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Asset Growth and Stock Market Returns: A Time-Series Analysis*

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Abstract

I find that aggregate asset growth constructed from bottom-up data negatively predicts future market returns both in and out-of-sample and this result is robust across G7 countries. I further show that aggregate asset growth contains information about future market returns not captured by traditional macroeconomic variables and other measures of investment or growth. The forecasting ability of asset growth is strongly correlated with its propensity to predict more optimistic analyst forecasts and subsequent downward revisions, earnings surprise, and systematic errors in investors' expectations. The time-varying risk premium also appears key in explaining the documented return predictability.

JEL classification: G12, G14

Keywords: Asset growth, Return predictability, Time-varying risk premium, Forecast errors, extrapolation

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1. Introduction

It is well documented that firms experiencing rapid growth through equity or debt offerings subsequently have low stock returns, whereas firms experiencing contraction via spinoffs, share repurchases, and debt prepayments enjoy high future returns. Cooper, Gulen, and

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Schill (2008) create a simple but comprehensive measure of firm growth, total asset growth, and find that it is a strong and negative predictor of cross-sectional variation in stock returns. Other studies show that the asset growth effect applies to stocks of all sizes (Lipson, Mortal, and Schill, 2011) and is robust in international equity markets (e.g., Watanabe *et al*., 2013; Titman, Wei, and Xie, 2013). Recent studies show that an investment factor formed by sorting on total asset growth adds much explanatory power for the cross-section of average stock returns and anomaly returns (e.g., Fama and French, 2015, 2016; Hou, Xue, and Zhang, 2015).

Although there is abundant evidence on the firm-level asset growth effect, most analyses focus on the cross-section of stock returns. In this article, I test whether the asset growth effect shows up in aggregate data, and whether the firm-level asset growth effect extends to the aggregate level. It is known that firm-level relations do not necessarily hold at the aggregate level. For example, Kothari and Shanken (1997), and Pontiff and Schall (1998) provide evidence that the aggregate book-to-market ratio positively predicts stock market returns, consistent with firm-level evidence. Baker and Wurgler (2000) find that the poor return performance following equity issuance extends to the market level. However, Hirshleifer, Hou, and Teoh, (2009) find a reversal in the accrual-return relation from negative at the firm level (Sloan, 1996) to positive at the aggregate level. Therefore, it remains an open empirical question whether an asset growth effect exists for the aggregate stock market.

As my main test variable, I construct an aggregate measure of total asset growth, namely, the percentage change in total assets, using firm-level data. I then empirically explore the ability of aggregate asset growth (AG, hereafter) to forecast excess stock market returns. I find that for the 1972–2016 period, AG is a strong and negative predictor of future stock market returns. In-sample tests show that a one-standard-deviation increase in quarterly AG is associated with a decline of approximately 2.4% in one-quarter-ahead market returns, with R^2 statistics of 7.18% at the quarterly horizon. The predictability remains strong while controlling for well-known macroeconomic variables that are related to time-varying risk premia. Motivated by Goyal and Welch (2008), I perform an extensive set of out-of-sample tests using AG and find positive and significant out-of-sample R^2 values (Campbell and Thompson, 2008) ranging from 2.52% to 8.32%, which are considerably larger than those for the popular predictors in the literature. Variance decomposition analysis shows that both the investment and financing subcomponents of asset growth contribute significantly to return predictability.

It is important to note that AG has several influential observations. For example, AG is above 10% only during the tech bubble period from 1999Q4 to 2000Q2 and the market return following this period is extremely low. In addition, AG is negative only during the recent financial crisis from 2008Q4 to 2009Q1 and the market return following this period is high. In robustness tests, I find that the removal of these influential observations reduces the in-sample predictive coefficient and R^2 of AG by about one third and one half, respectively, for one-quarter-ahead market returns. However, the predictive coefficient on AG remains statistically significant at the 5% level, indicating that AG remains a negative predictor of stock market returns. To further alleviate the concern that the empirical pattern documented in the USA is attributable to influential observations or data-snooping biases, I extend the analysis to the other G7 countries. I find that the predictability remains statistically significant and economically large in the majority of these countries.

I conduct additional robustness checks on the predictive power of AG. First, I find that AG remains a strong predictor of future market returns after controlling for several well-documented investment- or growth-related variables. Second, I use equal-weighted instead of value-weighted stock market returns as the dependent variable and find similar results. Third, the results are robust to an alternative measure of AG, defined as the quarterly growth rate of aggregate total assets based on all firms. Fourth, I conduct seasonality tests on AG and show that year-on-year growth also predicts returns. Finally, motivated by Moller and Rangvid (2015, 2017) regarding the end-of-year effect of macroeconomic growth, I investigate the predictability of AG separately for each of the four calendar quarters and find that the predictive power is not concentrated at the end of year.

The main finding that AG negatively predicts stock returns can be consistent with both rational and behavioral explanations. The rational explanation, based on the *q*-theory of investment or the real option model, argues that returns reflect compensation for risk, in that firms make large investments when discount rates (i.e., costs of capital) are lower.[1] On the behavioral side, the extrapolation explanation (Titman, Wei, and Xie, 2004; Cooper, Gulen, and Schill, 2008) argues that investors excessively extrapolate on past growth when valuing firms. In addition, the mispricing explanation of Van Binsbergen and Opp (2017) shows that the asset growth effect results from firms with inflated (deflated) prices overinvesting (underinvesting) in capital today. The negative relation between investment or growth and future stock returns arises when investors are subsequently surprised by the performance reversal.

It is empirically difficult to completely disentangle the rational and mispricing explanations for the asset growth effect, since proxies for investment frictions and for limits-to-arbitrage are highly correlated (Lam and Wei, 2011). Moreover, investors' subjective expectations of both risk and returns on stocks are strongly influenced by perceptions of economic conditions (Amromin and Sharpe, 2014). To examine these alternative interpretations, I first investigate the relations between AG and variables that are known to be linked to business cycles or the time-varying risk premium, such as the output gap (Cooper and Priestley, 2009), the investment-capital-ratio (Cochrane, 1991, 1996), and aggregate expected investment growth (AEIG) (Li, Wang, and Yu, 2017). For all three measures, I find strong and positive predictive power on AG. In addition, AG has a strong negative correlation with measures of economic uncertainty such as dispersion in GDP growth, industrial production growth, and dispersion in aggregate corporate profits (Anderson, Ghysels, and Juergens, 2009; Bali, Brown, and Tang, 2017). Since increases in uncertainty implies higher costs of capital, AG decreases and is negatively related to lower future market returns. Thus, the time-varying risk premium due to the lower aggregate quantity of risk following periods of high AG can contribute to the predictive ability of AG.

The overextrapolation hypothesis argues that investors excessively extrapolate on past growth when valuing firms and are subsequently surprised by the bad earnings news, possibly due to manager overinvestment and empire building. I find AG strongly predicts aggregate earnings news based on analyst forecast revisions, as well as analyst forecast errors.[2] Moreover, high AG is associated with lower earnings announcement returns and greater earnings disappointment. To the extent that analyst forecast errors and revisions

1 See Cochrane (1991, 1996), Berk, Green, and Naik (1999), Carlson, Fisher, and Giammarino (2004), Liu, Whited, and Zhang (2009), and Li and Zhang (2010).

2 Changes in analyst forecasts offer an attractive way to measure earnings news because they represent changes in the market's earnings expectations.

convey earnings news to the market, these findings suggest that failing to recognize the predictable component of forecast errors and revisions could result in return predictability.

This study contributes to the literature along several dimensions. First, the time-series predictability associated with AG complements the cross-sectional analyses of Cooper, Gulen, and Schill (2008). Second, I present evidence showing that both the time-varying risk premium and investor behavioral biases play an important role in market return predictability. These findings extend those of Lam and Wei (2011) on distinguishing alternative explanations of the source of asset growth.[3] Finally, the evidence in this study also extends the results of Li and Yu (2012) by showing that investors' behavioral biases play an important role in return predictability.

The remainder of the article is organized as follows. Section 2 presents the data and the variable construction. Section 3 describes the empirical methods and results. Section 4 investigates a number of possible explanations for the source of market return predictability. Section 5 concludes the article.

2. Data and Variable Construction

2.1 Data

The aggregate stock market return is computed as the excess return, which is the continuously compounded log return on the CRSP value-weighted index (VWRET) and the S&P500 index (including dividends) minus the risk-free rate. The sample of firm-level accounting information and the book value of total assets are obtained from Compustat's quarterly files for the period from 1972Q1 to 2016Q4. The starting quarter is restricted by the availability of quarterly data in Compustat. Following Cooper, Gulen, and Schill (2008), I define firm-level asset growth as the percentage change in the book value of total assets,

$$\mathrm{AG}_{j,t} = \frac{\mathrm{AT}_{j,t} - \mathrm{AT}_{j,t-1}}{\mathrm{AT}_{j,t-1}}. \tag{1}$$

I exclude financial firms (SIC codes 6000–6999) from the sample. I compute aggregate asset growth (AG) as the value-weighted average of firm-level asset growth, using market capitalization as of the end of the fiscal quarter. This bottom-up aggregation approach is similar to that of Hirshleifer, Hou, and Teoh (2009), who construct an aggregate measure of accruals and examine its relation to stock market returns.[4] To ensure that accounting information is known to investors at the beginning of the return quarter, I assume a 6-month gap for the accounting information to become public following Fama and French (1992) and Kothari and Shanken (1997).[5]

3 Lam and Wei (2011) examine alternative explanations for the firm-level asset growth effect and find that both the rational and behavioral explanations appear to complement each other in explaining the asset growth anomaly.

4 To avoid influential observation problems, I follow Cooper, Gulen, and Schill (2008) and winsorize firm-level asset growth if it is below the first percentile or above the 99th. I obtain qualitatively similar results without winsorization.

5 Unlike earnings, quarterly data items such as total assets might not be available upon earnings announcement dates. As a result, I choose the more conservative 6-month gap instead of 3-month between fiscal quarter end and the return tests to avoid look-ahead bias in the predictive regressions (i.e., Hou, Xue, and Zhang, 2015). Specifically, if quarterly asset growth is computed at the end of 1972Q1 in Compustat, the market returns of 1972Q4 will be used as the one-quarter-ahead

To relate my findings to the voluminous body of literature on market return predictability, I compare the predictive ability of AG to that of the commonly used predictive variables. These variables include the log earnings-to-price ratio (EP), the log dividend-to-price ratio (DP), the book-to-market ratio (BM), the Treasury bill rate (TBL), the term spread (TMS), the default yield (DFY), net equity issuance (NTIS), equity variance (SVAR), the consumption-wealth ratio (CAY), and the output gap (Cooper and Priestley, 2009).

2.2 Descriptive Statistics

Table I reports summary statistics for the stock market returns, AG, and other return predictors for the period from 1972Q1 to 2016Q4. In Panel A, the quarterly average of the value-weighted excess return (VWRET) is 1.3% and the quarterly average excess return on the S&P500 is 0.6%, with standard deviations of 8.7% and 8.2%, respectively. Unlike scaled-price variables such as the earnings-to-price or book-to-market ratio, which are highly persistent, AG shows a first-order autocorrelation of 0.56. The augmented Dickey–Fuller test rejects the null that AG has a unit root.

Panel B of Table I presents the correlations between one-quarter-ahead market returns and AG. Regardless of the measures of stock market returns, all simple correlations of one-quarter-ahead market returns with AG are negative and of large magnitude, ranging from −25% to −28%. In addition, AG is correlated with macroeconomic or business cycle variables and the absolute value of the correlations ranges from 0.12 (with the book-to-market ratio) to 0.55 (with the investment-to-capital ratio). Moreover, AG is correlated with the output gap (Cooper and Priestley, 2009), with a correlation coefficient 0.37. These findings suggest that it is important to control for these variables in the regression when examining the predictive power of AG on stock market returns.

3. Empirical Methods

I run a predictive regression of future nonoverlapping quarterly stock market returns on AG and other return predictors, denoted by X_{t-1}:

$$R_{t+1} = \alpha + \beta X_{t-1} + u_t, \;\; u_t \sim \text{i.i.d.}(0, \sigma_u^2) \tag{2}$$

$$X_t = \phi + \rho X_{t-1} + v_t, \;\; v_t \sim \text{i.i.d.}(0, \sigma_v^2). \tag{3}$$

Mankiw and Shapiro (1986) and Stambaugh (1986) show that the predictive regression coefficient is subject to an upward small-sample bias if innovations in the independent variables are negatively correlated with contemporaneous returns. Stambaugh (1999) shows that in a general autoregressive framework, the bias in the OLS estimate of β in the predictive regression is proportional to the bias in the OLS estimate of ρ in the first-order autoregression for the predictive variable:

$$E(\hat{\beta} - \beta) = (\sigma_{uv}/\sigma_v^2)E(\hat{\rho} - \rho). \tag{4}$$

The downward bias in the autoregression coefficient introduces an upward bias in the predictive regression coefficient if the residuals from the two equations are negatively correlated. This bias is more pronounced when the sample size is small or when the independent variable is highly persistent.

aggregate returns used in the predictive regression (i.e., allowing a 6-month gap for quarterly accounting information to become public).

Table I. Summary statistics

The table reports the summary statistics for market returns, aggregate asset growth (AG), and other return predictors. Quarterly market returns (in logarithm) are computed by compounding monthly returns for each quarter. VWRET (excess) is the value-weighted excess market return. S&P500 (excess) is the S&P500 excess return. VWRET (raw) is the value-weighted raw market return. S&P500 (raw) is the S&P500 raw return. AG is the value-weighted averages of firm-level asset growth, defined as the quarter-on-quarter percentage change in the book value of total assets. Other predictive variables follow the definitions in Goyal and Welch (2008). EP is the log earnings-to-price ratio. DP is the log dividend-to-price ratio. BM is the book-to-market ratio. TBL is the 30-day T-bill rate. TMS is the difference between long-term yield on government bonds and the Treasury-bill. DFY is the difference between BAA and AAA-rated corporate bonds. NTIS is the net equity issuance. SVAR is the equity variance. IK is the investment-to-capital ratio. CAY is the consumption-wealth ratio. GAP is the output gap. p(ADF) is the p-value associated with the augmented Dickey–Fuller test of unit root. The sample period is 1972Q1–2016Q4.

Panel A: summary statistics and autocorrelations

Name	Mean	Std. dev	Q1	Median	Q3	Autocorrelation			p(ADF)
						1	2	3	
VWRET (excess)	0.013	0.087	−0.025	0.025	0.062	0.06	−0.07	−0.04	0.00
SPRET (excess)	0.006	0.082	−0.033	0.017	0.054	0.09	−0.05	−0.04	0.00
VWRET (raw)	0.024	0.086	−0.011	0.036	0.078	0.04	−0.06	−0.06	0.00
SPRET (raw)	0.017	0.081	−0.020	0.024	0.068	0.03	−0.03	−0.03	0.00
AG	0.033	0.016	0.025	0.031	0.039	0.56	0.38	0.33	0.00
EP	−2.835	0.483	−3.093	−2.877	−2.482	0.94	0.84	0.74	0.02
DP	−3.623	0.431	−3.963	−3.581	−3.308	0.98	0.96	0.93	0.69
BM	0.495	0.284	0.291	0.383	0.708	0.98	0.96	0.94	0.70
TBL	0.048	0.035	0.017	0.049	0.068	0.93	0.88	0.85	0.47
TMS	0.021	0.015	0.011	0.024	0.032	0.81	0.66	0.59	0.00
DFY	0.011	0.005	0.008	0.010	0.013	0.84	0.68	0.57	0.01
NTIS	0.008	0.020	−0.002	0.012	0.024	0.91	0.80	0.66	0.01
SVAR	0.007	0.011	0.003	0.004	0.007	0.40	0.16	0.09	0.00
IK	0.036	0.004	0.033	0.036	0.038	0.97	0.90	0.81	0.01
CAY	−0.002	0.026	−0.016	−0.006	0.023	0.95	0.91	0.87	0.25
GAP	1.036	7.201	−5.152	0.691	6.116	0.91	0.85	0.77	0.06

Panel B: correlations between one-quarter-ahead market returns and AG

	VWRET (excess)	S&P500 (excess)	VWRET (raw)	S&P500 (raw)	AG
VWRET (excess)	1	0.99	0.99	0.99	−0.28
SPRET (excess)		1	0.98	0.99	−0.27
VWRET (raw)			1	0.99	−0.26
SPRET (raw)				1	−0.25
AG					1

(continued)

Table I. Continued

Panel C: correlations between predictive variables

	AG	EP	DP	BM	TBL	TMS	DFY	NTIS	SVAR	IK	CAY	GAP
AG	1	0.04	−0.26	−0.12	0.22	−0.35	−0.13	0.05	0.04	0.55	−0.01	0.37
EP		1	0.72	0.78	0.65	−0.36	0.12	0.13	−0.29	0.15	0.04	0.18
DP			1	0.91	0.67	−0.16	0.48	0.08	−0.03	−0.09	0.21	−0.07
BM				1	0.67	−0.28	0.47	0.18	−0.08	0.08	−0.07	0.16
TBL					1	−0.61	0.24	0.15	−0.14	0.50	0.33	0.38
TMS						1	0.07	0.03	0.08	−0.61	0.20	−0.56
DFY							1	−0.28	0.43	−0.22	0.01	−0.27
NTIS								1	−0.19	0.11	0.07	0.26
SVAR									1	−0.05	0.03	−0.03
IK										1	0.01	0.83
CAY											1	−0.18

AG is not a scaled-price variable and is not highly persistent, with a first-order autocorrelation of 0.56. Empirically, I do not find that innovations in AG are negatively correlated with contemporaneous stock returns. Consequently, there is no strong reason to suspect that the regression coefficients in Equation (2) should be affected by small sample bias. The results remain similar when I follow Nelson and Kim (1993) in using a randomization procedure to generate empirical p-values for the coefficients of AG (e.g., Kothari and Shanken, 1997; Pontiff and Schall, 1998; Baker, Taliaferro, and Wurgler, 2006).

3.1 In-Sample Results

Table II presents the results for the predictive regression of quarterly stock market returns on AG for both excess and raw returns. From 1972 to 2016, AG is a strong negative predictor of market returns, with a slope estimate of −2.43% ($t = -4.39$) for the value-weighted excess market return and −2.25 ($t = -4.09$) for the S&P500 return. This magnitude is economically large: a one-standard-deviation increase in AG is associated with an approximately 2.43% decline in one-quarter-ahead value-weighted market returns. For raw returns, the slope estimates are smaller but still economically large. The adjusted R^2 values vary from 5.72% to 7.18% for all specifications. The randomization p-values confirm that AG remains a negative and significant predictor of future market returns. The return predictability extends to the second quarter and generally becomes nonsignificant for three- and four-quarter-ahead stock market returns. Overall, the results presented in Table II indicate that AG is a strong negative predictor of future market returns.

To provide a further robustness check with respect to small-sample bias, Figure 1 shows the density plots of the predictive coefficients from regressing simulated market returns on AG under the null hypothesis of no predictability. The randomization procedure is conducted for 5,000 iterations. The randomization p-value is computed based on the empirical distribution of the estimated slopes. When I compare the average estimated coefficients from the simulation to the actual predictive coefficients, the results confirm the significance of the bootstrap p-values: small-sample bias accounts for at most 1% of the actual slope coefficient estimate.

Does the cross-sectional asset growth effect documented by Cooper, Gulen, and Schill (2008) mechanically translate into time-series predictability? Table III shows that this is

Table II. Univariate regression

The table reports the predictive regression of quarterly stock market returns on aggregate asset growth (AG):

$$R_{t+\tau} = \alpha + \beta \mathrm{AG}_t + u_t,$$

where $\tau = 1, 2, 3, 4$. The quarterly stock market returns are nonoverlapping and computed by compounding monthly returns for each quarter. VWRET is the value-weighted excess or raw return. SPRET is the S&P500 excess or raw return. AG is the value-weighted averages of firm-level asset growth, defined as the quarter-on-quarter percentage change in book value of total assets. The coefficients are multiplied by 100 and expressed in percentage. The independent variable is standardized to have zero mean and unit variance. T-statistics are computed using Newey–West standard errors. Rand.p is the bootstrap p-value calculated following Nelson and Kim (1993). *, ** and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The sample period is 1972Q1–2016Q4.

	Excess returns				Raw returns			
	β (%)	t-stat	Rand. p	Adj. R^2 (%)	β (%)	t-stat	Rand. p	Adj. R^2 (%)
				Panel A: $\tau = 1$				
VWRET	−2.43***	−4.39	0.00	7.18	−2.23***	−4.25	0.00	6.07
S&P500	−2.25***	−4.09	0.00	6.83	−2.05***	−4.00	0.00	5.72
				Panel B: $\tau = 2$				
VWRET	−1.09***	−2.94	0.00	0.98	−0.92**	−2.29	0.02	0.54
S&P500	−0.95***	−2.82	0.01	0.74	−0.78**	−2.16	0.02	0.33
				Panel C: $\tau = 3$				
VWRET	−0.64	−0.75	0.21	−0.04	−0.51	−0.55	0.32	−0.23
S&P500	−0.57	−0.72	0.27	−0.11	−0.43	−0.51	0.35	−0.30
				Panel D: $\tau = 4$				
VWRET	−0.09	−0.17	0.40	−0.56	0.02	0.03	0.43	−0.57
S&P500	−0.18	−0.35	0.35	−0.53	−0.07	−0.12	0.32	−0.57

unlikely to be the case. First, Table III shows that the time-series predictability seems pervasive and robust in all four subsamples except for the second subperiod. For example, the predictive coefficients for VWRET are −2.96, −2.79, and −2.94, respectively, for the first, third, and fourth subsamples, all of which are economically significant and the predictability is particularly strong for more recent subperiods. In sharp contrast, Panel D of Table III shows that cross-sectional asset growth is insignificant during the most recent decade, consistent with anomalies attenuating over time (Mclean and Pontiff, 2016). However, the time-series predictability remains strong and pervasive for the last subperiod, with highly significant predictive coefficients. The source of time-series predictability is investigated in later sections.

Finally, I investigate the incremental forecasting power of AG while controlling for a large set of economic variables related to macroeconomic or business-cycle fundamentals,

$$R_{t+1} = \alpha + \beta \mathrm{AG}_t + \gamma X_t^k + \epsilon_{t+1}, \qquad k = 1, \ldots, 11, \tag{5}$$

where R_{t+1} is the excess market return and X_t^k is a vector of 11 control variables.

A

Simulation V.S. actual results

Returns	Average estimated β	Actual β	Average/Actual	Rand.p
VWRET (excess)	-0.012	-2.43	0.51%	0.000
S&P500 (excess)	-0.020	-2.25	0.90%	0.000
VWRET (raw)	-0.016	-2.23	0.73%	0.000
S&P500 (raw)	-0.007	-2.05	0.33%	0.000

B

Density plots of estimated predictive coefficients

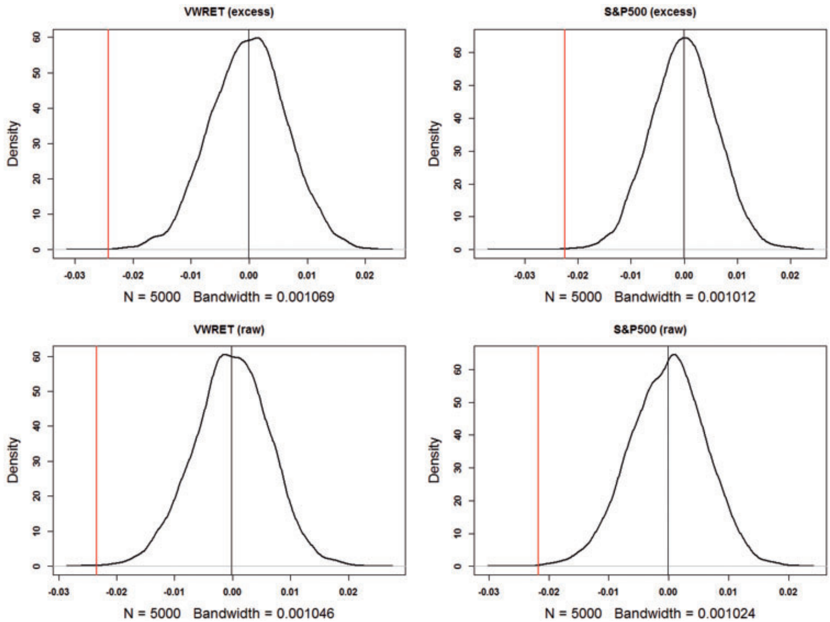

Figure 1. Density plots of predictive coefficients under the null of no predictability.
This figure plots the estimated predictive coefficients β from regressing simulated one-quarter-ahead market returns on aggregate asset growth, under the null of no predictability. The randomization is conducted for 5,000 iterations. Randomization p-value is computed based on the empirical distribution of estimated coefficients β (in percent). Vertical line to the left reports the actual β (in percent). The sample period is 1972Q1–2016Q4.

Panel A of Table IV shows that the estimates of the slope β in Equation (5) are negative and large, in line with the univariate regression results reported in Table II. More important, β remains statistically significant when augmented by other economic predictive variables. Panel B shows the results for the multivariate regression when simultaneously controlling for all eleven predictors. Interestingly, the magnitude of the coefficients of AG is almost the same as that in the univariate regression: a one-standard-deviation increase in AG is associated with an approximately 2.81% ($t = -4.16$) decrease in one-quarter-ahead market returns. These results suggest that adding other control variables has little effect on the ability of AG to predict future market returns.

3.2 Out-of-Sample Results

To examine the robustness of the in-sample results, Table V reports the results for out-of-sample tests of return predictability. I study the out-of-sample predictive power of AG relative

Table III. Time series predictability and the cross-sectional asset growth effect

The table reports the predictive regression of one-quarter-ahead stock market returns on aggregate asset growth (AG) for four different subperiods. For the same subperiod, the table also reports the cross-sectional portfolios of individual stocks sorted by firm-level asset growth. For the cross-sectional portfolio results, decile portfolio are formed by sorting stocks based on their lagged quarterly asset growth at the end of each quarter so that decile 1 (10) is the portfolio with the lowest (highest) asset growth. We track the post-formation portfolio returns each quarter and then rebalance. We also present results for the fifth decile. Table reports the average returns, the Fama-French three-factor alpha, the Fama-French-Carhart four-factor alpha, and the Fama-French-Carhart-Pastor-Stambaugh five-factor alpha with liquidity factor as an additional factor. *, ** and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Panel A uses data from 1972Q1 to 1982Q4. Panel B uses data from 1983Q1 to 1992Q4. Panel C uses data from 1993Q1 to 2002Q4, and Panel D uses data from 2003Q1 to 2016Q4.

Time-series regression: $R_{t+1} = \alpha + \beta AG_t + u_t$					Cross-sectional portfolio sorts				
	β (%)	t-stat	Rand. P	Adj. R^2 (%)		Average return	FF 3-factor alpha	FFC 4-factor alpha	FFCPS 5-factor alpha
	Panel A: 1972Q1–1982Q4					Panel A: 1972Q1–1982Q4			
VWRET	−2.96	−1.42	0.16	6.30	Low AG	1.61	0.21	0.28	0.26
					5	1.49	0.36	0.38	0.36
SP500	−2.90	−1.43	0.16	7.10	High AG	0.89	−0.46	−0.42	−0.42
					High–Low	−0.72***	−0.67***	−0.70***	−0.68***
					t–stat	(−2.26)	(−2.33)	(−2.49)	(−2.42)
	Panel B: 1983Q1–1992Q4					Panel B: 1983Q1–1992Q4			
VWRET	−1.73	−1.44	0.16	1.77	Low AG	1.13	−0.07	−0.01	0.00
					5	1.30	0.04	0.12	0.13
SP500	−1.47	−1.29	0.21	0.78	High AG	1.04	−0.20	−0.22	−0.22
					High–Low	−0.10	−0.13	−0.21	−0.21
					t-stat	(−0.46)	(−0.68)	(−1.13)	(−1.13)

(continued)

Table III. Continued

Time-series regression: $R_{t+1} = \alpha + \beta AG_t + u_t$					Cross-sectional portfolio sorts				
	β (%)	t-stat	Rand. P	Adj. R^2 (%)		Average return	FF 3-factor alpha	FFC 4-factor alpha	FFCPS 5-factor alpha
Panel C: 1993Q1–2002Q4					Panel C: 1993Q1–2002Q4				
VWRET	−2.79***	−3.79	0.00	7.02	Low AG	0.92	0.18	0.79	0.79
					5	1.15	0.10	0.51	0.48
SP500	−2.62***	−3.42	0.00	7.07	High AG	0.14	−0.68	−0.08	−0.08
					High–Low	−0.78***	−0.86***	−0.88***	−0.87***
					t–stat	(−2.68)	(−3.11)	(−2.95)	(−2.77)
Panel D: 2003Q1–2016Q4					Panel D: 2003Q1–2016Q4				
VWRET	−2.94***	−3.43	0.00	12.12	Low AG	0.91	−0.22	−0.10	−0.05
					5	1.37	0.42	0.42	0.40
SP500	−2.82***	−3.56	0.00	12.31	High AG	0.70	−0.42	−0.40	−0.40
					High–Low	−0.21	−0.20	−0.29	−0.35
					t-stat	(−0.76)	(−0.78)	(−1.37)	(−1.51)

Table IV. Bivariate and multivariate regression

The table reports the coefficients and *t*-statistics from time series regressions of one-quarter-ahead stock market returns on aggregate asset growth (AG) and other return predictors. Panel A shows the bivariate regression and Panel B shows the multivariate regression results. VWRET is the value-weighted excess return. S&P500 is the S&P500 excess return. AG is the value-weighted averages of firm-level asset growth, defined as the quarter-on-quarter percentage change in book value of total assets. The independent variables are defined in Table I and standardized to have zero mean and unit variance. The coefficients are multiplied by 100 and expressed in percentage. *T*-statistics are computed using Newey–West standard errors. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The sample period is 1972Q1–2016Q4.

Panel A: bivariate regression

	VWRET $R_{t+1} = \alpha + \beta AG_t + \gamma X_t + \epsilon_t$					S&P500 $R_{t+1} = \alpha + \beta AG_t + \gamma X_t + \epsilon_t$				
	β (%)	*t*-stat	γ (%)	*t*-stat	Adj. R^2 (%)	β (%)	*t*-stat	γ (%)	*t*-stat	Adj. R^2 (%)
EP	−2.44***	−4.27	0.33	0.48	6.80	−2.26***	−4.25	0.07	0.11	6.31
DP	−2.41***	−4.38	0.06	0.09	6.66	−2.33***	−4.47	−0.32	−0.49	6.44
BM	−2.43***	−4.53	0.02	0.02	6.66	−2.30***	−4.59	−0.40	−0.60	6.53
TBL	−2.39***	−4.25	−0.16	−0.25	6.69	−2.16***	−4.05	−0.40	−0.65	6.53
TMS	−2.36***	−4.12	0.20	0.28	6.70	−2.17***	−3.96	0.24	0.35	6.38
DFY	−2.39***	−4.44	0.32	0.40	6.79	−2.25***	−4.34	0.00	0.00	6.30
NTIS	−2.42***	−4.45	−0.09	−0.10	6.67	−2.24***	−4.30	−0.15	−0.18	6.34
SVAR	−2.44***	−4.59	0.25	0.28	6.74	−2.25***	−4.38	0.05	0.06	6.31
IK	−2.43***	−4.15	0.01	0.01	6.66	−2.23***	−3.84	−0.04	−0.06	6.31
CAY	−2.42***	−4.38	1.18**	2.22	8.44	−2.24***	−4.18	1.11**	2.09	8.07
GAP	−1.98***	−3.68	−1.24*	−1.94	7.70	−1.74***	−3.35	−1.36**	−2.16	7.85

Panel B: multivariate regression

Dep. Var	AG	EP	DP	BM	TBL	TMS	DFY	NTIS	SVAR	IK	CAY	GAP	Adj. R^2 (%)
VWRET	−2.81***	1.35	−5.43*	7.67**	−6.59***	−3.16***	0.64	0.39	0.28	0.68	4.93***	−3.83**	14.49
t-stat	(−4.16)	(0.88)	(−1.88)	(2.28)	(−3.62)	(−2.80)	(0.48)	(0.47)	(0.28)	(0.63)	(3.46)	(−2.60)	
S&P500	−2.67***	1.36	−4.86*	6.53*	−6.25***	−3.07***	0.56	0.44	0.10	0.82	4.48***	−4.05***	14.73
t-stat	(−4.09)	(0.91)	(−1.70)	(1.95)	(−3.45)	(−2.74)	(0.44)	(0.53)	(0.10)	(0.88)	(3.00)	(−2.81)	

Table V. Out-of-sample forecasting results

The table reports results from one-step-ahead out-of-sample forecasts of quarterly market returns. VWRET is the value-weighted excess return. S&P500 is the S&P500 excess return. Recursive (expanding window) forecasts are made for four out-of-sample forecast periods: 1985 to 2016, 1990 to 2016, and 1995 to 2016, and 2000 to 2016. AG is the aggregate asset growth. Other predictive variables follow the definitions in Goyal and Welch (2008). EP is the log earnings-to-price ratio. DP is the log dividend-to-price ratio. BM is the book-to-market ratio. TBL is the 30-day T-bill rate. TMS is the difference between long term yield on government bonds and the Treasury-bill. DFY is the difference between BAA and AAA-rated corporate bonds. NTIS is the net equity issuance. SVAR is the equity variance. IK is the investment-to-capital ratio. CAY is the consumption-wealth ratio. GAP is the output gap. OOS R^2 is the Campbell and Thompson (2008) out-of-sample statistic. Statistical significance for the OOS R^2 is based on the p-value from the Clark and West (2007) out-of-sample MSPE-adjusted statistic. The sample period is 1972Q1–2016Q4. *, ** and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Returns	OOS Statistics	AG	EP	DP	BM	TBL	TMS	DFY	NTIS	SVAR	IK	CAY	GAP
Panel A: 1985Q1–2016Q4 out-of-sample period													
VWRET	OOS R^2 (%)	4.13***	−4.24	−5.07	−6.38	−0.67	−1.59	−3.83	−3.52	−31.65	−1.52	1.29*	1.94**
	p-value	(0.00)	(0.80)	(0.70)	(0.93)	(0.42)	(0.37)	(0.87)	(0.35)	(0.37)	(0.26)	(0.08)	(0.03)
S&P500	OOS R^2 (%)	2.52***	−4.18	−5.56	−6.49	−1.03	−2.53	−5.62	−3.88	−31.44	−3.19	0.32**	0.10**
	p-value	(0.01)	(0.81)	(0.71)	(0.95)	(0.69)	(0.42)	(0.89)	(0.26)	(0.39)	(0.41)	(0.03)	(0.04)
Panel B: 1990Q1–2016Q4 out-of-sample period													
VWRET	OOS R^2 (%)	7.24***	−4.03	−5.35	−2.15	−0.89	−1.27	−4.80	−5.97	−5.22	−0.91	−1.20	1.33**
	p-value	(0.00)	(0.75)	(0.83)	(0.84)	(0.44)	(0.37)	(0.93)	(0.98)	(0.89)	(0.22)	(0.15)	(0.05)
S&P500	OOS R^2 (%)	6.95***	−3.73	−5.43	−1.85	−1.33	−2.53	−6.79	−7.47	−5.57	−2.86	−1.18	1.64*
	p-value	(0.01)	(0.73)	(0.80)	(0.83)	(0.72)	(0.48)	(0.93)	(0.97)	(0.90)	(0.37)	(0.17)	(0.09)
Panel C: 1995Q1–2016Q4 out-of-sample period													
VWRET	OOS R^2 (%)	7.22***	−3.44	−5.14	−1.70	−0.96	−1.52	−4.75	−4.72	−6.04	−0.03	−0.23	2.95**
	p-value	(0.01)	(0.74)	(0.92)	(0.98)	(0.50)	(0.50)	(0.98)	(0.98)	(0.90)	(0.25)	(0.11)	(0.05)
S&P500	OOS R^2 (%)	6.83***	−3.27	−5.29	−1.52	−1.47	−2.74	−6.69	−5.99	−6.52	−1.87	0.42**	0.66*
	p-value	(0.01)	(0.72)	(0.91)	(0.97)	(0.76)	(0.62)	(0.98)	(0.98)	(0.92)	(0.43)	(0.03)	(0.10)
Panel D: 2000Q1–2016Q4 out-of-sample period													
VWRET	OOS R^2 (%)	8.32***	−2.66	0.33	−0.55	−2.66	−1.18	−1.48	−5.29	−9.28	4.45**	−2.58	6.28**
	p-value	(0.00)	(0.61)	(0.31)	(0.72)	(0.75)	(0.44)	(0.72)	(0.97)	(0.97)	(0.04)	(0.35)	(0.02)
S&P500	OOS R^2 (%)	7.35***	−2.52	0.86	−0.79	−3.19	−2.54	−2.14	−6.74	−10.08	3.02*	−2.39	4.56**
	p-value	(0.00)	(0.60)	(0.24)	(0.84)	(0.95)	(0.55)	(0.71)	(0.97)	(0.98)	(0.09)	(0.17)	(0.03)

to the historical average benchmark. The baseline model contains only an intercept and generates stock return forecasts equal to the historical mean. Following Campbell and Thompson (2008), I use the out-of-sample R^2 statistic for the out-of-sample forecast evaluation:

$$R^2_{\mathrm{OS}} = 1 - \frac{\sum_{t=1}^{T} (\hat{r}_t - r_t)^2}{\sum_{t=1}^{T} (\bar{r}_t - r_t)^2}, \tag{6}$$

where T is the out-of-sample window, $\sum_{t=1}^{T} (\bar{r}_t - r_t)^2$ is the mean squared forecast error of the historical average benchmark model, and $\sum_{t=1}^{T} (\hat{r}_t - r_t)^2$ is the mean squared forecast error of the predictive variables. If $R^2_{\mathrm{OS}} > 0$, the model with the main predictive variables outperforms the historical average forecast. To evaluate the statistical significance of R^2_{OS}, I use the Clark and West (2007) out-of-sample mean squared prediction error (MSPE) adjusted statistic, which corresponds to a one-sided test of the null hypothesis $R^2_{\mathrm{OS}} = 0$ against the alternative hypothesis $R^2_{\mathrm{OS}} > 0$. The MSPE-adjusted statistic for the one-step-ahead forecast is defined as follows:

$$\mathrm{MSPE}_{\mathrm{adj}} = \hat{f}_{t+1} = (r_{t+1} - \bar{r}_{t+1})^2 - [(r_{t+1} - \hat{r}_{t+1})^2 - (\bar{r}_{t+1} - \hat{r}_{t+1})^2], \tag{7}$$

where r_{t+1} is the actual return, $\bar{r}_{t+1}$ is the historical average and $\hat{r}_{t+1}$ is the forecast made by the predictive variables. Similar to Goyal and Welch (2008), I generate out-of-sample forecasts using a recursive (expanding) estimation window. This out-of-sample forecasting exercise simulates the situation of an investor in real time.

Table V reports the out-of-sample performance of AG and the other eleven macroeconomic variables across different forecasting periods. As indicated by the negative R^2_{OS} statistics in Table V, most of the eleven economic predictors fail to outperform the prevailing mean benchmark in terms of the MSPE at the quarterly horizon, confirming the findings of Goyal and Welch (2008). Although the investment-to-capital ratio (IK) and CAY can sometimes generate positive R^2_{OS} values, the forecasting performance is not stable across all subsample periods. The only macroeconomic variable that can generate a stable and significant R^2_{OS} value is the output gap used by Cooper and Priestley (2009). In contrast, the R^2_{OS} statistics for AG are all positive and significant, according to the Clark and West (2007) MSPE-adjusted statistic and, given their range from 4.13% to 8.32%, are of considerably larger magnitude than any of those obtained by the other predictors. More important, the superior performance of AG is not confined to any particular period, since the results are robust to different starting dates for the out-of-sample tests and are more pronounced for the most recent decade. This is a notable result, since Goyal and Welch (2008) conclude that by and large, many of the predictive variables perform poorly out-of-sample, particularly for recent decades.

To further investigate the out-of-sample performance of AG, I decompose the MSPE into forecast variance and the squared forecast bias, following Rapach, Strauss, and Zhou (2010) for the predictors that can deliver positive R^2_{OS} values, including AG, IK, CAY, and GAP. Figure 2 shows that the historical average has the lowest forecast variance and that AG has the smallest forecast bias of all the predictors. In contrast, the forecasting performance of IK and CAY is not stable across the subsample periods. Overall, Figure 2 shows that the sizable reduction in the MSPE relative to the historical average in Table V stems from the very small forecasting bias of AG.

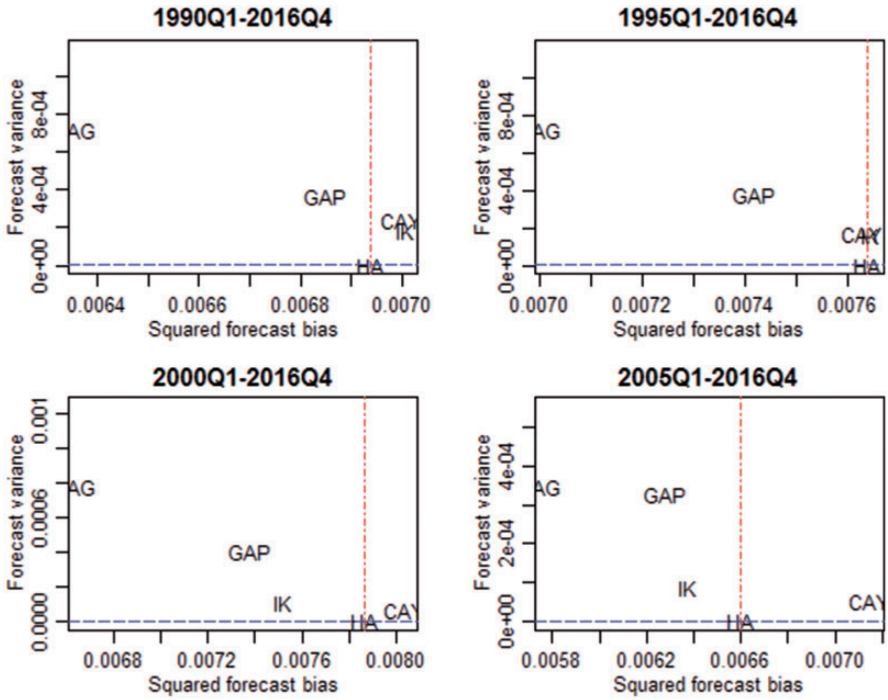

Figure 2. Scatterplots of forecast variance and squared forecast bias.
This figure shows the scatterplots depicting the forecast variance (vertical line) and squared forecast bias (horizontal line) for the predictors and the historical average (HA), for four different out-of-sample forecasting periods. The dotted (horizontal) and dashed (vertical) lines correspond to the forecast variance and squared forecast bias of the historical average benchmark, respectively. AG is aggregate asset growth. IK is investment-to-capital ratio. CAY is the consumption-wealth ratio. GAP is the output gap. The sample period is 1972Q1–2016Q4.

Next, I conduct a forecast encompassing test that provides strong evidence that AG contains distinct information above and beyond that contained in existing predictors. Following Harvey, Leybourne, and Newbold (1998), Rapach, Strauss, and Zhou (2010), and Li, Ng, and Swaminathan (2013), I explore the information content of AG relative to that of the other forecasting variables. The null hypothesis is that the forecast of model i encompasses the forecast of model j against the one-sided alternative that the forecast of model i does not encompass that of model j. Define $g_{t+1} = (\hat{\epsilon}_{i,t+1} - \hat{\epsilon}_{j,t+1})\hat{\epsilon}_{i,t+1}$, where $\hat{\epsilon}_{i,t+1}$ ($\hat{\epsilon}_{j,t+1}$) is the forecast error based on predictive variable i (j), that is, $\hat{\epsilon}_{i,t+1} = r_{t+1} - \hat{r}_{i,t+1}$ and $\hat{\epsilon}_{j,t+1} = r_{t+1} - \hat{r}_{j,t+1}$. The Harvey, Leybourne, and Newbold (1998) test can then be conducted as follows:

$$\text{HLN} = q/(q-1)[\hat{V}(\bar{g})^{-1/2}]\bar{g}, \tag{8}$$

where $\bar{g}$=1/q$\sum_{k=1}^{q} g_{t+k}$ and $\hat{V}(\bar{g}) = (1/q^2)\sum_{k=1}^{q}(g_{t+k} - \bar{g})^2$. The statistical significance of the test statistic is assessed according to the t_{q-1} distribution.

Table VI provides p-values corresponding to the Harvey, Leybourne, and Newbold (1998) forecast encompassing test statistic applied to the 2000–16 out-of-sample forecasts.

Table VI. Forecast encompassing test results

The table reports the *p*-values of the forecasting encompassing test statistic of Harvey, Leybourne, and Newbold (1998) (HLN statistic), which corresponds to a one-sided (upper-tail) test of the null hypothesis that the forecast from the row variable (R) encompasses the forecast from the column variable (C) against the alternative hypothesis that the forecast from the row variable (R) does not encompass the forecast from the column variable (C). The dependent variable in the regressions is the value-weighted excess return (VWRET) applied to 2000Q1–2016Q4 out-of-sample period.

	Column variable (C)											
Row variable (R)	AG	EP	DP	BM	TBL	TMS	DFY	NTIS	SVAR	IK	CAY	GAP
AG		0.58	0.79	0.70	0.63	0.64	0.52	0.57	0.50	0.57	0.25	0.35
EP	0.01		0.57	0.53	0.34	0.62	0.42	0.38	0.37	0.47	0.09	0.03
DP	0.03	0.15		0.62	0.42	0.39	0.45	0.40	0.48	0.52	0.08	0.04
BM	0.01	0.23	0.21		0.41	0.57	0.60	0.64	0.36	0.33	0.06	0.09
TBL	0.01	0.45	0.35	0.18		0.52	0.30	0.35	0.49	0.31	0.08	0.07
TMS	0.01	0.27	0.22	0.22	0.13		0.39	0.29	0.28	0.53	0.09	0.04
DFY	0.01	0.37	0.29	0.16	0.16	0.38		0.67	0.44	0.40	0.05	0.06
NTIS	0.01	0.43	0.22	0.24	0.16	0.25	0.21		0.27	0.38	0.08	0.06
SVAR	0.01	0.45	0.32	0.21	0.15	0.20	0.42	0.35		0.51	0.09	0.07
IK	0.02	0.34	0.32	0.24	0.16	0.24	0.36	0.29	0.39		0.05	0.07
CAY	0.03	0.45	0.32	0.24	0.13	0.45	0.24	0.39	0.40	0.30		0.12
GAP	0.04	0.39	0.35	0.21	0.18	0.44	0.24	0.37	0.37	0.20	0.08	

The *p*-values correspond to an upper tail test of the null hypothesis that the forecast from the row variable (R) encompasses the forecast from the column variable (C) against the alternative hypothesis that it does not. The results show that one cannot reject the null that AG encompasses the other forecasting variables while one can strongly reject the null that AG is encompassed by the other forecast variables. This suggests that AG is more informative than the other forecasting variables in predicting future returns.

3.3 Evidence from International Data

Given the strong predictability of AG for future market returns in the USA, in this section I extend the analysis to the other G7 countries: Canada, France, Germany, Italy, Japan, and the UK. The international evidence also alleviates the concern that the empirical pattern documented in the USA is attributable to data-snooping biases. I select these countries because of the availability of accounting data to construct asset growth and market data for aggregate stock returns. The results are presented in Table VII. On the quarterly horizon, I find a negative relation between AG and future stock market returns in every country, with statistically significant coefficients for Canada, Germany, Italy, and the UK (with marginally significant coefficients for France). Although the magnitude of the economic value based on the predictive coefficients and the statistical significance based on the R^2 values are lower for these countries, besides the USA, this result could be driven by the smaller sample available for these countries and the smaller number of cross-sectional firms. Overall, the

Table VII. International evidence

The table reports the coefficients and t-statistics from time series regressions of one-quarter-ahead stock market returns on aggregate asset growth (AG) in the remaining G7 countries:

$$R_{t+1} = \alpha + \beta \mathrm{AG}_t + u_t.$$

AG is the country-specific aggregate asset growth, computed as the value-weighted average of firm-level asset growth, defined as the year-on-year percentage change in book value of total assets (Datastream Field 02999). Aggregate market returns (in logarithm) are computed by compounding monthly returns using the MSCI world index for developed markets, in excess of the risk-free rate (excess return) or inflation (real return). Sample begins in 1983 for Canada, Germany, Italy, Japan, and UK and, in 1982 for France and ends in 2016. t-statistics are computed using Newey–West standard errors. Rand.p is the bootstrap p-value calculated following Nelson and Kim (1993). *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Excess returns				Real returns			
Countries	β (%)	t-stat	Rand.p	Adj. R^2 (%)	β (%)	t-stat	Rand.p	Adj. R^2 (%)
Canada	−1.43***	−2.87	0.01	1.85	−1.22**	−2.52	0.03	1.22
France	−1.02*	−1.95	0.08	0.94	−0.92*	−1.75	0.08	0.86
Germany	−1.28**	−2.43	0.03	1.26	−1.01**	−2.30	0.03	0.97
Italy	−1.42***	−3.25	0.00	1.55	−1.01**	−2.50	0.02	1.44
Japan	−0.25	−0.52	0.32	0.35	−0.18	−0.34	0.57	0.29
UK	−1.68***	−3.25	0.00	2.20	−1.42***	−2.83	0.01	1.93

evidence from the international data that excess or real stock returns are predictable by AG provides support for the in-sample predictability based on US data.

3.4 Robustness Checks

I conduct a number of robustness checks on the predictive power of AG and present the results in Table VIII. It is important to note that AG has several influential observations. For example, AG is above 10% only during the tech bubble period from 1999Q4 to 2000Q2 and the market return following this period is extremely low. In addition, AG is negative only during the recent financial crisis from 2008Q4 to 2009Q1 and the market return following this period is high. Panel A of Table VIII reports the predictive coefficient on AG after removing these influential observations. The results in Panel A show that AG remains a negative predictor of stock market returns. Panel B presents the in-sample bivariate predictive regression that includes AG and the alternative measures of investment or growth.[6] Panel B shows that AG remains a strong predictor for market returns. In Panel C,

6 Numerous studies have examined return effects across the components of asset financing and investment, including the aggregate investment-to-capital ratio (Cochrane, 1991), the share of equity issuance (Baker and Wurgler, 2000), growth in capital investments (Titman, Wei, and Xie, 2004), aggregate accruals (Hirshleifer, Hou, and Teoh, 2009), cumulative accruals or net operating assets (Arif and Lee, 2014), and growth in fixed investment (Kothari, Lewellen, and Warner, 2006).

Table VIII. Robustness checks

Panel A reports the predictive coefficient on AG after removing the influential observations of aggregate asset growth (AG) when AG is negative during the financial crisis period (from 2008Q4 to 2009Q1) or above 10% (during the tech bubble period from 1999Q4 to 2000Q2). Panel B reports the predictive coefficient on AG in bivariate regressions using AG and other measures of investment or growth, one at a time. The dependent variable is the one-quarter-ahead value-weighted stock market returns. The control variables include growth in capital investments (Capital Inv), aggregate accruals, net operating assets (NOA), aggregate growth in fixed investments (Fixed Inv), and equity share. The independent variables are standardized to have zero mean and unit variance. The coefficients are multiplied by 100 and expressed in percentage. Panel C of the table reports the univariate predictive regression coefficient (β) on AG using the equal-weighted market returns. Panel D constructs an alternative measure of aggregate asset growth defined as the quarterly growth rate of aggregate total assets based on all firms within the quarter. Panel E constructs the year-on-year growth measure using total assets in quarter t relative to quarter $t-4$. Panel F reports the predictive regression results for the four calendar quarters separately. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: removing the influential observations of AG

Value-weighted excess returns				Value-weighted raw returns			
β (%)	t-stat	Rand.p	Adj.R^2 (%)	β (%)	t-stat	Rand.p	Adj.R^2 (%)
−1.76***	−2.65	0.02	3.60	−1.56**	−2.36	0.03	2.75

Panel B: controlling for other measures of investments or growth

Control vars.	Capital Inv	Accruals	NOA	Fixed Inv	Equity share
	−1.95**	−2.21***	−2.12***	−2.37***	−2.60***
t-stat	(−2.63)	(−3.60)	(−2.83)	(−3.15)	(−4.08)

Panel C: predicting equal-weighted returns

	Equal-weighted excess returns				Equal-weighted raw returns			
	β (%)	t-stat	Rand.p	Adj.R^2 (%)	β (%)	t-stat	Rand.p	Adj.R^2 (%)
	−2.46**	−2.77	0.01	3.92	−2.26**	−2.62	0.01	3.29
	Value-weighted excess returns			Value-weighted raw returns				
	β (%)	t-stat	Rand.p	Adj.R^2 (%)	β (%)	t-stat	Rand.p	Adj.R^2 (%)
Panel D: alternative measure of aggregate asset growth								
	−2.03**	−2.67	0.02	2.51	−1.96**	−2.43	0.03	2.27
Panel E: year-on-year asset growth								
	−1.30***	−3.44	0.01	1.63	−1.20***	−3.10	0.01	1.35
Panel F: predictability using the four calendar quarters separately								
Q1	−3.39***	−3.89	0.01	9.30	−3.16***	−3.63	0.01	8.00
Q2	1.05	1.41	0.21	−1.10	0.99	1.40	0.20	−1.23
Q3	−1.24**	−2.14	0.09	1.07	−1.19**	−2.13	0.30	0.66
Q4	1.43	1.47	0.23	1.69	1.58	1.49	0.25	2.63

I use the equal-weighted stock market return as the dependent variable and find similar results. The coefficients of AG are −2.46% ($t = -2.77$) and −2.26% ($t = -2.62$), respectively, for the equal-weighted excess and raw market returns.[7] In Panel D, I construct an alternative measure of AG, defined as the quarterly growth rate of aggregate total assets based on all firms within the quarter, rather than taking the value-weighted average of firm-level asset growth. Panel D shows that the alternative measure of AG also significantly predicts future stock market returns.[8]

Since AG is computed from bottom-up firm accounting data, I conduct two additional tests on the seasonality of AG and its predictive power. In Panel E of Table VIII, instead defining AG as quarter-on-quarter growth, I compute year-on-year asset growth using a firm's total assets in quarter t relative to quarter $t-4$. Panel E shows that year-on-year asset growth also significantly predicts one-quarter-ahead value-weighted market returns. Finally, motivated by the findings of Moller and Rangvid (2015, 2017) on the end-of-the-year growth effect, I examine whether AG at the end of the year (fourth quarter or December) strongly influences expected returns compared to AG during the rest of the year.[9] For example, for Q1 in year t, I compute AG from Q4 in year $t-1$ to Q1 in year t and use this measure to predict the one-quarter-ahead value-weighted returns. I then repeat this procedure for each of the four calendar quarters. Panel F shows that AG in the first and third calendar quarters significantly predicts future market returns, but is no longer significant for the second and fourth quarters. The absence of an end-of-year effect indicates that AG may contain unique information about stock market returns different from the macroeconomic growth documented by Moller and Rangvid (2015, 2017).

3.5 Decomposing Asset Growth

Because total asset growth is a comprehensive measure of firm growth, in this section I examine whether growth in the various components of asset growth is uniformly associated with a negative return effect. To better understand the drivers of return predictability, I follow Cooper, Gulen, and Schill (2008) and decompose firm-level asset growth from both the investment side and the financing side of the balance sheet. The asset investment decomposition is as follows:

$$\text{Total asset growth (AG)} = \Delta\text{Cash} + \Delta\text{CurAsst} + \Delta\text{PPE} + \Delta\text{OthAssets}, \tag{9}$$

where ΔCash is cash growth; ΔCurAsst is growth in noncash current assets; ΔPPE is growth in property, plant, and equipment; and ΔOthAssets is the growth in other assets. Similarly, I construct an asset financing identity as follows:

$$\text{Total asset growth (AG)} = \Delta\text{OpLiab} + \Delta\text{RE} + \Delta\text{Stock} + \Delta\text{Debt}, \tag{10}$$

where ΔOpLiab is growth in operating liabilities, ΔRE is growth in retained earnings, ΔStock is growth in equity financing, and ΔDebt is the growth in debt financing.

7 Consistent with the equal-weighted return results, in untabulated results, I find that the predictive power of AG is of similar magnitude in both small and large stock portfolios.

8 The results are similar if I construct AG using only S&P500 firms. The coefficients of AG are −2.12% ($t = -2.45$) and −2.08% ($t = -2.57$), respectively, for the S&P500 excess and raw returns.

9 Moller and Rangvid (2015, 2017) show that macroeconomic growth at the end of the year strongly predicts future market returns and provide evidence consistent with time-varying risk aversion linked to macroeconomic growth.

Panel A of Table IX reports the variance decomposition results on AG and its subcomponents. It shows that ΔCash accounts for the highest variation (37.74%) in AG in the asset decomposition and ΔCurAsst has the second highest (25.03%), whereas ΔStock financing has the highest variation (46.06%) in the financing decomposition of AG. Consistent with these findings, Panel B shows that growth in cash and changes in noncash operating assets are associated with significant negative coefficients, −2.71 ($t = -3.80$) and −2.32 ($t = -3.58$). With respect to the asset financing decomposition, equity financing has the most significant coefficient, −1.41 ($t = -2.89$). These results are consistent with the findings of Baker and Wurgler (2000), who find that equity issuance is a strong negative predictor of stock market returns.

Overall, the decomposition results in Table IX suggest that asset growth benefits from the predictability of all subcomponents of growth. In the following section, I delve into different economic explanations of market return predictability.

4. Economic Explanations

The return predictability of AG could be due to the time-varying risk premium or investors' behavioral biases. I perform several analyses in this section to differentiate these potential explanations. In Section 4.1, I explore the relation between AG and proxies of aggregate investments and fundamentals as well as proxies for economic uncertainty. The evidence reveals the importance of the time-varying risk premium in the return predictability. In Section 4.2, I discuss the behavioral explanations of whether investor extrapolation plays a role in the documented results.

4.1 Risk-Based Explanation

I first investigate the relation between AG and the variables that are known to be related to business cycles or the time-varying risk premium. These variables include the output gap (GAP; see Cooper and Priestley, 2009), the investment-to-capital ratio (IK; see Cochrane, 1991, 1996), and AEIG (see Li, Wang, and Yu, 2017).[10] To test these relations, Table X shows the regression coefficients of the various measures of macroeconomic conditions using future AG as a dependent variable, controlling for lagged AG. Panel A shows that GAP positively predicts future AG for all considered time horizons. Given that the output gap of Cooper and Priestley (2009) measures economic fundamentals and is a production-based business cycle variable, the findings in Panel A are consistent with the risk-based explanation. Panel B shows that IK positively predicts AG, consistent with the interpretation of Cochrane (1991, 1996) on the time-varying discount rate or expected returns to capital. Finally, Panel C shows that AEIG positively predicts AG up to three quarters. Given that AEIG is shown to be negatively related to the quantity of aggregate risk (Li, Wang, and Yu, 2017), this finding lends further support to the risk-based explanation.

10 Cooper and Priestley (2009) demonstrate that as a prime business cycle indicator, the output gap predicts stock market returns through time-varying risk premium channel. Cochrane (1991, 1996) shows that the predictability associated with IK for stock market returns is consistent with the *q*-theory of investment and the time-varying discount rate or expected return to capital. Li, Wang, and Yu (2017) show that the predictability of AEIG is related to a lower aggregate quantity of risk following a high AEIG.

Table IX. Aggregate asset growth and its subcomponents

Panel A reports the variance decomposition results on aggregate asset growth (AG) and its subcomponents. Var% measures the relative importance of the subcomponent and is defined as the covariance between the subcomponent and AG, divided by the variance of AG. Panels B and C report the coefficients and *t*-statistics (in parentheses) from time series regressions of one-quarter-ahead stock market returns on the subcomponents of aggregate asset growth, from an asset decomposition and a financing decomposition. In the asset decomposition, asset growth is the sum of: (i) ΔCash (growth in cash), (ii) ΔCurAsst (growth in non-cash current assets), (iii) ΔPPE (growth in property, plant, and equipment), and (iv) ΔOthAssets (growth in other assets). In the financing decomposition, asset growth is the sum of: (i) ΔOpLiab (growth in operating liabilities), (ii) ΔDebt (growth in debt financing), (iii) ΔStock (growth in equity financing), and (iv) ΔRE (growth in retained earnings). VWRET is the value-weighted excess return. S&P500 is the S&P500 excess return. The independent variables are standardized to have zero mean and unit variance. The coefficients are multiplied by 100 and expressed in percentage. *t*-statistics are computed using Newey–West standard errors. The sample period is 1974Q1-2016Q4. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Asset decomposition					Financing decomposition			
	ΔCash	ΔCurAsst	ΔPPE	ΔOthAssets		ΔOpLiab	ΔDebt	ΔStock	ΔRE
Panel A: variance decomposition of aggregate asset growth									
Var%	37.74%	25.03%	21.33%	15.90%	Var%	36.12%	5.41%	46.06%	12.42%

Asset decomposition						Financing decomposition					
Constant	ΔCash	ΔCurAsst	ΔPPE	ΔOthAssets	Adj R^2 (%)	Constant	ΔOpLiab	ΔDebt	ΔStock	ΔRE	Adj R^2 (%)
Panel B: dependent variable = VWRET											
1.33	−2.71***				8.97	1.24	−1.35*				1.86
(2.04)	(3.80)					(1.88)	(−1.83)				
1.34		−2.32***			6.41	0.55		−0.97			0.70
(2.09)		(−3.58)				(0.87)		(−1.08)			
1.27			−1.68**		3.18	1.26			−1.41***		2.07
(1.96)			(−1.99)			(1.95)			(−2.89)		
1.33				−0.84	0.35	1.26				−0.94	0.60
(1.98)				(−1.09)		(1.92)				(−1.43)	

(continued)

Table IX. Continued

Asset decomposition						Financing decomposition					
Constant	ΔCash	ΔCurAsst	ΔPPE	ΔOthAssets	Adj R^2 (%)	Constant	ΔOpLiab	ΔDebt	ΔStock	ΔRE	Adj R^2 (%)
Panel C: dependent variable = S&P500											
0.58	−2.57***				8.88	0.54	−1.17*				1.43
(0.90)	(−3.61)					(0.83)	(−1.71)				
0.59		−2.26***			6.74	0.55		−0.87			0.55
(0.95)		(−3.75)				(0.87)		(−1.04)			
0.56			−1.79**		4.13	0.55			−1.11**		1.27
(0.90)			(−2.20)			(0.87)			(−2.37)		
0.58				−0.54	−0.16	0.56				−0.99	
(0.88)				(−0.75)		(0.87)				(−1.63)	0.89

I further investigate the relation between AG and measures of economic uncertainty. Following Anderson, Ghysels, and Juergens (2009), I use forecasts on macroeconomic variables and aggregate corporate profits from the Survey of Professional Forecasters (SPF) as measures of aggregate uncertainty.[11] The bottom three panels of Table X show strong negative correlations between AG and all three uncertainty measures. Specifically, Panel D measures aggregate uncertainty using the forecast dispersion in GDP growth and shows that higher uncertainty is associated with lower AG. When uncertainty is measured by dispersion in industrial production growth (Panel E) and dispersion in aggregate corporate profits (Panel F), high uncertainty also implies lower future AG. Since increases in uncertainty imply higher costs of capital, AG decreases and is negatively related to lower future market returns. In addition, the negative relation between aggregate uncertainty and asset growth can also be consistent with real option theory (Berk, Green, and Naik, 1999), which predicts that the risk premium is lower after growth options are exercised through investment or growth. Overall, Table X shows that the time-varying risk premium due to the lower aggregate quantity of risk following periods of high growth can contribute to the ability of AG to predict returns.

4.2 Behavioral Explanations

I examine the behavioral explanation using AG in two steps. In the first step, I show that AG is a robust negative predictor of aggregate analyst forecast errors and forecast revisions. In the second step, I examine stock returns around earnings announcements to infer expectation errors implied by the market's response to earnings news. I show that AG negatively predicts announcement returns. To the extent that analyst forecast errors and revisions convey earnings news to the market, these findings suggest that failing to recognize the predictable component of forecast errors and revisions could result in return predictability.

4.2.a. Predicting analyst earnings forecast revisions and forecast errors

I construct measures of aggregate earnings news based on analyst earnings forecast revisions (Chan, Jegadeesh, and Lakonishok, 1996; Da and Warachka, 2009). Changes in analyst forecasts offer an attractive way to measure earnings news because they represent changes in the market's earnings expectations (e.g., Ivkovic and Jegadeesh, 2004; Jegadeesh *et al.*, 2004). Therefore, I examine the following predictive regression of aggregate earnings forecast revisions on asset growth:

$$\mathrm{REV}_{t+\tau} = \alpha + \beta \mathrm{AG}_t + \gamma_1 \mathrm{REV}_t + \gamma_2 X_t^k + \epsilon_{t+\tau} \tag{11}$$

$$\mathrm{FE}_{t+\tau} = \alpha + \beta \mathrm{AG}_t + \gamma_1 \mathrm{FE}_t + \gamma_2 X_t^k + \epsilon_{t+\tau} \qquad k = 1, \ldots, 11, \tag{12}$$

where REV is earnings forecast revisions, defined as the value-weighted firm-level forecast revisions; FE is realized analyst forecast errors; and τ represents different time horizons, with $\tau = 1$, 2, 3, or 4 quarters. X_t is a vector of control variables that includes the eleven macroeconomic and business cycle variables defined in Table IV. To address the concern that analyst forecast errors tend to be persistent, I also control for lagged earnings forecast revisions and forecast errors.

11 Anderson, Ghysels, and Juergens (2009) show a positive relation between uncertainty and expected market excess returns.

Table X. Aggregate asset growth, macroeconomic conditions, and economic uncertainty

This table reports the regression coefficients using aggregate asset growth as a dependent variable. Panels A to C report the regression coefficients on various measures of macroeconomic conditions or investment growth, controlling for lagged aggregate asset growth:

$$\text{AG}_{t+\tau} = \alpha + \beta X_t + \gamma \text{AG}_t + \epsilon_{t+\tau}, \qquad \text{X=GAP, IK, or AEIG},$$

where AG is the aggregate asset growth, and $\tau = 1, 2, 3, 4$. GAP is the output gap, IK is the investment-to-capital ratio, and AEIG is the aggregate expected investment growth. Panels D to F report the regression coefficients on various measures of macroeconomic uncertainty, controlling for lagged aggregate asset growth:

$$\text{AG}_{t+\tau} = \alpha + \beta X_t + \gamma \text{AG}_t + \epsilon_{t+\tau}, \quad \text{X=Disper in RGDP, Disper in INDPROD, Disper in CORPF},$$

where Disper in RGDP is the dispersion in forecasts for real GDP growth, Disper in INDPROD is the dispersion in forecasts for industrial production growth, and Disper in CORPF is the dispersion in forecasts for corporate profits. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The sample period is 1972Q1 to 2016Q4.

	$\tau=1$	$\tau=2$	$\tau=3$	$\tau=4$	$\tau=5$	$\tau=6$
			Panel A: X = GAP			
Coef. *B*	3.64***	3.31***	2.75***	2.37***	2.00**	1.77**
t-stat	(3.88)	(3.69)	(3.07)	(2.68)	(2.41)	(2.30)
R^2 (%)	35.02	33.92	32.51	31.74	31.88	31.63
			Panel B: X = IK			
Coef. *B*	10.07***	9.17***	7.78***	6.67***	6.01**	5.68**
t-stat	(4.41)	(3.85)	(3.11)	(2.77)	(2.59)	(2.55)
R^2 (%)	38.71	37.02	35.03	33.73	33.86	33.65
			Panel C: X = AEIG			
Coef. *B*	8.56***	7.34**	7.78**	6.67*	6.01	5.68
t-stat	(3.49)	(2.64)	(2.35)	(1.78)	(1.43)	(1.08)
R^2 (%)	22.90	18.84	16.68	15.57	14.04	13.44
	$\tau=1$	$\tau=2$	$\tau=3$	$\tau=4$	$\tau=5$	$\tau=6$
			Panel D: X =Disper in RGDP			
Coef. β	−6.90**	−5.49**	−4.75*	−3.80	−3.15	−2.10
t-stat	(−2.42)	(−2.39)	(−2.13)	(−1.69)	(−1.47)	(−1.34)
R^2 (%)	29.74	29.61	29.41	27.50	27.10	26.85
			Panel E: X =Disper in INDPROD			
Coef. *B*	−4.50***	−3.99**	−1.29	−1.23	−1.06	−1.28
t-stat	(−2.85)	(−2.49)	(−0.54)	(−0.16)	(−0.02)	−0.45
R^2 (%)	30.18	30.00	29.48	29.57	28.60	30.29
			Panel F: X =Disper in CORPF			
Coef. β	−2.02***	−1.85**	−1.50*	−1.36	−0.75	−0.53
t-stat	(−2.83)	(−2.36)	(−1.95)	(−1.39)	(−0.83)	(−0.76)
R^2 (%)	30.61	30.08	30.88	30.84	30.34	30.21

Panel A of Table XII shows the results when the dependent variable is REV. The coefficients of AG are negative and significant for one- and two-quarter-ahead forecast revisions, indicating that analysts tend to revise their earnings forecasts downward, in the direction of high past AG. Panel B reports the results when the dependent variable is the aggregate forecast errors. In Panel B, the coefficients of AG are all negative and significant for all lags, consistent with asset growth having explanatory power for the realized analyst forecast errors. For example, focusing on one period lagged asset growth ($\tau = 1$), the coefficient of asset growth is -0.67 ($t = -3.26$) for univariate regression and -0.38 ($t = -4.38$) when macroeconomics and business cycle variables are controlled for.

Figure 3 plots the quarterly AG and analyst forecast revisions (REV) for the period from 1976Q1 to 2016Q4. The figure shows a strong and negative correlation between AG and REV. In periods in which high (low) asset growth is observed, analysts subsequently make downward (upward) revisions. Overall, the findings in Table XI and Figure 3 show that high market asset growth is associated with future downward revisions in earnings forecast. In periods of high asset growth, analysts issue more optimistic earnings forecasts and subsequently make downward revisions.

4.2.b. Predicting earnings announcement returns

Although AG negatively predicts earnings news, it is important to examine stock returns around earnings announcements to infer expectation errors implied by the market's response to earnings news (e.g., Bernard and Thomas, 1990; La Porta, 1996). If investors fail to incorporate the information in high (low) asset growth, they should be surprised by the subsequent unanticipated bad (good) news during earnings announcement days when the information becomes publicly available.

To construct aggregate earnings announcement returns, I obtain the earnings announcement dates from Compustat quarterly data and the daily returns from CRSP. For each S&P 500 firm from 1972Q1 to 2016Q4, I compute the abnormal return as the difference between the daily stock return and the expected return using the Fama-French three-factor, or Carhart (1997) four-factor model.[12] I then obtain cumulative abnormal returns (CARs) for each firm over the event window. The aggregate quarterly CARs are computed as the equal- or value-weighted average CARs for firms whose earnings announcements fall into the corresponding quarter. Finally, I obtain a quarterly time series of CARs around earnings announcements and examine their relation with AG:

$$\mathrm{CAR}_{t+\tau} = \alpha + \beta \mathrm{AG}_t + X_t^k + \epsilon_{t+\tau}, \qquad \tau = 1, \ldots, 4;\ k = 1, \ldots, 11, \tag{13}$$

where $\mathrm{CAR}_{t+\tau}$ denotes the quarterly CARs and X_t is a vector of control variables that includes the eleven macroeconomic and business cycle variables defined in Table IV.

Table XII reports the regression results using two event windows. The results suggest that AG is negatively related to future announcement returns, and that this effect is particularly strong for announcement-window returns during the first and second quarters. Table XII also shows that AG does not significantly predict announcement returns during third or fourth quarterly earnings announcements. This result suggests that a substantial

12 The estimation window is [–250, −10], and two different event windows are used: [−1, +1] and [−2, +2], where day 0 is the earnings announcement date. I require a 10-day gap between the estimation window and the event window to ensure that the estimators for the parameters of the benchmark model are not influenced by event-related returns.

Table XI. Predicting analyst earnings forecast errors and revisions

The table reports the slope coefficients and *t*-statistics from the predictive regression of aggregate analyst forecast revisions (Panel A) and forecast errors (Panel B) on aggregate asset growth:

$$\mathrm{REV}_{t+\tau} = \alpha + \beta \mathrm{AG}_t + \gamma_1 \mathrm{REV}_t + \gamma_2 X_t^k + \epsilon_{t+\tau}$$

$$\mathrm{FE}_{t+\tau} = \alpha + \beta \mathrm{AG}_t + \gamma_1 \mathrm{FE}_t + \gamma_2 X_t^k + \epsilon_{t+\tau} \qquad k = 1, \ldots, 11,$$

where REV (FE) is the analyst forecast revisions (errors). *T* represents different time horizons and $\tau = 1$, 2, 3, or 4 quarters. AG is aggregate asset growth. X_t is a vector of control variables that include the eleven macroeconomic and business cycle variables defined in Table IV. Forecast revisions is defined as the quarter-on-quarter percentage change in consensus forecasts. Forecast error is defined as the realized difference between earnings and the prevailing consensus forecasts, scaled by price per share. *T*-statistics are computed using Newey–West standard errors. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The sample period starts from 1976Q1 to 2016Q4.

Panel A: predicting analyst forecast revisions

	$\tau = 1$	$\tau = 2$	$\tau = 3$	$\tau = 4$
	Univariate with aggregate asset growth			
Coef. β	−0.67***	−0.64***	−0.32**	−0.15
t-stat	(−3.26)	(−2.89)	(−2.15)	(−1.21)
Adj. R^2 (%)	16.57	16.57	3.32	0.50
	Multivariate controlling for macroeconomic and business cycle variables			
Coef. β	−0.38***	−0.30***	−0.23*	0.07
t-stat	(−4.38)	(−2.97)	(−1.85)	(0.56)
Adj. R^2 (%)	51.74	50.32	48.28	46.57

Panel B: predicting analyst forecast errors

	$\tau = 1$	$\tau = 2$	$\tau = 3$	$\tau = 4$
	Univariate with aggregate asset growth			
Coef. β	−0.30***	−0.28***	−0.16*	−0.09
t-stat	(−2.78)	(−3.19)	(−1.69)	(−1.01)
Adj. R^2 (%)	7.08	6.13	1.51	0.12
	Multivariate controlling for macroeconomic and business cycle variables			
Coef. β	−0.36***	−0.31***	−0.14	0.22
t-stat	(−4.06)	(−2.45)	(−1.30)	(1.29)
Adj. R^2 (%)	53.32	54.24	50.70	51.28

portion of the expectation errors that are embedded in prices are gradually corrected during nonannouncement periods after the second quarter. Overall, the results in Tables XI and XII are consistent with the interpretation that investors are surprised by subsequent bad (good) earnings news associated with high (low) AG.

Table XII. Asset growth and CARs around earnings announcements

The table reports the coefficients and *t*-statistics from the predictive regression of quarterly CARs around the earnings announcements on aggregate asset growth, for different time horizon τ, where $\tau = 1$, 2, 3, or 4 quarters:

$$\mathrm{CAR}_{t+\tau} = \alpha + \beta \mathrm{AG}_t + \gamma X_t^k + u_t, \ \ \tau = 1, 2, 3, 4.$$

The quarterly CARs is the value-weighted average CARs of the S&P500 firms whose earnings announcements fall into the corresponding quarter. X_t^k is a vector of control variables that includes the eleven macroeconomic and business cycle variables defined in Table IV. Panel A reports the results for the event window [−1, +1] where day 0 is the earnings announcement day. Panel B reports the results for the event window [−2, +2]. Two benchmark models for measuring abnormal returns are used: the Fama-French three-factor model (FF3) and the Carhart four-factor model (Carhart). The estimation window is [−250, −5]. *t*-statistics are computed using Newey–West standard errors. The sample period is 1972Q1 to 2016Q4. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: predicting CARs [−1, +1]

Model		$\tau = 1$	$\tau = 2$	$\tau = 3$	$\tau = 4$
		Univariate			
FF3	Coef. β	−0.06**	−0.06***	−0.03	−0.01
	t-stat	(−2.47)	(−2.67)	(−0.71)	(−0.46)
	Adj. R^2 (%)	1.83	1.93	0.21	−0.52
Carhart	Coef. β	−0.07**	−0.06**	−0.04	−0.01
	t-stat	(−2.53)	(−2.48)	(−0.87)	(−0.50)
	Adj. R^2 (%)	3.65	2.45	1.00	−0.49
		Multivariate with controls			
FF3	Coef. β	−0.08***	−0.06**	−0.06	0.02
	t-stat	(−2.72)	(−2.25)	(−1.19)	−0.57
	Adj. R^2 (%)	9.27	7.46	4.75	3.70
Carhart	Coef. β	−0.10***	−0.07**	−0.08	0.02
	t-stat	(−3.16)	(−2.35)	(−1.31)	−0.41
	Adj. R^2 (%)	11.29	7.18	4.89	2.85

Panel B: predicting CARs [−2, +2]

Model		$\tau = 1$	$\tau = 2$	$\tau = 3$	$\tau = 4$
		Univariate			
FF3	Coef. β	−0.08**	−0.06**	−0.02	0.02
	t-stat	(−2.53)	(−2.67)	(−0.33)	(0.17)
	Adj. R^2 (%)	3.18	1.93	−0.44	−0.52
Carhart	Coef. β	−0.07**	−0.06**	−0.03	0.00
	t-stat	(−2.25)	(−2.48)	(−0.87)	(−0.06)
	Adj. R^2 (%)	2.37	2.45	0.16	−0.49
		Multivariate with controls			
FF3	Coef. β	−0.07**	−0.06**	−0.07	0.04
	t-stat	(−2.36)	(−2.19)	(−1.56)	(0.87)
	Adj. R^2 (%)	10.15	10.01	8.37	6.44
Carhart	Coef. β	−0.09***	−0.06**	−0.05	0.03
	t-stat	(−3.56)	(−2.30)	(−1.59)	(1.11)
	Adj. R^2 (%)	11.27	9.48	7.21	4.98

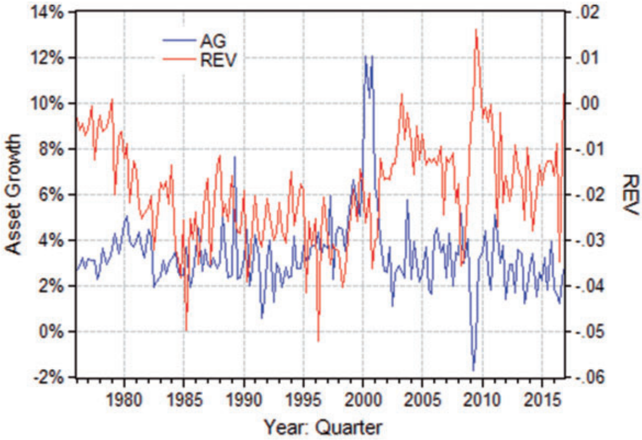

Figure 3. Aggregate asset growth and earnings forecast revisions.
This figure plots quarterly aggregate asset growth (AG) and analyst forecast revisions (REV). Analyst forecast revisions (REV) is the value-weighted average of the firm-level forecast revisions. Forecast revision (REV), is defined as quarter-on-quarter percentage change in consensus forecasts. The sample period starts from 1976Q1 to 2016Q4.

5. Conclusion

In this article, I examine whether the firm-level asset growth effect extends to the aggregate stock market and explore the source of market return predictability. Using time-series regressions analyses, I show that at the market level, AG negatively predicts future market returns. The market return predictability is statistically significant and economically large, holds both in and out-of-sample, and this effect is robust when controlling for a large set of macroeconomic and business cycle variables and across G7 countries. The predictability is relatively strong in the short-run, extending to two-quarters-ahead, and then becomes insignificant. The decomposition framework shows that the ability of asset growth to predict stock market returns is attributable to its ability to capture common return effects across the components of firms' total investment or financing activities.

I find a strong and positive predictive power of AG for variables that are known to be related to business cycles or the time-varying risk premium. In addition, the evidence that AG negatively predicts measures of economic uncertainty further suggests the role of the time-varying risk premium in return predictability. I also find strong evidence that high AG is associated with more optimistic analyst forecasts and subsequent downward revisions. In addition, asset growth negatively predicts earnings announcement returns. These findings are consistent with the interpretation that investors fail to incorporate the information in asset growth into stock prices, and are subsequently surprised by the subsequent unanticipated bad (good) news associated with high (low) past asset growth. Collectively, the results show that both the time-varying risk premium and investor behavioral biases play an important role in the predictive power of AG. Thus, the findings in this study extend those of Lam and Wei (2011) by showing that both the rational and behavioral explanations appear to complement each other in explaining the asset growth anomaly.

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