GDP Growth Expectations and Cash-flow Risk Premium*

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June 29, 2026

JEL Classification: G12, G14, G17, E32, E44

Keywords: cash-flow risk, ICAPM and CCAPM, procyclical and countercyclical stocks, Livingston Survey.

*We thank Doug Breeden, Ravi Jagannathan, and the participants at the conference in honor of Douglas Breeden at Duke University for valuable comments.

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Abstract

We demonstrate that procyclical stocks, whose cash flows covary positively with expected economic growth, earn significantly higher returns than countercyclical stocks. Using nearly 75 years of survey-based real GDP growth expectations as a model-free measure of economic state, we establish that this forecast comoves with consumption and predicts market returns, real GDP growth, and consumption growth, providing a novel empirical bridge between the Intertemporal and Consumption Capital Asset Pricing Models. Tradable portfolios sorted on cash-flow risk generate economically large, statistically significant premia robust to standard factor controls.

While most researchers agree on the importance of economic expectations in asset pricing, there is little consensus on how to measure them empirically. In this paper, we propose using the expected real growth rate of Gross Domestic Product (GDP) from the Livingston Survey as a forward-looking measure of economic conditions. We show that this measure comoves with contemporaneous consumption growth and predicts future market returns, real GDP growth, and consumption growth. These properties qualify it as both a state variable in Merton's (1973) Intertemporal Capital Asset Pricing Model (ICAPM) and a practical proxy for consumption in Breeden's (1979) Consumption CAPM (CCAPM). We document that the cash-flow beta with respect to innovations in expected real GDP growth carries a large, positive premium in the cross section of equity portfolios.

Breeden (1979) shows that the single consumption beta in the CCAPM encompasses both the market beta and the betas with state variables in the ICAPM. We argue that GDP forecasts operationalize this theoretical link. Because consumption constitutes approximately two-thirds of GDP, survey expectations of future GDP growth serve as a practical and timely proxy for expected consumption growth. When future GDP and consumption are expected to increase, investors tend to consume more today under reasonable assumptions, leading to comovement between expected GDP growth and current consumption growth. Empirically, we demonstrate not only this contemporaneous comovement but also predictive relationships: expected real GDP growth positively forecasts realized GDP and consumption growth over the next two semesters, while negatively predicting market returns over the subsequent three semesters. Thus, revisions in expected GDP growth capture the forward-looking component of economic conditions relevant for asset pricing.

Our empirical strategy leverages this insight by constructing a cash-flow beta with respect to innovations in expected real GDP growth. This approach allows us to directly test whether exposure to cash-flow risk is priced in the cross section of equity returns. Following Bansal, Dittmar, and Lundblad (henceforth BDL, 2005), we compute cash flows for decile portfolios sorted on size, book-to-market (BM) ratio, and past returns (momentum). We first regress each portfolio's cash-flow growth on the long-run evolution of expected real GDP growth over the past K semesters, allowing the residual to be serially correlated over L lags. The slope coefficient from this regression, which we refer to as gamma (γ), is one of the two risk measures we employ. Using the estimated gamma coefficients, we apply Campbell's (1991) return decomposition procedure to separate unexpected returns into innovations (news) in future cash flows and expected returns. We then compute the beta of cash-flow news with respect to revisions in expected real GDP growth for each portfolio. The resulting cash-flow beta, the second of the two risk measures, is generally higher for assets known to earn higher average returns–small stocks, value stocks, and past winners.

The slope coefficient from a cross-sectional regression of returns on cash-flow beta measures the procyclicality premium. We jointly estimate the time-series and cross-sectional parameters in a single Generalized Method of Moments (GMM) system. This single-stage approach avoids the errors-in-variables (EIV) bias inherent in standard two-pass regressions and is robust to heteroskedastic and autocorrelated errors. The estimated procyclicality premium is significantly positive for both equally weighted and value-weighted portfolios.

We gauge the economic significance of cash-flow risk by forming tradable portfolios of the 30 characteristic portfolios used as test assets. Each semester, we estimate cash-flow betas and gammas using rolling GMM on the past cumulative sample to avoid look-ahead bias. We then sort the test assets by their rolling cash-flow beta or gamma to form equally weighted decile portfolios. The zero-cost portfolio that is long the highest decile and short the lowest decile earns a large, significant premium ranging between 1.70% and 4.38% per semester, depending on asset weighting and the risk measure used. These premia remain significant after adjusting for the market, size, and book-to-market factors. They also survive the additional inclusion of the momentum factor, except when value-weighted assets are sorted on their rolling betas.

These results are based on optimal lag lengths of $K = 2$ and $L = 1$. These values maximize the four-factor alphas of the long-short portfolios based on rolling cash-flow betas and gammas among $1 \leq K \leq 4$ and $1 \leq L \leq 4$. The optimal value of $K = 2$ is consistent with the predictive power of expected real GDP growth rate over the next two semesters for aggregate returns, realized real GDP growth, and consumption growth. The optimal value of $L = 1$ suggests a parsimonious model in which residual cash-flow growth is serially correlated over only the past semester.

Our paper is most closely related to the literature on the pricing of cash-flow risk within consumption-based asset pricing. BDL (2005) show that the consumption beta of cash flows can account for a sizable portion of the cross-sectional variation in characteristic portfolio returns. Da (2009) links an asset's expected return to the covariance and duration of cash flows using accounting earnings. Duffee (2005) finds that the conditional covariance between aggregate stock return and consumption growth is high when stock market wealth is high relative to consumption and that, after accounting for this variation, the relation between expected stock return and the conditional covariance is negative. Xu (2021) shows that this seemingly puzzling phenomenon is driven by the procyclicality of the dividend component of the aggregate stock return: the covariance between aggregate dividends and consumption growth is lower in recessions than in non-recession periods. Following this literature, we employ the cash-flow beta rather than return beta to measure risk, but we focus on covariation with changes in expected aggregate production rather than realized consumption growth.

Our paper also joins the literature on expectations and asset returns. Much of this literature examines the relationship between macroeconomic forecasting variables and subjective expectations on one hand, and the relationship between subjective expectations and realized outcomes on the other. Consistent with the results of Campbell and Diebold (2009), Greenwood and Shleifer (2014) show that several survey-based forecasts are contrarian predictors of market returns and are also at odds with fundamental predictive measures. In recent work, Nagel and Xu (2023) find that the *negative* of prior realized industrial production predicts expected market returns from the Livingston Survey, although with modest economic magnitude. Similarly, De la O and Myers (2021) find that the dividend-price ratio explains relatively little of the market forecast, whereas Dahlquist and Ibert (2024) exploit the panel nature of the Livingston Survey and document a strong countercyclical pattern for one-year-ahead S&P 500 forecasts. Moller, Pedersen, Steffensen, and Andreasen (2024) show that professional economists in the Livingston Survey exhibit countercyclical expectations for stock returns and cash flows, which align strongly with predictions from rational models such as the long-run risk model of Bansal and Yaron (2004). Unlike these studies, we use GDP and CPI forecasts from the Livingston Survey rather than equity index forecasts.

There is also recent related work on expectations as a priced factor in the cross section. Brandon and Wang (2020) propose aggregate earnings expectations as a candidate pricing variable, compare it to expected GDP growth, and replicate an earlier version of Goetzmann, Watanabe, and Watanabe (2022) for different subperiods. They point out that expected GDP growth is not necessarily correlated with beliefs about earnings but may share a common determinant, such as sentiment about the economy. Along these lines Hasan et al. (2023) explicitly test whether an aggregate market emotion index is priced in the cross section of U.S. stocks. In related work, Shen, Yu, and Zhao (2017) show that variation in an aggregate sentiment index attenuates the expected relationship between macroeconomic factor exposure and expected return. Thus there may be a common driver of macroeconomic and market expectations, but it apparently has countercyclical implications for realized market outcomes. In this paper we focus on sensitivity to revisions in expert predictions about the future state of the economy as a pervasive risk factor and test whether it is priced in the cross section as predicted by asset pricing theory.

The rest of the paper is organized as follows. Section 1 provides the theoretical motivation and empirical confirmation for the use of GDP forecasts from the Livingston Survey. We then explain how we measure cash-flow risk and test cross-sectional pricing. Section 2 presents the main results. We show that the cash-flow beta with respect to revisions in expected real GDP growth, along with the gamma measure, carries a statistically significant, positive premium. We demonstrate the economic significance of the premium using calendar-time portfolios and detail the selection of optimal lag lengths. The final section concludes.

1. Pricing of Procyclicality Risk

1.1 Theoretical Motivation

As emphasized by Breeden (1979), the change in economic state under the ICAPM is closely related to consumption fluctuations under the CCAPM. In consumption-based asset-pricing models, aggregate consumption growth plays a key role. It perfectly describes marginal utility in Breeden's (1979) seminal work on the CCAPM and is augmented by the growth in aggregate wealth in Bansal and Yaron's (2004) long-run risk model. In this paper, we take a slightly different approach and examine the source of consumption, namely, aggregate production, and more precisely, its expectations. We are motivated by the fact that consumption comprises approximately two-thirds of GDP in the United States and that expectations about GDP, rather than consumption, are readily available in surveys. We use expected GDP rather than realized GDP to gauge the expected growth in future consumption that is presumably reflected in current asset prices.

To fix the idea, consider an economy populated by investors who maximize time-separable, state-independent utility in markets where asset prices and state variables follow continuous diffusion processes, such as those analyzed by Merton (1973) and Breeden (1979). For ease of exposition, we further assume that investor heterogeneity, if any, can be aggregated to construct a representative investor and that there is only one state variable. Let $U(C_t)$ be the utility function defined over consumption C_t and $J(W_t, S_t)$ be the value function for wealth W_t in state S_t. The Euler equation implies that the stochastic discount factor M is proportional to the marginal utility,

$$M \propto U_c = J_w, \tag{1}$$

where the equality follows from the envelope condition and the subscripts denote partial derivatives with respect to their upper-case arguments.[1] Applying Ito's lemma to each term gives

$$dM \propto U_{cc} dC \simeq J_{ww} dW + J_{ws} dS, \tag{2}$$

where the approximate equality $\simeq$ signifies the omission of drift terms that do not affect the computation of covariances to follow. Divide each term by Equation (1), flip the sign, and rearrange to obtain

$$-\frac{dM}{M} = -\frac{U_{cc}C}{U_c}\frac{dC}{C} \simeq -\frac{J_{ww}W}{J_w}\frac{dW}{W} - \frac{J_{ws}S}{J_w}\frac{dS}{S}, \tag{3}$$

where the first equality holds by canceling the proportionality constant. The excess return on

[1]The envelope condition follows from the first-order condition with respect to consumption in the Hamilton-Jacobi-Bellman equation for optimality and states that every dollar consumed is worth every dollar saved for future consumption.

security i including dividends, dP_i/P_i, is given by its covariance with Equation (3),[2]

$$
\begin{aligned}
E\left[\frac{dP_i}{P_i} - rdt\right] &= -\frac{dM}{M}\frac{dP_i}{P_i} \\
&= -\frac{U_{cc}C}{U_c}\frac{dC}{C}\frac{dP_i}{P_i} \quad \text{(CCAPM)} \\
&= -\frac{J_{ww}W}{J_w}\frac{dW}{W}\frac{dP_i}{P_i} - \frac{J_{ws}S}{J_w}\frac{dS}{S}\frac{dP_i}{P_i}. \quad \text{(ICAPM)}
\end{aligned} \tag{4}
$$

That is, the CCAPM and the ICAPM are equivalent. Noting this equivalence, Breeden (1979, Equation (15)) emphasizes that the CCAPM is potentially testable because consumption is observable, while a test of the ICAPM requires the identification of the state variables.[3]

We build on this observation. Researchers have proposed a wealth of macroeconomic and market variables that predict the aggregate equity return. Of those, we are particularly interested in the forecast of aggregate production as a source of consumption. Campbell and Diebold (2009) show that the expected real GDP growth rate from the Livingston Survey predicts the market return, which qualifies it as a state variable in S. According to Equation (3), consumption in the middle term should reflect the change in the economic state in the rightmost term. The next section confirms these points.

1.2 Empirical Confirmation

This section provides empirical support for the theoretical motivation laid out above. Following Campbell and Diebold (2009), we construct the expected real GDP growth rate ($EGDP$) from the

[2] Much of the exposition here is due to Back (2017, pp.359-360). The first line of Equation (4) follows from pricing both a riskless bond with instantaneous risk-free rate r–which requires the drift of dM/M be $-r\,dt$–and security i, which requires $M \cdot P_i$ be a martingale and hence the drift of $d(M \cdot P_i)$ be zero.

[3] A rigorous test of the CCAPM would restrict the price of consumption risk to be the relative risk aversion, $-U_{cc}C/U_c$, as implied by Equation (4). If the utility is power with constant relative risk aversion (CRRA) γ, it equals the CRRA coefficient, $-\frac{U_{cc}C}{U_c} = \gamma$. Generally, it is a nonlinear function of consumption growth.

Livingston Survey as

$$EGDP_t^{t+1,t+2} = \ln \frac{GDPX_t^{t+2}}{CPI_t^{t+2}} - \ln \frac{GDPX_t^{t+1}}{CPI_t^{t+1}}, \tag{5}$$

where $GDPX$ and CPI are the median forecasts of nominal GDP and the CPI, respectively, the subscript denotes the current period, and the superscripts denote the forecast period. The series is computed semiannually beginning in the second half of 1951. We use the two-period-ahead forecast in Equation (5) rather than the next period's forecast because the base levels necessary to compute the latter are unavailable prior to June 1992. Table 1 shows the summary statistics of $EGDP$ along with the other variables to be introduced. The mean expected real GDP growth rate since the second half of 1951 is 1.24% per semester.

Panel A of Table 2 demonstrates that survey participants can predict future output growth. We regress the realized real GDP growth rate ($RGDP_t \equiv \ln GDP_t - \ln GDP_{t-1}$) on the contemporaneous ($EGDP_t^{t+1,t+2}$) or lagged expected real GDP growth rate up to three lags ($EGDP_{t-1}^{t,t+1}$, $EGDP_{t-2}^{t-1,t}$, or $EGDP_{t-3}^{t-2,t-1}$). The t-statistics in parentheses are based on Newey-West standard errors with two semiannual lags. The estimated predictive coefficients are positive and significant for the first and second lags in Columns (2) and (3), respectively. The latter matches the forecast horizon, while the former has a near-unit coefficient of 0.972 with a t-statistic of 3.25. This implies that, by what they label the two-semester-ahead forecast, participants effectively forecast the next semester's real GDP growth with remarkable accuracy.

This suggests that expected real GDP growth can also forecast consumption growth, given consumption's large share of GDP. Panel B confirms this by replacing the dependent variable with the growth rate of consumption, $g_{c,t} \equiv \ln C_t - \ln C_{t-1}$. Interestingly, the statistical significance of the first two lags is stronger than that of the realized real GDP growth, and the contemporaneous relation is also positive and significant. This may reflect the fact that consumption is a smooth part of the whole output.

The predictability of consumption growth has pricing implications. Panel C shows that the expected real GDP growth rate significantly forecasts the market return, and somewhat unexpectedly, even at the third lag. The predictive relation is negative, suggesting that in good times, current equity prices tend to be high and future returns low. This is consistent with the findings of Campbell and Diebold (2009). Panel D controls for prominent predictors, such as the first lags of the aggregate dividend yield (DY_{t-1}), default spread (DEF_{t-1}), term spread ($TERM_{t-1}$), and consumption-to-wealth ratio (CAY_{t-1}). The return predictability by expected real GDP growth is robust and is the most significant predictor in columns (2)–(4).

1.3 Methodology

In a decomposition of an asset's return into cash flow and risk premium, we expect the GDP forecast to capture the former rather than the latter, because cash flows or dividends are paid out of firms' output, which is aggregated to form part of the GDP at the macroeconomic level. Therefore, we measure the risk, or procyclicality, of a stock by cash-flow beta rather than return beta. A body of work on cash-flow risk (BDL (2005), Da (2009), Xu (2021)) also focuses on the cash-flow beta.

1.3.1 Measuring Procyclicality of Cash Flows

We measure cash flow betas using a generalized version of BDL's (2005) specification to accommodate the fact that the forecasts in the Livingston Survey have specific time horizons. Define

$$g_{e,t} \equiv EGDP_t^{t+1,t+2} \tag{6}$$

for notational simplicity. We assume that the real GDP growth expectation evolves smoothly over time,

$$g_{e,t} = c_{e0} + \rho_e g_{e,t-1} + \zeta_{e,t}, \tag{7}$$

where c_{e0} is the intercept and $\zeta_{e,t}$ is an i.i.d. error term. This corresponds to Equation (6) of BDL (2005), which instead models the stickiness of consumption growth. The sensitivity of portfolio i's cash-flow growth with respect to a long-run evolution of real GDP growth expectation is measured by

$$g_{i,t} = c_{i0} + \sum_{k=1}^{K} \gamma_{i,k} g_{e,t-k} + u_{i,t}, \tag{8}$$

$$u_{i,t} = \sum_{j=1}^{L} \rho_{i,j} u_{i,t-j} + \zeta_{i,t}, \tag{9}$$

where c_{i0} is the intercept and $u_{i,t}$ and $\zeta_{i,t}$ are i.i.d. shocks. We allow the $\gamma_{i,k}$ coefficient to vary across the lags for both theoretical and empirical reasons. Theoretically, the two-period-ahead forecast from the survey corresponds to $k = 2$ at the semiannual frequency. However, other lags should also help explain $g_{i,t}$ if expectations are slowly revised as in (7). In particular, the first lag, $g_{e,t-1} \equiv EGDP_{t-1}^{t,t+1}$, should incorporate information that became available after $EGDP_{t-2}^{t-1,t}$ was forecast a semester earlier, even though the horizon is mismatched. Empirically, this seems to be the case in Panels A and B of Table 2, where $EGDP_{t-1}^{t,t+1}$ strongly predicts the growth of both realized real GDP and consumption. In contrast, Equation (7) of BDL (2005) employs a trailing K-period moving average of consumption growth on the right-hand side, which is equivalent to restricting $\gamma_{i,k}$ to be constant over the K lags. Despite the slight difference in coefficient restrictions, both specifications attempt to capture long-run risk. We search over K and L and find the optimal values to be $K = 2$, which includes the first two lags of $g_{e,t}$, and $L = 1$, which parsimoniously accounts for residual autocorrelation over the past semester only. We focus on these choices of K and L until we explain the detail of the search in Section 2.4.

Rewrite Equation (9) using the lag operator,

$$(1 - \rho_{i,1}\mathcal{L} - \rho_{i,2}\mathcal{L}^2 - ... - \rho_{i,L}\mathcal{L}^L)u_{i,t} = \zeta_{i,t}. \tag{10}$$

Pre-multiplying the lag-operator polynomials in the parentheses of Equation (10) to both sides of Equation (8) and rearranging the result gives

$$g_{i,t} = \sum_{j=1}^{L} \rho_{i,j} g_{i,t-j} - \sum_{j=0}^{L}\sum_{k=1}^{K} \rho_{i,j}\gamma_{i,k} g_{e,t-k-j} + \zeta_{i,t}, \tag{11}$$

where $\rho_{i,0} \equiv -1$ by convention.

1.3.2 Cash-flow Beta and Cross-sectional Tests

Define the vector of length $K + 2L$,

$$z_{i,t} \equiv (g_{i,t} \quad g_{i,t-1} \quad \cdots \quad g_{i,t-(L-1)} \quad g_{e,t} \quad g_{e,t-1} \quad \cdots \quad g_{e,t-(K+L-1)})'. \tag{12}$$

Equations (7) and (11) can now be written compactly as a first-order vector autoregression (VAR) with i.i.d. errors,

$$z_{i,t} = A_i z_{t-1} + \epsilon_{i,t}, \tag{13}$$

where the forms of matrix A_i and the error vector $\epsilon_{i,t}$ can be found in Appendix A.

Using the log-linear approximation of the change in the log price-to-dividend ratio from Campbell and Shiller (1988), Campbell (1991) derives the expression for the unexpected stock return,

$$r_{i,t} - E_{t-1}[r_{i,t}] = (E_t - E_{t-1}) \left[\sum_{j=0}^{\infty} \kappa_i^j g_{i,t+j} - \sum_{j=1}^{\infty} \kappa_i^j r_{i,t+j} \right] \equiv \eta_{CFi,t} - \eta_{ERi,t}, \tag{14}$$

where κ_i is a constant slightly smaller than one,[4]

$$\eta_{CFi,t} \equiv (E_t - E_{t-1}) \left[\sum_{j=0}^{\infty} \kappa_i^j g_{i,t+j} \right], \tag{15}$$

is the cash-flow news, and

$$\eta_{ERi,t} \equiv (E_t - E_{t-1}) \left[\sum_{j=1}^{\infty} \kappa_i^j r_{i,t+j} \right] \tag{16}$$

is the expected-return news. Since $g_{i,t}$ is the first element of $z_{i,t}$, we can extract it from the vector by $g_{i,t} = e_1' z_{i,t}$, where e_1 is a choice vector with one in the first element and zero elsewhere. Iterate Equation (13) forward to compute the cash-flow news (15) as

$$\eta_{CFi,t} = (E_t - E_{t-1}) \left[\sum_{j=0}^{\infty} \kappa_i^j e_1' z_{i,t+j} \right] = e_1' \left[\sum_{j=0}^{\infty} \kappa_i^j A_i^j \right] \epsilon_{i,t} = e_1'(I - \kappa_i A_i)^{-1} \epsilon_{i,t}, \tag{17}$$

where I is the identity matrix.

Using the Campbell (1991) decomposition (14), an asset's return beta with revisions in expected GDP can also be decomposed as

$$\beta_i = \frac{Cov(r_{i,t} - E_{t-1}[r_{i,t}], \zeta_{e,t})}{Var(\zeta_{e,t})} = \frac{Cov(\eta_{CFi,t} - \eta_{ERi,t}, \zeta_{e,t})}{Var(\zeta_{e,t})} = \beta_{CFi} - \beta_{ERi}. \tag{18}$$

As noted already, we employ the cash-flow beta, β_{CFi}, as a measure of procyclicality risk. It is

[4]We use $\kappa_i = 0.975$ for six months somewhat arbitrarily in the estimation to follow.

the slope coefficient in the time-series regression of the cash-flow news in Equation (17) on the innovation in the expected real GDP growth rate in Equation (7),

$$\eta_{CFi,t} = \beta_{CFi}\zeta_{e,t} + \xi_{i,t}, \tag{19}$$

where we omit the intercept because we demean both the dependent and independent variables. The procylicality premium, λ_e, measures the cross-sectional relation between the expected return and the cash-flow beta,

$$E[r_{i,t}] = \lambda_0 + \beta_{CFi}\lambda_e. \tag{20}$$

1.4 Computing Cash Flows

We compute cash flows following BDL (2005). The CRSP dataset provides the total return (RET) and the return without dividend ($RETX$) for individual stocks, both of which can be aggregated to the portfolio level. Starting with the initial value of $p_{i,0} = 1$, the price, $p_{i,m}$, and the dividend, $d_{i,m}$, of the i'th portfolio in month m can be recursively constructed as

$$p_{i,m} = (1 + RETX_{i,m})p_{i,m-1}, \tag{21}$$

$$d_{i,m} = (RET_{i,m} - RETX_{i,m})p_{i,m-1}. \tag{22}$$

To align the timing with the Livingston Survey, we add monthly observations of $d_{i,m}$ within each semiannual period to construct the semiannual dividend series, $d_{i,t}$. The semiannual dividend is deseasonalized by the trailing two-period moving average,

$$\bar{d}_{i,t} = \frac{d_{i,t}}{(d_{i,t-1} + d_{i,t-2})/2}. \tag{23}$$

We deflate the deseasonalized dividend by the Personal Consumption Expenditures Price Index ($PCEPI$) and take the log first difference to compute the real dividend growth rate,[5]

$$g_{i,t} = \log \frac{\bar{d}_{i,t}}{PCEPI_t} - \log \frac{\bar{d}_{i,t-1}}{PCEPI_{t-1}}. \tag{24}$$

This is used as the dependent variable in Equation (8).

2. Result

2.1 GMM Estimation of Cash-flow Risk Premium

Following Cochrane (2005), we combine the moment conditions for the time-series regressions (19) and the cross-sectional regression (20) in a single GMM system. This approach avoids the errors-in-variables problem from estimating the regressions sequentially and accommodates potentially heteroskedastic, autocorrelated errors. For numerical stability, we impose an OLS cross-sectional restriction to make the system just identified. Details are provided in Appendix B. We first fit Equations (19) and (20) using the two-pass Fama-MacBeth procedure and use the estimated coefficients as initial values for the GMM.

Tables 3 and 4 report the estimated coefficients using the equally and value-weighted portfolios, respectively. Each table starts with the procyclicality premium, λ_e (multiplied by 10^4), followed by the cross-sectional intercept, λ_0 (multiplied by 100), and the cash-flow betas of the size, BM, and momentum decile portfolios. The estimated cross-sectional premium is statistically significant; it is $\lambda_e = 4.56 \times 10^{-4}$ ($t = 4.78$) using equally weighted portfolios and $\lambda_e = 4.60 \times 10^{-4}$ ($t = 5.93$) using value-weighted portfolios. However, the intercept λ_0 is significantly positive regardless of weighting, implying that cash-flow risk alone cannot explain the cross section of the 30 test assets.

[5] The Personal Consumption Expenditures Price Index is downloaded from the St. Louis Fed's FRED system. The series name is $PCEPI$.

The remaining 30 rows of each table show the cash-flow betas of the test assets in Equation (19). We see that the cash-flow beta increases almost monotonically with past return across the momentum deciles (MOM) and similarly with the book-to-market ratio (BM), except that some mid-BM deciles exhibit large betas. The relation is much flatter across the size deciles ($SIZE$). However, the estimated cash-flow betas are generally larger for portfolios known to earn higher average returns, such as small stocks, value stocks, and momentum winners (consistent with Table III of BDL (2005)).[6]

This pattern aligns with the significantly positive estimates of the procyclicality premium, λ_e. We will revisit these points visually when we discuss Figures 1 and 2.

2.2 Rolling Estimation of Risk Measures

We employ a rolling estimation procedure to shed more light on the characteristics of the test assets. Each semester, we measure cash-flow betas and gammas using the past cumulative sample based on the GMM system described in Appendix A. Requiring a minimum of 40 semesters (20 years), our estimation starts in December 1984. Table 5 reports the mean returns ($\overline{R}$), mean rolling cash-flow betas ($\overline{\beta}$), full-sample cash-flow betas (β_F), mean rolling gammas ($\overline{\gamma}$), and full-sample gammas (γ_F) of the 30 equally weighted characteristic portfolios, and Table 6 those of the 30 value-weighted portfolios. The portfolios clearly exhibit the size, value, and momentum effects. As already known in the literature, the size and value effects are stronger among equally weighted portfolios in Table 5, while the momentum effect is stronger among value-weighted portfolios in Table 6 for our sample period. We can glean a generally positive, albeit noisy, relation between returns and cash-flow risk measures, whether $\overline{\beta}$, β_F, $\overline{\gamma}$, or γ_F is used.

[6] Using recursive utility models, Xiao, Faff, Gharghori, and Min (2013) find that small stocks, value stocks, and momentum winners have high betas with innovations in future consumption growth and that the exposure to consumption risk is priced. The cross-sectional pattern of betas is consistent with our paper, however, with an important distinction: they use return beta with consumption growth, while we employ cash-flow beta with expected real GDP growth.

To appreciate these points visually, Figures 1 and 2 plot the mean returns of the 30 equally and value-weighted portfolios, respectively, against the risk measures. In each figure, the mean returns are plotted against the mean rolling cash-flow betas ($\overline{\beta}$) in Panel A, mean rolling gammas ($\overline{\gamma}$) in Panel B, full-sample betas (β_F) in Panel C, and full-sample gammas (γ_F) in Panel D. The positive relation between return and the cash-flow risk measure is clear in all panels, although Panel A of Figure 2 displays an outlier.

We can connect the plots of full-sample betas to the GMM result in the previous section. Inspection reveals that the full-sample beta estimates (β_F) in Tables 5 and 6 are identical to the GMM estimates in Tables 3 and 4, respectively. This occurs because we supply the full-sample betas as initial values to the GMM; since the system is just identified and the cross-sectional moment conditions correspond to the OLS (see Appendix B), the GMM immediately converges without discernible parameter changes from the initial values. Therefore, our GMM estimates are virtually identical to the full-sample Fama-MacBeth estimates, with standard errors nonetheless accounting for residual heteroskedasticity and autocorrelation. Thus, if we fit a line, the slope coefficient in Panel C of Figures 1 and 2 would equal the procyclicality premium λ_e in Tables 3 and 4, respectively. This visual inspection confirms the significantly positive GMM estimates of the procyclicality premium in those tables.

2.3 Economic Significance of Cash-flow Risk

The analysis so far measures risk premium by cross-sectional regressions. While this closely follows the theoretical restrictions, the estimated premium does not have a straightforward interpretation. We address this issue by forming tradable portfolios of the characterestic portfolios. To distinguish between them, we call the latter portfolios “test assets” (a terminology inherited from cross-sectional asset-pricing tests) or simply “assets” for the rest of this and next sections.

Using either the rolling cash-flow betas or the gammas estimated in Section 2.2, we sort the 30 (equally or value-weighted) test assets to form equally weighted decile portfolios each semester. One can interpret the resulting portfolios as funds of funds. Tables 7 and 8 report the characteristics of the portfolios of equally and value-weighted assets, respectively. High cash-flow beta portfolios are procyclical because their cash flow news comoves with the innovation to the expected real GDP growth rate (see Equation (7)). Likewise, high gamma portfolios are also procyclical as their cash flows grow more with a long-run evolution of real GDP growth expectations (see Equation (8)). The tables show that assets exhibit a spectrum of cyclicality, ranging from being countercyclical (negative $\overline{\beta}$ or $\overline{\gamma}$) to procyclical (positive $\overline{\beta}$ or $\overline{\gamma}$).

In both tables, the average return ($\overline{R}(\beta)$ and $\overline{R}(\gamma)$, in percent) tends to increase with decile ranking, although the relation is not monotonic. The 10-1 spread return on the zero-cost portfolio that is long decile 10 and short decile 1 is statistically significant and economically large across the sorting keys and the weighting methods, varying between 1.70% (t = 2.22) and 4.38% (t = 6.11) per semester. Interestingly, all the Fama-French three-factor alphas ($\alpha 3$) are larger than the corresponding returns (especially for value-weighted portfolios) and significant at the 1% level. The four-factor alphas ($\alpha 4$) that additionally adjust for the momentum factor are also significant and sizable, except for the cash-flow beta-sorted portfolios of value-weighted assets in the left half of Table 8.

Figures 3 and 4 plot these relations. We can discern the positive association between the average return and the cash-flow risk measures, somewhat more clearly for the equally weighted assets due to a tighter distribution.

2.4 Optimal Specification

We have so far focused on the lag lengths of $K = 2$ and $L = 1$ in Equations (8) and (9). These are the result of an economic rather than purely statistical optimization. Specifically, we vary K and L and select the combination that yields the largest four-factor alphas of the long-short portfolios based on rolling cash-flow betas and gammas. Although this procedure is heuristic and might not produce a clear solution ex ante, it turns out to do so in our sample.

Panels A and B of Table 9 present the four-factor alphas of long-short portfolios sorted on rolling cash-flow beta using equally and value-weighted assets, respectively, and Panels C and D the corresponding results for portfolios sorted on rolling gamma. In each panel, we vary the lag lengths over $K = 1, 2, 3, 4$ and $L = 1, 2, 3, 4$. Except for Panel B where all the estimates are insignificant, the alpha is largest and most significant at $K = 2$ and $L = 1$ in each panel. These maximum alphas are reported in the row labeled $\alpha 4$ in Tables 7 and 8. The optimality at $K = 2$ is intuitive because it exactly covers the forecast horizon of the GDP and the CPI from the Livingston Survey.

2.5 Quarterly Results using Survey of Professional Forecasters

Appendix C shows the quarterly, rather than semiannual, results using the Survey of Professional Forecasters. The results are generally similar, with the cross-sectional premia carrying similar statistical significance. The portfolio results are stronger. Whether this is due to twice higher frequency needs to be carefully examined.

3. Conclusion

We provide robust evidence that cash-flow risk tied to expected economic growth is a priced factor in the cross section of U.S. equity returns. Our central contribution is to show that survey-based GDP growth expectations act as a powerful, forward-looking proxy for consumption growth and hence qualify as a state variable in asset pricing models. The expected real GDP growth rate not only comoves with contemporaneous consumption growth but also predicts realized real GDP growth and consumption growth positively, and future aggregate returns negatively, controlling for existing predictive variables. Thus, it satisfies the qualifications for an ICAPM state variable that affects consumption in the CCAPM, as emphasized by Breeden (1979).

Our empirical methodology closely follows Bansal, Dittmar, and Lundblad (2005), who measure cash-flow risk using the comovement between consumption growth and cash-flow growth of characteristic portfolios. We extend their methodology to accommodate the specific forecast horizon of the Livingston Survey. We find that cash-flow betas estimated from our methodology are generally larger for small stocks, value stocks, and momentum winners–portfolios known to earn higher average returns. This pattern is consistent with our significantly positive estimates of the procyclicality premium.

Our analysis leaves several questions open for future research. First, the cross-sectional intercept is significantly positive, implying that cash-flow risk alone cannot fully explain the cross section of characteristic portfolios. The procyclicality premium is economically large but not large enough to completely account for the size, value, and momentum effects. Second, we could explore a broader set of test assets beyond the 30 characteristic-sorted portfolios. Ideally, we would use individual stocks to increase cross-sectional variation in risk measures. However, the periodicity of dividends is a major obstacle in calculating cash flows. A practical workaround is to add more anomaly portfolios. Finally, we do not explore the macroeconomic implications of our findings. For example, how does the procyclicality premium vary over business cycles? Does it increase during recessions when consumption is low and marginal utility is high? How does it relate to macroeconomic uncertainty? We leave these important questions for future research.

Appendices

A. Computing Cash-flow News

Expanding the double summation in Equation (11) with the convention $\rho_{i,0} \equiv -1$ reads

$$
\begin{aligned}
\overbrace{-\rho_{i,0}}^{=1}&(\gamma_{i,1}g_{e,t-1} + \gamma_{i,2}g_{e,t-2} + \gamma_{i,3}g_{e,t-3} + ... + \gamma_{i,K}g_{e,t-K}) \\
&-\rho_{i,1}(\gamma_{i,1}g_{e,t-2} + \gamma_{i,2}g_{e,t-3} + ... + \gamma_{i,K-1}g_{e,t-K} + \gamma_{i,K}g_{e,t-(K+1)}) \\
&\quad -\rho_{i,2}(\gamma_{i,1}g_{e,t-3} + ... + \gamma_{i,K-2}g_{e,t-K} + \gamma_{i,K-1}g_{e,t-(K+1)} + \gamma_{i,K}g_{e,t-(K+2)}) \\
&\quad ... \\
&\quad - \rho_{i,L}(\gamma_{i,1}g_{e,t-L-1} + \gamma_{i,2}g_{e,t-L-2} + ... + \gamma_{i,K}g_{e,t-(K+L)}).
\end{aligned} \tag{A.1}
$$

Consider the h'th lag of the expected real GDP growth rate, $g_{e,t-h}$, for $1 \leq h = k + j \leq K + L$.

Collecting the terms involving $g_{e,t-h}$, we see that its coefficient is

$$\phi_{i,h} \equiv - \sum_{j=\max(0,h-K)}^{\min(L,h-1)} \rho_{i,j}\gamma_{i,h-j}. \tag{A.2}$$

The A_i matrix in Equation (13) is of size $K + 2L$ by $K + 2L$ and has the form,

$$
A = \begin{bmatrix}
\rho_{i,1} & \rho_{i,2} & \rho_{i,3} & ... & \rho_{i,L-1} & \rho_{i,L} & \phi_{i,1} & \phi_{i,2} & ... & \phi_{i,K+L-1} & \phi_{i,K+L} \\
1 & 0 & 0 & ... & 0 & 0 & 0 & 0 & ... & 0 & 0 \\
0 & 1 & 0 & ... & 0 & 0 & 0 & 0 & ... & 0 & 0 \\
0 & 0 & 1 & ... & 0 & 0 & 0 & 0 & ... & 0 & 0 \\
\vdots & & & \ddots & & & & & ... & 0 & \vdots \\
0 & 0 & 0 & ... & 1 & 0 & 0 & 0 & ... & 0 & 0 \\
0 & 0 & 0 & ... & 0 & 0 & \rho_e & 0 & ... & 0 & 0 \\
0 & 0 & 0 & ... & 0 & 0 & 1 & 0 & ... & 0 & 0 \\
0 & 0 & 0 & ... & 0 & 0 & 0 & 1 & ... & 0 & 0 \\
\vdots & & & ... & & & & & \ddots & 0 & \vdots \\
0 & 0 & 0 & ... & 0 & 0 & 0 & 0 & ... & 1 & 0
\end{bmatrix}. \tag{A.3}
$$

The residual vector is

$$\epsilon_{i,t} = (\zeta_{i,t} \quad 0 \quad ... \quad 0 \quad \overbrace{\zeta_{e,t}}^{(L+1)\text{'th element}} \quad 0 \quad ... \quad 0)', \tag{A.4}$$

where $\zeta_{i,t}$ and $\zeta_{e,t}$ are the errors in Equations (9) and (7), respectively, and the latter is placed in the $(L+1)$'th element of $\epsilon_{i,t}$. All the other elements of $\epsilon_{i,t}$ are zero, because the corresponding equations are identities. We separately fit the univariate equation (7) as an AR(1) model, and Equations (8) and (9) as an AR(K) model with an error term autocorrelated at order L. The estimated coefficients ρ_e, $\gamma_{i,k}$, and $\rho_{i,j}$ are used to construct the A_i matrix in Equation (A.3) with $\phi_{i,h}$ in Equation (A.2). The residuals from the univariate regressions are fed to $\epsilon_{i,t}$ in Equation (A.4), and then to Equation (17) along with A_i, to compute the cash-flow news.

B. GMM Estimation

Collect the portfolio returns, $r_{i,t}$, cash-flow news, $\eta_{CFi,t}$, and cash-flow betas, β_{CFi}, in vectors $\boldsymbol{r}_t$, $\boldsymbol{\eta}_t$ and $\boldsymbol{\beta}$, respectively, all of which have a length equal to the number of portfolios, N. Write the moment conditions for the time-series and cross-sectional regressions in Equations (19) and (20), respectively, as

$$\begin{bmatrix} \boldsymbol{I}_N & 0 \\ 0 & \boldsymbol{G} \end{bmatrix} \begin{bmatrix} E_T[(\boldsymbol{\eta}_t - \boldsymbol{\beta}\zeta_{e,t})\zeta_{e,t}] \\ E_T\left[\boldsymbol{r}_t - [\boldsymbol{1}_N \quad \boldsymbol{\beta}] \begin{bmatrix} \lambda_0 \\ \lambda_e \end{bmatrix}\right] \end{bmatrix} = 0, \tag{B.5}$$

where $\boldsymbol{I}_N$ is the identity matrix of size N, $E_T[\cdot]$ denotes the sample mean, and $\boldsymbol{1}_N$ is a length-N vector of ones. With N columns, the $\boldsymbol{G}$ matrix pre-multiplies the N cross-sectional moment conditions in the second $E_T[\cdot]$ operator and controls which of them is set to zero. When G is the identity matrix, all the cross-sectional moments are set to zero, which overidentifies the system. In this case, however, we find that the estimation is numerically unstable with our sample. Therefore, following Cochrane (2005, p.242), we set $\boldsymbol{G} = [\boldsymbol{1}_N \quad \boldsymbol{\beta}]'$, the regressor of the cross-sectional regression, to just identify the system. This is equivalent to running an OLS in the cross-sectional regression. With this choice of $\boldsymbol{G}$, Equation (B.5) has a total of $N+2$ moment conditions for $N+2$ parameters.

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Table 1: Summary statistics

	Mean	Stdev	Min	Max	N	Start	End
$EGDP$	1.23	0.67	-1.75	2.99	149	195112	202512
g_c	1.57	1.35	-5.00	5.98	132	195912	202506
$RGDP$	1.52	1.74	-9.09	8.98	149	195106	202506
$MKTRF$	4.18	11.59	-29.05	41.57	149	195012	202412
DY	2.96	1.19	1.11	6.57	149	195012	202412
DEF	0.08	0.04	0.03	0.28	151	195012	202512
$TERM$	0.11	0.10	-0.22	0.31	146	195306	202512
CAY	-0.04	1.92	-4.95	3.07	135	195206	201906

This table shows the mean (%), standard deviation (Stdev, %), minimum (Min, %), and maximum (Max, %), all in percent, as well as the number of observations (N) and the starting and ending dates of selected variables. $EGDP$ is the expected real GDP growth rate from the Livingston Survey. g_c is the consumption growth rate. $RGDP$ is the realized real GDP growth rate. $MKTRF$ is the semi-annually compounded excess market return. DY is the dividend yield. DEF is the monthly default spread. $TERM$ is the monthly term spread. CAY is the quarterly consumption-to-wealth ratio. Since CAY is available only up to the third quarter of 2019, we lag the last available value up to the ending date shown.

Table 2: Predictive Ability of Real GDP Expectations

Panel A: Regression of Realized Real GDP Growth Rate

Dependent Variable: $RGDP_t$								
	(1)		(2)		(3)		(4)	
Intercept	0.014***	(4.10)	0.005	(1.36)	0.009***	(3.63)	0.013***	(3.70)
$EGDP_t^{t+1,t+2}$	0.067	(0.23)						
$EGDP_{t-1}^{t,t+1}$			0.846***	(3.55)				
$EGDP_{t-2}^{t-1,t}$					0.458***	(2.66)		
$EGDP_{t-3}^{t-2,t-1}$							0.170	(0.71)

Panel B: Regression of Consumption Growth Rate

Dependent Variable: $g_{c,t}$								
	(1)		(2)		(3)		(4)	
Intercept	0.01***	(2.73)	0.007**	(2.04)	0.008**	(2.50)	0.013***	(4.34)
$EGDP_t^{t+1,t+2}$	0.42	(1.47)						
$EGDP_{t-1}^{t,t+1}$			0.671***	(3.25)				
$EGDP_{t-2}^{t-1,t}$					0.589***	(2.84)		
$EGDP_{t-3}^{t-2,t-1}$							0.181	(0.94)

(Continued)

Panel C: Regression of Market Return

	Dependent Variable: $MKTRF_t$			
	(2)	(3)	(4)	(5)
Intercept	0.017(0.88)	0.068***(4.24)	0.084***(4.78)	0.092***(5.15)
$EGDP_t^{t+1,t+2}$	1.906(1.48)			
$EGDP_{t-1}^{t,t+1}$		-2.242* (-1.92)		
$EGDP_{t-2}^{t-1,t}$			-3.538***(-2.86)	
$EGDP_{t-3}^{t-2,t-1}$				-4.188***(-3.24)

Panel D: Regression of Market Return with Controls

	Dependent Variable: $MKTRF_t$							
	(1)		(2)		(3)		(4)	
Intercept	-0.096*	(-1.95)	-0.025	(-0.54)	-0.013	(-0.29)	-0.009	(-0.22)
$EGDP_t^{t+1,t+2}$	3.845*	(1.92)						
$EGDP_{t-1}^{t,t+1}$			-3.061*	(-1.92)				
$EGDP_{t-2}^{t-1,t}$					-3.943***	(-3.02)		
$EGDP_{t-3}^{t-2,t-1}$							-4.448***	(-3.63)
DY_{t-1}	1.176*	(1.74)	0.305	(0.50)	0.285	(0.54)	0.304	(0.64)
DEF_{t-1}	-14.807	(-0.49)	13.589	(0.47)	13.179	(0.49)	12.522	(0.44)
$TERM_{t-1}$	2.599**	(2.22)	2.186**	(1.99)	2.147**	(2.05)	2.238**	(2.29)
CAY_{t-1}	16.856	(1.60)	21.746**	(2.47)	22.300**	(2.57)	21.924**	(2.41)

Panel A shows regressions of the realized real GDP growth rate ($RGDP_t$) on the contemporaneous ($EDGP_t^{t+1,t+2}$) or lagged expected real GDP growth rate up to three lags ($EDGP_{t-1}^{t,t+1}$, $EDGP_{t-2}^{t-1,t}$, or $EDGP_{t-3}^{t-2,t-1}$). Panels B and C replace the dependent variable by the consumption growth rate ($g_{c,t} \equiv \ln C_t - \ln C_{t-1}$) and the market return ($MKTRF_t$), respectively. Panel D adds the following control variables to the market regression: the first lags of the aggregate dividend yield (DY_{t-1}), default spread (DEF_{t-1}), term spread ($TERM_{t-1}$), and consumption-to-wealth ratio (CAY_{t-1}). ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. In parentheses are the t-statistics based on the Newey-West standard errors with two semiannual lags.

Table 3: Estimated GMM Parameters, Equally Weighted Portfolios

	Estimate	Std. Error	t value	$Pr(>\|t\|)$
$\lambda_e \times 10^4$	4.54	0.95	4.79	0.00
$\lambda_0 \times 100$	6.04	1.33	4.53	0.00
$SIZE1$	2.47	4.99	0.49	0.62
$SIZE2$	3.99	4.49	0.89	0.37
$SIZE3$	-3.68	4.02	-0.92	0.36
$SIZE4$	1.63	5.99	0.27	0.79
$SIZE5$	-1.69	3.67	-0.46	0.64
$SIZE6$	-0.16	2.93	-0.06	0.96
$SIZE7$	3.08	2.85	1.08	0.28
$SIZE8$	-9.19	4.14	-2.22	0.03
$SIZE9$	1.55	3.23	0.48	0.63
$SIZE10$	0.85	1.12	0.76	0.45
$BM1$	-7.70	3.50	-2.20	0.03
$BM2$	-20.38	3.88	-5.25	0.00
$BM3$	2.14	7.41	0.29	0.77
$BM4$	-5.99	4.35	-1.38	0.17
$BM5$	3.13	4.43	0.71	0.48
$BM6$	20.33	5.37	3.79	0.00
$BM7$	-9.18	4.76	-1.93	0.05
$BM8$	3.33	6.11	0.54	0.59
$BM9$	56.61	8.81	6.42	0.00
$BM10$	36.12	6.55	5.51	0.00
$MOM1$	-98.71	27.05	-3.65	0.00
$MOM2$	-46.90	15.19	-3.09	0.00
$MOM3$	-25.68	11.10	-2.31	0.02
$MOM4$	-20.35	7.89	-2.58	0.01
$MOM5$	-29.47	6.32	-4.66	0.00
$MOM6$	-11.34	12.36	-0.92	0.36
$MOM7$	0.17	7.62	0.02	0.98
$MOM8$	-11.60	8.17	-1.42	0.16
$MOM9$	20.79	8.76	2.37	0.02
$MOM10$	51.44	17.67	2.91	0.00

This table shows the premia and cash-flow betas estimated by the GMM in Appendix B using equally weighted characteristic portfolios. The top two rows report the cross-sectional premium (λ_e) and the constant (λ_0). The remaining rows are the cash-flow betas of the size, BM, and momentum decile portfolios, labeled as SIZE, BM, and MOM followed by the decile rank.

Table 4: Estimated GMM Parameters, Value-weighted Portfolios

	Estimate	Std. Error	t value	$Pr(>\|t\|)$
$\lambda_e \times 10^4$	4.58	0.77	5.95	0.00
$\lambda_0 \times 100$	4.86	1.07	4.54	0.00
$SIZE1$	4.88	5.36	0.91	0.36
$SIZE2$	6.23	5.73	1.09	0.28
$SIZE3$	-2.48	4.69	-0.53	0.60
$SIZE4$	3.56	6.03	0.59	0.55
$SIZE5$	-1.74	3.62	-0.48	0.63
$SIZE6$	0.74	3.84	0.19	0.85
$SIZE7$	6.04	2.74	2.21	0.03
$SIZE8$	-7.33	4.49	-1.63	0.10
$SIZE9$	2.30	3.39	0.68	0.50
$SIZE10$	1.90	1.32	1.44	0.15
$BM1$	0.24	3.95	0.06	0.95
$BM2$	-12.19	5.18	-2.35	0.02
$BM3$	20.93	10.50	1.99	0.05
$BM4$	-5.86	12.85	-0.46	0.65
$BM5$	46.42	9.33	4.97	0.00
$BM6$	16.20	12.40	1.31	0.19
$BM7$	1.67	8.14	0.21	0.84
$BM8$	28.29	12.81	2.21	0.03
$BM9$	52.51	10.78	4.87	0.00
$BM10$	35.26	11.98	2.94	0.00
$MOM1$	-114.94	40.26	-2.86	0.00
$MOM2$	-72.94	29.19	-2.50	0.01
$MOM3$	-52.24	17.57	-2.97	0.00
$MOM4$	-35.95	13.15	-2.73	0.01
$MOM5$	-44.83	12.78	-3.51	0.00
$MOM6$	-21.37	22.82	-0.94	0.35
$MOM7$	10.22	12.83	0.80	0.43
$MOM8$	-10.04	13.59	-0.74	0.46
$MOM9$	47.85	12.87	3.72	0.00
$MOM10$	77.95	26.75	2.91	0.00

This table shows the premia and cash-flow betas estimated by the GMM in Appendix B using value-weighted characteristic portfolios. The top two rows report the cross-sectional premium (λ_e) and the constant (λ_0). The remaining rows are the cash-flow betas of the size, BM, and momentum decile portfolios, labeled as SIZE, BM, and MOM followed by the decile rank.

Table 5: Returns, Cash-flow Betas, and Gammas of Equally Weighted Portfolios

	$\overline{R}$	$\overline{\beta}$	β_F	$\overline{\gamma}$	γ_F
SIZE1	7.2	6.7	2.5	2.0	-0.9
SIZE2	5.2	11.6	4.0	1.9	1.3
SIZE3	5.3	5.0	-3.7	2.4	-0.8
SIZE4	5.1	-2.0	1.6	0.9	1.9
SIZE5	5.6	-2.7	-1.7	-2.1	-2.0
SIZE6	5.4	5.3	-0.2	2.1	0.5
SIZE7	5.4	8.3	3.1	3.6	2.7
SIZE8	5.5	-2.5	-9.2	-0.4	-1.0
SIZE9	5.1	3.9	1.5	2.2	0.9
SIZE10	4.8	0.3	0.9	0.3	0.4
BM1	2.8	-8.0	-7.7	-1.9	-1.9
BM2	4.6	-15.0	-20.4	-5.2	-7.1
BM3	5.2	-2.4	2.1	3.0	4.6
BM4	6.1	-5.4	-6.0	-2.5	-2.9
BM5	6.1	4.2	3.1	1.1	0.6
BM6	6.4	14.4	20.3	5.2	7.1
BM7	7.4	0.6	-9.2	0.0	-3.7
BM8	7.9	9.8	3.3	1.4	-1.3
BM9	8.8	30.4	56.6	8.7	18.8
BM10	9.4	36.9	36.1	11.4	11.5
MOM1	2.5	5.6	-98.7	-13.0	-42.9
MOM2	2.9	-23.4	-46.9	-12.0	-20.8
MOM3	4.2	-21.1	-25.7	-9.3	-9.6
MOM4	5.3	-14.0	-20.3	-6.8	-8.3
MOM5	5.7	-12.9	-29.5	-4.0	-7.4
MOM6	6.2	-21.1	-11.3	-4.9	-7.1
MOM7	7.0	-5.2	0.2	-0.1	1.5
MOM8	7.5	-2.9	-11.6	-0.5	-1.5
MOM9	8.1	19.2	20.8	6.5	7.4
MOM10	8.3	32.9	51.4	12.9	17.1

$\overline{R}$ is the mean return. $\overline{\beta}$ is the mean rolling cash-flow beta. β_F is the full-sample cash-flow beta. $\overline{\gamma}$ is the mean rolling gamma. γ_F is the full-sample gamma.

Table 6: Returns, Cash-flow Betas, and Gammas of Value-weighted Portfolios

	$\overline{R}$	$\overline{\beta}$	β_F	$\overline{\gamma}$	γ_F
SIZE1	5.8	6.3	4.9	2.0	-0.5
SIZE2	5.4	14.0	6.2	3.0	2.1
SIZE3	5.7	5.6	-2.5	2.9	-0.8
SIZE4	5.4	-1.5	3.6	1.6	2.6
SIZE5	5.7	-3.4	-1.7	-2.2	-2.2
SIZE6	5.5	4.7	0.7	2.3	0.6
SIZE7	5.3	9.3	6.0	4.1	3.6
SIZE8	5.6	-2.1	-7.3	-0.3	-1.0
SIZE9	5.2	4.7	2.3	1.7	0.2
SIZE10	4.7	0.8	1.9	0.2	0.8
BM1	4.6	10.9	0.2	3.4	-0.3
BM2	5.1	-27.0	-12.2	-10.6	-6.3
BM3	4.9	22.4	20.9	10.5	11.7
BM4	4.8	-8.1	-5.9	0.4	2.4
BM5	5.0	29.9	46.4	6.3	12.8
BM6	5.2	13.7	16.2	5.8	8.2
BM7	5.5	6.1	1.7	-1.4	-1.3
BM8	6.1	11.0	28.3	4.1	5.5
BM9	5.9	24.7	52.5	9.5	22.2
BM10	6.3	42.5	35.3	9.6	7.9
MOM1	-3.9	-5.1	-114.9	-20.5	-50.8
MOM2	0.7	-40.9	-72.9	-14.0	-33.1
MOM3	2.8	-32.0	-52.2	-8.9	-17.4
MOM4	3.9	-23.7	-36.0	-8.7	-10.9
MOM5	4.5	-21.1	-44.8	-4.9	-10.4
MOM6	4.4	-35.3	-21.4	-10.8	-13.6
MOM7	5.1	0.4	10.2	5.2	5.6
MOM8	6.0	-12.0	-10.0	-2.5	1.0
MOM9	6.1	22.7	47.8	6.7	18.6
MOM10	7.6	68.2	78.0	22.5	24.8

$\overline{R}$ is the mean return. $\overline{\beta}$ is the mean rolling cash-flow beta. β_F is the full-sample cash-flow beta. $\overline{\gamma}$ is the mean rolling gamma. γ_F is the full-sample gamma.

Table 7: Rolling Beta and Gamma Portfolios of Equally Weighted Assets

	$\overline{\beta}$	$\overline{R}(\beta)$	$\overline{\gamma}$	$\overline{R}(\gamma)$
1	-23.99	5.19	-11.46	4.21
2	-13.89	5.53	-5.67	5.65
3	-7.24	4.53	-2.95	4.93
4	-3.61	4.85	-1.20	5.04
5	-0.76	6.11	-0.04	6.05
6	2.62	6.45	1.07	6.68
7	5.79	5.96	2.03	6.47
8	9.29	5.77	2.97	5.17
9	16.98	6.02	5.22	6.42
10	33.61	8.77	11.01	8.58
10-1		3.58*** (6.21)		4.38*** (6.11)
$\alpha 3$		3.68*** (5.79)		4.65*** (6.26)
$\alpha 4$		3.11*** (4.54)		2.47*** (3.85)

Equally weighted test assets are sorted by cash-flow beta or gamma to form equally weighted decile portfolios semi-annually. Returns are realized in the next semester. $\overline{\beta}$ and $\overline{R}(\beta)$ are the average cash-flow betas and returns (in percent) of the decile portfolios formed on cash-flow beta. $\overline{\gamma}$ and $\overline{R}(\gamma)$ are the average gammas and returns of the decile portfolios formed on gamma. "10-1" denotes the zero-cost portfolio long decile 10 and short decile 1. $\alpha 3$ is the intercept from the regression of the 10-1 portfolio return on the Fama-French three factors. $\alpha 4$ additionally controls for the momentum factor. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. t-statistics are in parentheses.

Table 8: Rolling Beta and Gamma Portfolios of Value-Weighted Assets

	$\overline{\beta}$	$\overline{R}(\beta)$	$\overline{\gamma}$	$\overline{R}(\gamma)$
1	-39.90	4.66	-15.70	3.08
2	-23.43	5.02	-8.89	5.09
3	-9.46	4.43	-3.42	5.15
4	-2.49	4.66	-0.65	4.81
5	2.49	4.78	1.06	5.08
6	5.88	5.42	2.44	5.41
7	9.11	4.94	3.52	4.86
8	14.63	3.16	4.82	4.01
9	23.83	5.29	7.36	4.91
10	47.88	6.35	15.05	6.30
10-1		1.70** (2.22)		3.22*** (3.38)
$\alpha 3$		2.66*** (3.62)		4.78*** (5.73)
$\alpha 4$		0.45 (0.72)		2.19*** (3.16)

Value-weighted test assets are sorted by cash-flow beta or gamma to form equally weighted decile portfolios semi-annually. Returns are realized in the next semester. $\overline{\beta}$ and $\overline{R}(\beta)$ are the average cash-flow betas and returns (in percent) of the decile portfolios formed on cash-flow beta. $\overline{\gamma}$ and $\overline{R}(\gamma)$ are the average gammas and returns of the decile portfolios formed on gamma. "10-1" denotes the zero-cost portfolio long decile 10 and short decile 1. $\alpha 3$ is the intercept from the regression of the 10-1 portfolio return on the Fama-French three factors. $\alpha 4$ additionally controls for the momentum factor. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. t-statistics are in parentheses.

Table 9: Four Factor Alphas of Rolling Long-Short Portfolios

Panel A: Cash-flow Beta Portfolios of Equally Weighted Assets

		L							
		1		2		3		4	
	1	1.63	(1.56)	1.68	(1.55)	1.59	(1.49)	1.50	(1.36)
K	2	3.11***	(4.54)	2.49***	(3.17)	2.31***	(2.82)	1.72*	(1.96)
	3	1.90**	(2.42)	1.34	(1.54)	1.35	(1.42)	1.65*	(1.79)
	4	0.48	(0.46)	0.11	(0.12)	0.07	(0.07)	0.25	(0.28)

Panel B: Cash-flow Beta Portfolios of Value-weighted Assets

		L			
		1	2	3	4
	1	0.18(0.20)	-0.34(-0.43)	-0.23(-0.28)	-0.64(-0.73)
K	2	0.45(0.72)	0.81(1.23)	0.64(0.99)	0.49(0.74)
	3	0.65(0.95)	0.64(0.97)	0.24(0.33)	0.71(1.01)
	4	-0.11(-0.11)	-0.60(-0.65)	-0.35(-0.38)	0.10(0.11)

Panel C: Gamma Portfolios of Equally Weighted Assets

		L							
		1		2		3		4	
	1	1.55**	(2.05)	1.23*	(1.79)	1.44*	(1.92)	0.77	(0.91)
K	2	2.47***	(3.85)	2.06***	(3.06)	1.92***	(2.80)	1.72***	(2.78)
	3	1.47**	(2.36)	1.47**	(2.31)	1.59**	(2.20)	1.28*	(1.88)
	4	0.68	(1.03)	-0.11	(-0.14)	-0.18	(-0.23)	-0.14	(-0.19)

Panel D: Gamma Portfolios of Value-weighted Assets

		L							
		1		2		3		4	
	1	0.83	(1.27)	1.03	(1.55)	1.26*	(1.82)	0.88	(1.28)
K	2	2.19***	(3.16)	1.86**	(2.49)	1.73**	(2.39)	1.27	(1.65)
	3	1.97***	(2.73)	1.63**	(2.20)	1.44*	(1.96)	1.38*	(1.78)
	4	2.15***	(3.13)	1.54**	(1.99)	1.87**	(2.32)	1.16	(1.61)

Assets with weighting stated in the panel title are sorted by cash-flow beta (Panels A and B) or gamma (Panels C and D) to form equally weighted decile portfolios semi-annually. Returns are realized in the next semester. The four-factor alpha of the zero-cost portfolio long decile 10 and short decile 1 is reported for $1 \leq K \leq 4$ and $1 \leq L \leq 4$. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. t-statistics are in parentheses.

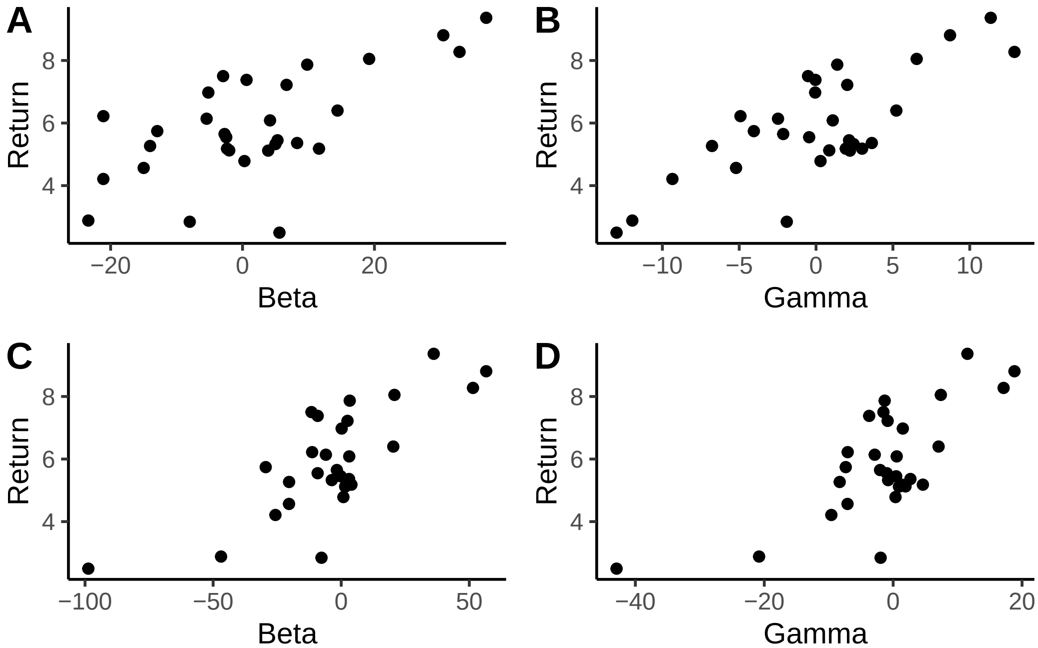

Figure 1: Returns, Betas, Gammas of Equally Weighted Assets

Mean returns of equally weighted characteristic portfolios are plotted against the mean rolling cash-flow betas ($\overline{\beta}$, Panel A), mean rolling gammas ($\overline{\gamma}$, Panel B), full-sample betas (β_F, Panel C), and full-sample gammas (γ_F, Panel D).

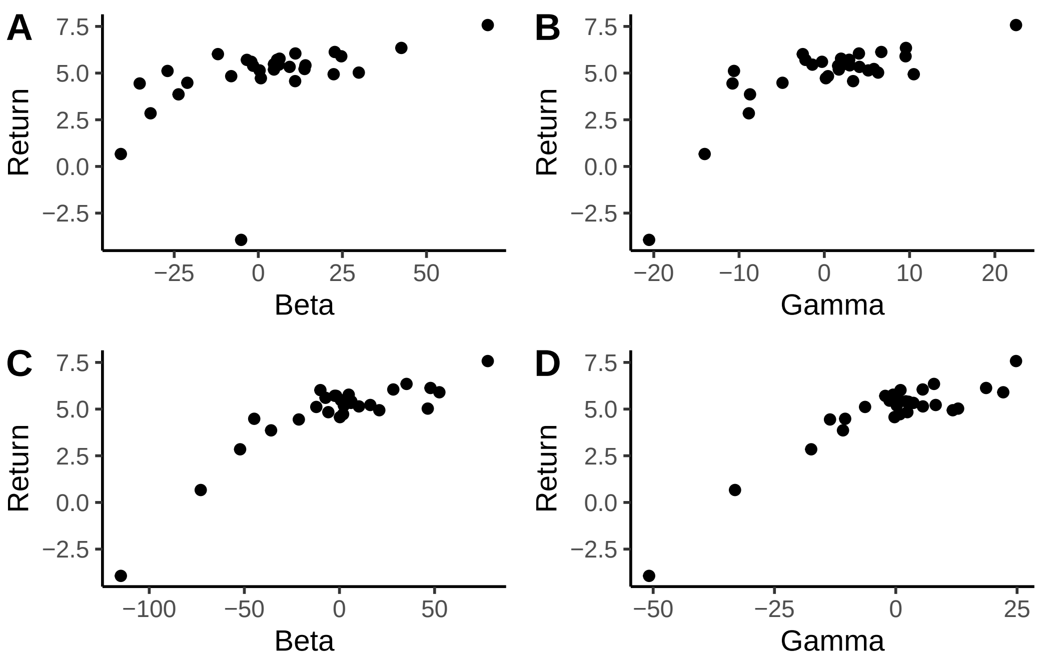

Figure 2: Returns, Betas, Gammas of Value-Weighted Assets

Mean returns of value-weighted characteristic portfolios are plotted against the mean rolling cash-flow betas ($\overline{\beta}$, Panel A), mean rolling gammas ($\overline{\gamma}$, Panel B), full-sample betas (β_F, Panel C), and full-sample gammas (γ_F, Panel D).

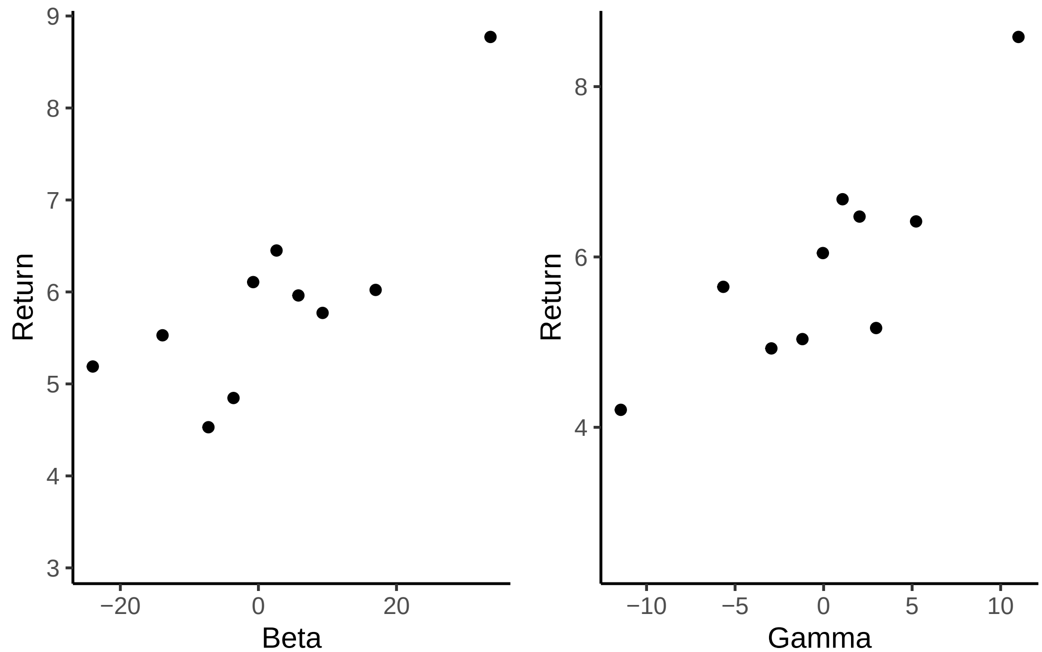

Figure 3: Rolling Beta and Gamma Portfolios of Equally Weighted Assets
Portfolios of equally weighted assets are formed on rolling cash-flow betas (left panel) or gammas (right panel). Mean portfolio returns are plotted against mean rolling cash-flow betas or gammas.

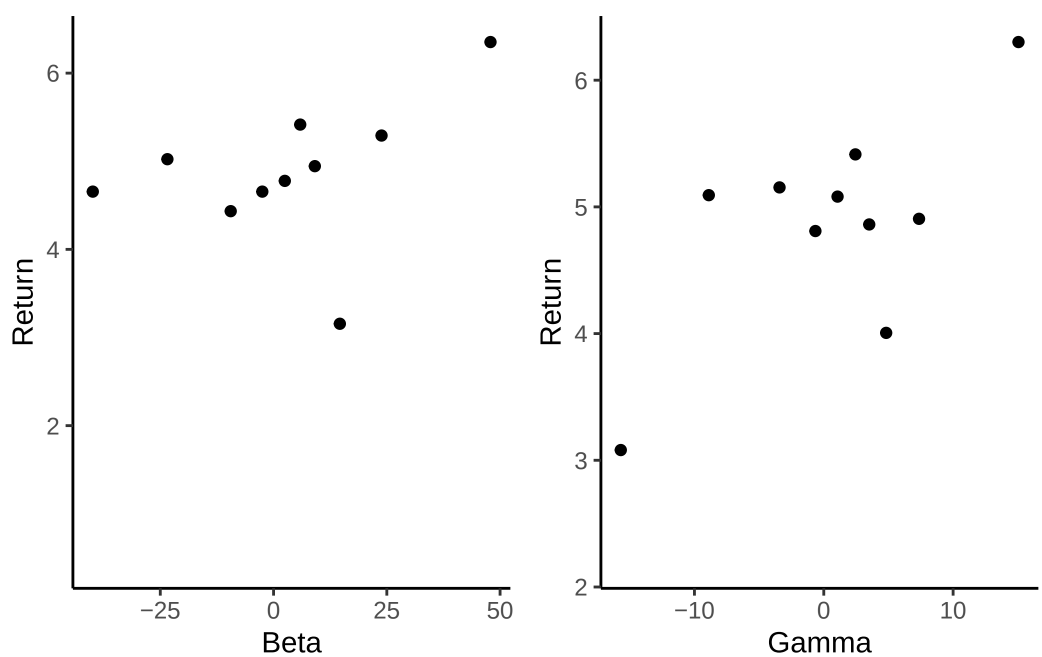

Figure 4: Rolling Beta and Gamma Portfolios of Value-Weighted Assets
Portfolios of value-weighted assets are formed on rolling cash-flow betas (left panel) or gammas (right panel). Mean portfolio returns are plotted against mean rolling cash-flow betas or gammas.

C. Quarterly SPF Tables and Figures

This section shows the quarterly, rather than semiannual, results with the Survey for Professional Forecasters.

Table C.1: Summary statistics

	Mean	Stdev	Min	Max	N	Start	End
$EGDP$	1.30	0.88	-2.06	5.05	229	196812	202512
g_c	0.73	0.92	-6.70	4.54	227	196903	202509
$RGDP$	0.68	1.07	-7.88	7.76	227	196903	202509
$MKTRF$	1.79	8.71	-26.46	23.17	225	196812	202412
DY	2.69	1.10	1.09	5.68	225	196812	202412
DEF	0.09	0.04	0.05	0.28	229	196812	202512
$TERM$	0.12	0.11	-0.22	0.37	229	196812	202512
CAY	-0.08	2.04	-4.95	3.80	204	196812	201909

This table shows the mean (%), standard deviation (Stdev, %), minimum (Min, %), and maximum (Max, %), all in percent, as well as the number of observations (N) and the starting and ending dates of selected variables. $EGDP$ is the expected real GDP growth rate from the Livingston Survey. g_c is the consumption growth rate. $RGDP$ is the realized real GDP growth rate. $MKTRF$ is the semi-annually compounded excess market return. DY is the dividend yield. DEF is the monthly default spread. $TERM$ is the monthly term spread. CAY is the quarterly consumption-to-wealth ratio. Since CAY is available only up to the third quarter of 2019, we lag the last available value up to the ending date shown.

Table C.2: Predictive Ability of Real GDP Expectations

Panel A: Regression of Realized Real GDP Growth Rate

Dependent Variable: $RGDP_t$				
	(1)	(2)	(3)	(4)
Intercept	0.003 (1.32)	0.000 (-0.20)	0.003*** (2.75)	0.004*** (3.21)
$EGDP_t^{t+1,t+2}$	0.301* (1.71)			
$EGDP_{t-1}^{t,t+1}$		0.554*** (3.98)		
$EGDP_{t-2}^{t-1,t}$			0.279*** (4.49)	
$EGDP_{t-3}^{t-2,t-1}$				0.219*** (3.33)

Panel B: Regression of Consumption Growth Rate

Dependent Variable: $g_{c,t}$				
	(1)	(2)	(3)	(4)
Intercept	0.002* (1.96)	0.003*** (2.62)	0.004*** (4.17)	0.004*** (3.68)
$EGDP_t^{t+1,t+2}$	0.408*** (6.56)			
$EGDP_{t-1}^{t,t+1}$		0.339*** (5.15)		
$EGDP_{t-2}^{t-1,t}$			0.238*** (4.25)	
$EGDP_{t-3}^{t-2,t-1}$				0.225*** (2.78)

(Continued)

Panel C: Regression of Market Return

Dependent Variable: $MKTRF_t$				
	(2)	(3)	(4)	(5)
Intercept	0.012(0.93)	0.02*(1.74)	0.016(1.46)	0.026***(2.65)
$EGDP_t^{t+1,t+2}$	0.480(0.59)			
$EGDP_{t-1}^{t,t+1}$		-0.17 (-0.24)		
$EGDP_{t-2}^{t-1,t}$			0.132(0.19)	
$EGDP_{t-3}^{t-2,t-1}$				-0.537 (-0.94)

Panel D: Regression of Market Return with Controls

Dependent Variable: $MKTRF_t$				
	(1)	(2)	(3)	(4)
Intercept	-0.018(-0.73)	-0.014 (-0.60)	-0.022(-0.78)	-0.014(-0.51)
$EGDP_t^{t+1,t+2}$	-0.451(-0.47)			
$EGDP_{t-1}^{t,t+1}$		-0.618 (-0.77)		
$EGDP_{t-2}^{t-1,t}$			-0.070(-0.08)	
$EGDP_{t-3}^{t-2,t-1}$				-0.453(-0.61)
DY_{t-1}	0.268(0.90)	0.268 (0.88)	0.299(0.97)	0.279(0.94)
DEF_{t-1}	6.750(0.28)	3.686 (0.15)	7.810(0.29)	3.597(0.13)
$TERM_{t-1}$	0.669(0.97)	0.702 (1.05)	0.693(1.04)	0.720(1.10)
CAY_{t-1}	11.578(1.58)	11.829*(1.83)	9.789(1.49)	10.234(1.61)

Panel A shows regressions of the realized real GDP growth rate ($RGDP_t$) on the contemporaneous ($EDGP_t^{t+1,t+2}$) or lagged expected real GDP growth rate up to three lags ($EDGP_{t-1}^{t,t+1}$, $EDGP_{t-2}^{t-1,t}$, or $EDGP_{t-3}^{t-2,t-1}$). Panels B and C replace the dependent variable by the consumption growth rate ($g_{c,t} \equiv \ln C_t - \ln C_{t-1}$) and the market return ($MKTRF_t$), respectively. Panel D adds the following control variables to the market regression: the first lags of the aggregate dividend yield (DY_{t-1}), default spread (DEF_{t-1}), term spread ($TERM_{t-1}$), and consumption-to-wealth ratio (CAY_{t-1}). ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. In parentheses are the t-statistics based on the Newey-West standard errors with two semiannual lags.

Table C.3: Estimated GMM Parameters, Equally Weighted Portfolios

	Estimate	Std. Error	t value	$Pr(>\|t\|)$
$\lambda_e \times 10^4$	4.54	1.14	4.00	0.00
$\lambda_0 \times 100$	2.91	0.69	4.22	0.00
$SIZE1$	1.15	2.61	0.44	0.66
$SIZE2$	4.61	2.26	2.04	0.04
$SIZE3$	0.23	2.25	0.10	0.92
$SIZE4$	6.53	2.26	2.89	0.00
$SIZE5$	-2.20	1.50	-1.47	0.14
$SIZE6$	0.28	1.35	0.21	0.83
$SIZE7$	0.47	1.50	0.31	0.76
$SIZE8$	1.19	1.64	0.72	0.47
$SIZE9$	0.82	1.59	0.51	0.61
$SIZE10$	2.06	0.92	2.23	0.03
$BM1$	-1.73	2.39	-0.72	0.47
$BM2$	-3.88	1.69	-2.29	0.02
$BM3$	1.74	2.24	0.78	0.44
$BM4$	-1.50	3.66	-0.41	0.68
$BM5$	2.31	1.27	1.82	0.07
$BM6$	4.83	1.65	2.93	0.00
$BM7$	-3.94	2.00	-1.97	0.05
$BM8$	5.91	2.08	2.84	0.00
$BM9$	19.39	2.91	6.67	0.00
$BM10$	12.71	3.58	3.55	0.00
$MOM1$	-38.31	8.20	-4.67	0.00
$MOM2$	-34.44	16.86	-2.04	0.04
$MOM3$	-16.70	7.90	-2.11	0.03
$MOM4$	-15.22	4.28	-3.56	0.00
$MOM5$	-7.01	3.17	-2.21	0.03
$MOM6$	-10.42	2.34	-4.46	0.00
$MOM7$	8.55	4.15	2.06	0.04
$MOM8$	1.16	3.94	0.30	0.77
$MOM9$	19.35	4.90	3.95	0.00
$MOM10$	31.30	9.11	3.44	0.00

This table shows the premia and cash-flow betas estimated by the GMM in Appendix B using equally weighted characteristic portfolios. The top two rows report the cross-sectional premium (λ_e) and the constant (λ_0). The remaining rows are the cash-flow betas of the size, BM, and momentum decile portfolios, labeled as SIZE, BM, and MOM followed by the decile rank.

Table C.4: Estimated GMM Parameters, Value-weighted Portfolios

	Estimate	Std. Error	t value	$Pr(>\|t\|)$
$\lambda_e \times 10^4$	4.41	1.41	3.14	0.00
$\lambda_0 \times 100$	2.37	0.64	3.72	0.00
$SIZE1$	2.49	2.65	0.94	0.35
$SIZE2$	7.30	2.78	2.63	0.01
$SIZE3$	1.92	2.88	0.67	0.50
$SIZE4$	8.48	2.62	3.24	0.00
$SIZE5$	-0.62	1.68	-0.37	0.71
$SIZE6$	2.07	1.55	1.34	0.18
$SIZE7$	2.30	1.55	1.49	0.14
$SIZE8$	2.77	1.72	1.61	0.11
$SIZE9$	2.99	1.64	1.82	0.07
$SIZE10$	3.61	0.78	4.62	0.00
$BM1$	3.38	2.25	1.51	0.13
$BM2$	-1.53	2.62	-0.58	0.56
$BM3$	7.14	4.06	1.76	0.08
$BM4$	3.87	5.26	0.74	0.46
$BM5$	22.53	2.68	8.40	0.00
$BM6$	1.27	3.40	0.37	0.71
$BM7$	-0.21	2.67	-0.08	0.94
$BM8$	9.15	4.71	1.94	0.05
$BM9$	31.17	4.32	7.22	0.00
$BM10$	13.82	5.44	2.54	0.01
$MOM1$	-52.70	13.75	-3.83	0.00
$MOM2$	-53.64	29.93	-1.79	0.07
$MOM3$	-22.83	12.33	-1.85	0.06
$MOM4$	-18.07	9.26	-1.95	0.05
$MOM5$	-8.55	6.97	-1.23	0.22
$MOM6$	-13.33	6.70	-1.99	0.05
$MOM7$	17.83	8.14	2.19	0.03
$MOM8$	8.92	9.39	0.95	0.34
$MOM9$	28.40	7.52	3.77	0.00
$MOM10$	35.75	10.73	3.33	0.00

This table shows the premia and cash-flow betas estimated by the GMM in Appendix B using value-weighted characteristic portfolios. The top two rows report the cross-sectional premium (λ_e) and the constant (λ_0). The remaining rows are the cash-flow betas of the size, BM, and momentum decile portfolios, labeled as SIZE, BM, and MOM followed by the decile rank.

Table C.5: Returns, Cash-flow Betas, and Gammas of Equally Weighted Portfolios

	$\overline{R}$	$\overline{\beta}$	β_F	$\overline{\gamma}$	γ_F
SIZE1	3.4	5.7	1.1	0.8	0.6
SIZE2	2.5	7.6	4.6	1.9	2.7
SIZE3	2.6	2.5	0.2	0.5	0.4
SIZE4	2.5	5.3	6.5	1.9	3.4
SIZE5	2.8	-1.3	-2.2	-0.4	-0.3
SIZE6	2.7	3.4	0.3	0.8	0.7
SIZE7	2.7	2.9	0.5	0.6	1.1
SIZE8	2.8	1.6	1.2	0.4	1.3
SIZE9	2.6	2.4	0.8	0.5	0.6
SIZE10	2.5	2.7	2.1	0.7	0.9
BM1	1.3	-1.2	-1.7	-0.6	-0.4
BM2	2.3	-4.2	-3.9	-1.2	-0.8
BM3	2.6	1.8	1.7	0.1	0.9
BM4	3.0	0.5	-1.5	0.0	0.9
BM5	3.1	3.6	2.3	1.0	1.1
BM6	3.1	4.4	4.8	0.9	1.6
BM7	3.6	-0.1	-3.9	0.6	0.4
BM8	3.8	6.8	5.9	2.2	2.5
BM9	4.4	12.8	19.4	2.6	6.2
BM10	4.6	16.7	12.7	4.5	6.0
MOM1	1.2	-6.6	-38.3	-1.1	-10.4
MOM2	1.3	-10.8	-34.4	-4.1	-7.1
MOM3	2.0	-10.3	-16.7	-3.8	-6.2
MOM4	2.6	-7.2	-15.2	-2.2	-3.7
MOM5	2.8	-2.2	-7.0	-0.6	-1.9
MOM6	3.1	-7.2	-10.4	-1.8	-2.2
MOM7	3.4	2.1	8.6	0.9	1.8
MOM8	3.6	0.5	1.2	1.7	2.8
MOM9	3.8	13.5	19.3	4.3	7.3
MOM10	3.9	17.2	31.3	6.0	9.1

$\overline{R}$ is the mean return. $\overline{\beta}$ is the mean rolling cash-flow beta. β_F is the full-sample cash-flow beta. $\overline{\gamma}$ is the mean rolling gamma. γ_F is the full-sample gamma.

Table C.6: Returns, Cash-flow Betas, and Gammas of Value-weighted Portfolios

	$\overline{R}$	$\overline{\beta}$	β_F	$\overline{\gamma}$	γ_F
SIZE1	2.7	5.3	2.5	0.9	1.2
SIZE2	2.6	9.2	7.3	2.5	4.1
SIZE3	2.7	3.5	1.9	0.8	1.0
SIZE4	2.6	6.6	8.5	2.5	4.3
SIZE5	2.8	-0.8	-0.6	-0.3	0.1
SIZE6	2.7	4.1	2.1	1.0	1.1
SIZE7	2.7	3.5	2.3	0.7	1.4
SIZE8	2.8	2.3	2.8	0.5	1.5
SIZE9	2.7	4.1	3.0	0.9	1.2
SIZE10	2.5	3.2	3.6	1.0	1.4
BM1	2.3	7.1	3.4	1.8	1.5
BM2	2.7	-7.7	-1.5	-0.9	0.4
BM3	2.6	5.6	7.1	0.8	2.0
BM4	2.6	4.7	3.9	2.7	4.3
BM5	2.6	24.9	22.5	5.6	6.5
BM6	2.7	-1.4	1.3	-0.5	0.4
BM7	2.8	1.1	-0.2	0.5	1.1
BM8	3.0	2.1	9.1	1.4	2.7
BM9	2.9	19.8	31.2	4.8	9.5
BM10	3.2	19.1	13.8	5.5	5.7
MOM1	-2.2	-25.6	-52.7	-5.0	-14.1
MOM2	0.3	-15.1	-53.6	-5.9	-10.0
MOM3	1.5	-10.4	-22.8	-4.3	-10.7
MOM4	2.0	-5.2	-18.1	-1.5	-2.5
MOM5	2.4	-1.8	-8.5	1.0	-0.9
MOM6	2.4	-5.1	-13.3	-1.1	-1.0
MOM7	2.7	7.5	17.8	1.1	2.5
MOM8	3.0	5.3	8.9	3.8	6.0
MOM9	3.0	12.5	28.4	4.9	10.3
MOM10	3.6	26.6	35.8	7.3	10.0

$\overline{R}$ is the mean return. $\overline{\beta}$ is the mean rolling cash-flow beta. β_F is the full-sample cash-flow beta. $\overline{\gamma}$ is the mean rolling gamma. γ_F is the full-sample gamma.

Table C.7: Rolling Beta and Gamma Portfolios of Equally Weighted Assets

	$\overline{\beta}$	$\overline{R}(\beta)$	$\overline{\gamma}$	$\overline{R}(\gamma)$
1	-11.18	1.86	-3.68	1.73
2	-5.27	2.08	-1.52	2.35
3	-1.42	2.56	-0.47	2.21
4	0.19	2.47	0.13	2.42
5	1.59	2.65	0.57	2.77
6	2.67	2.68	0.74	3.08
7	3.52	2.76	0.95	2.91
8	5.20	2.90	1.49	2.46
9	9.05	3.00	2.55	3.34
10	16.61	3.97	4.97	3.66
10-1		2.11***(6.54)		1.93***(5.50)
$\alpha 3$		2.25***(7.24)		2.12***(6.07)
$\alpha 4$		1.40***(5.12)		1.00***(3.58)

Equally weighted test assets are sorted by cash-flow beta or gamma to form equally weighted decile portfolios semi-annually. Returns are realized in the next semester. $\overline{\beta}$ and $\overline{R}(\beta)$ are the average cash-flow betas and returns (in percent) of the decile portfolios formed on cash-flow beta. $\overline{\gamma}$ and $\overline{R}(\gamma)$ are the average gammas and returns of the decile portfolios formed on gamma. "10-1" denotes the zero-cost portfolio long decile 10 and short decile 1. $\alpha 3$ is the intercept from the regression of the 10-1 portfolio return on the Fama-French three factors. $\alpha 4$ additionally controls for the momentum factor. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. t-statistics are in parentheses.

Table C.8: Rolling Beta and Gamma Portfolios of Value-Weighted Assets

	$\overline{\beta}$	$\overline{R}(\beta)$	$\overline{\gamma}$	$\overline{R}(\gamma)$
1	-18.66	0.81	-5.36	0.79
2	-5.53	2.18	-1.22	2.27
3	-0.96	2.29	-0.06	2.28
4	1.47	2.54	0.55	2.30
5	3.13	2.55	0.87	2.74
6	3.94	2.76	1.06	2.54
7	5.02	2.36	1.48	2.36
8	7.76	2.01	2.69	1.91
9	13.16	2.41	4.03	2.82
10	25.72	3.00	6.72	2.90
10-1		2.19***(4.15)		2.11***(3.66)
$\alpha 3$		2.85***(6.71)		2.91***(6.02)
$\alpha 4$		1.33***(4.32)		1.10***(3.32)

Value-weighted test assets are sorted by cash-flow beta or gamma to form equally weighted decile portfolios semi-annually. Returns are realized in the next semester. $\overline{\beta}$ and $\overline{R}(\beta)$ are the average cash-flow betas and returns (in percent) of the decile portfolios formed on cash-flow beta. $\overline{\gamma}$ and $\overline{R}(\gamma)$ are the average gammas and returns of the decile portfolios formed on gamma. "10-1" denotes the zero-cost portfolio long decile 10 and short decile 1. $\alpha 3$ is the intercept from the regression of the 10-1 portfolio return on the Fama-French three factors. $\alpha 4$ additionally controls for the momentum factor. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. t-statistics are in parentheses.

Table C.9: Four Factor Alphas of Rolling Long-Short Portfolios

Panel A: Cash-flow Beta Portfolios of Equally Weighted Assets

		L			
		1	2	3	4
K	1	0.87***(2.96)	1.05***(3.99)	1.31***(4.83)	1.26***(4.07)
	2	1.40***(5.12)	1.49***(5.36)	1.44***(5.10)	1.28***(4.15)
	3	1.44***(5.26)	1.32***(5.13)	1.13***(4.37)	1.21***(4.35)
	4	0.96***(3.43)	1.02***(3.65)	0.94***(3.53)	1.20***(4.73)

Panel B: Cash-flow Beta Portfolios of Value-weighted Assets

		L			
		1	2	3	4
K	1	0.95***(2.92)	1.11***(3.76)	1.23***(4.08)	1.26***(4.15)
	2	1.33***(4.32)	1.26***(4.02)	1.24***(3.99)	1.26***(3.81)
	3	0.89***(3.11)	0.90***(3.12)	1.01***(3.54)	0.99***(3.47)
	4	0.87***(3.00)	0.70** (2.42)	0.83***(2.90)	1.04***(3.56)

Panel C: Gamma Portfolios of Equally Weighted Assets

		L			
		1	2	3	4
K	1	0.96***(3.05)	0.97***(3.15)	1.27***(4.46)	1.30***(4.76)
	2	1.00***(3.58)	1.17***(4.53)	1.19***(4.77)	1.14***(4.46)
	3	1.20***(4.38)	1.16***(4.12)	0.96***(3.56)	0.91***(3.22)
	4	0.83***(3.23)	0.85***(3.17)	0.76***(2.97)	0.70***(2.78)

Panel D: Gamma Portfolios of Value-weighted Assets

		L			
		1	2	3	4
K	1	0.50 (1.61)	1.05***(3.26)	1.14***(3.56)	1.15***(3.41)
	2	1.10***(3.32)	1.16***(3.35)	1.34***(3.97)	1.38***(4.05)
	3	0.70** (2.25)	0.78***(2.62)	0.78** (2.55)	0.86***(2.77)
	4	1.07***(3.03)	0.76** (2.40)	1.05***(3.46)	0.86***(2.64)

Assets with weighting stated in the panel title are sorted by cash-flow beta (Panels A and B) or gamma (Panels C and D) to form equally weighted decile portfolios semi-annually. Returns are realized in the next semester. The four-factor alpha of the zero-cost portfolio long decile 10 and short decile 1 is reported for $1 \leq K \leq 4$ and $1 \leq L \leq 4$. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. t-statistics are in parentheses.

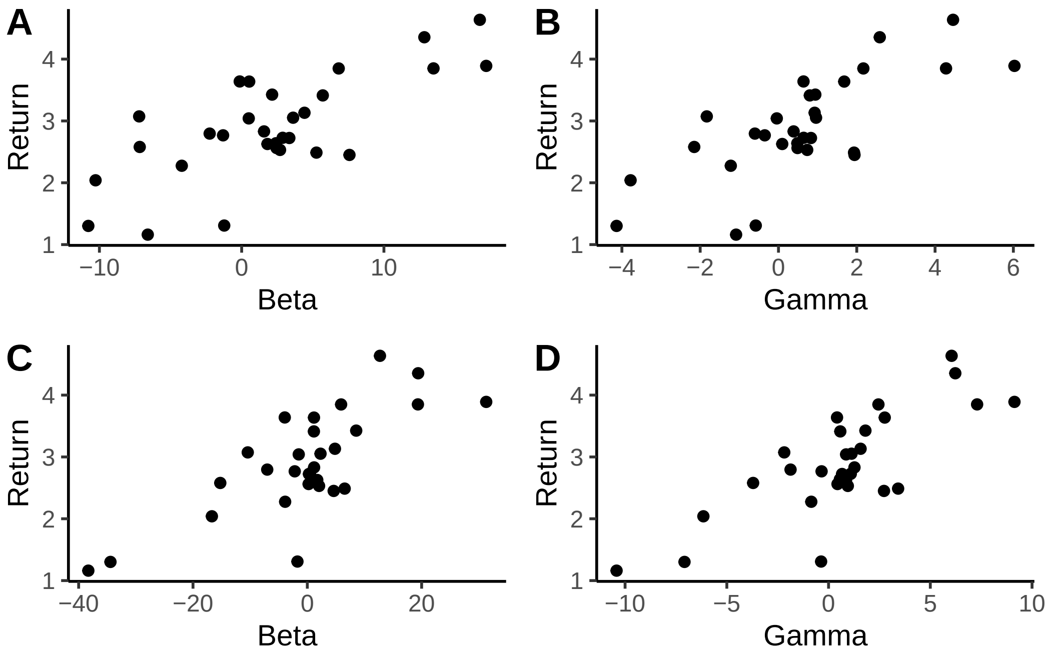

Figure C.1: Returns, Betas, Gammas of Equally Weighted Assets

Mean returns of equally weighted characteristic portfolios are plotted against the mean rolling cash-flow betas ($\overline{\beta}$, Panel A), mean rolling gammas ($\overline{\gamma}$, Panel B), full-sample betas (β_F, Panel C), and full-sample gammas (γ_F, Panel D).

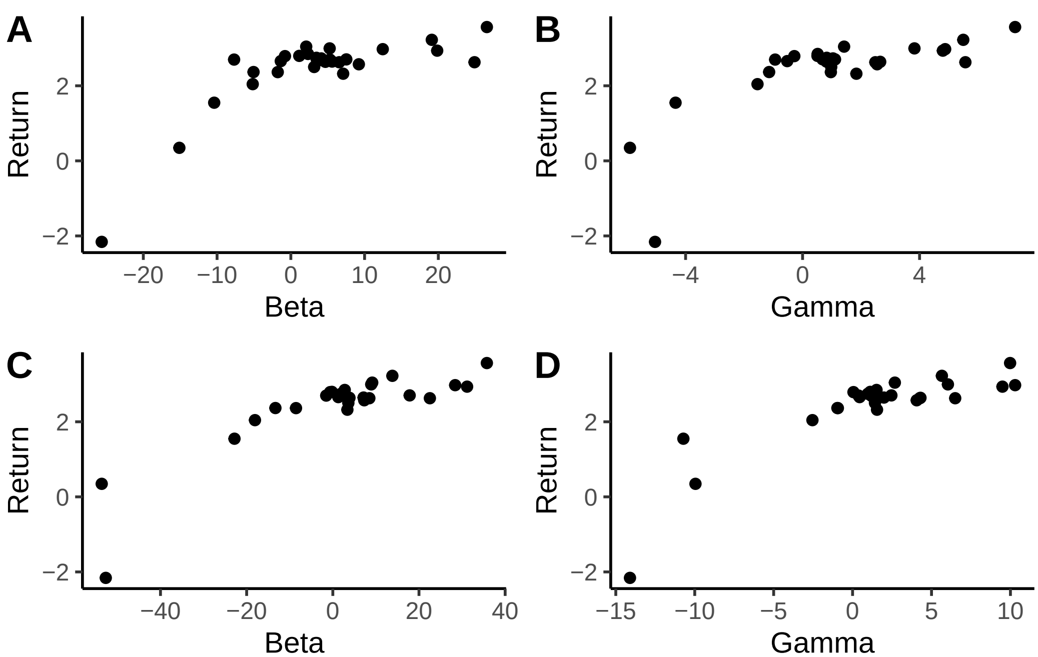

Figure C.2: Returns, Betas, Gammas of Value-Weighted Assets

Mean returns of value-weighted characteristic portfolios are plotted against the mean rolling cash-flow betas ($\overline{\beta}$, Panel A), mean rolling gammas ($\overline{\gamma}$, Panel B), full-sample betas (β_F, Panel C), and full-sample gammas (γ_F, Panel D).

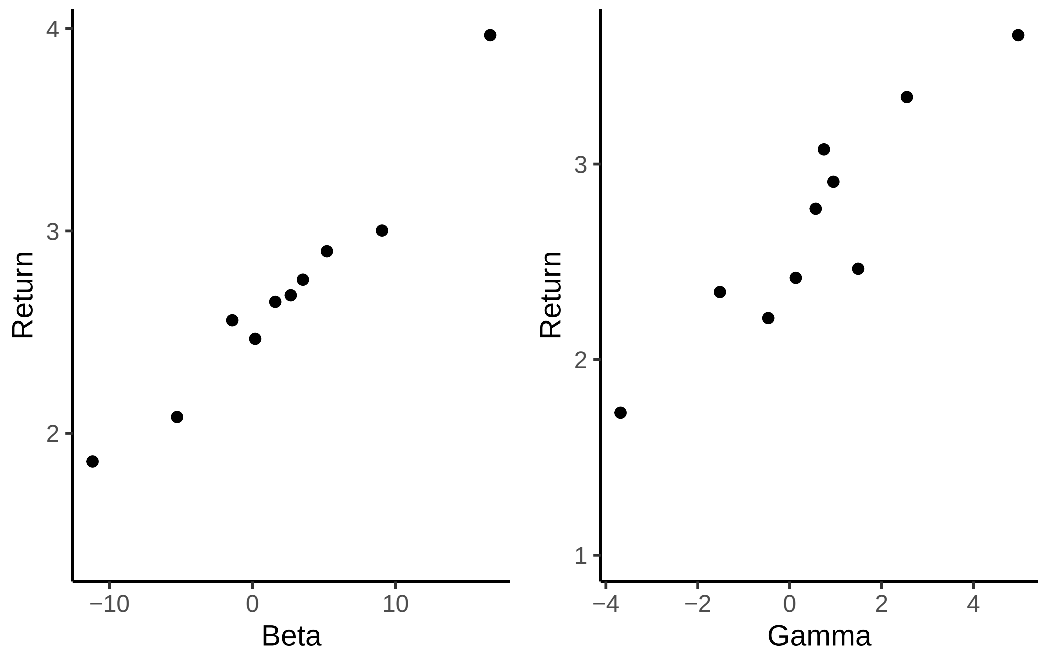

Figure C.3: Rolling Beta and Gamma Portfolios of Equally Weighted Assets

Portfolios of equally weighted assets are formed on rolling cash-flow betas (left panel) or gammas (right panel). Mean portfolio returns are plotted against mean rolling cash-flow betas or gammas.

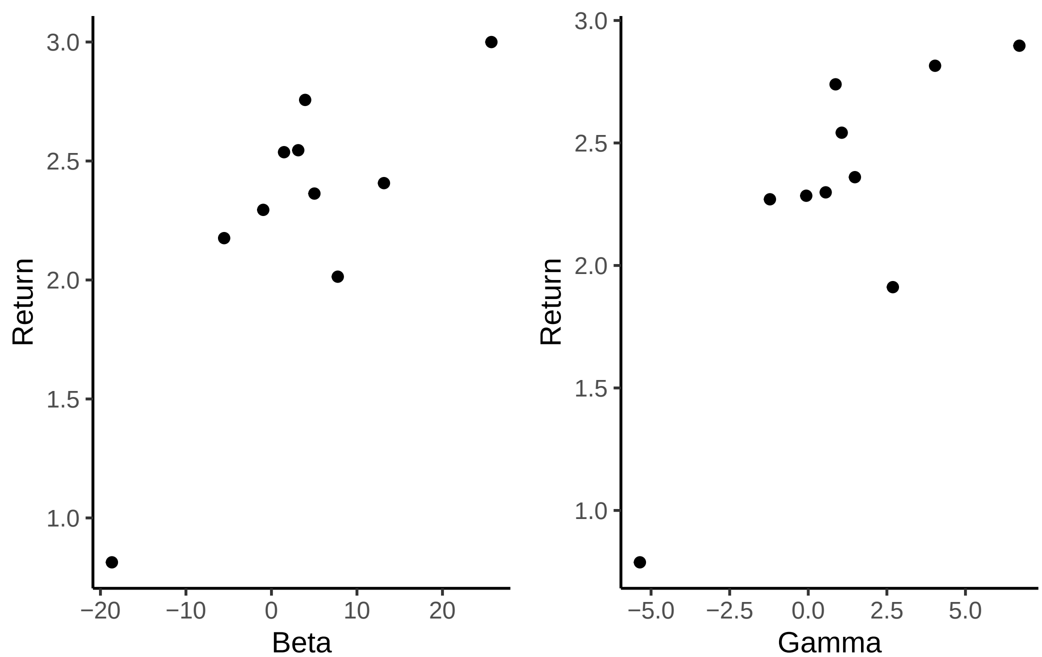

Figure C.4: Rolling Beta and Gamma Portfolios of Value-Weighted Assets

Portfolios of value-weighted assets are formed on rolling cash-flow betas (left panel) or gammas (right panel). Mean portfolio returns are plotted against mean rolling cash-flow betas or gammas.