7.70
t_{NW}	(-4.51)	(2.23)	(2.53)	(0.45)	(1.18)	(-0.66)	(-2.86)	(-0.47)	(-3.39)	(1.77)
t_{HD}	(-2.79)	(1.61)	(1.7)	(0.32)	(0.58)	(-0.38)	(-1.65)	(-0.34)	(-2.2)	(1.16)
R^2_{Adj}										34.38
2Y	-1.98	0.22	2.31	3.75	5.18	-8.49	-8.07	4.84	-2.67	11.26
t_{NW}	(-3.98)	(2.95)	(2.62)	(2.07)	(2.71)	(-2.01)	(-2.12)	(2.49)	(-3.63)	(1.77)
t_{HD}	(-2.71)	(1.68)	(1.19)	(1.12)	(1.36)	(-0.98)	(-1.09)	(1.36)	(-1.84)	(0.94)
R^2_{Adj}										54.58
3Y	-1.54	0.29	2.70	5.24	3.77	-12.79	-5.79	6.02	-3.36	3.10
t_{NW}	(-4.41)	(3.4)	(2.69)	(2.23)	(1.27)	(-2.74)	(-1.75)	(2.72)	(-4.06)	(0.46)
t_{HD}	(-1.78)	(1.46)	(0.88)	(1.08)	(0.83)	(-1.08)	(-0.59)	(1.41)	(-1.4)	(0.18)
R^2_{Adj}										62.19
5Y	-1.28	0.33	3.15	5.07	7.34	-5.73	-7.49	8.74	-3.65	-14.07
t_{NW}	(-2.77)	(3.86)	(2.69)	(2.17)	(2.24)	(-0.88)	(-1.89)	(3.28)	(-3.52)	(-2.7)
t_{HD}	(-1.1)	(1.11)	(0.58)	(0.84)	(1.35)	(-0.33)	(-0.55)	(1.71)	(-0.76)	(-0.56)
R^2_{Adj}										69.50

Table 3: Monthly overlapping regressions for subsamples

This table reports the coefficients of aggregate expected investment growth (AEIG) from predictive regressions of log of future cumulative excess market returns over 1-month (1M), 3-month (3M), 1-year (1Y), 2-year (2Y), 3-year (3Y), and 5-year (5Y) horizons onto lagged predictors. The first column is for the univariate regression with AEIG as the only predictor, and the other columns report the coefficients for AEIG in bivariate regressions using AEIG and other predictive variables one at a time. These variables include: log of dividend yield (DP), Lettau and Ludvigson (2001)'s consumption-wealth ratio (CAY), term spread (TMS), stock variance (SVAR), default yield spread (DFY), inflation (INFL), detrended T-bill rate (TBL), Campbell and Cochrane (1999)'s surplus ratio (SPLUS), investment-to-capital ratio (I/K), and Jones and Tuzel (2013)'s log of the ratio of new orders to shipments (NO/S). To smooth out seasonality, we use the prior 12-month moving average of AEIG. The early sample in Panel A is from June 1953 to December 1983 in all specifications except for the last specification (NO/S), which is from February 1958 to December 1983. The later sample in Panel B is from January 1984 to December 2015. The t-statistics based on Newey-West standard errors (t_{NW}) and Hodrick's (1992) standard errors (t_{HD}) are in parentheses. Adjusted R-squares (R^2_{Adj}) are reported in percentages.

Control	Panel A: Early subsample										
Vars.	N/A	DP	CAY	TMS	SVAR	DFY	INFL	TBL	SPLUS	I/K	NO/S
1M	-0.13	-0.12	-0.11	-0.12	-0.13	-0.17	-0.12	-0.12	-0.14	-0.11	-0.15
t_{NW}	(-3.02)	(-2.48)	(-2.25)	(-2.81)	(-3.06)	(-3.56)	(-2.5)	(-2.91)	(-3.08)	(-2.35)	(-2.77)
t_{HD}	(-2.91)	(-2.51)	(-2.25)	(-2.6)	(-2.95)	(-3.39)	(-2.42)	(-2.51)	(-3.04)	(-2.29)	(-2.47)
R^2_{Adj}	1.74	2.50	4.09	4.21	1.50	2.98	1.98	6.74	2.73	3.67	2.87
3M	-0.44	-0.38	-0.35	-0.39	-0.43	-0.52	-0.40	-0.39	-0.45	-0.36	-0.48
t_{NW}	(-3.48)	(-2.78)	(-2.5)	(-3.25)	(-3.4)	(-3.95)	(-2.86)	(-3.46)	(-3.4)	(-2.76)	(-3.36)
t_{HD}	(-3.2)	(-2.71)	(-2.42)	(-2.87)	(-3.19)	(-3.65)	(-2.72)	(-2.86)	(-3.28)	(-2.58)	(-2.74)
R^2_{Adj}	6.02	8.94	11.86	11.07	6.90	9.24	6.88	13.50	8.63	10.27	10.87
1Y	-1.85	-1.54	-1.50	-1.71	-1.83	-2.07	-1.76	-1.78	-1.83	-1.66	-1.73
t_{NW}	(-5.04)	(-3.87)	(-4.17)	(-5.13)	(-4.84)	(-4.98)	(-5.12)	(-5.05)	(-4.31)	(-5.31)	(-5.16)
t_{HD}	(-3.79)	(-3.01)	(-2.8)	(-3.53)	(-3.78)	(-4.21)	(-3.42)	(-3.63)	(-3.74)	(-3.29)	(-2.95)
R^2_{Adj}	22.67	36.21	34.33	27.52	23.97	27.55	23.42	24.86	31.62	26.90	31.22
2Y	-2.85	-2.36	-2.38	-2.90	-2.82	-2.92	-2.80	-2.97	-2.78	-2.65	-2.07
t_{NW}	(-3.48)	(-3.65)	(-3.53)	(-3.56)	(-3.42)	(-3.31)	(-3.32)	(-3.98)	(-3.55)	(-3.5)	(-2.56)
t_{HD}	(-3.74)	(-2.67)	(-2.99)	(-3.86)	(-3.71)	(-4.1)	(-3.68)	(-3.89)	(-3.59)	(-3.52)	(-2.23)
R^2_{Adj}	33.72	49.42	46.38	33.91	35.41	33.85	33.66	38.75	42.48	36.73	20.74
3Y	-3.00	-2.31	-2.33	-3.01	-2.97	-2.95	-2.92	-3.00	-2.64	-2.70	-2.29
t_{NW}	(-3.78)	(-4.62)	(-3.82)	(-3.62)	(-3.7)	(-3.92)	(-3.61)	(-3.95)	(-3.49)	(-3.78)	(-3.4)
t_{HD}	(-3)	(-1.63)	(-2.31)	(-3.07)	(-2.94)	(-3.37)	(-3.18)	(-3)	(-2.22)	(-2.88)	(-2.06)
R^2_{Adj}	32.79	44.93	52.67	32.58	33.90	32.93	33.23	34.83	43.20	41.06	19.61
5Y	-3.69	-2.15	-2.66	-3.64	-3.64	-3.66	-3.53	-3.69	-2.49	-3.13	-2.39
t_{NW}	(-2.68)	(-2.37)	(-2.62)	(-2.71)	(-2.62)	(-2.73)	(-2.76)	(-2.67)	(-1.87)	(-3.33)	(-2.38)
t_{HD}	(-2.88)	(-0.74)	(-2.2)	(-2.89)	(-2.76)	(-3.08)	(-3.16)	(-2.88)	(-1.27)	(-2.84)	(-1.84)
R^2_{Adj}	29.30	43.89	54.89	34.00	29.62	29.47	34.09	29.08	50.72	57.56	15.73

Control					Panel B: Late subsample						
Vars.	N/A	DP	CAY	TMS	SVAR	DFY	INFL	TBL	SPLUS	I/K	NO/S
1M	-0.13	-0.13	-0.13	-0.16	-0.13	-0.15	-0.13	-0.13	-0.13	-0.18	-0.14
t_{NW}	(-2.79)	(-2.29)	(-2.5)	(-3.17)	(-2.63)	(-3.28)	(-2.81)	(-2.78)	(-2.69)	(-2.91)	(-2.81)
t_{HD}	(-2.11)	(-1.75)	(-1.93)	(-2.49)	(-2)	(-2.4)	(-2.12)	(-2.13)	(-2.01)	(-2.3)	(-2.13)
R^2_{Adj}	1.44	1.18	1.28	1.48	3.41	1.58	1.24	1.20	1.32	1.39	1.24
3M	-0.40	-0.37	-0.37	-0.46	-0.39	-0.44	-0.40	-0.40	-0.38	-0.52	-0.39
t_{NW}	(-3.54)	(-2.69)	(-3.02)	(-3.78)	(-3.4)	(-3.94)	(-3.52)	(-3.5)	(-3.4)	(-3.22)	(-3.48)
t_{HD}	(-2.11)	(-1.65)	(-1.9)	(-2.42)	(-2.07)	(-2.27)	(-2.11)	(-2.2)	(-2)	(-2.22)	(-2.02)
R^2_{Adj}	4.42	4.21	4.56	4.74	4.79	4.63	4.29	4.18	4.59	4.58	4.45
1Y	-1.60	-1.44	-1.49	-1.52	-1.61	-1.58	-1.59	-1.58	-1.49	-1.85	-1.52
t_{NW}	(-5.2)	(-4.55)	(-4.5)	(-4.31)	(-5.26)	(-4.84)	(-5.44)	(-4.8)	(-4.91)	(-5.1)	(-4.54)
t_{HD}	(-2.24)	(-1.73)	(-2.01)	(-2.1)	(-2.25)	(-2.16)	(-2.23)	(-2.24)	(-2.1)	(-2.16)	(-2.09)
R^2_{Adj}	19.05	19.15	20.21	19.03	19.21	18.85	21.31	18.91	20.94	19.28	21.51
2Y	-2.86	-2.44	-2.61	-2.26	-2.88	-2.75	-2.85	-2.68	-2.59	-2.82	-2.74
t_{NW}	(-4.82)	(-3.35)	(-3.91)	(-3.51)	(-4.84)	(-4.41)	(-4.93)	(-5.21)	(-4.5)	(-3.44)	(-4.01)
t_{HD}	(-2.28)	(-1.82)	(-2.01)	(-1.72)	(-2.29)	(-2.18)	(-2.27)	(-2.12)	(-2.04)	(-2.05)	(-2.12)
R^2_{Adj}	31.08	31.98	34.36	37.54	31.94	31.32	31.98	34.61	35.96	30.90	33.87
3Y	-3.39	-2.66	-2.95	-2.51	-3.40	-3.31	-3.38	-3.28	-3.01	-2.32	-3.26
t_{NW}	(-6.12)	(-3.62)	(-4.33)	(-3.77)	(-6.12)	(-4.96)	(-6.17)	(-5.56)	(-5.27)	(-2.61)	(-4.85)
t_{HD}	(-2.03)	(-1.54)	(-1.66)	(-1.44)	(-2.03)	(-2)	(-2.03)	(-1.94)	(-1.77)	(-1.45)	(-1.88)
R^2_{Adj}	31.95	34.19	37.48	42.42	31.97	31.93	32.17	32.73	38.81	34.60	34.11
5Y	-4.29	-2.84	-3.67	-3.43	-4.32	-3.94	-4.28	-4.29	-4.02	-2.23	-3.98
t_{NW}	(-4.33)	(-2.59)	(-3.25)	(-3.91)	(-4.44)	(-3.16)	(-4.35)	(-4.49)	(-4.05)	(-1.83)	(-4.66)
t_{HD}	(-2.08)	(-1.35)	(-1.44)	(-1.64)	(-2.1)	(-1.96)	(-2.08)	(-2.03)	(-1.87)	(-1.32)	(-1.84)
R^2_{Adj}	40.15	46.75	45.02	47.70	41.89	42.68	40.39	39.96	43.18	47.59	48.02

Table 4: Non-overlapping regressions

This table reports the coefficients of aggregate expected investment growth (AEIG) from non-overlapping predictive regressions of log of future cumulative excess market returns over 1-month (1M), 3-month (3M), 1-year (1Y), 2-year (2Y), 3-year (3Y), and 5-year (5Y) horizons onto lagged predictors. The first column is for the univarate regression with AEIG as the only predictor, and the other columns report the coefficients for AEIG in bivariate regressions using AEIG and other predictive variables, one at a time. These variables include: log of dividend yield (DP), Lettau and Ludvigson (2001)'s consumption-wealth ratio (CAY), term spread (TMS), stock variance (SVAR), default yield spread (DFY), inflation (INFL), detrended T-bill rate (TBL), Campbell and Cochrane (1999)'s surplus ratio (SPLUS), investment-to-capital ratio (I/K), and Jones and Tuzel (2013)'s log of the ratio of new orders to shipments (NO/S). To smooth out seasonality, we use the prior 12-month moving average of AEIG. The t-statistics based on Newey-West standard errors (t_{NW}) are in parentheses. Adjusted R-squares (R^2_{Adj}) are reported in percentages. Our sample data are from June 1953 to December 2015 for all specifications except for the last specification (NO/S), which is from February 1958 to December 2015.

Control Vars.	N/A	DP	CAY	TMS	SVAR	DFY	INFL	TBL	SPLUS	I/K	NO/S
1M	-0.12	-0.12	-0.11	-0.12	-0.12	-0.12	-0.12	-0.11	-0.13	-0.09	-0.13
t_{NW}	(-3.68)	(-3.47)	(-3.34)	(-3.58)	(-3.44)	(-3.7)	(-3.6)	(-3.36)	(-3.96)	(-2.51)	(-3.42)
R^2_{Adj}	1.53	1.40	2.28	1.85	2.41	1.53	1.53	3.29	2.02	1.78	1.54
3M	-0.40	-0.39	-0.37	-0.39	-0.40	-0.40	-0.39	-0.37	-0.42	-0.32	-0.38
t_{NW}	(-3.76)	(-3.35)	(-3.44)	(-3.75)	(-3.69)	(-3.8)	(-3.78)	(-3.72)	(-4.13)	(-2.66)	(-4.18)
R^2_{Adj}	4.37	3.99	6.04	4.98	3.98	4.34	4.72	6.27	5.50	4.72	7.57
1Y	-1.54	-1.58	-1.47	-1.49	-1.60	-1.56	-1.48	-1.51	-1.64	-1.42	-1.48
t_{NW}	(-4.55)	(-4.43)	(-4.31)	(-4.52)	(-4.92)	(-4.3)	(-4.35)	(-4.36)	(-4.78)	(-3.98)	(-5.03)
R^2_{Adj}	18.71	17.35	22.74	23.50	20.94	17.51	20.00	18.19	24.80	17.82	29.54
2Y	-2.22	-1.98	-2.16	-2.13	-2.25	-2.24	-1.98	-2.22	-2.32	-1.90	-2.27
t_{NW}	(-3.5)	(-3.29)	(-3.27)	(-3.33)	(-3.58)	(-3.61)	(-3.56)	(-3.77)	(-3.6)	(-3.21)	(-2.87)
R^2_{Adj}	25.26	24.10	30.64	25.71	22.96	22.97	26.16	22.60	32.75	24.98	26.41
3Y	-3.26	-3.05	-3.24	-3.95	-3.15	-3.33	-3.15	-3.66	-3.74	-2.93	-3.53
t_{NW}	(-4.52)	(-2.91)	(-3.84)	(-7.43)	(-3.83)	(-4.92)	(-5.71)	(-5.9)	(-5.27)	(-3.39)	(-2.71)
R^2_{Adj}	28.36	24.41	41.52	43.47	30.85	24.49	32.51	30.00	41.22	32.09	38.41
5Y	-4.37	-3.97	-4.04	-4.01	-4.33	-5.05	-4.45	-4.49	-4.79	-2.99	-4.12
t_{NW}	(-9.05)	(-7.02)	(-6.14)	(-7.52)	(-8.87)	(-14.63)	(-8.13)	(-9.51)	(-5.36)	(-6.48)	(-2.21)
R^2_{Adj}	54.34	50.74	68.46	81.03	49.30	59.55	49.53	64.57	65.22	69.12	25.89

Table 5: Small sample bias

This table reports the results of small sample properties of the return predictive regression using Monte Carlo experiments. Size(NW) (Size(HD)) is the percentage of times the absolute value of the Newey-West (Hodrick's (1992)) t-statistic for the coefficient of AEIG being greater than 1.96. $t_{2.5}$(NW) and $t_{97.5}$(NW) ($t_{2.5}$(HD) and $t_{97.5}$(HD)) are the 2.5% and 97.5% quantiles of the Newey-West (Hodrick's (1992)) t-statistics for the coefficient of AEIG in Monte Carlo experiments, respectively. $R^2_{2.5}$ and $R^2_{97.5}$ are the 2.5% and 97.5% quantiles of the R^2 (in percentages) in Monte Carlo experiments. In Panel A, the simulation is conducted assuming no correlation between AEIG and market returns. In Panel B, the simulation takes into account a positive correlation between AEIG and market returns in the prior 2-12 months, as in the empirical data. The sample is monthly from June 1953 to December 2015.

	1M	3M	1Y	2Y	3Y	5Y
Panel A: No correlation						
size(NW)	0.06	0.08	0.13	0.14	0.15	0.17
$t_{2.5}$(NW)	-1.99	-2.21	-2.53	-2.68	-2.80	-2.85
$t_{97.5}$(NW)	2.03	2.25	2.54	2.73	2.79	2.92
size(HD)	0.05	0.05	0.05	0.06	0.06	0.06
$t_{2.5}$(HD)	-1.94	-1.94	-1.98	-2.01	-1.99	-2.02
$t_{97.5}$(HD)	1.98	2.00	1.99	2.03	2.03	2.09
$R^2_{2.5}$	-0.13	-0.13	-0.13	-0.14	-0.14	-0.14
$R^2_{97.5}$	0.53	1.87	7.20	12.05	15.09	18.68
Panel B: With correlation						
size(NW)	0.05	0.08	0.11	0.12	0.13	0.16
$t_{2.5}$(NW)	-2.17	-2.36	-2.65	-2.82	-3.03	-3.41
$t_{97.5}$(NW)	1.78	1.95	2.17	2.16	2.07	1.93
size(HD)	0.05	0.05	0.05	0.05	0.05	0.06
$t_{2.5}$(HD)	-2.09	-2.09	-2.08	-2.12	-2.17	-2.30
$t_{97.5}$(HD)	1.73	1.72	1.72	1.69	1.63	1.60
$R^2_{2.5}$	-0.13	-0.13	-0.13	-0.14	-0.14	-0.14
$R^2_{97.5}$	0.52	1.79	6.45	9.81	11.45	13.45

Table 6: Out-of-sample analysis

This table reports the results of out-of-sample forecasts. At each month t, 1-month, 3-month, 1-year, 2-year, 3-year, and 5-year log of future cumulative excess returns are regressed onto predictive variables using data up to month t. The estimated coefficients are then used to construct the expected market returns. We use the following predictive variables: aggregate expected investment growth (AEIG), log of dividend yield (DP), an out-of-sample equivalent measure of the consumption-wealth ratio (CAYA) as in Lettau and Ludvigson (2001), term spread (TMS), stock variance (SVAR), default yield spread (DFY), inflation (INFL), detrended T-bill rate (TBL), Campbell and Cochrane (1999)'s surplus ratio (SPLUS), and investment-to-capital ratio (I/K). We report the out-of-sample R^2 from Campbell and Thompson (2008) in (I), which compares the mean squared errors of the competing strategy with the strategy that is based on the historical mean of market returns, and the MSFE-adj statistics from Clark and West (2007) in (II) which tests the null hypothesis that the mean squared errors based on the historical mean of market returns are greater than the mean squared errors of the competing strategy. We test two types of competing strategies: Panel A is for the univariate strategy, and Panel B is for the bivariate strategy using AEIG and one of the macro signals. Except for CAYA, we use the first ten years of data for the initial estimation and add one month at a time, repeating the estimation recursively. For CAYA, the initial sample period is from June 1953 to March 1968. Out-of-sample R-squares are reported in percentages. The sample is monthly from June 1953 to December 2015, except for NO/S, which is from February 1958 to December 2015.

	(I) Out-of-sample R^2						(II) MSFE-adj					
	1M	3M	1Y	2Y	3Y	5Y	1M	3M	1Y	2Y	3Y	5Y
Panel A: Univariate strategy												
AEIG	1.08	3.47	16.25	21.73	18.65	14.66	2.48	2.80	2.89	2.28	2.04	2.13
DP	-0.75	-1.98	-10.83	-22.41	-19.27	-14.95	1.06	1.47	1.93	1.26	1.01	1.71
CAYA	-1.42	-3.28	-9.31	-7.64	-5.78	-14.79	0.65	1.01	2.11	2.27	2.04	3.21
TMS	-0.71	-2.17	-1.54	4.45	7.47	-5.30	2.10	1.93	2.11	1.53	1.61	2.02
SVAR	0.23	-5.98	-8.09	-6.28	-9.35	-7.27	0.77	-0.46	0.60	1.61	-0.36	1.19
DFY	-0.58	-2.18	-4.07	-6.42	-17.80	-19.03	0.15	-0.23	-0.55	-1.70	-2.03	-1.12
INFL	-0.47	-0.76	0.97	1.03	0.51	-12.17	1.61	1.43	1.50	1.66	1.72	0.88
TBL	1.05	0.20	-2.95	-2.99	-5.95	-1.64	2.98	2.14	0.63	-0.03	-1.53	-0.64
SPLUS	-0.26	-1.03	-3.04	-0.39	2.54	-17.14	1.46	1.29	1.46	2.24	2.12	1.56
I/K	0.71	1.75	4.89	9.78	17.76	18.77	2.34	2.37	2.12	2.33	2.49	2.29
NO/S	-0.11	1.45	7.29	4.20	3.17	10.69	0.75	1.87	2.38	1.51	1.35	1.90
Panel B: Bivariate strategy												
DP	0.29	1.35	3.37	0.55	1.16	-5.27	1.85	2.38	2.67	1.73	1.40	1.81
CAYA	-0.63	-0.20	6.41	15.36	17.97	7.85	1.81	2.57	2.95	2.57	2.51	3.66
TMS	0.50	1.76	16.93	25.09	22.79	15.34	2.92	3.03	3.15	2.56	2.55	2.82
SVAR	1.19	-2.64	10.32	18.95	12.97	11.30	1.99	1.92	3.07	2.61	2.11	2.49
DFY	0.53	1.75	14.82	17.65	3.39	-5.33	1.99	2.26	2.86	2.14	1.64	1.25
INFL	0.51	2.37	16.67	22.45	18.40	5.56	2.55	2.71	3.11	2.52	2.27	2.12
TBL	2.03	3.81	14.72	20.57	15.54	13.40	3.56	3.15	2.64	2.55	2.01	2.05
SPLUS	1.10	3.38	18.71	30.89	31.00	21.54	2.53	2.66	3.32	3.26	3.25	3.00
IK	0.69	2.08	14.36	22.71	26.70	23.03	2.77	3.04	2.87	2.34	2.34	2.39
NOS	0.68	4.14	19.06	18.17	16.74	19.67	2.26	2.99	3.51	2.44	2.23	2.32

Table 7: Alternative expected investment growth measures

This table examines alternative expected investment growth measures in predicting log of future cumulative value-weighted excess market returns over 1-month (1M), 3-month (3M), 1-year (1Y), 2-year (2Y), 3-year (3Y), and 5-year (5Y) horizons. AEIG is the benchmark aggregate expected investment growth. In Panel A, we use the median forecasted one-year business fixed investment growth (BFIX) from the Livingston Survey (`BFIX_B12M_Median` series). Panel B constructs aggregate expected investment growth using aggregate q, cf, and momentum (AEIG_{AG}). To ensure that the first-stage coefficients are stable, we require a minimum of ten years of data to do the first-stage estimation. We report the coefficients of the univariate regressions using AEIG_{AG} and bivariate regressions using AEIG and AEIG_{AG}. The t-statistics based on Newey-West standard errors (t_{NW}) and Hodrick's (1992) standard errors (t_{HD}) are in parentheses. Adjusted R-squares (R^2_{Adj}) are reported in percentages. The sample is monthly from December 1990 to December 2015 for Panel A, and from June 1960 to December 2015 for Panel B.

	Panel A: `BFIX_B12M_Median`			Panel B: AEIG_{AG}		
	Univariate	Bivariate		Univariate	Bivariate	
	BFIX	AEIG	BFIX	AEIG_{AG}	AEIG	AEIG_{AG}
1M	0.02	-0.17	0.11	-0.02	-0.13	0.01
t_{NW}	(0.17)	(-3.09)	(1.09)	(-0.94)	(-2.7)	(0.38)
t_{HD}	(0.19)	(-2.23)	(1.16)	(-0.99)	(-2.34)	(0.41)
R^2_{Adj}	-0.31		2.04	-0.01		0.98
3M	0.02	-0.50	0.32	-0.07	-0.40	0.04
t_{NW}	(0.06)	(-3.97)	(1.08)	(-0.92)	(-3.23)	(0.48)
t_{HD}	(0.07)	(-2.2)	(1.14)	(-0.95)	(-2.45)	(0.51)
R^2_{Adj}	-0.33		6.64	0.20		3.47
1Y	-0.47	-1.87	0.65	-0.18	-1.71	0.29
t_{NW}	(-0.68)	(-4.95)	(1.08)	(-0.65)	(-6)	(0.97)
t_{HD}	(-0.57)	(-2.3)	(0.76)	(-0.64)	(-2.83)	(0.92)
R^2_{Adj}	0.69		22.32	0.45		15.50
2Y	-1.42	-3.35	0.48	-0.15	-3.01	0.70
t_{NW}	(-1.73)	(-6.79)	(1.19)	(-0.31)	(-5.78)	(1.29)
t_{HD}	(-1.19)	(-2.32)	(0.37)	(-0.27)	(-2.89)	(1.12)
R^2_{Adj}	4.14		37.63	0.07		26.21
3Y	-2.13	-3.82	-0.02	-0.07	-3.15	0.88
t_{NW}	(-1.87)	(-6.4)	(-0.02)	(-0.12)	(-4.56)	(1.21)
t_{HD}	(-1.56)	(-2.02)	(-0.01)	(-0.08)	(-2.24)	(0.88)
R^2_{Adj}	6.84		37.98	-0.12		22.01
5Y	-4.63	-3.98	-2.19	-0.19	-3.60	1.02
t_{NW}	(-5.72)	(-2.39)	(-1.26)	(-0.31)	(-3.71)	(1.31)
t_{HD}	(-2.88)	(-1.66)	(-1.23)	(-0.13)	(-1.9)	(0.58)
R^2_{Adj}	25.14		48.88	0.01		19.60

Table 8: International evidence with monthly overlapping regressions

This table reports univariate predictive regressions of the log of future cumulative market excess returns over 1-month (1M), 3-month (3M), 1-year (1Y), 2-year (2Y), 3-year (3Y), and 5-year (5Y) horizons on AEIG in the G7 countries excluding US. We construct AEIG for the other G7 countries as in US. The aggregate market returns in these countries are the value-weighted dollar-denominated returns from Fama and French data library, and the market excess return is in excess of the US T-bill rate. The sample starts from June 2001 for Canada, June 1995 for Germany, June 1992 for France and UK, June 1998 for Italy, and June 1997 for Japan, and ends in December 2015. The t-statistics based on Newey-West standard errors (t_{NW}) and Hodrick's (1992) standard errors (t_{HD}) are in parentheses. Adjusted R-squares (R^2_{Adj}) are reported in percentages.

	Canada	Germany	France	UK	Italy	Japan
1M	-0.11	-0.15	-0.05	-0.01	-0.06	-0.20
t_{NW}	(-0.85)	(-2.42)	(-0.93)	(-0.39)	(-1.04)	(-2.54)
t_{HD}	(-1.05)	(-2.55)	(-0.9)	(-0.37)	(-0.86)	(-2.24)
R^2_{Adj}	0.42	1.17	-0.18	-0.32	-0.11	2.76
3M	-0.35	-0.46	-0.12	-0.06	-0.20	-0.69
t_{NW}	(-0.9)	(-2.51)	(-0.99)	(-0.71)	(-1.3)	(-3.52)
t_{HD}	(-1.11)	(-2.63)	(-0.81)	(-0.6)	(-1.07)	(-2.56)
R^2_{Adj}	2.11	4.17	0.05	-0.10	0.79	9.46
1Y	-1.33	-1.39	-0.45	-0.48	-1.06	-3.23
t_{NW}	(-1.37)	(-1.81)	(-0.93)	(-1.82)	(-1.86)	(-5.98)
t_{HD}	(-1.09)	(-2.26)	(-0.91)	(-1.48)	(-1.48)	(-3.44)
R^2_{Adj}	8.66	9.43	0.94	3.76	7.37	39.96
2Y	-2.58	-1.35	-1.21	-1.06	-1.76	-5.31
t_{NW}	(-2.44)	(-0.87)	(-1.49)	(-2.03)	(-2.12)	(-7.66)
t_{HD}	(-1.2)	(-1.18)	(-1.73)	(-1.96)	(-1.66)	(-3.64)
R^2_{Adj}	23.86	4.52	4.73	9.85	11.18	59.70
3Y	-3.44	-1.46	-1.43	-1.73	-2.10	-4.68
t_{NW}	(-2.9)	(-0.73)	(-1.95)	(-3.08)	(-2.51)	(-6.09)
t_{HD}	(-1.27)	(-0.82)	(-1.51)	(-2.58)	(-1.48)	(-2.92)
R^2_{Adj}	38.71	4.10	5.54	21.28	13.04	39.59
5Y	-3.30	-1.03	-0.79	-2.57	-1.35	-1.43
t_{NW}	(-3.97)	(-0.9)	(-0.82)	(-6.81)	(-1.34)	(-1.6)
t_{HD}	(-1.45)	(-0.39)	(-0.69)	(-2.8)	(-0.57)	(-1.12)
R^2_{Adj}	33.03	1.34	1.30	41.24	3.15	4.09

Table 9: AEIG and economic growth

This table reports the results of the predictive regressions of measures of aggregate economic growth by AEIG. These measures include fixed investment growth (FINVG), non-residential investment growth (NRG), GDP growth (GDPG), industrial production growth (IPG), aggregate consumption growth (CONG), Chicago Federal Reserve National Activity Index (CFNAI), earnings growth (EG), and dividend growth (DG) in the subsequent first, second, third, and fourth quarter, as well as in the subsequent first, second, third, and fifth year. Earnings and dividend growth are calculated as the change in the log of aggregate earnings and dividends from Robert Shiller's website. AEIG is the value-weighted firm-level expected investment growth based on the subset of firms with fiscal year end of December. The t-statistics based on Newey-West standard errors (t_{NW}) are in parentheses. Adjusted R-squares (R^2_{Adj}) are reported in percentages. The sample is quarterly from June 1953 to December 2015.

	FINVG	NRG	GDPG	IPG	CONG	EG	DG
Q1	0.62	0.57	0.21	0.11	0.15	0.03	0.05
t_{NW}	(3.57)	(3.79)	(3.66)	(2.97)	(3.38)	(0.13)	(0.91)
R^2_{Adj}	11.30	9.49	7.21	7.24	6.42	-0.39	1.22
Q2	0.33	0.44	0.10	0.05	0.07	-0.25	0.04
t_{NW}	(2.1)	(2.9)	(1.66)	(1.62)	(1.89)	(-0.82)	(0.81)
R^2_{Adj}	2.82	5.57	1.29	1.35	1.24	0.39	1.10
Q3	0.08	0.29	0.02	0.00	0.02	-0.43	0.04
t_{NW}	(0.56)	(1.9)	(0.48)	(-0.09)	(0.58)	(-1.24)	(0.78)
R^2_{Adj}	-0.21	2.14	-0.29	-0.40	-0.25	1.87	0.75
Q4	-0.18	0.05	-0.07	-0.03	-0.01	-0.52	0.02
t_{NW}	(-1.17)	(0.3)	(-1.12)	(-0.88)	(-0.19)	(-1.59)	(0.58)
R^2_{Adj}	0.59	-0.33	0.59	0.35	-0.38	2.88	0.06
Y1	0.50	0.45	0.18	0.11	0.14	-0.86	0.22
t_{NW}	(2.93)	(3.09)	(3.16)	(0.78)	(2.91)	(-0.82)	(1.01)
R^2_{Adj}	13.85	11.05	15.03	-0.52	12.55	0.27	1.73
Y2	-0.16	-0.03	-0.11	-0.42	-0.07	-1.38	-0.10
t_{NW}	(-1.27)	(-0.2)	(-2.3)	(-4.78)	(-1.71)	(-2.91)	(-0.77)
R^2_{Adj}	-0.03	-1.64	4.23	15.94	1.63	3.24	-0.95
Y3	-0.27	-0.38	-0.06	-0.09	-0.02	-0.17	-0.33
t_{NW}	(-2.53)	(-3.24)	(-1.51)	(-0.95)	(-0.42)	(-0.58)	(-2.99)
R^2_{Adj}	2.68	7.53	0.31	-0.82	-1.47	-1.65	5.90
Y5	0.08	0.07	0.04	-0.09	0.03	-0.05	0.12
t_{NW}	(0.56)	(0.38)	(0.75)	(-0.96)	(0.75)	(-0.11)	(1.31)
R^2_{Adj}	-1.37	-1.48	-0.93	-0.88	-0.89	-1.78	-0.76

Table 10: AEIG and economic uncertainty

This table examines the relation between aggregate expected investment growth (AEIG) and economic uncertainty. We consider six uncertainty measures: Forecast dispersions in the growth rates of business fixed investment (BFIG), gross domestic product (GDPG), and industrial production (IPG) from the Livingston Survey (Panel A), SVAR, conditional market variance (CVAR), and the Chicago Board Options Exchange (CBOE) Volatility Index (VIX) (Panel B). We report the results from the regressions of AEIG on each of the uncertainty measures. AEIG is the value weighted firm-level expected investment growth for the subsample of firms with fiscal year end of December. The dispersion from the Livingston survey is based on the forecasts in BFIG, GDPG, and IPG for the subsequent 12 months (i.e., from the base period to 12 months after the date when the survey is conducted, or B12M). SVAR is stock variance calculated as the sum of squared daily market returns. CVAR is estimated from the GARCH(1,1) models using daily market returns. To smooth out seasonality, we use the prior 12-month moving average of SVAR, CVAR, and the squared VIX. We standardize all variables to have zero mean and unit standard deviation. The t-statistics based on Newey-West standard errors (t_{NW}) are in parentheses. Adjusted R-squares (R^2_{Adj}) and the coefficient on VIX are reported in percentages. The sample in Panel A is at a biannual frequency, from December 1990 to December 2015 for BFIG, from June 1971 to December 2015 for GDPG, and from June 1953 to December 2015 for IPG. The sample in Panel B is at a monthly frequency, from June 1953 to December 2015 for SVAR and CVAR, and from January 1986 to December 2015 for VIX.

Panel A: Livingston Survey			
	BFIG	GDPG	IPG
Coeff	-0.28	-0.44	-0.27
t_{NW}	(-2.54)	(-3.15)	(-2.64)
R^2_{Adj}	6.94	18.08	6.54
Panel B: Market-based uncertainty			
	SVAR	CVAR	VIX
Coeff	-0.21	-0.23	-0.19
t_{NW}	(-3.37)	(-2.06)	(-2.67)
R^2_{Adj}	4.27	6.27	3.41

Table 11: AEIG and sentiment

This table reports the relation between AEIG and sentiment. We consider four sentiment measures: S^{BW} is the Baker and Wurgler investor sentiment index, S^{PLS} is the aligned investor sentiment index in Huang, Jiang, Tu, and Zhou (2015), ICS is the University of Michigan consumer sentiment index, the aggregate investment rate (INV) is calculated as the value-weighted firm-level investment to average total assets following Arif and Lee (2014), and EQIS is the percent equity issuing measure from Baker and Wurgler (2000), calculated as the ratio of equity issuing activity as a fraction of total issuing activity. Panel A reports the pairwise correlation coefficients of these variables. Panel B reports the coefficients of the univariate predictive regressions (Uni) of the log of future cumulative excess market returns over 1-month (1M), 3-month (3M), 1-year (1Y), 2-year (2Y), 3-year (3Y), and 5-year (5Y) horizons onto each one of the sentiment measures, and corresponding bivariate regressions (Bi) on AEIG and one sentiment measure. The t-statistics based on Newey-West standard errors (t_{NW}) and Hodrick's (1992) standard errors (t_{HD}) are in parentheses. Adjusted R-squares (R^2_{Adj}) and the coefficients on ICS are reported in percentages. The sample is monthly from June 1953 to December 2015, except for S^{BW} and S^{PLS}, which are from July 1965 to December 2014.

Panel A: Correlation matrix

	AEIG	S^{BW}	S^{PLS}	ICS	INV	EQIS
AEIG	1.00					
S^{BW}	0.41	1.00				
S^{PLS}	0.52	0.73	1.00			
ICS	0.27	0.12	0.00	1.00		
INV	0.47	0.36	0.48	-0.17	1.00	
EQIS	0.01	0.27	0.58	-0.18	0.06	1.00

Panel B: Return predictive regressions

	Panel B.1: S^{BW}			Panel B.2: S^{PLS}			Panel B.3: ICS			Panel B.4: INV			Panel B.5: EQIS		
	Uni	Bi		Uni	Bi		Uni	Bi		Uni	Bi		Uni	Bi	
	S^{BW}	AEIG	S^{BW}	S^{PLS}	AEIG	S^{PLS}	ICS	AEIG	ICS	INV	AEIG	INV	EQIS	AEIG	EQIS
1M	-0.00	-0.10	-0.00	-0.01	-0.04	-0.01	-0.01	-0.12	0.00	-0.18	-0.10	-0.09	-0.04	-0.12	-0.04
t_{NW}	(-1.64)	(-2.01)	(-0.79)	(-3.9)	(-0.74)	(-2.73)	(-0.56)	(-3.83)	(0.16)	(-2.5)	(-2.37)	(-1.06)	(-2.22)	(-3.69)	(-2.26)
t_{HD}	(-1.64)	(-1.76)	(-0.81)	(-3.3)	(-0.66)	(-2.45)	(-0.62)	(-3.25)	(0.18)	(-2.51)	(-2.3)	(-1.16)	(-2.34)	(-3.12)	(-2.29)
R^2_{Adj}	0.38		0.88	2.03		1.97	-0.06		1.40	0.88		1.61	0.50		2.01
3M	-0.01	-0.32	-0.00	-0.02	-0.16	-0.02	-0.04	-0.38	0.00	-0.47	-0.34	-0.17	-0.12	-0.38	-0.12
t_{NW}	(-1.52)	(-2.55)	(-0.57)	(-4.49)	(-1.1)	(-2.94)	(-0.7)	(-4.38)	(0.04)	(-2.3)	(-3.06)	(-0.69)	(-2.07)	(-4.47)	(-2.13)
t_{HD}	(-1.48)	(-1.96)	(-0.57)	(-3.17)	(-0.85)	(-2.25)	(-0.78)	(-3.38)	(0.04)	(-2.23)	(-2.68)	(-0.72)	(-2.13)	(-3.29)	(-2.08)
R^2_{Adj}	1.02		3.06	5.29		5.59	0.18		4.69	1.95		4.89	1.31		6.08
1Y	-0.03	-1.55	-0.00	-0.05	-1.26	-0.02	-0.17	-1.54	-0.01	-1.63	-1.46	-0.34	-0.24	-1.54	-0.23
t_{NW}	(-1.41)	(-5.06)	(-0.09)	(-3.06)	(-2.91)	(-1.07)	(-1.18)	(-5.76)	(-0.06)	(-2.5)	(-5.28)	(-0.57)	(-0.98)	(-6.16)	(-0.95)
t_{HD}	(-1.24)	(-2.52)	(-0.07)	(-2.24)	(-1.85)	(-0.92)	(-0.94)	(-3.63)	(-0.05)	(-2.07)	(-3.21)	(-0.41)	(-1.07)	(-3.57)	(-1.01)
R^2_{Adj}	2.54		14.52	9.04		15.96	1.32		18.42	5.76		18.62	1.23		19.66
2Y	-0.03	-2.85	0.02	-0.06	-2.57	-0.00	-0.34	-2.37	-0.09	-2.58	-2.30	-0.53	-0.11	-2.44	-0.08
t_{NW}	(-0.91)	(-6.11)	(1.19)	(-2)	(-4.26)	(-0.14)	(-1.62)	(-5.55)	(-0.59)	(-2.47)	(-4.53)	(-0.66)	(-0.26)	(-5.39)	(-0.19)
t_{HD}	(-0.66)	(-2.7)	(0.59)	(-1.68)	(-2.16)	(-0.1)	(-1.12)	(-3.27)	(-0.31)	(-1.82)	(-3.25)	(-0.39)	(-0.24)	(-3.29)	(-0.18)
R^2_{Adj}	1.08		23.52	6.88		22.67	3.22		26.15	8.16		26.19	0.01		26.00
3Y	-0.00	-3.13	0.05	-0.04	-3.03	0.03	-0.40	-2.46	-0.15	-3.23	-2.26	-1.22	0.11	-2.57	0.14
t_{NW}	(-0.09)	(-5.53)	(1.89)	(-1.06)	(-4.67)	(1.04)	(-1.44)	(-5.93)	(-0.69)	(-2.54)	(-4.18)	(-0.91)	(0.22)	(-6.11)	(0.28)
t_{HD}	(-0.05)	(-2.23)	(0.93)	(-0.8)	(-1.94)	(0.63)	(-0.98)	(-2.63)	(-0.36)	(-1.75)	(-2.48)	(-0.69)	(0.18)	(-2.67)	(0.23)
R^2_{Adj}	-0.17		21.12	1.64		18.98	3.68		23.54	10.29		24.22	0.00		23.29
5Y	-0.02	-3.35	0.04	-0.04	-3.46	0.04	-0.84	-2.57	-0.55	-2.90	-2.87	-0.31	0.11	-2.96	0.14
t_{NW}	(-0.44)	(-3.23)	(0.6)	(-0.68)	(-2.42)	(0.43)	(-2.63)	(-4.33)	(-1.96)	(-1.45)	(-3.98)	(-0.13)	(0.15)	(-5.1)	(0.2)
t_{HD}	(-0.28)	(-1.87)	(0.46)	(-0.7)	(-1.65)	(0.52)	(-1.36)	(-2.1)	(-0.9)	(-1.26)	(-2.25)	(-0.14)	(0.11)	(-2.34)	(0.14)
R^2_{Adj}	0.27		17.69	1.46		17.55	10.66		25.63	5.66		21.32	-0.06		21.40

Table 12: Predicting earnings surprises and forecast errors

Every December of year t, we run univariate and multivariate predictive regressions of earnings announcement returns and forecast errors on lagged AEIG with or without macro controls, and report the coefficients in Panel A. Following Arif and Lee (2014), EAR in Panel A.1 is the earnings announcement returns, calculated as the value-weighted average firm-level earnings announcement return in year $t+1$, with weights being the market cap at the end of December in year t. The firm-level earnings announcement return is the average cumulative stock return over the (-1,+1) three-day event window centered around the firm's quarterly earnings announcement dates in year $t+1$. $\text{Error}_{\text{ROA}}$ in Panel A.2 is the one-year-ahead analyst forecast errors, calculated as the value-weighted difference between the forecasted one-year-ahead ROA at the end of December in year t and the actual realized ROA in year $t+1$. The forecasted ROA is the median EPS forecast multiplied by shares outstanding and normalized by total assets as of December in year t. $\text{Error}_{\text{LTG}}$ in Panel A.3 is the long-term forecast errors, calculated as the value-weighted difference between the forecast long-term earnings and the actual realized ROA, which is the arithmetic average of actual ROA in year $t+2$ and year $t+3$. AEIG and macro controls are defined the same as in Table 2. Panel B reports the coefficients from predictive regressions of the log of future cumulative excess market returns during year $t+1$ on AEIG, with or without controlling for GDPG, EAR, or forecast errors. GDPG is the GDP growth in year $t+1$. The t-statistics based on Newey-West standard errors (t_{NW}) are in parentheses, and adjusted R-squares (R^2_{Adj}) are reported in percentages. Our sample period is annual from 1971 to 2015 for tests related to earnings announcement returns, and from 1981 to 2015 for tests related to forecast errors.

Panel A: Predicting earnings surprises and forecast errors

	AEIG	DP	CAY	TMS	SVAR	DFY	INFL	TBL	SPLUS	IK	R^2_{Adj}
					Panel A.1: EAR						
Coeff	-0.00										
t_{NW}	(-0.57)										-1.93
Coeff	-0.01	0.00	0.08	-0.09	0.20	-0.13	-0.06	-0.06	-0.02	0.36	
t_{NW}	(-1.21)	(1.13)	(2.86)	(-2.14)	(1.74)	(-0.77)	(-0.44)	(-1.45)	(-1.8)	(1.86)	15.5
					Panel A.2: $\text{Error}_{\text{ROA}}$						
Coeff	0.00										
t_{NW}	(0.18)										-2.89
Coeff	0.01	0.01	0.01	-0.07	-0.38	0.28	-0.03	-0.07	0.03	0.53	
t_{NW}	(0.25)	(4.57)	(0.51)	(-1.93)	(-1.82)	(1.89)	(-0.23)	(-2.32)	(1.78)	(1.58)	38.26
					Panel A.3: $\text{Error}_{\text{LTG}}$						
Coeff	0.53										
t_{NW}	(5.04)										26.97
Coeff	0.28	-0.01	-1.48	0.57	1.56	-3.98	-1.79	0.85	-0.12	-0.29	
t_{NW}	(1.86)	(-0.23)	(-3.09)	(1.05)	(0.93)	(-1.81)	(-1.91)	(2.06)	(-0.45)	(-0.12)	41.58

Panel B: Return predictive regressions

	AEIG	GDPG	EAR	$\text{Error}_{\text{ROA}}$	$\text{Error}_{\text{LTG}}$	R^2_{Adj}
Coeff	-1.56					
t_{NW}	(-4.34)					12.44
Coeff	-1.37	0.05				
t_{NW}	(-3.5)	(3.82)				43.52
Coeff	-1.28	0.04	15.03			
t_{NW}	(-3.77)	(3.5)	(4.43)			50.57
Coeff	-1.85	0.05		-0.01	0.36	
t_{NW}	(-2.68)	(2.76)		(-0.01)	(0.42)	45.65

Table 13: Horse race predictive regressions between AEIG and industry-level EIG

This table compares AEIG and industry-level EIG in predicting industry excess returns. We run panel regressions of the log of future cumulative value-weighted industry excess returns over 1-month (1M), 3-month (3M), 1-year (1Y), 2-year (2Y), 3-year (3Y), and 5-year (5Y) horizons onto lagged predictors. We use three industry classifications: 11 sectors in Global Industry Classification Standard (GICS) in Panel A, Fama and French 5 industries in Panel B, Fama and French 30 industries in Panel C.In each panel, the first two columns are for univariate regressions on AEIG and industry-level EIG, respectively, and the next two columns report the coefficients of AEIG and industry-level EIG from bivariate regressions that include both AEIG and industry-level EIG. AEIG is aggregate expected investment growth as defined in Table 2, and industry-level EIG is the value-weighted firm-level expected investment growth of firms in each industry. Financial and utility industries are excluded from our sample. The t-statistics based on Newey-West standard errors (t_{NW}) are in parentheses. Adjusted R-squares (R^2_{Adj}) are in percentages. The sample is from June 1953 to December 2015.

	Panel A: GICS				Panel B: FF5				Panel C: FF30			
	Univariate		Bivariate		Univariate		Bivariate		Univariate		Bivariate	
	AEIG	EIG_{GICS}	AEIG	EIG_{GICS}	AEIG	EIG_{FF5}	AEIG	EIG_{FF5}	AEIG	EIG_{FF30}	AEIG	EIG_{FF30}
1M	-0.12	-0.04	-0.11	-0.01	-0.12	-0.07	-0.12	0.00	-0.13	-0.04	-0.12	-0.01
t_{NW}	(-3.65)	(-3.23)	(-3.29)	(-0.98)	(-3.72)	(-3.11)	(-3.57)	(-0.11)	(-3.77)	(-3.03)	(-3.56)	(-0.66)
R^2_{Adj}	1.03	0.36		1.03	1.29	0.68		1.26	0.90	0.23		0.90
3M	-0.38	-0.15	-0.35	-0.04	-0.40	-0.22	-0.38	-0.02	-0.41	-0.13	-0.38	-0.03
t_{NW}	(-3.81)	(-3.46)	(-3.34)	(-1.16)	(-3.78)	(-3.25)	(-3.33)	(-0.29)	(-3.79)	(-3.09)	(-3.46)	(-0.83)
R^2_{Adj}	3.01	1.14		3.05	3.70	2.07		3.63	2.63	0.77		2.66
1Y	-1.46	-0.60	-1.29	-0.21	-1.53	-0.93	-1.36	-0.18	-1.54	-0.58	-1.35	-0.25
t_{NW}	(-4.94)	(-3.4)	(-3.98)	(-1.22)	(-5.05)	(-3.6)	(-3.37)	(-0.57)	(-4.13)	(-3.09)	(-3.12)	(-1.34)
R^2_{Adj}	11.65	5.15		12.00	14.47	9.30		14.36	9.47	4.23		10.06
2Y	-2.40	-0.97	-2.26	-0.15	-2.38	-1.54	-2.08	-0.28	-2.44	-0.65	-2.40	-0.05
t_{NW}	(-3.86)	(-3)	(-3.59)	(-0.68)	(-3.91)	(-3.43)	(-3.07)	(-0.7)	(-3.97)	(-2.08)	(-3.76)	(-0.3)
R^2_{Adj}	18.30	7.62		18.19	21.11	15.24		20.78	14.52	3.27		14.45
3Y	-2.94	-1.37	-2.31	-0.68	-3.17	-2.07	-2.20	-0.89	-3.06	-1.43	-2.55	-0.57
t_{NW}	(-3.82)	(-3.08)	(-2.53)	(-1.65)	(-4.51)	(-5.22)	(-2.05)	(-1.76)	(-3.99)	(-3.08)	(-2.82)	(-1.31)
R^2_{Adj}	14.90	9.97		16.41	20.10	17.21		20.76	12.55	7.12		13.24
5Y	-4.75	-2.17	-4.42	-0.30	-4.98	-3.50	-3.87	-0.98	-5.59	-2.79	-4.82	-0.74
t_{NW}	(-4.61)	(-3.92)	(-3.07)	(-0.4)	(-6.62)	(-6.17)	(-2.87)	(-1.01)	(-6.69)	(-4.86)	(-5.8)	(-1.14)
R^2_{Adj}	35.47	18.83		35.16	44.21	37.73		44.06	35.53	21.49		36.21

Figure 1: AEIG and actual aggregate investment growth

This figure plots the time series of aggregate expected investment growth (AEIG) and actual aggregate investment growth from 1954 to 2015. Aggregate investment is measured as the realized growth rate of gross private domestic investment. AEIG is constructed as the value-weighted average of firm-level expected investment growth based on the subsample of firms with fiscal year end of December. Since AEIG in a certain year measures the expectation of the realized investment growth in the next year, we lag AEIG by one year to align with the timing of the actual investment growth to facilitate illustration. Both variables are normalized to have zero mean and unit standard deviation.