Asset Growth Effect and Q Theory of Investment

Abstract

The recent linear factor models (e.g., Fama and French (2015) and Hou, Xue, and Zhang (2015)) use total asset growth as the measure of investment, largely due to its stronger return predictive power than its components such as the long-term and current asset growths. We offer an explanation of the latter finding by extending the standard q theory of investment into a two-capital setup in which firms use both long-term and current asset as production inputs. We uncover a novel asset imbalance channel which creates negative comovement between current and long-term asset growths that are unrelated to discount rate. This comovement is muted in the total asset growth, giving rise to its stronger return prediction. Once controlling for this comovement, the return predictive power of current and long-term asset growths substantially improves. Furthermore, we document strong evidences for the model's prediction that the asset growth effects are more prominent among firms with low asset imbalance. Our results support the q theory based explanation for the asset growth effect.

1 Introduction

The q theory of investment is the cornerstone of the investment-based asset pricing. One prediction of the theory is that lower cost of capital stimulates more investment, so current investment negatively predicts future stock returns.[1] Of all measures of investment, total asset growth in Cooper, Gulen, and Schill (2008) has probably received most attentions partly because of its stronger return predictive power than its components such as the long-term and current asset growths. Indeed, the investment factors in the recent multi-factor models in Fama and French (2015) and Hou, Xue, and Zhang (2015) are both based on the total asset growth. In justifying its use, Hou, Xue, and Zhang (2015) argue that the asset growth is the most comprehensive measure of investment-to-assets. However, it is unclear why a composite growth should predict returns better than its components.

In a nutshell, the stronger return predictive power of a variable than its components is consistent with the existence of a negatively correlated noise term that is unrelated to the expected return. As a simple example, consider a signal (think of it as a firm characteristic) Z which can be decomposed into signal X and signal Y, that is, Z = X +Y. Suppose both X and Y have an expected return component (R) and noise component (e) but with different signs on e, i.e., X = R + e and Y = R − e. Clearly, the existence of the noise lowers the informativeness about R of both X and Y, but e cancels out in Z, giving rise to the stronger return prediction of Z. In the context of the asset growth effect, the total asset growth is Z, whereas the current and long-term asset growths can be thought of as X and Y.

We show that a simple extension of the investment-based model in Kogan and Papanikolaou (2012) sheds light on the identity of this noise term. Unlike the conventional investment-based models that focus only on physical capital (or long-term asset), we assume a Cobb-Douglas production function that uses both long-term and current assets as production inputs. Firms choose investments in both types of assets to maximize firm value, subject to convex capital adjustment costs. The optimization conditions suggest that both current asset investment and long-term asset investment contain information about expected returns and expected profitability, with a lower expected returns and higher expected profitability associated with higher investments. More importantly, this extended model implies a third motivation for investment – asset imbalance. When the ratio of current asset to long-term asset (i.e., asset ratio) is higher than the steady state, a firm would reduce its current asset and expand its long-term asset. On the other hand, when the asset ratio is too low, the firm would liquidate its long-term asset for more current asset. The asset imbalance channel

[1] This prediction has been tested and confirmed empirically in the literature. Studies including Titman, Wei, and Xie (2004), Xing (2008) document that past investment rate or investment growth is indeed negatively associated with future returns.

has nothing to do with discount rate, but it generates a negative comovement in the current and long-term asset growths. This comovement therefore acts as the noise term discussed in the simple model that weakens the return predictive power of current and long-term asset growths.

We provide empirical evidences on this asset imbalance channel. First, controlling the ratio of current asset to long-term asset (or asset ratio) significantly improves the return predictive power of current and long-term asset growths. When we double sort stocks sequentially on their asset ratio and current (or long-term) asset growth, the conditional current (or long-term) asset growth premiums increases substantially from their unconditional premiums and are quantitatively similar to the total asset growth premium. Second, since cash flow news are more important than discount rate news at the firm level (Vuolteenaho (2002)), the cross-sectional variations of current and long-term asset growths are mostly driven by asset ratio and expected profitability. Therefore, controlling for current asset growth, the return predictive power of long-term asset growth should improve, and vice versa. Indeed, when we condition on current asset growth, the t-statistic of the long-term asset growth premium, which is closely related to its Sharpe ratio, increases in magnitude from -2.68 to -3.38. When we condition on long-term asset growth, the t-statistic of the current asset growth premium increases from -2.00 to -2.72. Third, we propose a measure of asset imbalance using the relative rankings of current and long-term asset growths in the cross section. All else being equal, when a firm invests similarly in current and long-term assets, its investment motive from asset imbalance is low, and current and long-term asset growths should be more informative about discount rate. Indeed, we find the premiums associated current, long-term, and total asset growths are substantially stronger among firms with low asset imbalance. In fact, the asset growth effect disappears among firms with highest asset imbalance. Finally, the imbalance channel is found to be pervasive in balance sheets. It also exists among components of current assets and between debt and equity.

We would like to point out that although our finding supports the q theory of investment, it does not differentiate the sources of the asset growth effect. Specifically, this premium can be consistent with both risk-based and behavioral explanations. On the risk side, firms with high asset growth have lower expected returns because they are less risky, and changes in investment and risk premiums can be simultaneously driven by exogenous shocks such as productivity shocks or project arrivals. In contrast, a plausible behavioral explanation posits that investors overreact to firms' investment behaviors so that stocks with high asset growths are overvalued and systematically have lower subsequent stock returns. Studies including Li and Zhang (2010), Lam and Wei (2011), Lipson, Mortal, and Schill (2011), and Watanabe, Xu, Yao, and Yu (2013) find evidences for both types of explanations.

The paper belongs to the large literature on the investment-based asset pricing. Starting from Cochrane (1991), this literature has grown substantially from the perspective of both theory and empirics. On the theory side, Berk, Green, and Naik (1999), Gomes, Kogan, and Zhang (2003), Zhang (2005), Carlson, Fisher, and Giammarino (2004), among many others, have studied models with capital adjustment frictions to offer insights on the asset pricing phenomena including the value premium and size premium. More recently, Papanikolaou (2011), Kogan and Papanikolaou (2013), Kogan and Papanikolaou (2014) document that the investment-specific technology shock that affects the efficiency of new capital goods relative to old capital goods can capture a broader cross-sectional asset returns, including the value, q, investment, market beta, and idiosyncratic volatility premiums. Li (2017) offers an investment-based model for a joint explanation for momentum profits and the value premium. On the empirical side, Liu, Whited, and Zhang (2009), Liu and Zhang (2014), and Goncalves, Xue, and Zhang (2019) show that the optimization condition for firm's investment can capture many cross-sectional asset phenomena such as premiums associated with price and earnings momentum, valuation ratios, and investment.

Despite the major focus on the physical capital in earlier studies, recent papers pay more attention to other types of assets. Prominent examples include: organizational capital (Eisfeldt and Papanikolaou (2013)), real estate (Tuzel (2010)), intangible capital (Lin (2012), Ai, Croce, and Li (2013), Belo, Lin, and Vitorino (2014), Kung and Schmid (2015)), inventories (Belo and Lin (2012), Jones and Tuzel (2013)), and a large line of research on labor or human capital (e.g., Belo, Lin, and Bazdresch (2014), Belo, Li, Lin, and Zhao (2017)). Cooper, Gulen, and Ion (2017) critique the wide usage of asset growth to measure investment. They argue that the q theory is more suitable for physical capital, i.e., long-term asset growth, whereas empirically investment factors based on long-term and current asset growths have much weaker performances than the investment factor based on total asset growth. We highlight a novel asset imbalance channel that creates an investment incentive among different types of assets and lowers the information about discount rate in current and long-term asset growths. Our results therefore provide a defense for the use the asset growth in the investment factors.

The paper proceeds as follows. In Section 2, we introduce the two-capital investment-based model to elucidate the intuition of the asset imbalance channel. We use the model to develop the hypotheses for empirical analyses in subsequent sections. In Section 3, we describe data sources and variable constructions, and replicate the finding that total asset growth subsumes current and long-term asset growths in stock return predictions. We provide empirical evidences for the asset imbalance channel and its impact on the relative return predictive powers of total asset growth and its components in Section 4. Section 5 concludes.

2 A q-theory model with two production inputs

Consider a dynamic investment-based asset pricing model based on Kogan and Papanikolaou (2012). We extend their model by having both long-term asset (K) and current asset (W) as production inputs. Long-term asset includes property, plant, and equipment and is generally considered as the physical capital. Current asset, which is usually ignored in the investment-based asset pricing literature, includes cash, account receivables, and inventory. The sum of long-term asset (K) and current asset (W) is total asset (A).

The firm's production function is Cobb-Douglas with both long-term and current assets as inputs. The operating profit, D_t, is equal to $X_t K_t^{\alpha} W_t^{1-\alpha}$. At time t, firms choose investment in long-term asset (I_t) and investment in current asset (J_t) to maximize the firm value. Investment incurs capital adjustment costs. Following the q theory literature (e.g., Hayashi (1982)), we assume the capital adjustment costs are homogenous of degree one with respect to capital and investment. Specifically, increasing the long-term asset by I_t units costs $\phi(I_t/K_t)K_t$, and increasing the current asset by J_t units costs $\psi(J_t/W_t)W_t$, where $\phi(\cdot)$ and $\psi(\cdot)$ are convex functions that captures decreasing returns to scale in capital installation.

Given the stochastic discount factor M_{t+1}, firm's problem can be written recursively as

$$\begin{aligned} V(X_t, K_t, W_t) = \max_{I_t, J_t} D_t - &\phi(I_t/K_t)K_t - \psi(J_t/W_t)W_t + E_t[M_{t+1}V(X_{t+1}, K_{t+1}, W_{t+1})]\} \\ s.t.\ K_{t+1} &= (1-\delta_K)K_t + I_t \\ W_{t+1} &= (1-\delta_W)W_t + J_t, \end{aligned} \tag{1}$$

where $V(X_t, K_t, W_t)$ is the firm's cum-dividend value at time t, and δ_K and δ_W are the depreciation rates of long-term and current assets, respectively. The capital accumulation equations capture the law of motion for these two types of assets.

Taking the first-order condition with respect to I_t, we have

$$\phi'\left(\frac{I_t^*}{K_t}\right) = E_t\left[M_{t+1}\frac{\partial V(X_{t+1}, K_{t+1}, W_{t+1})}{\partial K_{t+1}}\right]. \tag{2}$$

The left-hand-side of the equation is the marginal cost of one additional unit of investment in long-term assets (i.e., marginal q_K), and the right-hand-side of the equation is its marginal benefit, i.e., the discounted marginal continuation value of long-term asset. The optimal condition states that firms invests until the marginal benefit and marginal cost are equal.

A similar condition can be found in current asset investment J_t:

$$\psi'\left(\frac{J_t^*}{W_t}\right) = E_t\left[M_{t+1}\frac{\partial V(X_{t+1}, K_{t+1}, W_{t+1})}{\partial W_{t+1}}\right] \tag{3}$$

Since both the production function and adjustment cost functions are homogenous of degree one, firm value V_t is also homogenous of degree one with respect to K_t and W_t:

$$V(X_{t+1}, K_{t+1}, W_{t+1}) = \frac{\partial V(X_{t+1}, K_{t+1}, W_{t+1})}{\partial K_{t+1}} K_{t+1} + \frac{\partial V(X_{t+1}, K_{t+1}, W_{t+1})}{\partial W_{t+1}} W_{t+1} \tag{4}$$

Combining Eq. 2, Eq.3, and Eq. 4, we have

$$\phi'\left(\frac{I_t^*}{K_t}\right) K_{t+1} + \psi'\left(\frac{J_t^*}{W_t}\right) W_{t+1} = E_t[M_{t+1}V_{t+1}] = P_t, \tag{5}$$

where P_t is the ex-dividend value of the firm at time t. Eq 5 can be used to decompose firm value. If we define $P_t^K = \phi'\left(\frac{I_t^*}{K_t}\right) K_{t+1}$ and $P_t^W = \psi'\left(\frac{J_t^*}{W_t}\right) W_{t+1}$, $P_t = P_t^K + P_t^W$, so P_t^K and P_t^W measure the value of long-term and current assets, respectively.

Now we apply the Campbell and Shiller (1988) decomposition to the log of the price-income ratio:

$$\ln \frac{P_t}{D_t} \approx \text{const.} + E_t\left[\sum_{j=1}^{\infty} \rho^{j-1}(\Delta \ln D_{t+j} - \ln R_{t+j})\right], \tag{6}$$

where R_t denotes the gross stock return, the constant ρ depends on the average price-income ratio. Together with Eq. 5, we establish a relation between the firm's investments in long-term and short-term assets and its expected profitability and stock returns:

$$\ln\left[\phi'\left(\frac{I_t^*}{K_t}\right) K_{t+1} + \psi'\left(\frac{J_t^*}{W_t}\right) W_{t+1}\right] \approx \text{const.} + E_t\left[\ln D_{t+1} + \sum_{j=1}^{\infty}(\rho^j \Delta \ln D_{t+j+1} - \rho^{j-1}\ln R_{t+j})\right]. \tag{7}$$

When we assume the convex adjustment cost specification in Jermann (1998),

$$\begin{aligned} \phi\left(\frac{I}{K}\right) &= \frac{a_K}{\lambda_K + 1}\left(\frac{I}{K}\right)^{\lambda_K + 1} \\ \psi\left(\frac{J}{W}\right) &= \frac{a_W}{\lambda_W + 1}\left(\frac{J}{W}\right)^{\lambda_W + 1}, \end{aligned} \tag{8}$$

where λ_K and λ_W are inversely related to the elasticity of investment rate with respect to the marginal value of capital, Eq. 7 can be written as:

$$\begin{aligned} &\ln\left[a_K\left(\frac{K_{t+1}}{A_{t+1}}\right)\exp(\lambda_k \cdot ik_t^*) + a_W\left(\frac{W_{t+1}}{A_{t+1}}\right)\exp(\lambda_w \cdot jw_t^*)\right] \\ &\approx \text{const.} + E_t\left[\ln\frac{D_{t+1}}{A_{t+1}} + \sum_{j=1}^{\infty}(\rho^j \Delta \ln D_{t+j+1} - \rho^{j-1}\ln R_{t+j})\right], \end{aligned} \tag{9}$$

where we have defined $ik_t^* = \log(I_t^*/K_t)$ and $jw_t^* = \log(J_t^*/W_t)$.

Taking the first-order Taylor expansion of the left hand side of Eq. 9 around $ik^* = 0$ and $jw^* = 0$, we have

$$\left(\frac{a_K\frac{K_{t+1}}{A_{t+1}}}{a_W\frac{W_{t+1}}{A_{t+1}} + a_K\frac{K_{t+1}}{A_{t+1}}}\right)\lambda_K \cdot ik_t^* + \left(\frac{a_W\frac{W_{t+1}}{A_{t+1}}}{a_W\frac{W_{t+1}}{A_{t+1}} + a_K\frac{K_{t+1}}{A_{t+1}}}\right)\lambda_W \cdot jw_t^*$$
$$\approx \text{const.} + E_t\left[\ln\frac{D_{t+1}}{A_{t+1}} + \sum_{j=1}^{\infty}(\rho^j \Delta \ln D_{t+j+1} - \rho^{j-1}\ln R_{t+j})\right], \tag{10}$$

which suggests that the weighted average of investment rates (scaled by adjustment cost coefficient λ) depends on the expected profitability and expected return. In the special case with only physical (long-term) capital, Eq. 10 reduces to Eq. (17) in Kogan and Papanikolaou (2012). Intuitively, *ceteris paribus*, a firm's investment is positively related to its expected profitability and negatively related to the expected returns.

In the general case with both long-term and current assets, the expected profitability and expected returns (discount rate) affect investment rates in both long-term and current assets, giving rise to positive comovement in long-term and current asset growths, as we discuss in the next section. More importantly, Eq. 10 shows that relative strength of investment rates in these two types of assets also depends on the ratio of current asset to long-term asset, each multiplied by its adjustment cost coefficient a. All else being equal, when a firm has low current asset relative to long-term asset, possibly from large physical capital expansion in the past, its long-term asset investment ik^* would be low (or even negative), but its current asset investment jw^* would be high. On the other hand, when the current asset is high relative to long-term asset, the subsequent long-term asset investment is likely to be high and current asset investment tends to fall. These investments have nothing to do with discount rate, but are solely due to the asset imbalance between the current and long-term assets from their steady state. This motivation creates negatively correlated investments in these two assets (i.e., the noise terms) that weaken the return predictive power of both current and long-term asset growths. Since investment in the total asset (total asset growth) is the weighted average of the investments in current and long-term assets, part of the noise terms cancels out, so the total asset growth contains better information about discount rate than its two components.

Our discussions above have three immediate predictions on the investment-expected return relation, which are the three hypotheses in our empirical analysis. The first hypothesis is directly related to Eq. 10. If the ratio of current asset to long-term asset affects asset growths but is unrelated to discount rate, the current and long-term asset growth premiums conditional on the asset ratio should be stronger than the unconditional current and long-term asset growth premiums.

Hypothesis 1: Conditional on asset ratio, the return predictive power of both current and long-term asset growth improves.

The second hypothesis is closely related to the first hypothesis and is based on the finding of Vuolteenaho (2002) that cash flow news are more important than discount rate news for firm-level stock returns. If we extend this relative importance of cash flow news and discount rate news to explaining the firm-level investment, the majority of investment variations (both current and long-term asset growths) are driven by the interaction of expected profitability and asset imbalance. Therefore, double sorts on current and long-term asset growths can potentially improve the current and long-term asset growth premiums.

Hypothesis 2: Conditional on current asset growth, the long-term asset growth premium improves. Conditional on long-term asset growth, the current asset growth premium improves.

The last hypothesis is on the strength of the asset growth effects. If the asset imbalance channel is responsible for the relative return predictive power of total, current, and long-term asset growths, these asset growth effects should be stronger among firms with low asset imbalance than firms with high asset imbalance.

Hypothesis 3: The total, current, and long-term asset growth premiums are stronger among firms with low asset imbalance.

3 Asset growth effect

In this section, we replicate the asset growth effect and compare the return predictive power of total asset growth with its two components, the current and long-term asset growths. In Section 3.1, we describe the data sources and variable constructions. In Section 3.2, we confirm the total asset growth effect in our extended sample period from 1968 to 2019. Section 3.3 examines the return predictive power of current and long-term asset growths. We also do horse races between total asset growth and its two components, and confirm the finding that current and long-term asset growths are subsumed by total asset growth in return predictions.

3.1 Data

The data used in our analyses are standard in the asset pricing literature and come from several sources. The stock data are from the monthly database at the Center for Research in Security Prices (CRSP), the accounting data are from the Compustat Annually database, and the Fama and French factors are from the Fama/French data library. The benchmark sample includes all NYSE/AMEX/NASDAQ common stocks (with a share code SHRCD of 10 or 11, excluding financial stocks) from July 1968 to December 2019.

Our main variables of interest are the annual total asset growth rate (TAG), current asset growth (CAG), and long-term asset growth (LAG). Following Cooper, Gulen, and Schill (2008), we define TAG as the year-on-year percentage change in total asset growth (Compustat data item AT): $\text{TAG}_t = (\text{AT}_{t-1} - \text{AT}_{t-2})/\text{AT}_{t-2}$. We define CAG and LAG in a similar way, where the current asset is measured by the Compustat data item ACT and the long-term asset is measured by the difference between total asset and current asset. Other firm characteristics are defined following the existing literature. Book-to-market ratio (BM) is the book value of equity divided by market value at the end of last fiscal year. Firm size is measured by the market equity in million dollars at the end of previous June. Momentum is the prior 2-12 month cumulative returns. Long-term stock returns, r(13-60), is the prior 13-60 month cumulative returns. Following Novy-Marx (2013), the gross profitability (GP/A) is defined as gross profits (Compustat item REVT minus COGS) divided by total asset.

3.2 Asset growth premium

We first confirm the asset growth effect in our sample. At the end of June of each year t, we sort stocks into quintiles based on the total asset growth (TAG) of the fiscal year ending at t-1, with the quintile 5 (1) including firms with the highest (lowest) total asset growth. The portfolios are held from July of year t to June of year t+1 and rebalanced every year. Panel A of Table 1 reports the characteristics of these TAG portfolios, and several interesting observations emerge. First, there is a large cross-sectional difference in total asset growth, with TAG varying from -9% in the low TAG quintile to 34% in the high TAG quintile. Second, since total asset growth is the weighted average of current and long-term asset growths, the TAG sort also creates a monotonic pattern in LAG and CAG. The difference in LAG (CAG) between high and low TAG quintiles are 0.42 and 0.45, respectively. Third, stocks with high TAG are more like growth firms (low book-to-market ratio, or BM) and long-term winners (high prior 13-60 month stock returns), and stocks with low TAG tend to be value firms (high BM) and long-term losers. This is consistent with the finding in Fama and French (2015) and Hou, Xue, and Zhang (2015) that the value premium and long-term contrarian effect become insignificant after controlling for their investment factors. On the other hand, the relations between TAG and firm size, momentum, and gross profitability are weaker and non-monotonic. Compared to stocks with high total asset growths, low TAG stocks tend to be smaller measured from their market values.

[Insert Table 1 here]

In Panel B of Table 1, we report the mean, standard deviation, Sharpe ratio of the monthly value-weighted excess returns of TAG quintiles, as well as the results from the asset pricing tests, including the capital asset pricing model (CAPM), and the Fama and French three-factor model tests. The average excess return of the low TAG stocks is 0.78% per month, higher than the average excess return of 0.40% for the high TAG stocks. Their difference of −0.38% per month is about three standard deviations from zero with a monthly Sharpe ratio of −0.11 (or equivalently, an annual Sharpe ratio of −0.39). CAPM does not explain the TAG premium. In fact, the market exposure is higher for high TAG stocks than low TAG stocks, generating a CAPM alpha of even larger at −0.52% per month for the long-short portfolio. Including the size premium factor small-minus-big (SMB) and value premium factor high-minus-low (HML) weakens abnormal return of the TAG premium. Given the strong cross-sectional relation between TAG and BM reported in Panel A, the HML beta of the long-short portfolio is particularly strong at −0.72 with a t-statistic of −16.56. However, the three-factor alpha of TAG premium remains significant at −0.22% per month.

3.3 Long-term and current asset growth premiums

In this subsection, we examine the return predictive power of long-term and current asset growths and compare their performances with that of the total asset growth.

Panel A of Table 2 and Table 3 report the characteristics of long-term asset growth and current asset growth quintile portfolios, respectively. The total asset growth monotonically increases with both long-term and current asset growths, which is again expected as LAG and CAG are two components of total asset growth. Current (long-term) asset growth also increases with long-term (current) asset growth, with a difference of 14% (12%) between high and low LAG (CAG) stocks. This positive comovement reflects common responses of current and long-term assets to both cash flow news and discount rate news. As illustrated in Eq. 10, a positive shock to the expected profitability or a negative shock to the discount rate induces more investment in both long-term and current assets. In the meanwhile, the correlation is far from being perfect. For instance, the 14% CAG spread in the LAG sort is less than a quarter of the 59% CAG spread from the CAG sort. Ignoring measurement errors, this low positive correlation can be driven by the negative comovement between current and long-term asset growths from the asset imbalance motive discussed in Section 2. Table 2 and Table 3 also show that other characteristics of LAG and CAG portfolios share similar features as those in TAG portfolios, with high LAG and CAG stocks having lower BM ratios and better long-term past stock performance than low LAG and CAG stocks.

[Insert Table 2 Here]

[Insert Table 3 Here]

In Panel B of Table 2 and Table 3, we report the properties of excess returns of the LAG and CAG portfolios and the asset pricing tests results. The LAG premium is -0.35% per month with a Sharpe ratio of -0.11, and the CAG premium is -0.25% per month with a Sharpe ratio of -0.08. Controlling for the market factor tends to increase the performance of LAG and CAG premiums. The CAPM alpha is -0.44% for the LAG premium and -0.38% for the CAG premium. However, due to the large negative correlations with the HML factor, neither of the Fama and French three-factor model alphas for the LAG and CAG premiums are statistically significant at the 5% level. The abnormal return of the three-factor model becomes only -0.20% for the LAG premium and -0.14% for the CAG premium, representing reductions of more than 50% from the corresponding CAPM alphas.

To formally run the horse races between TAG and CAG (and LAG) in return predictions, we use double sorted portfolios. In Panel A.1 of Table 4., we create 5-by-5 portfolios sequentially sorted on TAG and then on LAG and report the LAG premium within each TAG quintile, as well as their average across TAG quintiles. The latter can be interpreted as the LAG premium conditional on TAG. Panel A.1 shows that controlling for TAG, the LAG premium is only statistically significant in the high TAG quintile, and is positive in the two lowest TAG quintiles. The conditional LAG premium is -0.10% per month (t-statistic $= -1.07$) and much smaller than the unconditional LAG premium of -0.35% per month in Table 2. When we switch the order of sorts in Panel A.2, the TAG premium is also only significant in high LAG quintile, possibly because of the strong LAG premium and correlation between TAG and LAG. However, the conditional TAG premium is -0.22% per month and more than two standard deviations from zero. Therefore, although both LAG and TAG strongly predict returns in the univariate sorts, the predictive power of LAG is dominated by TAG in this horse race. Similar results can be found in the double sorts on TAG and CAG. Controlling for TAG, the average CAG premium is statistically insignificant at only -0.06% per month. In contrast, the conditional TAG premium controlling for CAG remains strong at -0.29% per month with a t-statistic of -2.76.

[Insert Table 4 Here]

As a robustness check, we run Fama and MacBeth (1973) regressions of monthly stock returns on TAG, LAG, and CAG, along with other firm characteristics including book-to-market ratio, momentum, and gross profitability. In the first stage, we run cross-sectional return predictive regressions at each month, and in the second stage, we calculate the time-series average of the coefficients from the first-stage estimation as our coefficient estimates. The results are reported in Table 5. Specifications 1-6 are for the univariate regressions separately on each of these predictive variables. All three asset growths negatively and strongly predict future stock returns. The estimated coefficients are -0.48, -0.29, and -0.21 for TAG, CAG, and LAG, respectively, and all three coefficients have a t-statistic above 4 in absolute value. Book-to-market ratio, momentum, and gross profitability are positive return predictors, consistent with the findings from the literature. Specification 7 is a direct horse race between TAG, LAG, and CAG. When these three asset growths are included in the same specification, all coefficients have been weakened compared with those from univariate regressions. While the coefficient on TAG remains significant at -0.48 (t-statistic $= -4.37$), CAG and LAG have lost their return predictive power. The result is similar when we control for book-to-market, momentum, and gross profitability in Specification 8.

[Insert Table 5 Here]

To summarize, we confirm the finding in Cooper, Gulen, and Schill (2008) that while total, long-term, and current asset growth all negatively predict future stock returns, the total asset growth has the strongest predictive power. When we run horse races among these asset growths, the performances of long-term and current asset growths are subsumed by the total asset growth.

4 The asset imbalance channel

In the previous section, our empirical analyses show that the total asset growth performs better than long-term and current asset growths in stock return predictions. The investment-based model in Section 2 offers an explanation: when both current and long-term assets are considered as production inputs, firm's optimal investment policy would include another motive for firm's investment in these two assets – asset imbalance. When a firm's asset ratio, defined as the ratio of current asset to long-term asset, is higher than the steady state, its future long-term asset growth is high and current asset growth is low. On the other hand, when asset ratio is low, the firm has incentive to reduce its long-term asset in exchange for more current asset. The resulting changes in asset growths are unrelated to the discount rate, and importantly, the long-term and current asset growths from this motive move in the opposite direction. Therefore, asset imbalance lowers the informativeness of both long-term and current asset growths about future returns. In this section, we substantiate this asset imbalance channel with empirical evidences.

4.1 Asset ratio

One central idea of the asset imbalance channel is that asset ratio can forecast future current and long-term asset growths. If this channel exists, the current-to-long-term asset ratio (AR) should forecast long-term asset growth positively and current asset growth negatively.

Prior studies have examined the determinants of holdings and investments in current assets. Opler, Pinkowitz, Stulz, and Williamson (1999), for instance, argue that corporate cash holdings tradeoff the costs of lower rate of returns and benefits related to transaction costs and precautionary savings. They document that firms with strong growth opportunities, riskier cash flows, and less access to the capital markets hold relatively high ratios of cash to total non-cash assets. They also find firms that do well tend to accumulate more cash than predicted by the static tradeoff model where managers maximize shareholder wealth. Similarly, Carpenter, Fazzari, and Petersen (1994) document that inventory investment is highly procylical at both aggregate level and firm level with respect to firm-level cash flows. Since inventory investment is more reversible and subject to less adjustment cost than fixed investment, firms can reduce inventory quickly, relaxing the short-run financing constraints on the fixed investment activities.

Panel A of Table 6 examines the relation between asset ratio and standard firm-level characteristics, including the book-to-market ratio (BM), prior 2-12 month returns (MOM), market value (Size), and gross profitability (GP/A) of AR quintiles in our sample. Firms with more current asset relative to long-term asset tend to be small growth firms with high gross profitability, whereas the relation between AR and momentum is weak. Panel B presents the prior 4-year change in total, long-term, current assets and debts, change in market equity, and cumulative stock returns of these AR quintiles. On the asset side of the balance sheet, the current (long-term) asset grows faster (slower) for high AR firms than low AR firms, but this pattern is mechanical because the quintiles are based on the current-to-long-term asset ratio. Interestingly, the total asset also tends to grow faster for high AR firms, which is consistent with the higher profitability of these firms. On the right-hand-side of the balance sheet, although the pattern in the prior stock returns across AR quintiles is weak, high AR firms tend to have a larger increase in market value, indicating more equity issuance of these firms. In contrast, while high AR stocks slightly reduce their outstanding debts during prior years, low AR stocks have substantially increased their debts.

[Insert Table 6 Here]

Table 7 tests how asset ratio predicts future asset growths. We regress CAG or LAG at the fiscal year ending at t on the logarithm of AR at the fiscal year ending at t-1, with the control for CAG and LAG at t-1. In Specifications 2 and 4, we also control for CAG and LAG at t-2. Table 7 shows that the coefficients on asset ratio are indeed negative in predicting future current asset growth and positive in predicting future long-term asset growth, all of which are statistically significant from zero at the 1% level. Based on the results in Specifications 2 and 4, a one standard deviation increase in log asset ratio is associated with a -3.06% reduction in subsequent current asset growth and 14.7% increase in subsequent long-term asset growth.[2] The lower predictability of CAG than LAG is consistent with the notion that the adjustment cost is substantially higher for long-term asset than current asset (Carpenter, Fazzari, and Petersen (1994)). Interestingly, controlling for the asset ratio, the autoregressive coefficients of CAG and LAG are relatively weak. For instance, in Specification 2, the coefficient on CAG(t-1) is actually negative, and coefficient on CAG(t-2) is positive with a t-statistic of slightly greater than 2. Similarly, neither of the coefficients on LAG(t-1) and LAG(t-2) are statistically significant in Specification 4 in forecasting future LAG. However, we notice strong cross-predictions between current and long-term asset growths. In Specification 2, the forecasting power of LAG(t-1) and LAG(t-2) for future CAG is much greater than that of prior CAGs, and in Specification 4, the coefficients of CAG(t-1) and CAG(t-2) in predicting LAG at year t are more than 10 standard deviations from zero. One plausible explanation for this cross prediction is that when a firm accumulates a lot of cash (an important component of current asset) due to either superb past operations or external financing, it tends to use the money to purchase long-term capital. In turn, when a company depleted its current asset for long-term capital, it has the incentive to rebuild the current asset for precautionary savings.[3]

[Insert Table 7 Here]

4.2 Double sorts on asset ratio and asset growths

Hypothesis 1 states that the return predictive power of current and long-term asset growths should be enhanced after controlling for asset ratio, since the asset imbalance channel is

[2]These estimates are based on the average standard deviation of logAR of 1.32 in our sample.
[3]See, for example, Opler, Pinkowitz, Stulz, and Williamson (1999) and Bates, Kahle, and Stulz (2009).

unrelated to the discount rate. To test this hypothesis, we form 5-by-5 portfolios sequentially double sorted on asset ratio and CAG (and LAG). Table 8 reports the LAG premiums (Panel A) and CAG premiums (Panel B) within each AR quintile, as well as their averages across AR quintiles. As a comparison, we also report the unconditional LAG and CAG premiums from one-way sorts. Panel A shows that the LAG premium ranges from -0.32% per month in the AR quintile 3 to -0.39% per month in the AR quintile 1. The LAG premiums are statistically significant in three out of the five AR quintiles, and the average LAG premium across quintiles is -0.36% per month. This conditional LAG premium is comparable to the unconditional premium of -0.35% per month, but the t-statistic of the LAG premium, which is directly related to its Sharpe ratio, increases from -2.68 to -3.12. Therefore, conditional on asset ratio, we observe a substantial improvement in the long-term asset growth premium.

[Insert Table 8 Here]

Panel B of Table 8 reports the results for the double sorts on asset ratio and current asset growth. The CAG premium is negative and statistically significant in the AR quintiles 2, 3, and 5, and is marginally significant in the quintile 4. The conditional CAG premium averaging across AR quintiles is -0.38% per month, higher in magnitude than the unconditional CAG premium of -0.25% per month. The corresponding t-statistic increases by 60%.

Interestingly, the total asset growth premium also improves controlling for asset ratio. In Panel C of Table 8, we form double-sorted portfolios based on asset ratio and total asset growth. Conditional on AR, the TAG premium increases to -0.42% per month (t-statistic $= -3.17$) from the -0.38% (t-statistic $= -2.56$) unconditional TAG premium. This finding suggests that although the total asset growth, the weighted average of current and long-term asset growths, is less influenced by the asset imbalance channel, it is not completely isolated from it. In Section 4.5, we further exploit this pattern and examine the asset growth effects among firms with small and large asset imbalance.

Our results in this subsection confirm Hypothesis 1 that the return predictive power of current and long-term asset growths improves conditioning on asset ratio, and hence provides support for the asset imbalance channel in our investment-based model.

4.3 Double sorts on CAG and LAG

Although current and long-term asset growths predict future stock returns, the information content of these asset growths about discount rate remains low, especially at the firm level. For instance, Vuolteenaho (2002) shows that unlike the dominant role of discount rate news for the stock market return, cash flow news are much more important for firm-level stock returns. Extending this argument to investment, we expect both CAG and LAG are more informative about the firm-level expected profitability and asset ratio than discount rate. This implies that when we control for CAG (LAG) when examining the LAG (CAG) premium, we are more likely to have controlled for expected profitability and asset ratio, so double sorts on LAG and CAG should improve both LAG and CAG premiums.

Table 9 reports the results on the double sorts on LAG and CAG. In Panel A, the average LAG premiums from low to high CAG quintiles are −0.54%, −0.12%, −0.21%, −0.23%, and −0.74% per month, respectively, and the average conditional LAG premium is −0.37% per month. Although the economic magnitude of this conditional premium is only slightly larger than −0.35% for the unconditional LAG premium, the t-statistic and hence the corresponding Sharpe ratio increases by 30%. Similarly in Panel B, the CAG premium conditional on LAG is −0.26% per month, and the t-statistic is 36% higher than that for the unconditional CAG premium. Therefore, we provide empirical evidences for Hypothesis 2 that controlling for CAG and LAG would enhance the performance of the LAG and LAG premiums, respectively.

[Insert Table 9 Here]

4.4 A measure of asset imbalance

The two-capital investment-based model has another prediction on the asset growth effects. Among all stocks, asset growths (long-term, current, and total) in firms with low asset imbalance should contain better information about discount rate than in firms with high asset imbalance. As such, we expect the asset growth premiums to be stronger for low asset imbalance stocks (Hypothesis 3). In this section, we propose a direct measure of asset imbalance (AIB) and study its effect on the asset growth premiums.

Our measure of asset imbalance is simple to construct and economically intuitive. It is based on the relative rankings of current asset growth and long-term asset growth. Presumably, if the current and long-term asset growths move in the same direction, the asset imbalance is likely to be low. In contrast, if a stock has a large increase in long-term asset but a big reduction in the current asset, it is likely that its asset imbalance is high. Following this argument, we assign two indices from 1 to 10 to each stock, one based on the one-way sorts on current asset growth and the other one based on one-way sorts on long-term asset growth. AIB is then defined as the absolute value of the difference between these two indices. For instance, at some point in time, if a firm has a large CAG and the first index of 10, and in the meanwhile, the firm has a small LAG with the second index of 2, then AIB of the firm is $|10 - 2| = 8$, indicating that its current and long-term assets are rather imbalanced.

With this AIB measure, we form 5-by-5 portfolios sequentially double-sorted on AIB and asset growths (TAG, LAG, and CAG) compare the patterns of average stocks returns across these AIB quintiles. The results are reported in Table 10.

[Insert Table 10 Here]

Panel A of Table 10 reports the long-term asset growth premium within each AIB quintile. In line with Hypothesis 3, there is a strong decreasing trend in the LAG premium from low to high AIB quintiles. The LAG premium is -1.02% per month (t-statistic $= -3.96$) among firms with lowest asset imbalance, and it shrinks to only -0.06% per month among firms with highest asset imbalance. The last row of Panel A reports the LAG spread, the difference in LAG between high and low LAG quintiles, for each AIB quintile. Unlike the pattern for the LAG premium, the LAG spread displays a U shape across AIB quintiles. It is highest for the lowest AIB quintile (2.20) and lowest for the AIB quintile 3 (0.44), whereas the LAG spread is the second highest for firms with the highest asset imbalance (AIB5). These findings suggest that the difference in the LAG premium across AIB quintiles is unlikely to be driven by the difference in the LAG spread.

We find very similar results for the CAG premium (Panel B) and TAG premium (Panel C). The CAG premium is highest at -1.05% per month among lowest AIB stocks and becomes positive but small at 0.14% per month among stocks with highest AIB. Similarly, the TAG premium is -1.09% per month in the lowest AIB quintile (AIB1), as compared to only -0.05% in the highest AIB quintile (AIB5). Again, the CAG spread and TAG spread are unlikely to explain the difference in these premiums across AIB quintiles because neither asset growth spreads is monotonic with asset imbalance.

To further alleviate the concern that the stronger asset growth premiums based on total, current, and long-term asset growths within the lowest asset imbalance quintile may be simply due to the larger asset growth spreads in those firms, we repeat the Fama and MacBeth regressions in the first three specifications of Table 5 separately for stocks within the lowest 20% AIB percentiles, middle 20%-80% AIB percentiles, and top 20% AIB percentiles, as reported in Panels A, B, and C of Table 11, respectively. The point estimate for the coefficient of TAG is -0.48 for stocks in the bottom 20% AIB percentiles (Panel A), slightly smaller than -0.58 for stocks within 20%-80% AIB percentiles (Panel B), but significantly larger than those in the top 20% AIB percentiles (Panel C). More importantly, the $t-$statistic of these point estimates is strongest for low AIB stocks and weakest for high AIB stocks, indicating that TAG contains the best information about about expected returns when the asset imbalance is the smallest (low AIB). The results are even stronger for CAG and LAG.

In Specifications 2 and 3, both the point estimate and t-statistic decreases monotonically from Panel A to Panel C.

[Insert Table 11 Here]

As a measure of noisiness of the information contained in asset growths about discount rate, our asset imbalance measure (AIB) can be used to understand why total asset growth has a stronger return predictive power than current and long-term asset growths. In the investment-based model in Section 2, our interpretation is that since 1) the asset imbalance channel induces a negative comovement between current and long-term asset growths, and 2) the total asset growth is a weighted average of current and long-term asset growths, part of the asset growth movements due to asset imbalance can be cancelled out in the total asset growth. If this mechanism is true, we expect our asset imbalance measure (AIB) to be lower in the extreme (highest and lowest) TAG portfolios than the extreme CAG and LAG portfolios from which the asset growth premiums are mainly derived.

Table 12 reports the average AIB for the quintile portfolios sorted by long-term asset growth (Panel A), current asset growth (Panel B), and total asset growth (Panel C). The pattern in asset imbalance displays a U shape across both LAG and CAG quintiles. The average AIB reduces from 3.14 in the low LAG quintile to 2.10 in the 3rd LAG quintile, and then increases to 2.86 in the high LAG quintile. Similarly, the two CAG quintiles with highest AIB are CAG1 and CAG5, with an average AIB of 3.40 and 2.68, respectively, whereas the quintile with lowest AIB is CAG3. In contrast, the average AIB across total asset growth quintiles is hump-shaped (Panel C). The average AIB is 2.30 in the lowest TAG quintile and 2.17 for the highest TAG quintile, both of which are lower than those for the extreme LAG and CAG quintiles. These findings suggest that total asset growth is less "contaminated" by the asset imbalance channel than current and long-term asset growths, giving rise to its strongest return predictive power among the three asset growths.

[Insert Table 12 Here]

To conclude this subsection, we find asset growth premiums are substantially stronger among stocks with low asset imbalance, providing empirical evidences for Hypothesis 3. Based on our investment-based explanation, these stocks have weakest movement in current and long-term assets growths that is due to asset imbalance, and therefore, their asset growths are more informative about discount rate than stocks with high asset imbalance.

4.5 Asset imbalance effect in other parts of balance sheets

In the investment-based model in Section 2, we separate production inputs into two broad categories: current asset and long-term asset. In practice, various components of current assets may have different properties. While firms keep cash to alleviate concerns of possible future financial constraints for a precautionary saving purpose (e.g., Opler, Pinkowitz, Stulz, and Williamson (1999)), by extending sales credits to customers, account receivables can substantially improve a firm's revenues. On the other hand, inventories of raw materials and finished goods have been explicitly used in the literature as a production factor (e.g., Ramey (1989), Belo and Lin (2012)). In this subsection, we decompose current asset growth into cash growth (CASHG) and noncash asset growth (NOCASHG), with the latter being further decomposed into inventories growth (INVTG), receivables growth (RECTG), and other current asset growth (ACOG). We examine how these component growth rates predict stock returns relative to the current asset growth.

We run Fama and MacBeth (1973) return predictive regressions using the subsample of firms with non-missing current asset components, and the results are presented in Table 13. Specifications 1-4 compare the performances of current asset growth, cash growth, and non-cash growth. Since this sample is different from our benchmark sample, the return predictive power of current asset growth is slightly different from that in Table 5, with an estimated CAG coefficient of -0.44 (t-statistic = -6.77). Comparing the growth rates of cash and non-cash assets, non-cash asset growth is a much stronger return predictor, consistent with the finding in Cooper, Gulen, and Schill (2008). The coefficient on NOCASHG is -0.45 (t-statistic = -6.27), whereas the coefficient on CASHG is only -0.02, although the latter is also statistically significant from zero. In Specification 4 where CAG, CASHG, and NOCASHG are all included, the coefficient on CAG is the strongest among the three, and the coefficient on CASHG turns positive. Specifications 5-8 report the results for the three components of non-cash asset. Although all three components strongly predict future stock returns in univariate regressions, they lose predictive powers in their horse race with NOCASHG in Specification 8. In contrast, NOCASHG remains the strongest return predictor, with an t-statistic of -3.76 on the estimated coefficient. In Specification 9, we include all six variables, and again, we find the current asset growth, the growth rate of all current assets, has the strongest return predictive power.

[Insert Table 13 Here]

The result in Table 13 is interesting because it indicates that the asset imbalance channel exists beyond current and long-term assets. This makes sense because there are indeed many ways in which current assets can change from one form to another. For instance, when a firm sells its products from inventory, it may increases its account receivables while lowering inventories. Months later when the firm collects its account receivable from the customers, it raises cash holdings and lowers account receivables. These conversions among components of current assets are unlikely to be strongly related to the discount rate, but they would reduce the return predictive power of the growth rates of these current asset components.

Lastly, we study if the imbalance effect extends to the right hand side of the balance sheets. While there are substantive empirical evidences that both equity and debt issuance predict stock returns,[4] there are reasons to expect an imbalance effect between debt and equity. According to the trade-off theory of capital structure (e.g., Kraus and Litzenberger (1973), the optimal leverage reflects a trade-off between the tax benefits of debt and the deadweight costs of bankruptcy, so that leverage exhibits target adjustment so that deviation from the target are gradually eliminated (Myers (1984)). Indeed, Lemmon, Roberts, and Zender (2008) empirically document that leverage ratio is highly persistent and mean-reverting. Another, maybe more related motivation is from Whited and Zhao (2019). Whited and Zhao (2019) model the real benefit of a firm's finance to be a constant elasticity of substitution (CES) function of its debt and equity and consider this benefit would ultimately be reflected in its value added. If we replace the long-term and current assets with debt and equity in the production function in Section 2, we would see the imbalance effect also exists between equity and debt.

We confirm this conjecture in Table 14. As in Table 5, we run Fama and MacBeth (1973) regressions of monthly stock returns on total asset growth (TAG), book equity growth (BEG), and debt growth (DEBTG), and other firm characteristics including book-to-market ratio, momentum, and gross profitability. Specifications 1-6 are for the univariate regressions and Specifications 7-8 are for the horse races between TAG, DEBTG, and BEG. Confirming the findings in the literature, both debt and equity growths negatively predict future stock returns, with the t-statistics of the estimated coefficient being greater than 3 in absolute value for both variables. However, when we include TAG, BEG, and DEBTG in the same regression in Specification 7, the coefficients on BEG and DEBTG turn positive, whereas the coefficient on TAG becomes even stronger. The results are almost the same when we control for other firm characteristics in Specification 8.

[Insert Table 14 Here]

Taken together, the results in this subsection suggest that although we mainly focus on

[4] For instance, Richardson and Sloan (2003) show that debt and equity issuances are part of a larger net external financing effect. Pontiff and Woodgate (2008) find that seasoned equity offerings, repurchases, and merger effects are part of a broader growth in shares effect. Daniel and Titman (2006) document a negative relation between composite share issuance and future returns.

the imbalance effect between long-term and current assets, this channel appears to be quite broad and exists in components of current asset, components of non-cash asset, as well as debt and equity on the right hand side of the balance sheets.

5 Conclusion

In this paper, we provide a simple explanation for the weaker return predictive power of long-term and current asset growths than total asset growth. We extend the conventional one-capital framework with only physical capital (long-term asset) into a two-capital setup in which both long-term and current assets are used as production inputs. The optimization conditions imply a novel asset imbalance channel that induces a negative comovement between current and long-term asset growths and is unrelated to the discount rate effect. This asset imbalance channel weakens the return predictive power of long-term and current asset growths, but the total asset growth, which is the weighted average of long-term and current asset growths, is relatively less affected by construction and hence contains better information about discount rate. Our empirical analyses find compelling evidences for this asset imbalance effect. Overall, our findings support the q theory based explanation for the asset growth effect and provide a defense for the use of asset growth in the investment factors in the recent linear factor models.

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Table 1: The asset growth premium

This table reports the average firm characteristics in Panel A and the value-weighted average excess returns (Ret^e), standard deviation (Std), Sharpe ratio (SR) as well as the results of asset pricing tests for total asset growth (TAG) portfolios in Panel B. At the end of June of each year t, stocks are allocated into quintiles based on total asset growth, which is defined as the percentage change in total assets (Compustat data item AT) from the fiscal year ending in calendar year t-2 to fiscal year ending in calendar year t-1. LAG and CAG represent the percentage change in long-term assets (Compustat item AT minus ACT) and current assets (Compustat item ACT) from the fiscal year ending in calendar year t-2 to fiscal year ending in calendar year t-1, respectively. BM is the book value of equity divided by market value at the end of last fiscal year. Size is market equity in million dollars. MOM is the prior 2-12 month cumulative returns, r(13-60) is the prior 13-60 month cumulative returns. Gross profitability (GP/A) is defined as gross profits (Compustat item REVT minus COGS) divided by total assets. The abnormal returns are monthly and reported in percentages. t-statistics in parentheses are calculated based on the heteroskedasticity-consistent stand errors of Newey and West. The sample includes NYSE/AMEX/NASDAQ common stocks (excluding financial stocks) from July 1968 to December 2019.

Panel A: Characteristics of TAG portfolios

	Lo	2	3	4	Hi	Hi-Lo
TAG	-0.09	0.01	0.07	0.14	0.34	0.44
LAG	-0.08	0.01	0.06	0.13	0.35	0.42
CAG	-0.11	0.01	0.08	0.15	0.34	0.45
BM	0.94	0.87	0.75	0.63	0.51	-0.44
Size	121.31	411.99	591.61	628.67	452.59	331.29
MOM	0.08	0.10	0.10	0.09	0.05	-0.03
r(13-60)	-0.04	0.38	0.60	0.81	1.07	1.11
GP/A	0.30	0.32	0.34	0.37	0.34	0.04

Panel B: TAG portfolio returns and asset pricing tests

	Lo	2	3	4	Hi	Hi-Lo
Ret^e	0.78	0.63	0.57	0.54	0.40	-0.38
	(3.77)	(3.94)	(3.30)	(2.58)	(1.56)	(-2.56)
Std	4.87	4.07	4.23	5.02	6.09	3.37
SR	0.16	0.16	0.13	0.11	0.07	-0.11
			CAPM			
α	0.26	0.18	0.09	-0.02	-0.26	-0.52
	(3.05)	(3.32)	(1.91)	(-0.28)	(-2.59)	(-3.59)
MKT	1.00	0.86	0.91	1.06	1.26	0.26
	(39.27)	(53.15)	(60.75)	(51.1)	(45.57)	(6.13)
$R^2(\%)$	84.93	90.19	93.15	89.56	86.77	12.29
			Fama-French three-factor Model			
α	0.16	0.13	0.06	0.10	-0.07	-0.22
	(2.09)	(2.58)	(1.54)	(1.72)	(-0.97)	(-2.18)
MKT	1.00	0.89	0.95	1.01	1.14	0.14
	(49.42)	(58.01)	(83.6)	(66.6)	(48.08)	(4.58)
SMB	0.18	-0.06	-0.13	-0.01	0.19	0.00
	(5.17)	(-2.52)	(-8.31)	(-0.60)	(5.25)	(0.08)
HML	0.25	0.13	0.07	-0.30	-0.47	-0.72
	(6.97)	(4.68)	(2.28)	(-11.51)	(-15.4)	(-16.56)
$R^2(\%)$	87.74	91.29	94.20	92.30	92.63	47.51

Table 2: Long-term asset growth premium

This table presents the characteristics and average returns of long-term asset growth (LAG) portfolios. At the end of June of each year, firms are allocated into quintiles based on LAG. Panel A reports the average firm characteristics, and Panel B reports the value-weighted average excess returns (Ret^e), standard deviation (Std), Sharpe ratio (SR), and asset pricing test results of the LAG portfolios. The abnormal returns are monthly and reported in percentages. t-statistics in parentheses are calculated based on the heteroskedasticity-consistent stand errors of Newey and West. The sample includes NYSE/AMEX/NASDAQ common stocks (excluding financial stocks) from July 1968 to December 2019.

Panel A: Characteristics of LAG portfolios

	Lo	2	3	4	Hi	Hi-Lo
TAG	-0.06	0.02	0.06	0.12	0.29	0.34
LAG	-0.12	0.00	0.06	0.15	0.45	0.57
CAG	0.01	0.05	0.07	0.09	0.15	0.14
BM	0.88	0.84	0.75	0.65	0.55	-0.33
Size	113.40	384.88	707.55	680.47	390.83	277.43
MOM	0.09	0.10	0.10	0.08	0.05	-0.04
r(13-60)	0.04	0.40	0.61	0.75	0.89	0.85
GP/A	0.34	0.33	0.32	0.35	0.35	0.01

Panel B: LAG portfolio returns and asset pricing tests

	Lo	2	3	4	Hi	Hi-Lo
Ret^e	0.79	0.67	0.59	0.49	0.44	-0.35
	(3.64)	(4.03)	(3.59)	(2.34)	(1.72)	(-2.68)
Std	5.15	4.17	4.10	4.95	5.99	3.14
SR	0.15	0.16	0.14	0.10	0.07	-0.11
			CAPM			
α	0.23	0.21	0.13	-0.07	-0.21	-0.44
	(2.81)	(3.64)	(2.91)	(-0.99)	(-2.15)	(-3.36)
MKT	1.06	0.88	0.88	1.05	1.23	0.17
	(36.08)	(51.30)	(61.45)	(61.97)	(40.98)	(3.70)
$R^2(\%)$	85.82	89.36	92.47	90.88	86.02	6.03
			Fama-French three-factor Model			
α	0.18	0.16	0.12	0.03	-0.02	-0.20
	(2.28)	(2.89)	(2.99)	(0.41)	(-0.25)	(-1.90)
MKT	1.04	0.91	0.90	1.00	1.12	0.08
	(38.95)	(60.52)	(70.00)	(63.37)	(45.58)	(2.23)
SMB	0.20	-0.06	-0.12	0.03	0.16	-0.04
	(5.33)	(-2.00)	(-5.63)	(1.11)	(5.27)	(-0.93)
HML	0.12	0.12	0.02	-0.23	-0.48	-0.60
	(2.28)	(3.77)	(0.78)	(-7.63)	(-13.05)	(-8.57)
$R^2(\%)$	87.31	90.29	93.18	92.60	92.04	33.82

Table 3: Current asset growth premium

This table presents the characteristics and average returns of current asset growth (CAG) portfolios. At the end of June of each year, firms are allocated into quintiles based on CAG. Panel A reports the average firm characteristics, and Panel B reports the value-weighted average excess returns (Ret^e), standard deviation (Std), Sharpe ratio (SR), and asset pricing test results of the CAG portfolios. The abnormal returns are monthly and reported in percentages. t-statistics in parentheses are calculated based on the heteroskedasticity-consistent stand errors of Newey and West. The sample includes NYSE/AMEX/NASDAQ common stocks (excluding financial stocks) from July 1968 to December 2019.

Panel A: Characteristics of CAG portfolios

	Lo	2	3	4	Hi	Hi-Lo
TAG	-0.07	0.01	0.06	0.13	0.28	0.35
LAG	0.02	0.03	0.05	0.07	0.14	0.12
CAG	-0.16	-0.01	0.07	0.17	0.42	0.59
BM	0.87	0.84	0.74	0.64	0.55	-0.32
Size	175.32	375.48	481.47	562.87	429.14	253.82
MOM	0.07	0.09	0.09	0.09	0.07	0.00
r(13-60)	0.11	0.38	0.56	0.76	0.92	0.82
GP/A	0.27	0.35	0.37	0.38	0.31	0.04

Panel B: CAG portfolio returns and asset pricing tests

	Lo	2	3	4	Hi	Hi-Lo
Ret^e	0.68	0.61	0.57	0.58	0.43	-0.25
	(3.71)	(3.51)	(3.27)	(3.01)	(1.88)	(-2.00)
Std	4.54	4.29	4.30	4.79	5.72	3.05
SR	0.15	0.14	0.13	0.12	0.08	-0.08
CAPM						
α	0.18	0.12	0.08	0.05	-0.19	-0.38
	(2.44)	(2.64)	(1.47)	(0.73)	(-2.09)	(-2.99)
MKT	0.94	0.92	0.92	1.01	1.19	0.25
	(45.36)	(78.24)	(48.14)	(55.03)	(46.96)	(7.03)
R^2(%)	86.07	92.21	91.93	90.47	86.94	13.47
Fama-French three-factor Model						
α	0.10	0.10	0.08	0.15	-0.04	-0.14
	(1.50)	(2.06)	(1.65)	(2.75)	(-0.55)	(-1.43)
MKT	0.94	0.93	0.94	0.97	1.09	0.15
	(50.11)	(74.36)	(59.11)	(62.72)	(45.68)	(4.85)
SMB	0.14	-0.04	-0.13	-0.01	0.15	0.01
	(5.37)	(-1.49)	(-6.73)	(-0.21)	(3.92)	(0.25)
HML	0.20	0.07	0.00	-0.26	-0.37	-0.57
	(5.79)	(3.19)	(0.11)	(-10.16)	(-12.22)	(-12.15)
R^2(%)	88.04	92.46	92.64	92.68	91.17	40.78

Table 4: Double sorts on TAG and LAG (and CAG)

This table reports the results of the portfolios double sorted on TAG and LAG (and CAG). At the end of June each year we construct 5-by-5 portfolios sequentially sorted first on TAG and then LAG in Panel A.1, first on LAG and then TAG in Panel A.2, first on TAG and then CAG in Panel B.1, and first on CAG and then TAG in Panel B.2. Panel A.1 reports the LAG premium (the value-weighted excess return difference between high and low LAG quintile portfolios) within each TAG quintile and their average across TAG quintiles. Panel A.2 reports the TAG premium (the value-weighted excess returns between high and low TAG quintile portfolios) within each LAG quintile and their average across LAG quintiles. The results are similarly reported for double sorts on TAG and CAG in Panel B. Returns are monthly and reported in percentages. *t*-statistics in parentheses are calculated based on the heteroskedasticity-consistent stand errors of Newey and West. The sample includes NYSE/AMEX/NASDAQ common stocks (excluding financial stocks) from July 1968 to December 2019.

Panel A: Double sorts on LAG and TAG

Panel A.1: LAG premium conditional on TAG

	TAG1	TAG2	TAG3	TAG4	TAG5	Ave
LAG Prm.	0.15	0.07	-0.14	-0.09	-0.48	-0.10
	(0.74)	(0.51)	(-0.97)	(-0.53)	(-2.94)	(-1.07)

Panel A.2: TAG premium conditional on LAG

	LAG1	LAG2	LAG3	LAG4	LAG5	Ave
TAG Prm.	0.11	-0.24	-0.19	-0.02	-0.78	-0.22
	(0.52)	(-1.71)	(-1.24)	(-0.11)	(-3.87)	(-2.14)

Panel B: Double sorts on CAG and TAG

Panel B.1: CAG premium conditional on TAG

	TAG1	TAG2	TAG3	TAG4	TAG5	Ave
CAG Prm.	-0.14	0.03	0.12	-0.01	-0.27	-0.06
	(-0.77)	(0.26)	(1.10)	(-0.10)	(-1.35)	(-0.71)

Panel B.2: TAG premium conditional on CAG

	CAG1	CAG2	CAG3	CAG4	CAG5	Ave
TAG Prm.	-0.34	-0.25	-0.11	-0.14	-0.60	-0.29
	(-1.66)	(-1.61)	(-0.76)	(-0.74)	(-2.42)	(-2.76)

Table 5: Fama-Macbeth Regression: Full sample

This table presents Fama-MacBeth regressions of monthly returns on total asset growth (TAG), current asset growth (CAG), and long-term asset growth (LAG), and other firm characteristics, including book-to-market equity ratio (BM), momentum (MOM), and gross profitability (GP/A), over the period from July 1968 to December 2019. TAG, LAG and CAG are defined as the percentage change in total assets, long-term assets and current assets respectively from the fiscal year ending in calendar year t-2 to fiscal year ending in calendar year t-1. BM is the book value of equity divided by market value at the end of last fiscal year. MOM is the prior 2-12 month cumulative return. Gross profitability is defined as revenue minus cost of goods sold and then divided by total assets. We winsorize the data at the 1% and 99% levels to minimize the effect of outliers. t-statistics in parentheses are calculated based on the heteroskedasticity-consistent stand errors of Newey and West. The sample includes NYSE/AMEX/NASDAQ common stocks (excluding financial stocks) from July 1968 to December 2019.

Specification	1	2	3	4	5	6	7	8
Intercept	1.50	1.48	1.47	1.30	1.24	1.17	1.51	0.94
	(6.13)	(5.96)	(5.94)	(5.11)	(5.19)	(4.73)	(5.82)	(4.22)
TAG	-0.48						-0.48	-0.44
	(-5.39)						(-4.37)	(-4.54)
CAG		-0.29					0.00	0.01
		(-4.98)					(-0.05)	(0.10)
LAG			-0.21				-0.01	0.01
			(-4.80)				(-0.29)	(0.28)
BM				0.10				0.10
				(3.99)				(4.86)
MOM					0.44			0.39
					(2.30)			(2.06)
GP/A						0.63		0.68
						(3.88)		(4.54)
Adj. R^2(%)	0.39	0.3	0.25	0.32	1.29	0.36	0.5	2.26

Table 6: Characteristics of AR portfolios

This table presents the characteristics of asset ratio (AR) portfolios. Asset ratio is defined as the ratio of current asset to long-term asset. At the end of each June, firms are sorted into AR quintiles. Panel A reports the standard firm-level characteristics of AR portfolios, including firm size (Size), book-to-market ratio (BM), momentum (MOM),, and gross profitability (GP/A). Panel B reports the prior 4-year cumulative percentage change in total asset, long-term asset, current asset, market equity value, total debt, long-term debt, and short-term debt, as well as the prior 4-year cumulative stock return. The sample includes NYSE/AMEX/NASDAQ common stocks (excluding financial stocks) from July 1968 to December 2019.

Panel A: Firm-level characteristics

	Lo	2	3	4	Hi	Hi-Lo
Size	651.07	557.47	361.91	208.28	101.36	-549.71
BM	0.85	0.69	0.66	0.63	0.58	-0.27
MOM	0.09	0.08	0.08	0.07	0.04	-0.05
GP/A	0.16	0.31	0.40	0.43	0.40	0.24

Panel B: Prior 4-year changes in balance sheet items

	Lo	2	3	4	Hi	Hi-Lo
Δ log(Total asset)	0.44	0.47	0.45	0.48	0.55	0.11
Δ log(Long-term asset)	0.48	0.56	0.54	0.53	0.37	-0.11
Δ log(Current asset)	0.38	0.41	0.42	0.50	0.63	0.25
Δ log(Market equity)	0.37	0.38	0.37	0.42	0.48	0.11
Cumulative returns	0.53	0.54	0.53	0.51	0.47	-0.06
Δ log(Total debt)	0.43	0.49	0.39	0.22	-0.06	-0.49
Δ log(Long-term debt)	0.43	0.45	0.33	0.12	-0.23	-0.66
Δ log(Current debt)	0.37	0.34	0.28	0.14	-0.24	-0.61

Table 7: Asset ratio and future long-term and current asset growth

This table reports the relation between asset ratio and future long-term asset growth (LAG) and current asset growth (CAG). Asset ratio (AR) is defined as the ratio of current asset (Compustat data item ACT) to long-term asset (Compustat data item AT minus ACT). We run panel regressions of CAG and LAG at fiscal year ending at t on the logarithm of AR at fiscal year ending at t-1, controlling for CAG and LAG at fiscal years ending at t-1 and t-2. We winsorize the data at the 1% and 99% levels to minimize the effect of outliers. t-statistics in parentheses are based on the standard errors clustered at both firm and year levels. The sample is annual from 1968 to 2019.

Specification	1	2	3	4
Dep var	CAG(t)	CAG(t)	LAG(t)	LAG(t)
logAR(t-1)	-0.02	-0.03	0.14	0.12
	(-3.06)	(-8.80)	(14.70)	(15.97)
CAG(t-1)	0.03	0.00	0.24	0.21
	(3.07)	(-0.53)	(11.88)	(16.67)
LAG(t-1)	0.08	0.04	0.04	0.00
	(7.17)	(6.43)	(2.70)	(-0.16)
CAG(t-2)		0.02		0.08
		(2.13)		(10.45)
LAG(t-2)		0.02		0.00
		(3.31)		(-0.23)
Cons.	0.18	0.15	0.19	0.16
	(16.93)	(17.59)	(17.88)	(18.39)
R^2(%)	1.93	1.30	10.92	8.41
Obs.	137042	129494	137042	129494

Table 8: Double sorts on asset ratio and asset growth

This table examines the effect of asset ratio (AR) on the return predictive power of long-term asset growth (LAG), current asset growth (CAG), and total asset growth (TAG). AR is defined as the ratio of current asset to long-term asset. At the end of June each year t, we construct 5-by-5 portfolios sequentially sorted first on AR at fiscal year ending in t-2, and then by LAG at fiscal year ending in t-1 in Panel A, by CAG at fiscal year ending in t-1 in Panel B, or by TAG at fiscal year ending in t-1 in Panel C. We report the asset growth premium within each AR quintile and their average across AR quintiles. As a comparison, we also report the unconditional asset growth premium from one-way sorts in each panel. Returns are monthly and reported in percentages. t-statistics in parentheses are calculated based on the heteroscedasticity-consistent standard errors of Newey and West. The sample period is from July 1968 to December 2019.

Panel A: LAG premium conditional on AR

	AR1	AR2	AR3	AR4	AR5	Ave	Unc. LAG Prm.
LAG Prm.	-0.39	-0.36	-0.32	-0.35	-0.38	-0.36	-0.35
	(-2.65)	(-1.97)	(-1.70)	(-1.98)	(-1.72)	(-3.12)	(-2.68)

Panel B: CAG premium conditional on AR

	AR1	AR2	AR3	AR4	AR5	Ave	Unc. CAG Prm.
CAG Prm.	-0.22	-0.42	-0.34	-0.40	-0.52	-0.38	-0.25
	(-1.68)	(-2.42)	(-1.99)	(-1.94)	(-2.17)	(-3.25)	(-2.00)

Panel C: TAG premium conditional on AR

	AR1	AR2	AR3	AR4	AR5	Ave	Unc. TAG Prm.
TAG Prm.	-0.40	-0.49	-0.36	-0.31	-0.53	-0.42	-0.38
	(-2.71)	(-2.62)	(-1.77)	(-1.51)	(-2.20)	(-3.17)	(-2.56)

Table 9: Double sorts on CAG and LAG

This table reports the results of the portfolios double sorted on LAG and CAG. At the end of June each year we construct 5-by-5 portfolios sequentially sorted first on CAG and then LAG in Panel A, first on LAG and then CAG in Panel B. Panel A reports the LAG premium (the value-weighted excess return difference between high and low LAG quintile portfolios) within each CAG quintile and their average across CAG quintiles. Panel B reports the CAG premium (the value-weighted excess returns between high and low CAG quintile portfolios) within each LAG quintile and their average across LAG quintiles. Returns are monthly and reported in percentages. t-statistics in parentheses are calculated based on the heteroskedasticity-consistent stand errors of Newey and West. The sample includes NYSE/AMEX/NASDAQ common stocks (excluding financial stocks) from July 1968 to December 2019.

Panel A: LAG premium conditional on CAG

	CAG1	CAG2	CAG3	CAG4	CAG5	Ave	Unc. LAG Prm.
LAG Prm.	-0.54	-0.12	-0.21	-0.23	-0.74	-0.37	-0.35
	(-3.15)	(-0.62)	(-1.34)	(-1.36)	(-3.41)	(-3.38)	(-2.68)

Panel B: CAG premium conditional on LAG

	LAG1	LAG2	LAG3	LAG4	LAG5	Ave	Unc. CAG Prm.
CAG Prm.	-0.42	-0.09	-0.14	-0.12	-0.55	-0.26	-0.25
	(-2.49)	(-0.68)	(-0.97)	(-0.76)	(-2.78)	(-2.72)	(-2.00)

Table 10: Double sorts on asset imbalance and asset growth

This table examines the effect of asset imbalance (AIB) on the return predictive power of long-term asset growth (LAG), current asset growth (CAG), and total asset growth (TAG). Asset imbalance (AIB) is measured by the absolute value of the difference in the decile indexes sorted by CAG and LAG. At the end of June each year, we construct 5-by-5 portfolios sequentially sorted first on AIB, and then by LAG in Panel A, by CAG in Panel B, or by TAG in Panel C. We report the asset growth premium within each AIB quintile. We also report the asset growth spread (the difference in the asset growth between high and low asset growth quintiles). Returns are monthly and reported in percentages. t-statistics in parentheses are calculated based on the heteroscedasticity-consistent standard errors of Newey and West. The sample period is from July 1968 to December 2019.

Panel A: LAG premium conditional on AIB

	AIB1	AIB2	AIB3	AIB4	AIB5
LAG Prm.	-1.02	-0.52	-0.20	-0.38	-0.06
	(-3.96)	(-2.86)	(-0.97)	(-2.21)	(-0.33)
LAG spread	2.20	0.69	0.44	0.45	1.18

Panel B: CAG premium conditional on AIB

	AIB1	AIB2	AIB3	AIB4	AIB5
CAG Prm.	-1.05	-0.47	-0.25	-0.19	0.14
	(-4.24)	(-2.60)	(-1.38)	(-1.28)	(0.92)
CAG spread	2.00	0.70	0.48	0.52	1.03

Panel C: TAG premium conditional on AIB

	AIB1	AIB2	AIB3	AIB4	AIB5
TAG Prm.	-1.09	-0.62	-0.34	-0.32	-0.05
	(-4.27)	(-3.56)	(-1.77)	(-1.85)	(-0.29)
TAG spread	2.07	0.78	0.47	0.37	0.53

Table 11: Fama-MacBeth Regression for high and low Index Group

This table presents Fama-MacBeth regressions of monthly returns on total asset growth (TAG), current asset growth (CAG), and long-term asset growth (LAG) for subsamples of stocks within lowest 20% asset imbalance percentiles (Panel A), stocks within 20%-80% asset imbalance percentiles (Panel B) and stocks within top 20% asset imbalance percentiles (Panel C). Asset imbalance (AIB) is measured by the absolute value of the difference in the decile indexes sorted by CAG and LAG. TAG, LAG, and CAG are defined as the percentage change in total assets, long-term assets and current assets respectively from the fiscal year ending in calendar year t-2 to fiscal year ending in calendar year t-1. We winsorize the data at the 1% and 99% levels to minimize the effect of outliers. t-statistics in parentheses are calculated based on the heteroskedasticity-consistent stand errors of Newey and West. The sample includes NYSE/AMEX/NASDAQ common stocks (excluding financial stocks) from July 1968 to December 2019.

Panle A: Lowest 20% AIB percentiles				Panel B: 20%-80% AIB percentiles				Panel C: Top 20% AIB percentiles			
Specification	1	2	3	Specification	1	2	3	Specification	1	2	3
Intercept	1.5	1.48	1.46	Intercept	1.49	1.47	1.47	Intercept	1.54	1.52	1.50
	(6.05)	(5.90)	(5.84)		(6.37)	(6.13)	(6.16)		(5.61)	(5.46)	(5.49)
TAG	-0.48			TAG	-0.58			TAG	-0.24		
	(-5.50)				(-3.50)				(-1.38)		
CAG		-0.37		CAG		-0.24		CAG		-0.06	
		(-5.11)				(-2.65)				(-0.83)	
LAG			-0.29	LAG			-0.29	LAG			0.00
			(-5.30)				(-3.71)				(0.06)
Adj. R^2(%)	0.7	0.65	0.49	Adj. R^2(%)	0.24	0.18	0.17	Adj. R^2(%)	0.34	0.23	0.2

Table 12: Asset imbalance in CAG, LAG, and TAG quintiles

This table reports the average asset imbalance of the quintile portfolios sorted on long-term asset growth (Panel A), current asset growth (Panel B), and total asset growth (Panel C). Asset imbalance (AIB) is measured by the absolute value of the difference in the decile indexes sorted by CAG and LAG. The sample period is from July 1968 to December 2019.

Panel A: LAG quintiles

	LAG1	LAG2	LAG3	LAG4	LAG5
AIB	3.14	2.34	2.10	2.51	2.86

Panel B: CAG quintiles

	CAG1	CAG2	CAG3	CAG4	CAG5
AIB	3.40	2.30	2.08	2.50	2.68

Panel C: TAG quintiles

	TAG1	TAG2	TAG3	TAG4	TAG5
AIB	2.30	2.69	2.88	2.89	2.17

Table 13: Asset imbalance effect on current assets and its components

This table presents Fama-MacBeth regressions of monthly returns on the growth rate of current asset (CAG) and its components over the period from July 1968 to December 2019. These components include cash growth (CASHG) and non-cash current asset growth (NOCASHG). The non-cash current asset growth is further separated into inventory growth (INVTG), account receivables growth (RECTG), and other current assets growth (ACOG). We winsorize the data at the 1% and 99% levels to minimize the effect of outliers. t-statistics in parentheses are calculated based on the heteroskedasticity-consistent stand errors of Newey and West. The sample includes NYSE/AMEX/NASDAQ common stocks (excluding financial stocks) from July 1968 to December 2019.

Specification	1	2	3	4	5	6	7	8	9
Intercept	1.49	1.42	1.48	1.49	1.46	1.46	1.43	1.49	1.50
	(5.83)	(5.52)	(5.83)	(5.90)	(5.72)	(5.73)	(5.56)	(5.91)	(5.97)
CAG	-0.44			-0.34					-0.33
	(-6.77)			(-5.54)					(-5.35)
CASHG		-0.02		0.01					0.01
		(-2.91)		(1.69)					(1.57)
NOCASHG			-0.45	-0.20				-0.34	-0.12
			(-6.27)	(-3.06)				(-3.76)	(-1.30)
INVTG					-0.30			-0.09	-0.08
					(-5.50)			(-1.72)	(-1.63)
RECTG						-0.28		-0.05	-0.04
						(-5.97)		(-1.04)	(-0.81)
ACOG							-0.05	0.00	0.01
							(-3.12)	(0.02)	(0.71)
Adj. R^2(%)	0.31	0.08	0.28	0.41	0.24	0.2	0.09	0.43	0.55

Table 14: Asset imbalance effect on right-hand-side of balance sheet

This table presents Fama-MacBeth regressions of monthly returns on total asset growth (TAG), equity growth (BEG), and debt growth (DEBTG), and other firm characteristics over the period from July 1968 to December 2019. TAG, BEG and DEBTG are defined as the percentage change in total assets, book equity and total debt respectively from the fiscal year ending in calendar year t-2 to fiscal year ending in calendar year t-1. BM is the book value of equity divided by market value at the end of last fiscal year. MOM is the prior 2-12 month cumulative return. We winsorize the data at the 1% and 99% levels to minimize the effect of outliers. t-statistics in parentheses are calculated based on the heteroskedasticity-consistent stand errors of Newey and West. The sample includes NYSE/AMEX/NASDAQ common stocks (excluding financial stocks) from July 1968 to December 2019.

Specification	1	2	3	4	5	6	7	8
Intercept	1.51	1.46	1.43	1.31	1.23	1.26	1.51	1.03
	(6.13)	(5.87)	(5.67)	(5.12)	(5.16)	(4.99)	(6.14)	(4.54)
TAG	-0.58						-0.62	-0.55
	(-6.36)						(-7.09)	(-6.96)
BEG		-0.17					0.04	0.03
		(-3.56)					(0.91)	(0.79)
DEBTG			-0.02				0.01	0.01
			(-3.09)				(0.98)	(1.21)
BM				0.10				0.09
				(4.01)				(4.43)
MOM					0.42			0.37
					(2.07)			(1.84)
GP/A						0.43		0.45
						(2.77)		(3.16)
Adj. R^2(%)	0.35	0.28	0.06	0.32	1.33	0.37	0.46	2.29