Journal of Monetary Economics 117 (2021) 618–638

Contents lists available at ScienceDirect

Journal of Monetary Economics

journal homepage: www.elsevier.com/locate/jmoneco

Aggregate expected investment growth and stock market returns[☆]

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ARTICLE INFO

Article history:
Received 7 April 2019
Revised 25 March 2020
Accepted 27 March 2020
Available online 31 March 2020

JEL classification:
G12

Keywords:
Investment plan
Investment lags
Time-varying risk premium
Investor sentiment
Stock market prediction

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.

☆ We thank an anonymous referee, Adrien d' Avernas, Frederico Belo, Ilan Cooper, Fabian Hollstein, Urban Jermann (the editor), Travis Johnson, Leonid Kogan, David Lesmond, Xiaoji Lin, Yang Liu, Berardino Palazzo, Zhongzhi Song, Selale Tuzel, Quan Wen, Harold H. Zhang, Miao Zhang, Guofu Zhou, and seminar participants at Asian Development Bank Institute, Peking University, University of International Business and Economics, University of Sydney, and participants at 2018 SFS Cavalcade Conference, 2018 CICF, 2018 SGF Conference, 2018 NFA conference, 2018 CFEA, and 2019 CAPR Workshop on Investment & Production Based Asset Pricing at BI Norwegian Business School for helpful comments. Yu acknowledges financial support from the National Natural Science Foundation of China (Grant No. 71790591) all errors are our own.

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https://doi.org/10.1016/j.jmoneco.2020.03.016
0304-3932/

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 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 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 5.813 344.3401 Tm (accounting) TJ p1 422.0298 333.873 Tm ( ) Tj 0.0001 Tc /F1 1 Tf 7.9

the of predictors Section

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 rate, i.e., scaled lagged capital which is known to be persistent, Panel C shows that firm-level investment growth is in fact negatively autocorrelated. stock (Ret), flow and all variables (SG, CFG, EG and positively subsequent investment growth. Economically, a one increase in these variables is associated 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 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.

stock,
q, returns cash (CF), growth PG) predict
standard deviation with

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	−0.005
Std	0.561	1.011	0.393	0.167	0.203	0.157	0.185	0.320	0.477	0	0.696
Q1	−0.265	−0.400	−0.130	0.004	−0.028	−0.024	−0.032	0.075	0.000	0	−0.422
Median	0.077	0.254	0.091	0.084	0.017	0.018	0.010	0.158	0.078	0	−0.031
Q3	0.406	1.041	0.356	0.181	0.079	0.078	0.061	0.295	0.953	0	0.396

	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		
E	***	***	***	***	***	***	***	*	***		
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	.23	0.12	0.09	−0.12	−6.54
	(−17.15)	(8.82)	(14.13)	(9.97)	(13.71)	(16.45)	.11)	.89)	(8.37)	(−11.91)	(−4.18)
R^2_{adj}	2.47	1.66	7.46	0.78	2.21	2.21	.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 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 W01 0203.7871 Tm (err)16(o)2.5(r) TJ 0 Tc 8i8.51

consr4(uession) F2 1 Tf 6.3761 0 0 6.3761 421.1699sio06329 Tm ( ) TJ /F1 1 Tf 7.9701 0 0 7.9701 1

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,

y0 7.9701 380.196 230.3911 Tm [(,)4 TJ6/F1 1 Tf 7.3761 0 0 6

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:

$$\mathrm{IG}_{it} = b_{0,\tau} + b_{\mathrm{IG},\tau} \times \mathrm{IG}_{it-1} + b_{\mathrm{Ret},\tau} \qquad +$$

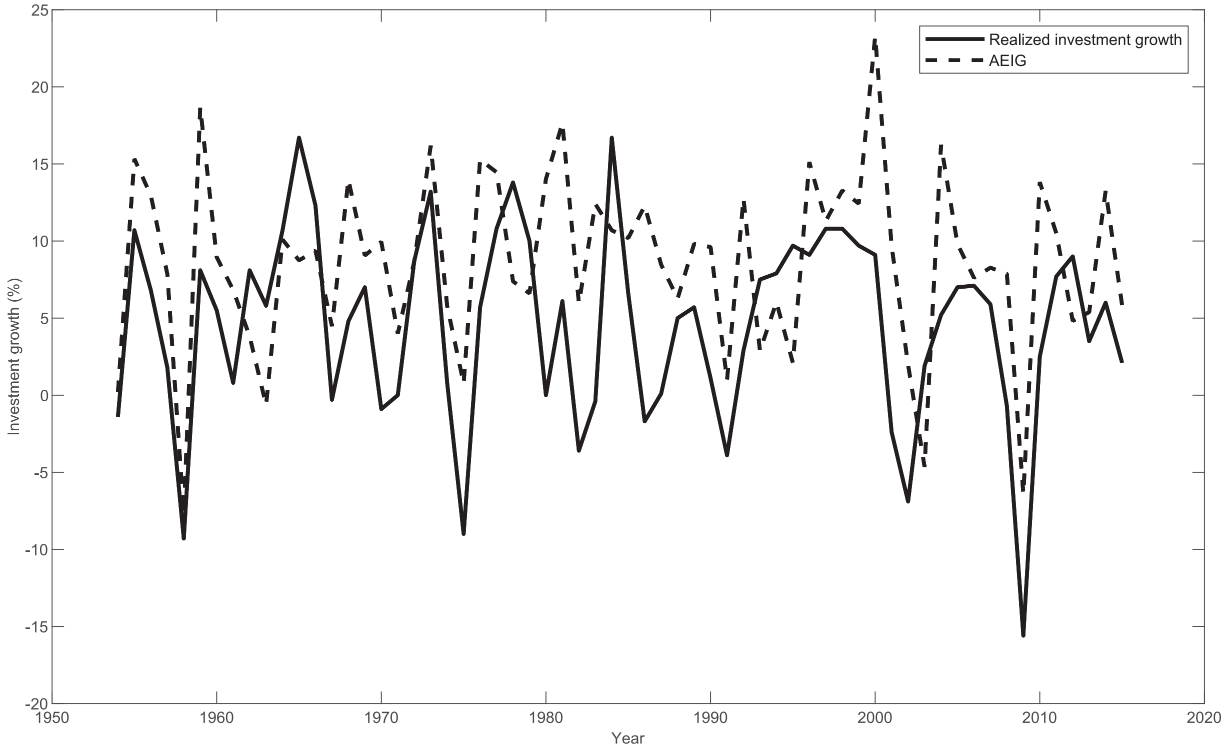

Fig. 1. AEIG and realized aggregate investment growth This figure plots the time series of aggregate expected investment growth (AEIG) and realized aggregate nonresidential investment growth from 1954 to 2015. AEIG is constructed as the value-weighted average of firm-level expected investment growth 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

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 $\hat{r}_{t+1} = \hat{a} + \hat{b} \times x_\tau$ 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

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

w6144.33.574 Tm ((26.3761 0 0 6.376 8.47.9701 37.118 459.567 0Tm ( ) TJ /F1 1 Tf 7.974 0 .3761 55 105.273 465.903 Tm (

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 betwef 7.9701 0 0 7.9701 20 gate 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

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
		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
	R^2_{adj}	0.51	[illegible]			.46	

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	AEIG0 Tc /8T4 Tf4 0.095.2.00 0 6.3761 209.5012 587.916 Tm [( )] TJ /F18874T4 Tf4 0 0 5.2573.5341 Tm [(.2)12(4))] TJ 0 Tc						

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

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

nt (2000) attributes to the friction of investm
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uent forecast errors or earnings surprises.

ent-based return predictors

the difference between AEIG and two recent investment-based return predictors discussed ear-
the ratio of new orders to shipment of durable goods in Jones and Tuzel (2013) and the second
investment rate in Arif and Lee (2014).
document that the ratio of new orders and shipment of durable goods (NO/S) captures the aggre-
n negatively predict market returns, especially at relatively shorter horizons. To the extent that new
estment, NO/S can be considered as another measure of aggregate investment plans. Indeed, high

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