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Aggregate expected investment growth and stock market returns☆

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ABSTRACT

A bottom-up measure of aggregate investment plans, namely, aggregate expected investment growth (AEIG) can negatively predict market returns. At the one-year horizon, the adjusted in-sample R^2 is 18.2% and the out-of-sample R^2 is 14.4%. The return predictive power is robust after controlling for standard macroeconomic return predictors and proxies for investor sentiment. Further analyses suggest that the predictive ability of AEIG is at least partially driven by the time-varying risk premium. These findings lend support to neoclassical models with investment lags.

1. Introduction

A basic idea in economics (e.g., Cochrane, 1991) states that capital expenditure decreases with cost of capital, so corporate investment should negatively predict stock returns. However, the existing literature finds mixed empirical 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., Baker and Wurgler, 2000; Lamont, 2000) find this return predictability quite weak. Lamont (2000) attributes this weak correlation to the friction of investment lags. Using the 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.

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This paper proposes a bottom-up measure of aggregate investment plans, referred to as the aggregate "expected" investment growth (AEIG). Consistent with the argument in Lamont (2000), AEIG is a strong and negative predictor for stock market returns from one-month to 5-year horizons. At the one-month horizon, the coefficient on AEIG is 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 18.2% and an out-of-sample R^2 of 14.4%, which is remarkably strong compared with most existing predictors.[1] The return predictive power peaks at about two years and remains relatively stable at longer horizons, so these findings are consistent with Liu et al. (2017) and Martin (2017) which highlight the high-frequency (i.e., low-persistence) fluctuations in the market risk premium. The result holds after controlling for other popular predictive variables, including the Treasury bill rate, term spread, default spread, as well as variables in more recent papers, including the aggregate investment rate in Arif and Lee (2014) and the ratio of new orders to shipments in Jones and Tuzel (2013). The return predictive power of AEIG is robust to additional tests including the subsample analysis, quantifying small sample biases, as well as exploring different AEIG construction procedures.

The predictive variable AEIG is constructed by aggregating firm-level expected investment growth (EIG). Since the data availability of investment guidance or analysts forecasts is quite limited, the firm-level EIG is estimated by taking advantage of valuable information in the cross section. Motivated by the existing literature, 11 variables are selected as the initial set of investment predictors. Some of these variables capture firms' fundamentals, such as cash flows and profitability or prior financing and investment decisions; other variables are more forward looking about future investment opportunities. The least absolute shrinkage and selection operator (LASSO) procedure is further used to select one of the best subsets of investment predictors and construct firm-level EIG as the out-of-sample predicted investment growth. AEIG is then defined as the market value weighted average of firm-level EIG.

The 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, firms initiate more investment plans and AEIG increases. This is followed by lower stock returns on average, giving rise to a negative correlation between AEIG and future market returns. 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 probably because they share this sentiment with investors. This mispricing is then corrected by disappointing future economic fundamentals when investors realize their prior expectation errors, giving rise to the return predictive ability of AEIG. Consistent with both views, AEIG is found to be negatively correlated with measures of economic uncertainty and positively correlated with measures of investor sentiment. However, the return predictive power of AEIG remains strong after controlling for these measures, and in fact, several of these uncertainty and sentiment measures are subsumed by AEIG in the horse race return predictive regressions. Therefore, these results suggest that AEIG contains additional information about the discount rate or investor sentiment beyond traditional uncertainty or sentiment measures.

Several analyses are preformed to further differentiate the risk-based and sentiment-based explanations. The first test examines the relation between AEIG and subsequent economic activities and finds a hump-shaped dynamics of aggregate investment, gross domestic product (GDP), consumption, and industrial production following periods of high AEIG. The economic growth tends to be positive in the first two or three quarters, followed by sharp declines in economic activities in the subsequent two to three years, a pattern that is similar to the negative responses of output, investment, and hiring to a spike in economic uncertainty documented in Bloom (2009). The similar dynamics suggests that AEIG can be closely related to the economic uncertainty and cost of capital in a rational framework.

The second test investigates whether AEIG is able to predict future earnings announcement returns and analyst forecast errors. If investors/managers/analysts share the same misperception, negative earnings surprises and positive forecast errors are expected to follow periods of high AEIG. However, among various earnings surprises measures examined, including earnings announcement returns, one-year-ahead analyst forecast errors on return on assets, and the long-term forecast errors, there is only some weak evidence for the long-term forecast errors. Furthermore, AEIG remains a strong market return predictor even after controlling for these ex post earnings surprises and forecast errors measures. These findings lend little support to this version of misperception-based explanations.

Lastly, we follow Jones and Tuzel (2013) and compare the performance of the industry-level EIG and AEIG in predicting industry-level returns. If investor sentiment is the driving force behind AEIG, then the industry-level EIG would dominate AEIG because it captures industry-level sentiment better. In the horse races between the industry-level and aggregate expected investment growths, AEIG almost drives out the predictive ability of industry-level EIG completely, which again suggests that investor sentiment is unlikely to be the main driver for the return predictive ability of AEIG. Although it is impossible to completely rule out all possible behavioral explanations, these analyses altogether are more consistent with the rational explanation based on time-varying risk premiums.

This paper contributes to the large literature that links financial markets with firms' investment decisions. Cochrane (1991) describes a production-based asset pricing model to tie stock returns to investment returns (marginal rates of trans-

[1] For example, in their abstract, Rapach et al. (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".

formation) which are inferred from investment data via a production function.[2] The study is closest to Lamont (2000). Lamont (2000) tests the importance of investment lags using the plant and equipment expenditure survey and documents a negative relation between investment plans and future market returns. Compared to this survey-based investment plans measure, AEIG has several advantages. First, AEIG is available at higher frequencies and has a more comprehensive coverage, which can be used to closely examine the relation between market returns and economic activities. The more timely information in AEIG about the expected return also allows investors to better time the market, whereas the survey-based measure of investment plans is only available at the annual frequency. Second, the AEIG measure is based on firm-level stock return and accounting data and hence is very easy to construct, whereas the survey-based measure in Lamont (2000) has been discontinued since 1994.[3] Therefore, AEIG can be considered as an alternative, more timely measure of aggregate investment plans.

Two other closely related papers are Jones and Tuzel (2013) and Arif and Lee (2014). Both papers examine the market return predictive power of aggregate investment-based variables. However, compared to the ratio of new orders to shipment (NO/S) – the aggregate investment plan proxy in Jones and Tuzel (2013), AEIG is a bottom-up measure from the aggregation of firm-level investment decision and can contain additional and potentially superior information about discount rates than the aggregate variables.[4] Furthermore, AEIG is broader in industry coverage than the ratio of new orders to shipment, which is only available for manufacturing industries. The aggregate *realized* investment (INV) from Arif and Lee (2014) is also a bottom-up measure, but it can be driven by completely different economic forces from AEIG. While Arif and Lee (2014) find more supportive evidences for the interpretation of their aggregate investment rate measure based on investor sentiment, the aggregate *expected* investment growth in this paper is more likely to originate from time-varying risk premiums. Importantly, AEIG can still significantly predict future market returns even after controlling for Arif and Lee's INV measure and Jones and Tuzel's NO/S measure. More detailed discussions on the difference between these investment-based market return predictors are provided in Section 4.6.

The paper proceeds as follows. Section 2 describes the data sources and variable constructions. Section 3 documents a negative relation between AEIG and future stock returns, and perform several robustness checks on this finding. Section 4 investigates the sources of return predictions of AEIG and differentiate explanations based on time-varying risk premiums from those based on investment sentiment. Section 5 concludes.

2. Aggregate expected investment growth

Because the aggregate-level and firm-level investment guidance or analysts forecasts are not available in the long sample period required for a return prediction analysis, a novel two-step estimation is used for the aggregate expected investment growth (AEIG) and justify its validity by comparing it with the realized investment growth. The first stage constructs firm-level expected investment growth (EIG), taking advantage of valuable accounting and financial information in the cross section. In the second stage, AEIG is then calculated as the bottom-up firm-level EIG. Section 2.1.1 discusses the initial set of investment predictors using the literature as the guidance. Section 2.1.2 uses the least absolute shrinkage and selection operator (LASSO) to select the model for firm-level expected investment growth (EIG). These EIGs are then aggregated into the aggregate expected investment growth (AEIG), whose properties are discussed in Section 2.1.3.

2.1. Investment predictors

Several variables have been shown in the literature to contain information about future investment. For instance, Fazzari et al. (1988) show that Tobin's q and cash flow are strong predictors of investment rate. Barro (1990) and Morck et al. (1990) document that past market returns are informative about future aggregate investment growth. The positive correlation between stock returns and future investment can be understood from a neoclassical model with investment lags, in which firms that experienced firm-specific productivity shocks have contemporaneous response in stock returns and delayed response in the capital expenditure (e.g., Lamont, 2000); it can also be due to (mis)valuation (e.g., Baker et al., 2003; Gilchrist et al., 2005; Morck et al., 1990; Panageas, 2005; Polk and Sapienza, 2008), or learning (e.g., Bond et al., 2012; Chen et al., 2006).[5] Besides stock returns, Morck et al. (1990) also find growth rate of fundamentals, including cash flow and sales, as well as debt and equity issues are strong predictors for investment. More recently, Chen et al. (2016) use an accounting identity approach to explore the determinants of investment growth, and document that earnings growth, lagged

[2] Other papers that study the implications of investment-based asset-pricing models on asset prices include (Belo, 2010; Cochrane, 1996; Jermann, 2010; Kogan and Papanikolaou, 2013; 2014; Li, 2018). Cochrane (2005) provides excellent reviews on this literature. This paper is also related to the vast literature on aggregate market return predictability, which is too large to cite here. See Koijen and Nieuwerburgh (2011) for review on recent studies.

[3] Moreover, the approach in this paper avoids the look-ahead bias that affects many of Lamont's results. As discussed in Jones and Tuzel (2013), the investment plans series is usually not collected until February or March of the year, but 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.

[4] In the same spirit, Yu (2011) finds that a bottom-up measure of disagreement has strong return predictive power. He argues that "bottom-up measure of disagreement likely offers a better signal-to-noise ratio than the top-down measure. Bottom-up disagreement is constructed using thousands of individual-stock forecasts while there are, on average, only 20 or so analysts in the sample covering S&P 500 EPS."

[5] We do not differentiate these alternative interpretations, but instead take their empirical findings as given to construct the aggregate expected investment growth (AEIG). Section 4 examines if the return predictive power of AEIG is more consistent with risk-based or behavioral explanations.

investment growth, stock return, net payout yield, and cash flow adjustment growth explain about 13% of the variation of firm-level investment growth in a panel vector autoregression (VAR) framework. At the aggregate level, Kothari et al. (2017) find that changes in profit, past returns, change in return volatility, along with a set of macro variables, can explain corporate investment growth.

Motivated by these findings in the literature, we start with a set of 11 investment growth and investment rate predictors: past investment growth (IG), Tobin's q (q), prior 12-month cumulative stock returns (Ret), cash flow growth (CFG), sales growth (SG), firms' debt financing condition (I_D), firms' equity financing condition (I_E), earnings growth (EG), profitability growth (PG), change in return volatility (ΔVOL), and cash flow (CF).[6] Table 1 reports the properties of these investment predictors. The average firm-level investment growth (IG) is about 6% per year, slightly below the median of 8%, but there is a large heterogeneity across firms. The cross-sectional standard deviation of IG is 56%, with the first quartile of - 27% and the third quartile of 41%. The average q is 0.34 with a standard deviation of 1.01. The average firm-level stock return is 15% per year, with an annual standard deviation of 39%. The growth rates of sales, cash flows, earnings, and profitability have similar volatility, ranging between 16% and 20% per year. For the two financing variables, 38% of firms issue debt in a typical year, as compared with only 14% for equity issuance. This difference in issuance rate may reflect a higher cost of equity financing than debt financing due to information asymmetry, as argued in the literature on the pecking order theory (e.g., (Myers and Majluf, 1984)). Finally, the average change in daily return volatility is very close to zero.

Panel B of Table 1 reports the correlation coefficients between these investment predictors. The contemporaneous correlations of investment growth (IG) with other predictors are all positive except for the change in return volatility (ΔVOL). Most of their economic magnitudes are small, despite the strong statistical significance. For instance, the correlation coefficients between IG and Ret, SG, CFG, EG, PG, and CF are all below 25%. The weak contemporaneous correlation between stock returns and investment has been used as evidence to support the existence of other types of investment frictions such as investment lags (e.g., Lamont, 2000). On the other hand, debt and equity financings are positively related to IG, whereas return volatility changes have a negative comovement with IG. The latter negative correlation can be consistent with the real option effect that greater uncertainty, as measured by stock return volatility, increases the option value of waiting and so lowers current investment (e.g., Bloom, 2009). It is worth noting that some of these predictors, such as those growth variables, are highly correlated. For example, the correlation between earnings growth (EG) and cash flow growth (CFG) is 73%, and the correlation between profitability growth (PG) and cash flow growth (CFG) is even higher of 90%. These high correlations imply that if all 11 variables are included into one linear model to predict future investment growth, the resulting multicollinearity may potentially inflate the variance of estimated coefficients and cause unstable out-of-sample predictions for investment growth. Next subsection will address this issue using the least absolute shrinkage and selection operator (LASSO).

Panel C of Table 1 shows the result from the univariate predictive regressions of the subsequent one-year investment growth on these predictors. At the end of each June, these predictors are aligned following the standard (Fama and French, 1992) timing and run panel regressions on the full sample. Unlike firm-level investment rate, i.e., investment scaled by lagged capital stock, which is known to be persistent, Panel C shows that firm-level investment growth is in fact negatively autocorrelated. q, stock returns (Ret), cash flow (CF), and all growth variables (SG, CFG, EG and PG) positively predict subsequent investment growth. Economically, a one standard deviation increase in these variables is associated with 6.38%, 13.73%, 3.80%, 4.31%, 4.47%, 4.97%, and 4.29% respectively in IG in the next year. Interestingly, while subsequent investment growth increases with equity issuance, the coefficient on debt issuance dummy is strongly negative. This negative coefficient may again reflect the lower cost of debt financing, so that the money raised from borrowing can be used for immediate capital expenditure.[7] Indeed, the contemporaneous correlation of IG with debt issuance is higher than with equity issuance (0.19 vs 0.09 as in Panel A of Table 1).

2.2. Variable selection

The previous subsection confirms that all 11 variables have strong predictive power for firm-level investment growth in the subsequent year. This subsection uses LASSO to select a subset of these predictors to form the estimate of the firm-level expected investment growth (EIG).

[6] IG is defined as the log growth rate of capital expenditure (Compustat item CAPX), i.e., $IG_t \equiv \log(CAPX_t/CAPX_{t-1})$. q is defined as defined as the log of the market value of the firm, i.e., sum of market equity, long-term debt, and preferred stock minus inventories and deferred taxes, divided by capital stock (Compustat item PPEGT). Ret is the prior 12-month cumulative returns. CFG is the change in cash flow (Compustat data items NI+DP) divided by capital (Compustat data item PPEGT). SG is the log growth rate of sales (Compustat data item Sale). I_D is equal to 1 if a firm increases its total debt by more than 10% and 0 otherwise, where new debt issues is defined by change in total debt (Compustat data items DLTT+DLC) divided by lag debt. I_E is equal to 1 if a firm increases its equity by more than 5% and 0 otherwise, where new share issues is defined as the sale of common and preferred stock (Compustat data item SSTK) divided by lag market equity after 1971, and the growth rate of the split-adjusted shares (Compustat data items CSHO $\times$ AJEX) before 1971 due to the data availability of SSTK. EG is defined as the change in earnings (Compustat data item IB) divided by capital (Compustat data item PPEGT). PG is defined as the change in profitability (Compustat data items EBITDA-(XINT-IDIT)-(TXT-TXDC)) divided by capital (Compustat data item PPEGT). ΔVOL is the change in total volatility of daily returns over the past year. Cash flow adjustment growth and net payout yield are not included because the Compustat data items needed to construct these measures, SSTK and PRSTKC, are only available from 1971.

[7] Morck et al. (1990) find a positive coefficient on debt issuance dummy in investment regressions because they consider the contemporaneous relation between debt financing and investment.

Table 1

Investment growth predictors This table reports the properties of investment growth predictors. These predictors include: lagged investment growth (IG), Tobin's q (q), past 12-month market return (Ret), sales growth (SG), cash flow growth (CFG), earnings growth (EG), profitability growth (PG), cash flow (CF), new debt dummy (I_D), new share dummy (I_E), and change in return volatility (ΔVOL). Panel A reports the time-series average of cross-sectional mean, standard deviation, the first quartile (Q1), median, and the third quartile (Q3) of predictive variables for the firm-level investment growth. Panel B reports the correlation matrix of these variables, where ***, ** and * refer to the *p*-value being less than 0.01, 0.05, and 0.1, respectively. Investment growth (IG) is defined as the log growth rate in capital expenditures (Compustat data item CAPX), i.e., $IG_t \equiv \log(CAPX_t/CAPX_{t-1}$. q is the logarithm of the market value (sum of market equity, long-term debt, and preferred stock minus inventories and deferred taxes) divided by capital (Compustat data item PPEGT). SG is the log growth rate of sales (Compustat data item Sale). Ret is the prior 12-month cumulative returns. I_E is equal to 1 if a firm increases its equity by more than 5% and 0 otherwise. New share issues is defined as the sale of common and preferred stock (Compustat data item SSTK) divided by lag market equity after 1971, and the growth rate of the split-adjusted shares (Compustat data items CSHO $\times$ AJEX) before 1971 due to the data availability of SSTK. I_D is equal to 1 if a firm increases its total debt by more than 10% and 0 otherwise. New debt issues is the change in total debt (Compustat data items DLTT+DLC) divided by lagged debt. CFG is defined as the change in cash flow (Compustat data items NI+DP) divided by capital (Compustat data item PPEGT). EG is defined as the change in earnings (Compustat data item IB) divided by capital (Compustat data item PPEGT). PG is defined as the change in profitability (Compustat data items EBITDA-(XINT-IDIT)-(TXT-TXDC)) divided by capital. ΔVOL is the change in the total volatility (in percentages) of daily returns over the past year. Panel C reports the in-sample univariate firm-level investment predictive regression. All predictive variables are winsorized at the 5% and 95% levels. The *t*-statistics are reported in parentheses with the standard errors clustered at both the firm and year levels. Adjusted R-squares are reported in percentages. The sample is annual from 1951 to 2014.

Panel A: Summary statistics

	IG	q	Ret	SG	CFG	EG	PG	CF	I_D	I_E	ΔVOL
Mean	0.063	0.345	0.150	0.098	0.027	0.033	0.015	0.173	0.377	0.142	−0.005
Std	0.561	1.011	0.393	0.167	0.203	0.157	0.185	0.320	0.477	0.343	0.696
Q1	−0.265	−0.400	−0.130	0.004	−0.028	−0.024	−0.032	0.075	0.000	0.000	−0.422
Median	0.077	0.254	0.091	0.084	0.017	0.018	0.010	0.158	0.078	0.000	−0.031
Q3	0.406	1.041	0.356	0.181	0.079	0.078	0.061	0.295	0.953	0.031	0.396

Panel B: Correlation matrix

	IG	q	Ret	SG	CFG	EG	PG	CF	I_D	I_E	ΔVOL
IG	1.00										
q	0.09***	1.00									
Ret	0.12***	0.20***	1.00								
SG	0.24***	0.23***	0.23***	1.00							
CFG	0.09***	0.21***	0.32***	0.39***	1.00						
EG	0.10***	0.23***	0.31***	0.48***	0.73***	1.00					
PG	0.07***	0.20***	0.34***	0.35***	0.90***	0.76***	1.00				
CF	0.17***	0.39***	0.23***	0.25***	0.49***	0.42***	0.45***	1.00			
I_D	0.19***	0.03***	−0.03***	0.18***	−0.02*	0.01***	−0.05***	0.03***	1.00		
I_E	0.09***	0.10***	0.08***	0.19***	0.07***	0.07***	0.06***	−0.06*	0.05***	1.00	
ΔVOL	−0.07***	−0.04***	−0.05	−0.05***	−0.06***	−0.04***	−0.06***	−0.08***	0.00	0.00	1.00

Panel C: Univariate investment growth predictive regressions

Predictor	IG	q	Ret	SG	CFG	EG	PG	CF	I_D	I_E	ΔVOL
Est.	−0.16	0.06	0.35	0.26	0.22	0.32	0.23	0.12	0.09	−0.12	−6.54
	(−17.15)	(8.82)	(14.13)	(9.97)	(13.71)	(16.45)	(12.11)	(8.89)	(8.37)	(−11.91)	(−4.18)
R^2_{adj}	2.47	1.66	7.46	0.78	2.21	2.21	2.32	1.73	0.25	0.89	1.15

LASSO is a panelized regression method that minimizes the sum of squared errors, with a constraint on the sum of the absolute values of coefficients (i.e., L_1 norm), to achieve better prediction accuracies. This constraint causes estimated coefficients to be biased, but it improves the overall prediction error of the model by decreasing the variance of coefficient estimates.[8] The selected model depends on the LASSO constraint parameter (λ) which captures the strength of penalty. When λ is small, few predictors are eliminated and the estimates are close to the one from OLS regressions. As the constraint parameter λ increases, more and more predictors are set to zero. One popular way of selecting the optimal λ is K-fold cross validation. However, studies show that selection of tuning parameter by cross validation often fails to achieve consistent variable selection (e.g., Chand, 2012; Wang et al., 2009). Furthermore, Fan and Tang (2013) argue that theoretically quantified optimal tuning parameters are not practically feasible, because they are valid only asymptotically and usually depend on unknown nuisance parameters in the true model.

Given the above issues, a different approach is used. To achieve the goal of finding a parsimonious model, $\lambda = 0.3$, along with a training-validation sample split of 6:4 (i.e., a validation parameter $V = 4/(4+6) = 0.4$), are chosen as the benchmark specification, so that about half of the 11 investment predictors are selected. The robustness of these results are then tested under alternative specifications, including the K-fold cross validation. Panel A of Table 2 reports the coefficients of the six selected variables: investment growth, past return, sales growth, earnings growth, profitability growth, and cash flow. All

[8] See Friedman et al. (2001) for an excellent textbook discussion on LASSO regressions.

Table 2
Model selection and properties of AEIG This table reports the result on the model selection in predicting firm-level investment growth and the properties of the constructed aggregate expected investment growth (AEIG). The predictive variables considered include: lag investment growth (IG), Tobin's q (q), sales growth (SG), cash flow growth (CFG), cash flow (CF), profitability growth (PG), earnings growth (EG), past 12-month market return (RET), new share dummy (I_E), new debt dummy (I_D), and change in return volatility (ΔVOL). LASSO is used to select the best model among all candidates consisting of panel regressions of firm-level investment growth onto different subsets of these predictors over the full sample period. Panel A reports the coefficients of investment growth predictors in the benchmark model, under the parameterization of 40% of the full sample being used as the validation sample (i.e., V = 0.4) and constraint parameter $\lambda = 0.3$. All predictive variables are winsorized at the 5% and 95% levels. The *t*-statistics are reported in parentheses with the standard errors clustered at both the firm and year levels. Adjusted R-squares (R^2_{adj}) are reported in percentages. Panel B compares the performance of the benchmark model with alternative models selected from LASSO. Specifications (2)-(5) are based on alternative validation and turning parameters, and Specification (6) is based on 10-fold cross validation (CV). The metrics in the model comparison include adjusted R-squares (R^2_{adj}) over the full sample and the average squared errors of the training sample (ASE (Train)) and validation sample (ASE (Validate)). The sample for Panels A and B is annual from 1951 to 2014. Panel C reports the mean, standard deviation (Std), 12th-order autocorrelation (AC(12)), skewness (Skew), and kurtosis (Kurt) of AEIG as well as its correlation with known return predictors in the literature, including log of dividend yield (DP), consumption-wealth ratio (CAY), term spread (TMS), default yield spread (DFY), inflation (INFL), detrended T-bill rate (TBL), surplus ratio (SPLUS), aggregate investment-to-capital ratio (I/K) and log new orders to shipments ratio (NO/S). The sample is monthly from June 1953 to December 2015, except for NO/S, which is from February 1958 to December 2015.

Panel A: Benchmark model

Predictor	IG	Ret	SG	EG	PG	CF	$R^2_{adj.}$
Est.	−0.21	0.31	0.28	0.05	0.04	0.09	13.33
	(−29.19)	(14.27)	(14.15)	(1.70)	(2.18)	(7.88)	

Panel B: Comparison with alternative models

Specification	(1) B.M.	(2) V = 0.3	(3) V = 0.5	(4) $\lambda = 0.2$	(5) $\lambda = 0.4$	(6) CV
$R^2_{adj.}$	13.33	13.33	13.33	14.03	12.37	14.09
ASE (Train)	0.335	0.333	0.334	0.325	0.342	0.318
ASE (Validate)	0.331	0.334	0.332	0.327	0.338	0.313

Panel C: Properties of AEIG

Mean	Std	AC(12)	Skew	Kurt
0.096	0.054	0.213	0.502	2.870

	DP	CAY	TMS	DFY	INFL	TBL	SPLUS	I/K	NO/S
Corr.	−0.28	−0.06	−0.21	−0.11	0.12	0.21	0.04	0.47	0.19

six predictors' coefficients have the same sign as in their univariate regressions in Table 1, and they jointly explain 13.33% of the variation in the future firm-level investment growth. The latter is comparable to the explanatory power reported in Chen et al. (2016).

Panel B of Table 2 compares the performance of the benchmark specification (B.M.) with alternative specifications. To measure performances, adjusted R^2 is used over the full sample, the average squared errors (ASE) of the training sample, i.e., ASE(Train), and the validation sample, i.e., ASE(Validate). Specifications (2) and (3) consider alternative values of validation parameter V. When V = 0.3, that is, when the training-validation sample split is 7:3, the adjusted R^2 is almost identical to that in the benchmark specification. While the ASE in the training sample is lower than the benchmark (0.333 vs 0.335), the ASE in the validation sample is slightly higher (0.334 vs 0.331). Similar results can be found in Specification (3) where V = 0.5. Therefore, the validation parameter has a minimal impact on the performance of selected models. Specifications (4) and (5) use alternative constraint parameter λ. When λ is decreased to 0.2, more predictors are selected and the adjusted R^2 is increased to 14.03%. In the meanwhile, ASE(Train) and ASE(Validate) are slightly reduced to 0.325 and 0.327, respectively. On the other hand, when λ is increased to 0.4, the adjusted R^2 becomes lower and ASEs in both training and validation samples are slightly higher. Specification (6) uses 10-fold cross validation to select constraint parameter, the performance further improves, with the corresponding adjusted R^2 being 14.09% and the ASE(Train) and ASE(Validate) of 0.318 and 0.313. Since these performance metrics are not economically and significantly better than those from the benchmark specification (about 5%-6% differences), the more parsimonious benchmark model (1) is used as the preferred specification. Section 3.2.3 shows that the stock return prediction of AEIG is robust to these alternative model selections.

Table 3

Return predictive regressions Panel A reports the coefficients of aggregate expected investment growth (AEIG) and the adjusted R-squares (R^2_{adj} in percentages) in the in-sample univariate regressions to predict 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. Panel B reports the coefficients of AEIG and the adjusted R-squares (R^2_{adj} in percentages) from the in-sample bivariate regressions on AEIG and one of the other return predictors, including log of dividend yield (DP), consumption-wealth ratio (CAY), term spread (TMS), default yield spread (DFY), inflation (INFL), detrended T-bill rate (TBL), surplus ratio (SPLUS), investment-to-capital ratio (I/K), and log of the ratio of new orders to shipments (NO/S). Panels C reports the coefficients of AEIG and the adjusted R-squares (R^2_{adj} in percentages) from the in-sample pooling regression that includes all variables from Panel B except NO/S. Panel D reports the coefficients of AEIG and the adjusted R-squares (R^2_{adj} in percentages) in non-overlapping univariate regression. The t-statistics based on Newey-West standard errors (t-stat) are reported in parentheses. Panel A also reports the t-statistics based on Hodrick's (1992) standard errors. Panel E reports the out-of-sample R^2 (in percentages) from Campbell and Thompson (2008). Panel E.1 is for the univariate regressions with AEIG, and Panel E.2 is for the bivariate regressions with AEIG and one other predictor from Panel B. The first ten years of data are used for the initial estimation and the estimation is updated every month. The sample is monthly from June 1953 to December 2015, except for the specifications with NO/S which are from February 1958 to December 2015.

Return horizon	1M	3M	1Y	2Y	3Y	5Y
Panel A: In-sample univariate regressions						
AEIG	−0.09	−0.31	−1.32	−1.97	−2.09	−2.55
t-stat	(−3.11)	(−3.99)	(−7.17)	(−5.31)	(−5.54)	(−5.72)
Hodrick t-stat	(−2.71)	(−2.98)	(−3.58)	(−3.39)	(−2.81)	(−2.61)
R^2_{adj}	1.21	4.13	18.20	22.93	20.60	21.47
Return horizon	1M	3M	1Y	2Y	3Y	5Y
Panel B: Coefficients of AEIG, controlling one-by-one for other predictors						
DP	−0.09	−0.28	−1.22	−1.80	−1.86	−2.16
t-stat	(−2.72)	(−3.39)	(−6.12)	(−5.74)	(−6.12)	(−4.39)
R^2_{adj}	1.18	4.32	19.24	24.92	23.11	26.84
CAY	−0.09	−0.29	−1.26	−1.87	−1.92	−2.34
	(−2.91)	(−3.72)	(−7.15)	(−5.37)	(−5.54)	(−4.80)
	2.04	6.53	25.01	35.30	39.90	44.75
TMS	−0.08	−0.28	−1.23	−1.81	−1.81	−2.19
	(−2.78)	(−3.67)	(−6.63)	(−4.69)	(−4.44)	(−5.64)
	1.34	4.54	20.06	25.91	27.66	29.41
DFY	−0.09	−0.30	−1.30	−1.96	−2.06	−2.45
	(−3.14)	(−4.00)	(−6.70)	(−5.23)	(−5.33)	(−5.54)
	1.11	4.14	18.47	22.97	20.74	24.72
INFL	−0.09	−0.29	−1.27	−1.93	−2.03	−2.49
	(−3.00)	(−3.69)	(−7.17)	(−5.07)	(−5.15)	(−5.72)
	1.17	4.64	20.07	23.75	21.33	22.30
TBL	−0.07	−0.26	−1.28	−2.05	−2.15	−2.64
	(−2.40)	(−3.46)	(−7.03)	(−5.18)	(−5.19)	(−6.21)
	2.77	5.96	18.41	23.58	20.86	21.82
SPLUS	−0.09	−0.30	−1.30	−1.93	−2.03	−2.45
	(−3.07)	(−3.97)	(−6.70)	(−5.07)	(−4.74)	(−5.29)
	1.45	4.99	22.11	31.30	33.94	37.59
IK	−0.07	−0.24	−1.18	−1.66	−1.38	−1.30
	(−1.92)	(−2.57)	(−5.83)	(−5.25)	(−4.18)	(−3.21)
	1.49	4.80	18.84	24.91	28.75	37.49
NOS	−0.09	−0.28	−1.09	−1.61	−1.84	−2.16
	(−2.81)	(−3.34)	(−5.25)	(−3.50)	(−3.90)	(−5.04)
	1.21	5.29	20.83	20.90	19.77	25.69
Panel C: Coefficients of AEIG, controlling for all other predictors						
AEIG	−0.05	−0.20	−1.11	−1.64	−1.38	−1.24
t-stat	(−1.55)	(−2.10)	(−4.62)	(−5.84)	(−5.19)	(−3.22)
R^2_{adj}	4.49	10.89	35.58	55.27	63.57	69.86
Panel D: Non-overlapping regressions						
AEIG	−0.09	−0.33	−1.26	−1.83	−2.27	−3.07
t-stat	(−3.11)	(−3.75)	(−4.69)	(−4.13)	(−2.15)	(−7.52)
R^2_{adj}	1.21	4.04	17.00	18.89	12.33	44.60
Return horizon	1M	3M	1Y	2Y	3Y	5Y
Panel E: OOS R^2, univariate and controlling one-by-one for other predictors						
N/A	0.95	3.13	14.40	17.68	15.79	15.15
DP	0.06	0.70	1.67	−2.35	−0.17	−3.84
CAY	1.12	3.77	18.26	21.89	23.57	17.11
TMS	0.14	1.02	13.02	14.51	13.85	8.63
DFY	0.21	0.69	10.94	8.84	−5.63	−14.66
INFL	0.24	1.80	14.35	17.26	14.54	3.21
TBL	1.56	2.91	13.01	15.14	11.12	14.64
SPLUS	0.70	2.10	11.44	16.98	13.25	−4.62
IK	0.88	2.61	11.06	16.08	16.35	18.03
NOS	0.40	3.13	15.96	12.60	10.98	14.36

2.3. AEIG Construction and properties

With firm-level investment predictors selected, the next step is to construct the aggregate expected investment growth. At the end of June, year $\tau+1$, the following panel investment growth predictive regression up to year τ is run:

$$\begin{aligned}\mathrm{IG}_{it} =& b_{0,\tau} + b_{\mathrm{IG},\tau}\times \mathrm{IG}_{it-1} + b_{\mathrm{Ret},\tau}\times \mathrm{Ret}_{it-1} + b_{\mathrm{SG},\tau}\times \mathrm{SG}_{it-1} + b_{\mathrm{EG},\tau}\times \mathrm{EG}_{it-1}\\ &+ b_{\mathrm{PG},\tau}\times \mathrm{PG}_{it-1} + b_{\mathrm{CF},\tau}\times \mathrm{CF}_{it-1} + \epsilon_{it},\ \ (t\le\tau)\end{aligned} \tag{1}$$

and compute the monthly firm-level EIG as the out-of-sample predicted investment growth based on the most updated estimated coefficients and values of the six investment growth predictors.[9] AEIG is then defined as the value-weighted average of firm-level EIG with the market value of equity from the previous month end as the weight.

In order to remove potential high-frequency noises, AEIG is further smoothed by computing its prior 12-month moving average. These "noises" can be considered as the short-run variations in AEIG that are not related to expected returns. These "noises" can reflect measurement errors; they can also capture short-run variations in the expected cash flow. Specifically, firms can initiate investment plans not only because the discount rate (expected return) falls, but also because expected cash flow rises. The short-run variation in expected cash flows can generate high-frequency movement in AEIG which lowers the return predictive power of AEIG. One way to detect these noises is to look at the autocorrelation of the raw AEIG without moving average. In the sample period from 1953 to 2015, the 12-month autocorrelation coefficient of the raw AEIG series is only 0.004. However, most leading asset pricing models, such as the Campbell and Cochrane (1999) habit formation model and Bansal and Yaron (2004) long-run risk model, imply that expected returns are quite persistent. More recently, studies such as Liu, Tao, Wu, and Yu (2016) and Martin (2017) highlight low-persistence fluctuations in the market risk premium, but these premiums are still much more persistent than the raw AEIG. Another way to observe high-frequency noises is to compare volatilities. The standard deviation of the raw AEIG is 6.5%, which is 20% higher than 5.4% volatility in the AEIG series after taking the 12-month moving average. Therefore, the expected return related component in AEIG is teased out by smoothing out the short-run noise in AEIG measurement using 12-month moving average.

Panel C of Table 2 reports the mean, standard deviation (Std), 12th-order autocorrelation (AC(12)), skewness (Skew), and kurtosis (Kurt) of AEIG. The standard deviation of AEIG is 5.4% per year, smaller than 6.2% for the realized aggregate nonresidential investment growth. Unlike predictive variables such as aggregate dividend-price ratio and consumption surplus ratio, which are highly persistent over time, the 12th-order autocorrelation coefficient for AEIG is only 0.21. This low persistence implies that if AEIG captures some component of the market risk premium, this component tends to be relatively short-lived. For the higher moments of AEIG, a small positive skewness of 0.5 and a kurtosis of 2.87 are observed.

Panel C also reports the correlation of AEIG with other known return predictive variables include log of dividend yield (DP), consumption-wealth ratio (CAY) from Lettau and Ludvigson (2001), term spread (TMS), default yield spread (DFY), inflation (INFL), detrended T-bill rate (TBL) detrended by the Hodrick-Prescott (HP) filter, consumption 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).[10] Among these predictors, I/K has the strongest comovement with AEIG, with a correlation coefficient of 0.47. Intuitively, when the economy is doing well, firms invest more and initiates more investment plans, so these two investment variables naturally move in tandem. The correlation of AEIG with dividend-price ratio, term spread, default yield, and detrended T-bill is -0.28, -0.21, -0.11, and 0.21, respectively, suggesting that AEIG tends to be procyclical and may capture some of these traditional measures of risk premiums. On the other hand, the correlation between AEIG and SPLUS is only 0.04. Since SPLUS is a common proxy for the aggregate risk aversion (Campbell and Cochrane, 1999), this weak correlation suggests that AEIG is unlikely to be driven by the time-varying price of risk.

Fig. 1 plots the time series of AEIG and the realized aggregate nonresidential investment growth from National Income and Product Account (NIPA). Since AEIG in a given year measures the expectation of investment growth in the subsequent year, AEIG is lagged by one year to align with the timing of the realized investment growth. Fig. 1 shows that AEIG predicts realized investment growth reasonably well. 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 subsequent one-year investment growth is 0.52 (untabulated).

In untabulated analyses, two additional justifications for the AEIG measure are provided. First, 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 0.67 in the sample from 1953 to 1994.[11] Second, AEIG is also expected by investors; AEIG is positively associated with the average forecasted one-year business fixed investment growth from the Livingston Survey, with a correlation coefficient of 0.45.

[9] Specifically, at the end of each month from June, year $\tau+1$ to May, year $\tau+2$, the out-of-sample EIG for firm i uses the values of $\mathrm{IG}_{i\tau}$, $\mathrm{SG}_{i\tau}$, $\mathrm{EG}_{i\tau}$, $\mathrm{PG}_{i\tau}$, and $\mathrm{CF}_{i\tau}$ in the fiscal year ending at year τ, the monthly updated prior 12-month stock return, along with the panel regression coefficients estimated at the end of June, year $\tau+1$.

[10] See, for example, Chen et al. (1986), Keim and Stambaugh (1986), Campbell and Shiller (1988), Fama and French (1988),Fama (1989), Fama (1990), Campbell (1991), Ferson et al. (1991), Lettau and Ludvigson (2001), and Lettau and Ludvigson (2005).

[11] The survey was discontinued in September 1994. We thank Selale Tuzel for sharing these hand-collected data on aggregate investment plans with us.

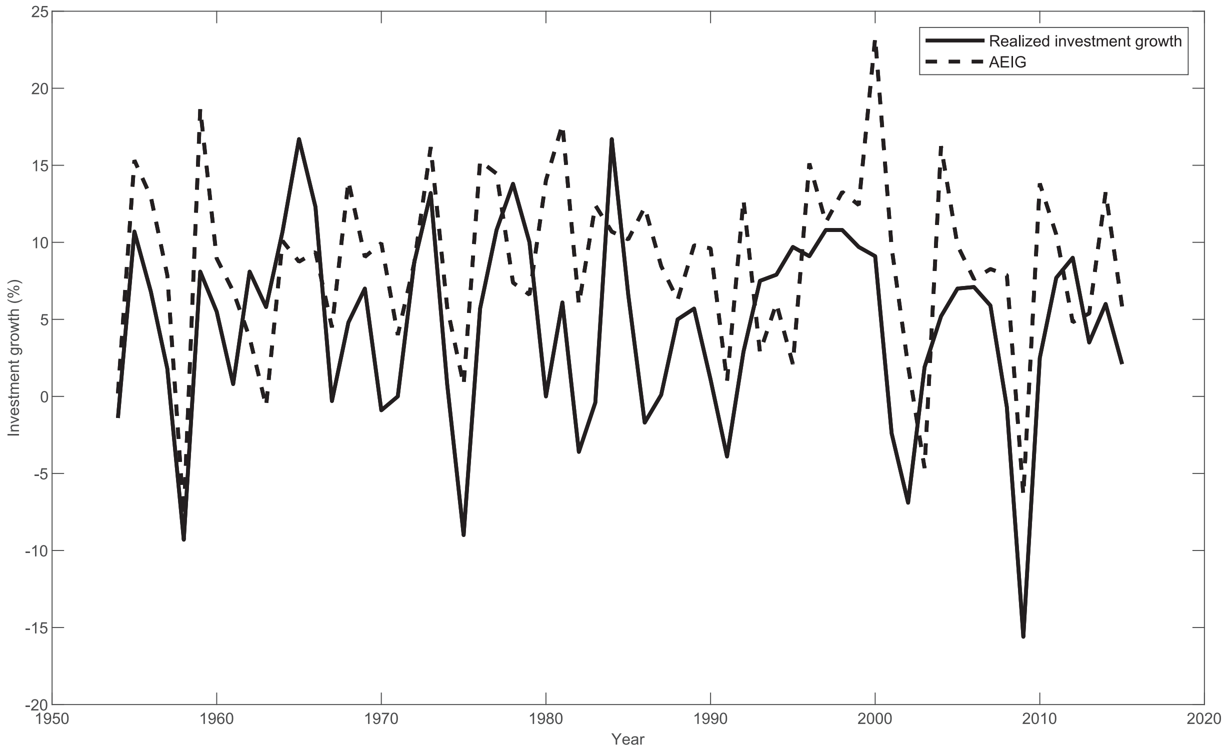

Fig. 1. AEIG and realized aggregate investment growth This figure plots the time series of aggregate expected investment growth (AEIG) and realized aggregate nonresidential investment growth from 1954 to 2015. AEIG is constructed as the value-weighted average of firm-level expected investment growth based on the subsample of firms with fiscal year ending on December. To facilitate comparison, AEIG is lagged by one year to align with the timing of the realized investment growth.

3. Stock return predictability

This section explores the relation between AEIG and future stock market returns.

3.1. Main results

Panel A, Table 3 reports 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 using the monthly overlapping sample.[12] The monthly market excess return is calculated as the difference between the value-weighted market returns from CRSP and the risk-free rate. The point estimate, the *t*-statistics based on Newey and West (1987) standard errors (*t*-stat) and the adjusted R^2 are reported. For robustness checks, the *t*-statistic based on Hodrick (1992) standard errors is also reported.

Panel A shows that for all horizons considered, the coefficient of AEIG is negative, indicating that higher AEIG predicts lower stock market returns. At the very short end of the spectrum (one-month), the coefficient on AEIG is -0.09 with a Newey-West *t*-statistic of -3.11 and a Hodrick *t*-statistic of -2.71, and the adjusted R^2 is 1.21%. The magnitude of the AEIG coefficient and the associated adjusted R^2 increase with horizons. At the one-year horizon, the coefficient on AEIG becomes -1.32 with a Newey-West *t*-statistic of -7.17, a Hodrick *t*-statistic of -3.58, and an adjusted R^2 of 18.2%. Economically, AEIG captures large time-series variations in expected excess market returns, with a one-standard-deviation increase in AEIG being associated with about a 6.6% decrease in annual expected market returns. This value is comparable with other prominent market return predictors in this literature. For example, a one-standard-deviation increase in DP, CAY, and the net payout ratio increases the risk premium by 3.6%, 7.39%, and 10.2% per annum, respectively.[13] The magnitude of AEIG coefficient continues to rise but at a lower rate beyond two years, suggesting that the expected return captured by AEIG is relatively short-lived.

[12] The analyses throughout the paper follow the majority of the literature and use the ordinary least squares (OLS) estimator. Untabulated analyses show that the results are quantitatively similar when the weighted least squares (WLS) estimator is used. Johnson (2019) assesses the performances of traditional and newer predictors in the market return predictive regressions using the WLS estimator.

[13] See Lettau and Ludvigson (2001) and Boudoukh et al. (2007).

Panel B reports the coefficient of AEIG and the adjusted R^2 in the bivariate regressions, with the control of the other return predictors from Panel C of Table 2 one at a time.[14] In almost all specifications, the coefficient on AEIG remains statistically significant at the 5% level and is quantitatively comparable to that from the univariate regression in Panel A. For instance, at the one-year horizon, the AEIG coefficient ranges from −1.3 when default yield or surplus ratio is included to −1.09 when new order to shipment ratio is controlled, and the adjusted R^2 ranges from 18.41% when T-bill rate is controlled to 25.01% when CAY is included. When all variables from Panel B (except NO/S) are controlled in the same specifications, Panel C of Table 3 finds qualitatively similar results.[15] Except for the very short end, AEIG remains a statistically significant predictor for future market returns, and the adjusted R^2 is further increased to 35.58% at the one-year horizon.[16]

The analyses above focus on the overlapping data. Panel D of Table 3 reports the results using non-overlapping data. In the univariate return predictive regressions, the magnitude of AEIG coefficient increases from −0.09 (t-statistic = −3.11) at the one-month horizon to −1.26 (t-statistic = −4.69) at the one-year horizon and −3.07 (t -statistic = −7.52) at the five-year horizon, and the corresponding adjusted R^2 increases from 1.21% to 17% and 44.6%. The results at longer horizons, especially at five years, should be interpreted with cautions, because there are not many observations at such low frequencies. Still, it is encouraging to see that the results from the non-overlapping sample are consistent with those in Panel A.

Now turn to the out-of-sample performance of AEIG. 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 $r_{t+1} = a + b \times x_t + \epsilon_{t+1}$ using data up to time τ and use $\hat{r}_{t+1} \equiv \hat{a} + \hat{b} \times x_\tau$ to forecast the return at time $\tau + 1$. Then they 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. As in Goyal and Welch (2008), the out-of-sample R^2 of a return predictive model is defined as

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

where $\sum_{\tau=1}^{T}(r_\tau - \hat{r}_\tau)^2$ is the mean squared forecast error (MSFE) of the testing model, and $\sum_{\tau=1}^{T}(r_\tau - \bar{r}_\tau)^2$ is the MSFE based on the historical mean of market excess returns. A positive R^2_{OOS} indicates that the testing model provides better market timing than the naive investment strategy based on the historical average market excess returns.

Panel E reports the R^2_{OOS} for the models tested in Panel A and Panel B. The first row is for the univariate predictive regression model with AEIG as the only predictor. At the one-month horizon, the R^2_{OOS} is 0.95%, and it increases to 14.40% at one year, 17.68% at two years, and then declines to 15.15% at five years. Therefore, the strong in-sample return predictive power of AEIG also extends to the out-of-sample test. The remaining of Panel E reports the result from bivariate models from Panel B. At the one-year horizon, the R^2_{OOS} ranges from 1.67% when the dividend-price ratio (DP) is included to 15.96% when NO/S is included. At the two-year horizon, the R^2_{OOS} ranges from −2.35% to 17.26%. Across the panel, only a few models generate negative R^2_{OOS}, and the causes of these weak performances are usually from the predictor other than AEIG. For instance, in the model with AEIG and dividend-price ratio (DP) as predictors, the R^2_{OOS} is rather weak within one year and becomes negative starting from the second year, but the low R^2_{OOS} is likely to be driven by the poor out-of-sample performance of DP. Indeed, an untabulated analysis shows that the R^2_{OOS} in the univariate model with DP alone is −0.75, −10.83, −22.41, and −14.95 at the one-month, one-year, two-year, and five-year horizons.

In another untabulated analysis, we examine whether AEIG has more out-of-sample return predictive power in booms or recessions. Using the data on US business cycle expansions and contractions from the National Bureau of Economic Research, the monthly R^2_{OOS} is only 0.71% in booms, which is much lower than 1.56% in recessions. This finding is consistent with Rapach and Zhou (2013), which find that the out-of-sample return predictability is stronger during recessions for most return predictors.

3.2. Robustness checks

This subsection checks the robustness of the return predictive power of AEIG in several ways. The main findings are summarized below, and the details of these analyses are left to the Appendix.

Section A of the Appendix examines the in-sample return predictive regressions of AEIG in two subpreiods separated by the mid-point of the full sample. The return predictive power of AEIG is robust and strong in both subsamples. Although at horizons within one year, the coefficients of AEIG and the associated t-statistics are about twice as large in the early sample as in the later sample, the difference gradually diminishes with horizons.

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[14] For brevity, only Newey and West (1987) t-statistics are reported for the rest of the paper.

[15] NO/S is excluded in the pooling regressions due to its data availability. The results are similar if NO/S is included and the sample starts in February 1958, the first month that NO/S is available.

[16] In untabulated analyses, additional predictors are controlled, including aggregate book-to-market ratio, aggregate earnings-price ratio from Goyal and Welch (2008), as well as more recently documented return predictors including the variance risk premium (Bollerslev et al. (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 et al. (2016)), and the debt-to-GDP ratio (Liu, 2019). The coefficient of AEIG remains significant at all horizons after controlling for these predictors. Given the important role of stock returns in the investment predictive regressions, the relation between AEIG and prior market returns is also examined in Section 3.2.5.

Section B of the Appendix evaluates the effect of small sample biases (e.g., Stambaugh, 1986; Stambaugh, 1999) on the AEIG return predictability using Monte Carlo simulations. Two models for the data generating processes of AEIG and market returns are considered. The first model assumes that AEIG and stock returns are independent of each other, and the second model takes into account of the positive correlation between AEIG and the prior 12-month market returns. In both cases, the finite sample bias is unlikely to drive the return predictive ability of AEIG.

Section C of the Appendix examines how alternative LASSO parameterizations in the AEIG construction (Section 2.2) affect the return prediction of AEIG. The results show that the predictive power of AEIG is very robust to alternative values of the validation parameter (V) and LASSO constraint parameter (λ). We also consider a 10-fold cross validation procedure to select the constraint parameter, and find the selected model and the constructed AEIG also has similar return predictive power as the benchmark AEIG.

To highlight the importance of the bottom-up approach, Section D of the Appendix studies two alternative aggregate expected investment growth measures that only use aggregate information. The first measure is the median forecasted one-year business fixed investment growth from the Livingston Survey, and the second measure is constructed in the same procedure as the estimation of the firm-level EIG but use aggregate investment growth as the dependent variable and lagged aggregate investment growth, prior 12-month market returns, lagged aggregate CF, lagged aggregate sales growth, lagged aggregate earnings growth, lagged aggregate profitability growth, and lagged aggregate cash flow growth as the independent variables (the predictors). The return predictive powers of both measures are substantially weaker than the benchmark AEIG.

Two aggregate expected growth measures based on firm-level earnings growth and sales growth are also examined. These two variables are constructed with exactly the same procedure as the AEIG construction but with sales growth or earnings growth on the left-hand-side of Eq. (1). Again, their return predictive powers are subsumed by AEIG. These results suggest that AEIG is not a simple combination of the investment predictors. Instead, investment growth, the left-hand-side variable in the first-stage EIG estimation, contains important information about future stock return that is not captured by variables such as sales growth and earnings growth.

Lastly, we check if AEIG return predictive power simply reflects the autocorrelation of market returns (e.g., Moskowitz et al., 2012) in Section E of the Appendix. In the horse races between AEIG and prior market returns for horizons ranging from 6 months to 60 months, the AEIG coefficients are almost the same as in the univariate regressions reported in Panel A, Table 3, indicating the AEIG predicts returns beyond the market return autocorrelation.

4. Interpretations

The previous section documents that AEIG has a robust predictive power for future market returns. This return predictability can be due to time-varying risk premiums, where the expected return rises with risk aversion (e.g., Campbell and Cochrane, 1999) or quantity of risk (e.g., Bansal and Yaron, 2004). It can also be driven by investor sentiment. High sentiment can push up current stock prices and investment plans, giving rise to a negative correlation between aggregate expected investment growth and future market returns when mispricing eventually gets corrected by economic fundamentals. For instance, when investors have extrapolative expectations biases (e.g., Barberis et al., 2015; Hirshleifer et al., 2015), this negative predictive relation naturally arises.

This section performs several analyses in an attempt to differentiate these two explanations. Section 4.1 documents strong correlations between AEIG and measures of economic uncertainty (negative) and investor's sentiment (positive). Section 4.2 runs horse races between AEIG and these measures in return predictive regressions. Section 4.3 explores the relation between AEIG and future economic activities. Section 4.4 examines the relation between AEIG and subsequent earnings surprises and analysts forecast errors. Following (Jones and Tuzel, 2013), Section 4.5 tests the relative performance of AEIG and industry-level EIG in predicting future industry returns. Section 4.6 further differentiates AEIG with the ratio of new orders to shipment (NO/S) from Jones and Tuzel (2013) and the investment rate measure (INV) in Arif and Lee (2014).

4.1. Relation between AEIG, uncertainty, and sentiment

The analysis starts with examining the relation between AEIG and time-varying risk premiums. Table 2 shows that AEIG is almost uncorrelated with consumption-surplus ratio. Because a high surplus ratio implies a low risk aversion (e.g., Campbell and Cochrane, 1999), the weak correlation suggests that the time-varying price of risk is unlikely to capture the negative AEIG coefficients in the predictive regressions in Section 3. Thus, the attentions are focused on economic uncertainty, i.e., the quantity of aggregate risk.

The first group of measures of uncertainty are forecast dispersions in business fixed investment growth (BFIG), GDP growth (GDPG), and industrial production growth (IPG) in the subsequent 12 months from the Livingston Survey.[17] Presumably, when the economic uncertainty is high, there are more disagreements among survey respondents about future economic growth. One caveat of these survey-based measures is that besides the actual uncertainty, forecast dispersions

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

Table 4
AEIG, uncertainty, and sentiment This table examines the relation between aggregate expected investment growth (AEIG), economic uncertainty, and investors' sentiment. The results from the regressions of AEIG on each one of the uncertainty or sentiment measures are reported, where all variables are normalized to have unit standard deviation. Panel A considers 9 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 in Panel A.1, market variance (SVAR), conditional market variance (CVAR), and the Chicago Board Options Exchange (CBOE) Volatility Index (VIX) in Panel A.2, economic policy uncertainty (EPU) from Baker et al. (2016), financial uncertainty (FUC) and macroeconomic uncertainty (MUC) from Jurado et al. (2015); Ludvigson et al. (2019) in Panel A.3. 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. The Hodrick-Prescott filter is used to detrend market-based and economic uncertainty measures. Panel B considers five sentiment measures: S(BW) is the Baker and Wurgler investor sentiment index, S(PLS) is the aligned investor sentiment index in Huang et al. (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. AEIG is the value weighted firm-level expected investment growth. To remove potential high-frequency noises, the prior 12-month moving average of AEIG, SVAR, CVAR, VIX, and EQIS is used. The *t*-statistics based on Newey-West standard errors (*t*-stat) are in parentheses. The sample in Panel A.1 is biannual 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 A.2 is monthly from June 1953 to December 2015 for SVAR and CVAR, and from January 1986 to December 2015 for VIX. The sample in Panel A.3 is monthly from June 1953 to December 2015 for EPU, and from July 1960 to December 2015 for FUC and MUC. The sample is Panel B monthly from June 1953 to December 2015 for ICS and EQIS, from July 1965 to December 2014 for S(BW) and S(PLS), and annual from 1953 to 2015 for INV.

Panel A: Uncertainty measures									
	Panel A.1:			Panel A.2:			Panel A.3:		
	Survey-based			Market-based			Policy, financial & macro		
	BFIG	GDPG	IPG	SVAR	CVAR	VIX	EPU	FUC	MUC
AEIG	−0.27	−0.34	−0.40	−0.31	−0.31	−0.54	−0.42	−0.33	−0.19
t-stat	(−2.39)	(−2.75)	(−3.64)	(−4.43)	(−4.93)	(−4.24)	(−3.65)	(−3.34)	(−1.42)

Panel B: Sentiment measures					
	S(BW)	S(PLS)	ICS	INV	EQIS
AEIG	0.29	0.38	0.33	0.30	0.15
t-stat	(2.33)	(2.68)	(2.65)	(1.71)	(1.78)

may also be affected by behavioral biases such as investor sentiment. To alleviate this concern, two market-based uncertainty measures are considered. 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. Another potential concern about the forecast dispersion measures is that the information sets and expectations of investors may be different from those of the survey respondents. Even though survey respondents disagree on future economic growth, investors may not feel the same way. Therefore, the Chicago Board Options Exchange (CBOE) Volatility Index (VIX) is used as the third market-based measure of uncertainty. Besides the survey-based and market-based uncertainty measures, the relation between AEIG and the economic policy uncertainty (EPU) from Baker et al. (2016), and financial uncertainty (FUC) and macroeconomic uncertainty (MUC) from Jurado et al. (2015) and Ludvigson et al. (2019) is also investigated. The relation between AEIG and these uncertainty measures may shed light on the underlying driving forces of AEIG.

Panel A of Table 4 reports the coefficient from the univariate regression of AEIG on each of these nine uncertainty measures. To facilitate interpretations, both AEIG and the independent variables in these regressions are standardized to have a unit standard deviation. Panel A.1 shows that all three survey-based measures have strongly negative comovement with AEIG. A one-standard-deviation increase in forecast dispersion in BFIX, GDPG, and IPG is associated with a 0.27-, 0.34-, and 0.4-standard-deviation decrease in AEIG, respectively, so high AEIG is associated with less disagreement in forecasting future economic growth. Results are similar when the market-based uncertainty measures are used in Panel A.2. Periods of high AEIG coincide with episodes of low market volatility, both realized and perceived. In Panel A.3, the correlation between AEIG and the economic policy uncertainty (EPU) is also negative, consistent with the empirical findings in Bloom (2009) and Gulen and Ion (2015) for a real option based explanation of the relation between policy uncertainty and real investment. Further, while AEIG has a strong negative correlation with financial uncertainty (FUC), its relation with the macroeconomic uncertainty (MUC) is substantially weaker. Therefore, if the time-varying economic uncertainty is the underlying source of AEIG, it is more likely to be driven by uncertainties about the financial markets rather than uncertainties about the real economic activity (Ludvigson et al., 2019).

Next test examines the correlations between AEIG and measures of investor sentiment. Five measures from the existing literature are used: the Baker and Wurgler sentiment index (S(BW)), the aligned investor sentiment data (S(PLS)) from Huang et al. (2015), the index of consumer sentiment (ICS) from the University of Michigan Survey of Consumers, the aggregate investment rate (INV) from Arif and Lee (2014), and the percent equity issuing measure (EQIS) from Baker and Wurgler (2000).[18][19] Panel B of Table 4 reports the results from the regression of the standarized AEIG on each one of these five standarized sentiment measures. All five sentiment measures have positive correlations with AEIG. The coefficient on the Baker and Wurgler sentiment index, the aligned sentiment index, the consumer sentiment index, the aggregate investment rate, and percent equity issuance is 0.29, 0.38, 0.33, 0.3, and 0.15, respectively, whose magnitudes are comparable to those from Panel A. These results confirms the earlier conjecture that AEIG can also be driven by investor sentiment.

4.2. Horse races with measures of uncertainty and sentiment

Given the strong correlation between AEIG and measures of economic uncertainty and investor sentiment, one may wonder how AEIG performs in the return predictive regressions in the presence of these variables. This subsection runs horse races between AEIG and these measures of uncertainty and sentiment. For each uncertainty or sentiment measure, we consider univariate return predictive regressions (Uni) only on this measure and bivariate regressions (Bi) in which AEIG is also included. The results are reported in Table 5.

Panel A, Table 5 reports the results from the horse race between AEIG and uncertainty measures. For the survey-based uncertainty measures (Panel A.1), the estimated coefficients are positive and statistically significant for most univariate specifications, consistent with the notion that higher uncertainty corresponds to higher risk premium. However, their explanatory powers for future market returns (adjusted R^2) are substantially weaker than AEIG. In the bivariate regressions, the survey-based measures lose their statistical significance, which is in contrast to the highly significant coefficients on AEIG. For the three market-based uncertainty measures (Panel A.2), positive predictive powers are again found in the univariate regressions. When controlling for AEIG, the coefficients on these market-based measures become substantially weaker, but at horizons of one month to one year, these measures can still strongly predict market returns. Meanwhile, controlling for SVAR, CVAR, and VIX also weakens the coefficients on AEIG, especially at shorter horizons, although AEIG remains significant in most of these bivariate specifications.[20] These results suggest that AEIG and these market-based uncertainty measures may contain independent information about future returns. Panel A.3 reports the results for EPU, FUC, and MUC. Although the economic policy uncertainty (EPU) significantly predict market returns in univariate regressions, it is only significant at shorter horizons after controlling for AEIG. For the two measures from Jurado et al. (2015) and Ludvigson et al. (2019), while the return predictive power of financial uncertainty (FUC) tends to be stronger at horizons of one or two years, the macroeconomic uncertainty (MUC) can only predicts market returns at the longer end of the horizons.

Panel B reports the horse race between AEIG and five sentiment measures. For the Baker and Wurgler sentiment index (S(BW)), its coefficients are negative but statistically insignificant, consistent with Baker and Wurgler (2007) who also find that the BW index predicts returns better in the cross section than in the aggregate. For the aligned investor sentiment index (S(PLS)), we confirm the finding in Huang et al. (2015) and find that S(PLS) has much stronger return predictive power than S(BW), especially at the short horizons up to one year. Although the AEIG coefficient becomes weaker in the bivariate regressions at the 1- and 3-month horizons after controlling for S(PLS), AEIG dominates S(PLS) from one year and beyond. This result suggests that while S(PLS) better captures investor sentiment at shorter horizons (1-month to 1-year), AEIG may contain additional information about time-varying risk premiums, especially at horizons longer than one year. The consumer sentiment index is only significant at the five-year horizon in the univariate regressions, but it is also subsumed by AEIG. Consistent with Arif and Lee (2014), INV is a strong return predictor. In the univariate regression, the coefficient of INV increases from -0.18 (t-statistic $= -2.50$) at one month to -1.63 (t -statistic $= -2.50$) at one year and -3.23 (t-statistic $= -2.54$) at three years. However, when controlling for AEIG, the predictive power of INV becomes weaker, whereas AEIG remains statistically significant. Lastly for the equity issuance (EQIS), while it has a stronger return predictive power at short horizons, it is clearly dominated by AEIG.

To summarize, AEIG is negatively correlated with measures of economic uncertainty and positively correlated with measures of investor sentiment. Nevertheless, the return predictive power of AEIG is not subsumed by these variables; if anything, many of them are dominated by AEIG. These results suggest that AEIG may contain additional information about the aggregate discount rate or investor sentiment beyond these measures of uncertainty and sentiment. Next subsections conduct further analyses to differentiate the risk-based and sentiment-based interpretations of AEIG.

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[18] 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. In an untabulated analysis, an alternative sentiment measure based on the aggregate asset growth from Wen (2019) is used, and deliver qualitatively similar results.

[19] Arif and Lee (2014) find that the aggregate corporate investment rate mirrors waves of investor optimism and pessimism and also predicts aggregate stock returns with a negative sign. Following Arif and Lee (2014), INV of year t is defined as the arithmetic average of aggregate investment rates in year t and year $t-1$, and this value is assigned 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.

[20] The coefficients of AEIG are less statistically significant in the horse race with VIX than with other uncertainty measures, and this could be due to the shorter sample period. The VIX data start in 1986, so the sample size in this specification is about half of the benchmark sample size. If the sample size had doubled while keeping the same point estimates and covariances, the coefficients of AEIG would be statistically significant at most horizons. Another important reason is the look-ahead bias of VIX that is introduced when detrending VIX using the HP filter. This detrending series is used to be consistent with Table 10, but this detrending procedure may strengthen the return predictive power of VIX, given the strong negative correlation between changes in VIX and market returns. When the raw VIX rather than the detrended VIX is used, the predictive power of VIX is significantly weaker and is subsumed by AEIG. These results are available upon request.

Table 5

Horse race between AEIG, uncertainty and sentiment measures This table the coefficients and adjusted R-squares (R^2_{adj} in percentages) 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 the uncertainty or sentiment measures, and corresponding bivariate regressions (Bi) that also include AEIG. Panel A considers 9 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 in Panel A.1, market variance (SVAR), conditional market variance (CVAR), and the Chicago Board Options Exchange Volatility Index (VIX) in Panel A.2, economic policy uncertainty (EPU) from Baker et al. (2016), financial uncertainty (FUC) and macroeconomic uncertainty (MUC) from Jurado et al. (2015); Ludvigson et al. (2019) in Panel A.3. The forecast dispersions are based on the forecasts from the base period to 12 months after the date when the survey is conducted (or B12M). SVAR is calculated as the sum of squared daily market returns. CVAR is estimated from the GARCH(1,1) models using daily market returns. The Hodrick-Prescott filter is used to detrend market-based and economic uncertainty measures. Panel B considers five sentiment measures: S(BW) is the Baker and Wurgler investor sentiment index, S(PLS) is the aligned investor sentiment index in Huang et al. (2015), ICS is the University of Michigan consumer sentiment index, INV is the aggregate investment rate from Arif and Lee (2014), and EQIS is the percent equity issuing measure from Baker and Wurgler (2000). To remove potential high-frequency noises, the prior 12-month moving average of SVAR, CVAR, VIX, and EQIS is used. The *t*-statistics based on Newey-West standard errors (*t*-stat) are in parentheses. The coefficients on ICS, BFIG, GDPG, IPG, VIX and EPU are reported in percentages. The sample is monthly from June 1953 to December 2015, except for BFIG (December 1990-December 2015), VIX (January 1986-December 2015), FUC and MUC (July 1960-December 2015), and S(BW) and S(PLS) (July 1965-December 2014).

Return horizon		1M	3M	1Y	2Y	3Y	5Y
Panel A: Uncertainty measures							
Panel A1: Survey-based uncertainty measures							
Uni	BFIG	−0.02	0.16	2.19	7.73	10.46	15.25
		(−0.09)	(0.24)	(1.06)	(2.40)	(3.25)	(11.19)
	R^2_{adj}	−0.33	−0.28	2.06	13.28	17.48	25.08
Bi	AEIG	−0.08	−0.23	−0.92	−1.64	−1.90	−2.56
		(−1.80)	(−2.03)	(−2.86)	(−2.34)	(−2.62)	(−3.97)
	BFIG	−0.15	−0.22	0.51	4.63	6.86	9.32
		(−0.63)	(−0.38)	(0.25)	(1.09)	(1.51)	(3.35)
	R^2_{adj}	0.51	2.45	12.78	29.55	33.03	46.14
Uni	GDPG	0.46	1.45	5.45	7.87	7.66	12.50
		(2.15)	(2.54)	(2.53)	(2.06)	(1.67)	(2.21)
		0.40	1.48	5.09	5.81	4.34	8.08
Bi	AEIG	−0.08	−0.27	−1.22	−1.84	−1.98	−2.28
		(−2.59)	(−3.29)	(−6.62)	(−5.55)	(−5.28)	(−3.95)
	GDPG	0.25	0.77	2.36	3.13	2.46	6.44
		(1.13)	(1.31)	(1.31)	(1.15)	(0.63)	(1.09)
		1.22	4.41	18.96	23.66	20.90	23.30
Return horizon		1M	3M	1Y	2Y	3Y	5Y
Uni	IPG	0.30	0.75	1.97	3.10	3.33	4.98
		(2.67)	(2.40)	(1.44)	(1.20)	(0.99)	(1.16)
		0.53	1.12	1.84	2.58	2.35	3.65
Bi	AEIG	−0.08	−0.28	−1.35	−2.01	−2.13	−2.52
		(−2.44)	(−3.36)	(−6.96)	(−5.62)	(−5.2)	(−3.99)
	IPG	0.16	0.27	−0.38	−0.42	−0.48	0.37
		(1.35)	(0.80)	(−0.29)	(−0.18)	(−0.15)	(0.09)
		1.24	4.13	18.15	22.86	20.54	21.37
Panel A2: Market-based uncertainty measures							
Uni	SVAR	0.04	0.12	0.36	0.45	0.33	0.50
		(2.90)	(3.87)	(2.95)	(3.06)	(2.57)	(4.11)
		1.30	4.59	9.56	8.28	3.41	5.35
Bi	AEIG	−0.07	−0.23	−1.13	−1.78	−2.01	−2.39
		(−2.23)	(−2.64)	(−4.76)	(−4.01)	(−4.73)	(−5.13)
	SVAR	0.03	0.10	0.23	0.24	0.09	0.21
		(2.15)	(2.75)	(1.68)	(1.57)	(0.69)	(1.77)
		1.86	6.61	21.64	25.04	20.74	22.24
Uni	CVAR	0.05	0.15	0.43	0.51	0.39	0.60
		(3.12)	(3.90)	(2.78)	(2.93)	(2.60)	(4.44)
		1.65	4.95	9.32	7.55	3.48	5.54
Bi	AEIG	−0.07	−0.22	−1.13	−1.79	−2.01	−2.38
		(−2.01)	(−2.47)	(−4.72)	(−4.01)	(−4.76)	(−5.16)
	CVAR	0.04	0.12	0.27	0.26	0.11	0.26
		(2.32)	(2.70)	(1.54)	(1.35)	(0.67)	(1.82)
		2.12	6.87	21.42	24.61	20.74	22.27
Uni	VIX	0.27	0.80	2.41	3.19	2.54	3.40
		(3.42)	(4.33)	(4.09)	(2.80)	(2.28)	(2.96)
		2.60	7.40	17.48	15.79	6.96	9.34
Bi	AEIG	−0.01	−0.05	−0.56	−1.51	−2.27	−3.14
		(−0.21)	(−0.37)	(−1.28)	(−1.86)	(−2.98)	(−3.45)
	VIX	0.26	0.75	1.85	1.67	0.23	0.10
		(2.87)	(3.16)	(2.37)	(1.08)	(0.14)	(0.06)
		2.34	7.25	20.51	27.86	26.32	38.16

(*continued on next page*)

Table 5 (*continued*)

Panel A3: Policy, financial, and macro uncertainty measures							
Uni	EPU	0.07	0.18	0.51	0.59	0.58	0.75
		(3.28)	(3.52)	(3.04)	(2.26)	(2.54)	(3.43)
		2.07	4.47	7.91	5.80	4.44	5.02
Bi	AEIG	−0.05	−0.21	−1.16	−1.90	−2.05	−2.49
		(−1.74)	(−2.77)	(−5.09)	(−4.43)	(−4.50)	(−4.89)
	EPU	0.06	0.13	0.22	0.10	0.05	0.08
		(2.63)	(2.57)	(1.23)	(0.41)	(0.23)	(0.30)
		2.28	5.97	19.29	22.97	20.52	21.40
Uni	FUC	0.13	0.51	2.75	4.27	2.52	4.42
		(1.22)	(1.95)	(4.12)	(3.18)	(1.83)	(3.08)
		0.15	1.29	10.22	13.95	3.71	8.15
Bi	AEIG	−0.08	−0.24	−0.95	−1.50	−1.83	−2.26
		(−2.19)	(−2.59)	(−3.37)	(−2.66)	(−3.48)	(−4.24)
	FUC	0.05	0.28	1.89	2.91	0.83	2.34
		(0.52)	(1.13)	(2.39)	(1.91)	(0.58)	(1.89)
		0.77	3.26	17.93	24.84	16.47	21.82
Return horizon		1M	3M	1Y	2Y	3Y	5Y
Uni	MUC	0.06	0.22	1.28	2.21	1.34	3.25
		(0.53)	(0.78)	(1.21)	(1.36)	(0.98)	(2.14)
		−0.08	0.17	2.40	4.15	1.09	4.94
Bi	AEIG	−0.09	−0.27	−1.14	−1.77	−1.91	−2.40
		(−2.50)	(−3.11)	(−4.73)	(−3.96)	(−4.29)	(−5.47)
	MUC	0.01	0.09	0.73	1.37	0.43	2.12
		(0.14)	(0.36)	(0.80)	(0.94)	(0.35)	(2.25)
		0.72	2.91	14.40	20.61	16.22	21.87
Panel B: Investor sentiment measures							
Uni	S(BW)	0.00	−0.01	−0.03	−0.03	0.00	−0.02
		(−1.64)	(−1.52)	(−1.41)	(−0.91)	(−0.09)	(−0.44)
	R^2_{adj}	0.38	1.02	2.54	1.08	−0.17	0.27
Bi	AEIG	−0.08	−0.25	−1.14	−1.95	−2.15	−2.76
		(−1.88)	(−2.34)	(−4.38)	(−4.80)	(−4.45)	(−3.98)
	S(BW)	0.00	−0.01	−0.01	0.01	0.03	0.02
		(−1.00)	(−0.82)	(−0.51)	(0.23)	(1.18)	(0.40)
	R^2_{adj}	0.91	3.06	13.21	18.31	16.18	19.52
Uni	S(PLS)	−0.01	−0.02	−0.05	−0.06	−0.04	−0.04
		(−3.90)	(−4.49)	(−3.06)	(−2.00)	(−1.06)	(−0.68)
		2.03	5.29	9.04	6.88	1.64	1.46
Bi	AEIG	−0.05	−0.16	−0.95	−1.73	−2.02	−2.77
		(−0.97)	(−1.31)	(−3.47)	(−4.48)	(−4.17)	(−3.20)
	S(PLS)	−0.01	−0.02	−0.03	−0.03	0.01	0.02
		(−2.76)	(−3.05)	(−1.65)	(−1.02)	(0.26)	(0.25)
		2.08	5.90	15.83	19.25	14.93	19.34
Uni	ICS	−0.01	−0.04	−0.17	−0.34	−0.40	−0.84
		(−0.56)	(−0.70)	(−1.18)	(−1.62)	(−1.44)	(−2.63)
		−0.06	0.18	1.32	3.22	3.68	10.66
Bi	AEIG	−0.10	−0.31	−1.35	−1.94	−2.01	−2.19
		(−3.19)	(−3.98)	(−6.58)	(−5.25)	(−5.34)	(−4.97)
	ICS	0.00	0.01	0.03	−0.05	−0.10	−0.48
		(0.26)	(0.17)	(0.25)	(−0.29)	(−0.45)	(−1.77)
		1.09	4.01	18.14	22.87	20.70	24.41
Uni	INV	−0.18	−0.47	−1.63	−2.58	−3.23	−2.90
		(−2.50)	(−2.30)	(−2.50)	(−2.47)	(−2.54)	(−1.45)
		0.88	1.95	5.76	8.16	10.29	5.66
Bi	AEIG	−0.08	−0.28	−1.23	−1.82	−1.88	−2.39
		(−2.56)	(−3.35)	(−6.19)	(−5.68)	(−5.84)	(−5.69)
	INV	−0.15	−0.36	−1.16	−1.87	−2.50	−1.95
		(−1.96)	(−1.69)	(−1.95)	(−2.88)	(−2.32)	(−0.98)
		1.73	5.19	20.96	27.05	26.55	23.88
Uni	EQIS	−0.04	−0.12	−0.24	−0.11	0.11	0.11
		(−2.22)	(−2.07)	(−0.98)	(−0.26)	(0.22)	(0.15)
		0.50	1.31	1.23	0.01	0.00	−0.06
Bi	AEIG	−0.09	−0.29	−1.30	−1.99	−2.16	−2.64
		(−2.75)	(−3.58)	(−6.93)	(−5.35)	(−6.03)	(−6.23)
	EQIS	−0.03	−0.09	−0.12	0.09	0.33	0.37
		(−1.77)	(−1.61)	(−0.49)	(0.23)	(0.65)	(0.53)
		1.48	4.83	18.40	22.93	21.60	22.33

4.3. AEIG and economic growth

By construction, AEIG captures one-year expected aggregate investment growth. Since business investment represents about 15% of GDP in the United States, AEIG should be closely related to the broader economic growth. This section studies their links.

Table 6 reports the results from the predictive regressions of fixed investment growth (FINVG) and non-residential investment growth (NRG), and broader economic growth measures, including GDP growth (GDPG), industrial production growth (IPG), and consumption growth (CONG), in the subsequent first, second, third, and fourth quarter as well as in the next year,

Table 6
AEIG and economic growth This table reports the results of the predictive regressions of future economic growth measures by AEIG. These measures include fixed investment growth (FINVG), non-residential investment growth (NRG), GDP growth (GDPG), industrial production growth (IPG), and aggregate consumption growth (CONG) in the subsequent first, second, third, and fourth quarter, as well as in the subsequent first, second, third, and fifth year. 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 are in parentheses. The sample is quarterly from June 1953 to December 2015.

Predictive horizon	Q1	Q2	Q3	Q4	Y1	Y2	Y3	Y5
FINVG	0.52	0.34	0.13	−0.09	0.41	−0.15	−0.22	0.06
	(3.54)	(2.54)	(1.20)	(−0.97)	(2.97)	(−1.65)	(−3.46)	(0.77)
NRG	0.54	0.47	0.31	0.11	0.42	−0.03	−0.33	0.00
	(4.08)	(3.30)	(2.29)	(0.96)	(3.59)	(−0.47)	(−4.35)	(0.05)
GDPG	0.17	0.11	0.03	−0.06	0.15	−0.09	−0.05	0.01
	(3.52)	(2.33)	(0.73)	(−1.75)	(2.99)	(−2.54)	(−1.88)	(0.38)
IPG	0.10	0.06	0.00	−0.03	0.10	−0.31	−0.01	−0.06
	(3.02)	(2.06)	(0.05)	(−1.91)	(1.48)	(−4.24)	(−0.13)	(−1.25)
CONG	0.14	0.08	0.02	−0.02	0.12	−0.05	−0.02	0.01
	(3.94)	(2.58)	(0.71)	(−0.59)	(3.77)	(−1.54)	(−0.75)	(0.48)

second year, third year, and fifth year on AEIG. The estimated coefficients on AEIG are significantly positive in the next quarter for all economic growth measures. A one percentage point increase in AEIG is associated with a 0.52% increase in FINVG, 0.54% increase in NRG, 0.17% increase in GDPG, 0.1% increase in IPG, and 0.14% increase in CONG. These effects decrease over time, and in the third quarter, the AEIG coefficient is only significantly positive for nonresidential investment growth. By the fourth quarter, the coefficients become negative for all but one specification (NRG), and none of them are statistically significant. When the quarterly growth rates are aggregated to the annual frequency, AEIG strongly predicts the subsequent one-year economic growth.

The picture looks quite different when focusing on longer horizons. The AEIG coefficient becomes significantly negative for GDPG and IPG in the second year, and for FINVG and NRG in the third year.[21] Combined with the results in the first year, these coefficients suggest a hump-shaped dynamics of economic activities following periods of high AEIG. 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. In the longer run of subsequent two or three years, AEIG predicts a sharp decline in economic activities. This hump-shaped dynamics is similar to with the findings in Bloom (2009) that aggregate investment rate, hiring rate, and GDP initially decline and then increase following a spike in economic uncertainty, which in turn hints the underlying relation between AEIG and economic uncertainty and lends support to the risk-based interpretation of AEIG. In a recent paper, Jones and Tuzel (2013) document that the ratio of new orders to shipments (NO/S) is another type of "peak indicator" in that high NO/S foretells an imminent business cycle peak, with predicted output that is higher in the very short run but lower for longer horizons. From this perspective, AEIG is similar to NO/S. Section 4.6 will further discuss the difference between AEIG and NO/S.

4.4. AEIG, earnings surprises, and forecast errors

This section tests the behavioral interpretation by examining the relation between AEIG, forecast errors, and earnings surprises. If AEIG predicts future stock returns because it captures investor sentiment, one should expect systematic negative earnings surprises and positive forecast errors following periods of high AEIG.

Panel A of Table 7 reports the results of the predictive regressions of earnings announcement returns (EAR), one-year-ahead analyst forecast errors ($\text{Error}_{\text{ROA}}$), and long-term forecast errors ($\text{Error}_{\text{LTG}}$) on the current value of AEIG, with and without controlling for other macro return predictive variables.[22] AEIG cannot predict the average earnings announcement returns in the subsequent year, with the AEIG coefficients being 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 indicates the different information contained in AEIG and INV. Panel A also shows that AEIG is not strongly associated with the one-year-ahead forecast errors, but for the long-term forecast errors,

[21] 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).

[22] Following Arif and Lee (2014), EAR is 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 $t+1$. $\text{Error}_{\text{ROA}}$ is calculated 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 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*. Error $_{\text{LTG}}$ is 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 $t+3$. The analyst forecast data are from I/B/E/S.

Table 7

Predicting earnings surprises and forecast errors This table reports the relation between AEIG and earnings surprises and forecast errors. Panel A reports the coefficient of AEIG in predicting earnings announcement returns and forecast errors in the subsequent year. Following Arif and Lee (2014), EAR 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 $t+1$. $Error_{ROA}$ in 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. $Error_{LTG}$ 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 3. 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-stat) are in parentheses. The 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.

	EAR		$Error_{ROA}$		$Error_{LTG}$	
Ctrl	N	Y	N	Y	N	Y
AEIG	0.00	−0.01	0.01	0.00	0.35	0.17
t-stat	(−0.38)	(−0.96)	(1.08)	(0.35)	(3.11)	(1.85)

Panel B: Return predictive regressions

Specification	1	2	3	4
AEIG	−1.37	−1.16	−1.07	−1.19
	(−5.25)	(−4.26)	(−4.67)	(−2.29)
GDPG		0.05	0.04	0.05
		(3.67)	(3.48)	(2.11)
EAR			14.61	
			(4.47)	
$Error_{ROA}$				−0.89
				(−0.65)
$Error_{LTG}$				−0.13
				(−0.13)

the AEIG coefficient in the univariate regression is significantly positive at 0.35 (t-statistic = 3.11), suggesting that analysts are overoptimistic about long-term growth when AEIG is high. However, once controlling for other macro variables, the coefficient on AEIG is reduced to 0.17 and becomes only marginally significant.

Panel B of Table 7 performs a related test that examines whether AEIG is able to predict future stock returns after controlling for ex post earnings surprises or forecast errors, as well as GDP growth. The rationale is that 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. Instead, the AEIG coefficient remains negative and statistically significant. Therefore, the empirical relation between AEIG and subsequent earnings surprises and forecast errors does not seem to be consistent with the investor-misperception-based or analyst-misperception-based interpretations.

4.5. Horse race with industry-level EIG

Another test that can potentially differentiate the risk-based and sentiment-based explanations is to perform a horse race between AEIG and industry-level EIG in predicting the returns of the same industries. The logic of this test, as discussed in Jones and Tuzel (2013), is following. Investment decisions are affected by news about future cash flow and news about discount rate. Compared with those in the aggregate, the investment decisions at the industry level tend to depend more on cash flow news and more likely to be affected by investor sentiment because the industry-level cash flows are on average more volatile than the aggregate cash flows. As a result, if investor sentiment drives the variation in expected investment growth and its return predictive ability, industry-level EIG should have stronger forecasting power for industry-level returns than AEIG.

Table 8
Horse race between AEIG and industry-level EIG This table compares AEIG and industry-level EIG in predicting industry excess returns. 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 are run onto lagged predictors. Three industry classifications are used: 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 3, 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 the sample. The *t*-statistics based on Newey-West standard errors (*t*-stat) are in parentheses. The sample is from June 1953 to December 2015.

Return horizons		1M	3M	1Y	2Y	3Y	5Y
Uni	AEIG	−0.08	−0.30	−1.15	−2.09	−2.08	−3.77
		(−2.81)	(−3.36)	(−4.40)	(−3.74)	(−1.73)	(−4.44)
	EIG_{GICS}	−0.02	−0.09	−0.42	−0.53	−0.72	−1.66
		(−1.80)	(−2.24)	(−2.88)	(−2.08)	(−1.77)	(−2.77)
Bi	AEIG	−0.08	−0.29	−1.02	−2.16	−1.82	−3.64
		(−2.87)	(−3.34)	(−3.63)	(−3.63)	(−1.32)	(−3.58)
	EIG_{GICS}	0.00	−0.02	−0.17	0.07	−0.28	−0.13
		(−0.29)	(−0.65)	(−1.11)	(0.44)	(−0.73)	(−0.27)
Uni	AEIG	−0.09	−0.33	−1.28	−2.03	−2.50	−3.58
		(−3.15)	(−3.64)	(−5.06)	(−3.50)	(−2.37)	(−3.84)
	EIG_{FF5}	−0.04	−0.16	−0.69	−1.04	−1.52	−2.56
		(−2.22)	(−2.68)	(−3.39)	(−2.45)	(−2.82)	(−3.21)
Bi	AEIG	−0.10	−0.33	−1.16	−2.12	−1.72	−2.58
		(−3.42)	(−3.49)	(−3.51)	(−3.23)	(−1.44)	(−3.36)
	EIG_{FF5}	0.00	−0.01	−0.13	0.09	−0.76	−0.97
		(0.16)	(−0.12)	(−0.55)	(0.24)	(−2.17)	(−1.48)
Uni	AEIG	−0.09	−0.32	−1.17	−2.08	−1.88	−3.83
		(−2.89)	(−3.30)	(−3.59)	(−4.00)	(−1.65)	(−4.50)
	EIG_{FF30}	−0.02	−0.09	−0.36	−0.53	−0.60	−1.30
		(−2.26)	(−2.61)	(−3.37)	(−2.32)	(−2.22)	(−1.99)
Bi	AEIG	−0.09	−0.30	−1.03	−2.06	−1.56	−3.45
		(−2.80)	(−3.09)	(−2.79)	(−3.84)	(−1.31)	(−4.24)
	EIG_{FF30}	−0.01	−0.03	−0.18	−0.02	−0.36	−0.44
		(−0.94)	(−1.17)	(−1.46)	(−0.12)	(−1.57)	(−0.94)

Panel regressions of industry-level excess returns are performed over the subsequent 1 month, 3 months, 1 year, 2 years, 3 years, and 5 years onto AEIG and industry-level EIG.[23] Three industry classifications are considered: 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 8 reports the results.

For each industry classification, the first two rows report the coefficient of AEIG and industry-level EIG from the univariate regressions. Table 8 shows that both AEIG and industry-level EIG strongly predict industry-level returns with a negative sign, but the coefficients are usually stronger for AEIG. For instance, when using the GICS classification, the *t*-statistic of the AEIG coefficient at the one-year horizon is −4.40, compared to −2.88 for the industry-level EIG. The pattern is similar when using the Fama and French 5 industries and the Fama and French 30 industries. The next two rows for each industry classification report the results from the horse race between AEIG and industry-level EIG. In the bivariate regressions, the coefficients on AEIG remain significantly negative in most specifications, whereas the return predictive power of industry-level EIG is weakened substantially.

Discussion: The results in Sections 4.3–4.5 suggest that the return predictive power of AEIG is more consistent with neoclassical models with investment lags and time-varying uncertainty. Cochrane (1991) argues that if capital stock could adjust *instantaneously* to changes in discount rate, there should be a positive contemporaneous correlation between investment growth and stock returns and a negative correlation between investment growth and future stock returns. However, Lamont (2000) finds little empirical evidence in supporting these predictions. Instead, he documents that the contemporaneous correlation between investment growth and stock returns is negative and the return predictive power of investment

[23] Using the same coefficients from the first stage EIG estimation in Section 2, the EIG of an industry is defined 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.

growth is rather weak.[24] Lamont (2000) attributes to the friction of investment lags. Intuitively, in response to a fall in aggregate uncertainty and discount rates, firms immediately increase planned investment along with a rise in stock prices, although the capital expenditure does not realize until subsequent years, so it is investment plans, rather than realized investment, that comove positively with stock returns and have the predictive power for future market returns. Moreover, the negative correlation between investment plans and expected returns reduces the contemporaneous correlation between realized investment growth and stock returns, which can becomes even negative when the investment plan friction is strong enough. Therefore, investment lags break the immediate temporal link between investments and stock prices implied from the standard q theory of investment.

Despite these supporting evidences for the risk-based explanations, behavioral explanations cannot be completely ruled out. For example, these findings can be consistent with the following scenario, in which investors and analysts are more rational than managers with extrapolative biases. For firms which have experienced good past performances, their managers may be over optimistic and initiate too many investment plans. If investors are capable of learning and realizing this behavioral bias sufficiently fast, the overinvestment will be factored into asset prices even before the subsequent earnings announcements. In this case, even though the aggregate investment plan strongly predicts future market returns, it has no predictive power for subsequent forecast errors or earnings surprises.

4.6. AEIG And other investment-based return predictors

This section examines the difference between AEIG and two recent investment-based return predictors discussed earlier. The first predictor is the ratio of new orders to shipment of durable goods in Jones and Tuzel (2013) and the second predictor is the aggregate investment rate in Arif and Lee (2014).

Jones and Tuzel (2013) document that the ratio of new orders and shipment of durable goods (NO/S) captures the aggregate risk premium and can negatively predict market returns, especially at relatively shorter horizons. To the extent that new orders capture future investment, NO/S can be considered 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 which is constructed using the aggregate-level data, 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 two variables have different breadths in industry coverage. While the new orders and shipments data only span manufacturing industries, AEIG covers most of the publicly traded companies and hence is more representative for the overall market. These differences potentially explain the low correlation between AEIG and NO/S (0.19 from Panel C of Table 2) and the stronger return predictive power of AEIG.

The aggregate corporate investment (INV) in Arif and Lee (2014) is also a bottom-up measure. An important difference between AEIG and INV is that AEIG is a measure of the *expected* investment growth, whereas INV is a measure of *realized* investment. In the presence of investment lags, neoclassical theories of investment predict that expected investment growth should capture cost of capital better than realized investment (e.g., Cochrane, 1991; Lamont, 2000), which is indeed confirmed empirically. Furthermore, INV and AEIG (and NO/S) have very different economic interpretations. While Arif and Lee (2014) argue that INV mainly captures the optimism and pessimism in investor sentiment, these empirical analyses show that the predictive power of AEIG is more likely to be driven by the time-varying risk premium, similar to NO/S in Jones and Tuzel (2013).

To further illustrate the difference of these investment-based predictors, we examine how they predict future cash flow growth. Both expected cash flow news and discount rate news can change investment and investment plans. However, the relation between investment decision and future *realized* cash flow depends on whether the cash flow expectation is rational or not. If this cash flow expectation is rational, investment should predict future cash flow with a positive sign, but if instead the cash flow expectation is driven by investor sentiment, investment is likely to be negatively correlated with future cash flow.

Using aggregate dividend as a measure of cash flow, Table 9 runs univariate predictive regressions of aggregate dividend growth in the subsequent four quarters and the first, second, third, and fifth years on AEIG, NO/S, or INV. In the subsequent year, the coefficients on INV are significantly negative, consistent with the sentiment-based interpretation in Arif and Lee (2014). Intuitively, when sentiment is high, the economy is too optimistic about future cash flows and hence overinvests. This is followed by negative dividend growth on average when the investment outcome turns out to be worse than expected. On the other hand, the coefficients of AEIG and NO/S in the first year are all positive, which is in line with rational cash flow expectations. Interestingly, the coefficients on AEIG are smaller in magnitude than NO/S, so AEIG appears to contain relatively less information about future cash flows and more information about discount rate, which may explain the stronger return predictive power of AEIG than NO/S.

[24] In the updated sample period, the contemporaneous correlation between nonresidential investment growth and stock returns - 0.33 (t-stat = - 2.22), and the correlation between nonresidential investment growth and future one-year stock returns is - 0.08 (t-stat = - 0.82).

Table 9
Relation between AEIG, NO/S, and INV and future dividend growth This table reports the results of the predictive regressions of measures of aggregate dividend growth in the subsequent first, second, third, and fourth quarter, as well as in the subsequent first, second, third, and fifth year by AEIG, the ratio of new orders to shipments (NO/S) from Jones and Tuzel (2013), and the aggregate investment rate (INV) from Arif and Lee (2014). AEIG is the value-weighted firm-level expected investment growth based on the subset of firms with fiscal year end of December. The aggregate dividend data are from Robert Shiller's website. The *t*-statistics based on Newey-West standard errors (*t*-stat) are in parentheses. The sample is quarterly from June 1953 to December 2015 for AEIG and INV, and from March 1958 to December 2015 for NO/S.

Predictive horizon	Q1	Q2	Q3	Q4	Y1	Y2	Y3	Y5
AEIG	0.05	0.04	0.04	0.03	0.16	−0.09	−0.23	0.06
	(1.18)	(0.90)	(0.83)	(0.64)	(0.83)	(−0.76)	(−5.45)	(0.79)
NO/S	0.19	0.18	0.15	0.10	0.60	−0.30	−0.46	−0.21
	(3.12)	(3.54)	(3.47)	(3.06)	(4.27)	(−1.03)	(−1.92)	(−1.26)
INV	−0.21	−0.25	−0.24	−0.21	−0.94	−0.56	0.04	0.75
	(−4.46)	(−4.92)	(−3.81)	(−3.11)	(−3.35)	(−1.91)	(0.16)	(2.95)

5. Conclusion

A new aggregate investment plan measure, namely, the aggregate expected investment growth (AEIG), is a strong predictor for future market returns. An increase in AEIG is associated with strong declines in the stock market, with an adjusted in-sample R^2 of 18.2% and an out-of-sample R^2 of 14.4% at the one-year horizon. This measure differs from the investment plan measures from Lamont (2000) and Jones and Tuzel (2013) in that it is a bottom-up measure that aggregates firm-level expected investment growth. It is also different from the aggregate investment rate in Arif and Lee (2014) in that it is an expected, not realized, investment measure. AEIG is easy to construct and is available at the monthly frequency; its return predictive power remains strong controlling for other macroeconomic variables that are well-known in predicting market returns, and is robust in various settings.

The market return predictive ability of AEIG can be consistent with both risk-based explanations and behavioral explanations. Indeed, there are strong negative correlations between AEIG and measures of economic uncertainty, and positive correlations between AEIG and measures of investment sentiment. Although it is impossible to completely rule out one explanation or the other, these analyses find more empirical evidence for the time-varying risk premium interpretation, lending support to the neoclassical models with investment lags.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jmoneco.2020.03.016.

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