Short-run and Long-run Consumption Risks, Dividend Processes and Asset Returns *

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Abstract

We examine the implications of short-run and long-run consumption risks on the momentum and long-term contrarian profits and the value premium in a unified economic framework. By introducing time-varying firm cash flow exposures to the short-run and long-run shocks in consumption growth, we find the otherwise standard intertemporal asset pricing model goes a long way towards generating the momentum and long-term contrarian profits and the value premium. The model also reproduces the size effect, the pairwise correlations between the profitabilities of these investment strategies, and the performance of the standard CAPM and the consumption-CAPM in explaining these well-documented return behaviors.

JEL Classifications: G12, E44

Keywords: Short-run and long-run consumption risks, Momentum and long-term contrarian profits, Value premium

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1 Introduction

We provide a unified consumption-based explanation for the widely documented asset return phenomena such as the momentum and long-term contrarian profits and the value premium. To motivate our analysis, we plot in Figure 1 the exposures to the high- and low- frequency components of aggregate consumption growth fluctuations of 10 momentum, 10 long-term contrarian, and 10 book-to-market portfolios.[1] The patterns in consumption risk exposures are striking: while long-term losers and value firms have clearly higher exposures to the low-frequency consumption risk than long-term winners and growth firms, the high-frequency consumption risk exposure increases from momentum losers to momentum winners. These patterns are consistent with the findings in Parker and Julliard (2005) and Hansen, Heaton, and Li (2008) who document that value portfolios have a higher exposure to the long-run economic shocks than growth portfolios, as well as the findings in Bansal, Dittmar, and Lundblad (2005) who demonstrate that the cash flow beta of momentum winner stocks is significantly higher than that of the momentum loser stocks. More importantly, the results shown in Figure 1 suggest that if the prices of risk for both high- and low-frequency consumption risks are positive, which is true under the standard assumptions of Bansal and Yaron (2004) (BY thereafter) and Bansal, Kiku, and Yaron (2012a), the low-frequency consumption risk should be the main driving force for the value premium and long-term contrarian profits, whereas the high-frequency consumption risk should be responsible for momentum profits.[2]

[Insert Figure 1 Here]

[1]Specifically, we decompose consumption growth variations at 2 to 8 year frequency (referred to as business cycle or high frequency) and 20 to 70 year frequency (referred to as technological innovation or low frequency) using band-pass filtering. Similar decomposition has been used in Comin and Gertler (2006) to investigate the medium-frequency oscillations between periods of robust growth versus relative stagnation. They refer to the frequencies between 2 to 32 quarters (the standard representation of business cycles) as the high-frequency component of the medium-term cycle, and frequencies between 32 and 200 quarters (8 to 50 years) as the medium-frequency component. They show that the medium-frequency component is highly persistent and features significant procyclical movements in technological change, and research and development (R&D), as well as the efficiency and intensity of resource utilization. Dew-Becker and Giglio (2014) documents that only economic shocks with cycles longer than the business cycle have a strong effect on asset pricing for Fama-French 25 size and book-to-market, and industry portfolios.

[2]Among others, papers that study the implication of frequency domains on asset prices include: Yu (2012), Otrok, Ravikumar, and Whiteman (2002), Daniel and Marshall (1997), Dew-Becker and Giglio (2014), Bandi and Tamoni (2014).

In this paper, we extend the long-run consumption risk model in BY and explore its implications for the cross section of asset returns by introducing a general but parsimonious specification of the firm-level dividend process.[3] We maintain the specification of BY on the representative agent preference and the aggregate consumption process. However, we introduce firms' cash flow processes to accommodate the variation in aggregate dividend growth, the exposures to the short-run and long-run consumption risks, and firm-specific dividend shocks. In addition, we allow firm cash flow exposure to the short-run and long-run consumption risks to be time-varying and correlate with the firm-specific dividend shocks. Our firm dividend process is related to Johnson (2002) but differs in that our firms are subject to time-varying exposures to both short-run and long-run risks.[4] It differs from Lettau and Wachter (2007) and Santos and Veronesi (2010) in that they pursue a top-down approach and model shares of individual firm dividend as a fraction of aggregate dividend. Their specifications imply that the heterogeneity of firm cash flow risk moves in tandem with the aggregate cash flow variability at any point in time. As a result, the risk premium of an investment strategy depends on firms' time-varying dividend shares.[5] We, however, take a bottom-up approach and start with firm-level dividend processes. In particular, we allow firm dividend growth to have time-varying sensitivities to components of aggregate consumption risks. This adds to the richness of firm heterogeneity and accommodates different exposures of the momentum, contrarian and valuation ratio portfolios to different components of aggregate consumption shocks uncovered in data.

[3]We use firm dividend and cash flow interchangeably in the paper. Several existing studies have provided explanations separately for the momentum profit and the value premium using specific firm dividend growth processes. For example, Johnson (2002) offers a rational explanation for the momentum profit using a single firm time-varying dividend growth process with a two-state regime model. One of the regimes corresponds to the normal state in which the dividend growth rate shocks last for a quarter to a business cycle. The other regime stands for a fundamental technological change in which firm dividend growth innovations are more or less permanent. On the other hand, Lettau and Wachter (2007), Santos and Veronesi (2010), among others, suggest that heterogeneity in firm cash flow helps generating the value premium.

[4]In addition, Johnson (2002) uses a partial equilibrium model and has no channel to generate a large value premium. In contrast, we use a general equilibrium model and attribute the profitability of various strategies to different components of consumption risks.

[5]Santos and Veronesi (2010) allows firms' dividend shares to be time-varying and stochastic. They show that substantial heterogeneity in firms' cash-flow risk yields both a value premium and some stylized facts of the cross-section of stock returns. However, they find the cash-flow risk has to be very large to generate empirically plausible value premiums, leading to a "cash-flow risk puzzle".

In our model, while individual stocks are identical ex ante, they have very different characteristics ex post after the realization of firm-specific cash flow shocks. Due to the lack of guidance from the existing literature on the calibration of our firm-level dividend process, we employ a simulated method of moments (SMM) approach to estimate these parameters. We avoid using the cross-sectional average returns of the momentum, contrarian, and valuation ratio portfolios as moment conditions. Instead, we estimate the parameters of firm dividend process using firm characteristics and aggregate moments, and explore the asset pricing implications of our model using the estimated parameter values. This approach mitigates the concern that the parameters of the dividend process are directly implied by returns on the target portfolios. Using these estimates and other widely used coefficients for the investor preferences and aggregate economic variables, we find that when sorting stocks into portfolios based on past short-term and long-term stock performances and the valuation ratios, we are able to generate a momentum profit of 7.35%, a contrarian profit of 5.07%, and a value premium of 9.83%. These results are consistent with their counterparts of 6.97%, 6.48%, and 6.91%, respectively, in the data from 1931 to 2011. While not imposed as a moment condition in our SMM estimation, we also generate a large size effect using the estimated parameter values.

Our analysis indicates that the different persistence of the short-run and long-run consumption risk exposures plays an important role in reconciling the co-existence of momentum and contrarian profits and the value premium. The short-run risk exposure is relatively short-lived, whereas the long-run risk exposure is persistent. Momentum portfolios are sorted on the stock return performance in the past several months, so they contain information about the short-run risk exposure. In contrast, sorting variables such as the dividend-price ratio are persistent and containing information about the long-run component of the risk exposure. Therefore, portfolios sorted by these characteristics should create a large dispersion on the persistent exposure to the long-run risk. Our analysis also highlights the importance of the correlation structure between the short-run and long-run risk exposure shocks and firm cash flow shocks. A positive cash flow shock is associated with an increase in the exposure to short-run risk leading to a positive correlation between firm dividend and the short-run consumption risk exposure. This positive correlation is consistent with a real option effect as studied in Sagi and Seasholes (2007). On the other hand, a negative cash flow shock also adversely affects a firm's equity valuation and increases the leverage of the firm (Black (1976) and Christie (1982)). This will lead to a negative correlation between a firm's cash flow shock and the long-run consumption risk exposure. Our estimation provides supporting evidence on these two correlation coefficients.

Taken together, our analyses provide a unified consumption-based explanation for the momentum and contrarian profits and the value premium. For momentum strategies, short-term winners have high dividend growth in the recent past. Dividend is persistent, generating a cash-flow effect; at the same time, a positive correlation between firm dividend shock and the exposure to short-run risk creates a discount effect. For our estimated parameter values, the cash flow effect dominates the discount effect, validating the momentum winners (losers) to have a good (bad) recent performance as well as positive differentials in expected returns. For the long-term contrarian profits and the value premium, the long-term losers and value firms had negative dividend shocks in the long past and high long-run consumption risk exposures due to the negative correlation between firm dividend shocks and long-run risk exposure. The cash flow effect reinforces the discount effect, giving rise to a high expected return relative to long-term winners and growth firms.

In addition to the unconditional asset return moments, the momentum profit is negatively correlated with the contrarian profit, the value premium, and the size premium in our simulation. The correlation coefficients are broadly consistent with the empirical estimates from the actual data. The intuition behind these findings are straightforward. Momentum portfolios sorted on the short-term stock return pick up the dispersion on the short-run risk exposure. Portfolios sorted by the long-term stock return, the dividend-price ratio, and firm size create a large dispersion on the long-run risk exposure. However, these portfolio sorts do not isolate the risk exposures from one factor to the other: growth firms also tend to have higher short-term stock return than value firms, implying a negative risk exposure to the short-run risk for the value-minus-growth portfolio. Similarly for the momentum strategy, the winners also tend to have a lower leverage and a lower sensitivity to the long-run risk than the losers because of good past performance. Thus, the momentum profit loads negatively on the long-run risk. The opposite responses of the value premium (and long-term contrarian profits) and the momentum profit to consumption shocks (both short-run and long-run) provide a natural explanation for the correlation coefficients between the profitabilities of these strategies.

The decomposition of risk exposures also sheds light on the performance of Capital Asset Pricing Model (CAPM) and Consumption-CAPM in explaining the cross-sectional stock returns. As emphasized in BY, the equity premium is mainly driven by long-run consumption variations; we should expect that the unconditional CAPM performs better for the portfolios sorted by the long-term past return performance and valuation ratios than the momentum portfolios. In contrast, the major contributing component of the consumption growth is its short-run fluctuations; we thus expect the returns of the momentum portfolios are better captured by the Consumption-CAPM. We confirm these predictions using the sample of observations between January 1931 and December 2011. For example, the beta to the aggregate consumption growth increases from -3.43 for short-term losers to 3.97 for short-term winners, in line with the patterns uncovered in the average returns. To the best of our knowledge, our paper is the first to document the monotonic pattern in consumption beta for the momentum portfolio returns when the consumption risk is measured in such a standard way.

Despite the success of our model in reproducing salient features of asset pricing phenomena, one should not simply take it for granted that our dividend process will necessarily generate the momentum and contrarian profits and the value premium. In an extensive sensitivity analysis, our main findings survive when the key parameters take economically plausible values that are consistent with the moment conditions. However, when the perturbation is set at a value that is far from standard confidence intervals, the model implied asset prices can vary in a significant way. In scenarios when some of the parameters take extreme values, either the momentum profit or value premium becomes negative. Therefore, the moment conditions from portfolio characteristics, exposures to consumption risks, and aggregate price-dividend ratio and equity premium provide valuable information on parameter values that governs firm dividend process, which in turn determines the risk exposures and expected returns of portfolios sorted by short-term and long-term past performance and valuation ratios.

Several recent papers explore a joint explanation of the value premium (or the long-term contrarian profit) and the momentum profit. For instance, Yang (2007) attempts to relate the momentum and the long-run contrarian profits to the long-run consumption risk in a theoretical study. However, as we pointed out in our consumption risk decomposition analysis, the momentum profit is primarily driven by firms' exposure to the short-run consumption risk. In addition, given the one-factor structure, his model is unable to reproduce the performance of CAPM and consumption CAPM from the empirical data. Li (2014) focuses on the production side of the economy and studies an investment-based explanation for the momentum profit and value premium by linking asset prices to economic fundamentals such as profitability and real investments. Liu, Zhang, and Fan (2011) explore the restrictions imposed by the momentum and contrarian profits on the stochastic discount factors from commonly used utility functions. They provide supporting evidence that the momentum and contrarian profits manifest the short-term continuation and long-term reversal in the macroeconomic fundamentals. Vayanos and Woolley (2013) propose a theory of momentum and reversal based on flows between investment funds. Albuquerque and Miao (2014) link the momentum and long-run reversals with heterogeneous information and investment opportunities. More recently, based on the assumption that shareholders located in different percentiles of the wealth distribution have marginal utilities that vary inversely with the capital share, Lettau, Ludvigson, and Ma (2015) find that a single risk factor, the capital share risk, is able to capture momentum profits and the value premium. Instead, our paper pursues a consumption-based explanation under the representative agent framework.[6]

[6]Our paper contributes to a large and still growing literature studying the asset pricing implications of the long-run risk framework. Besides the papers we previously discussed, a incomplete list of recent studies include: Malloy, Moskowitz, and Vissing-Jorgensen (2009), Drechsler and Yaron (2011), Bansal and Shaliastovich (2013), Bansal, Kiku, Shaliastovich, and Yaron (2014), Bansal and Shaliastovich (2011), Roussanov (2014), Croce, Lettau, and Ludvigson (2014), Kiku (2006), among many others. Other important contributions in the literature on the value premium from the perspective of rational expectations include, but are not limited to, Gomes, Kogan, and Zhang (2003), Zhang (2005), and Kogan and Papanikolaou (2014).

2 The Economic Model

2.1 The Basic Setup

In this section, we specify a long-run risk model based on case (I) of BY, which excludes stochastic volatility of consumption. The endowment economy features a representative agent and a large number of stocks. The representative agent has Epstein and Zin (1989) recursive preference, which allows a separation of relative risk aversion and the elasticity of intertemporal substitution (EIS). With the recursive preference, the representative agent maximizes the discounted lifetime utility V_t by solving the following dynamic optimization problem:

$$\begin{aligned} V_t &= \max_{C_t} \left((1-\delta) C_t^{1-\frac{1}{\psi}} + \delta \left(E_t[V_{t+1}^{1-\gamma}] \right)^{\frac{1-\frac{1}{\psi}}{1-\gamma}} \right)^{\frac{1}{1-\frac{1}{\psi}}} \\ &\text{s.t. } W_{t+1} = (W_t - C_t) R_{a,t+1} \end{aligned} \tag{1}$$

where δ is the subjective discount factor, ψ is EIS, and γ is the relative risk aversion. C_t is the consumption decision to be made by the agent. The budget constraint states that the wealth at $t+1$ equals the saving $(W_t - C_t)$ multiplied by the return on the consumption claim $R_{a,t+1}$.

The first-order condition implies that the stochastic discount factor (SDF) is (see, for example, Epstein and Zin (1989) and Hansen, Heaton, Lee, and Roussanov (2007)):

$$m_{t+1} = \theta \log \delta - \frac{\theta}{\psi} \Delta c_{t+1} + (\theta - 1) r_{a,t+1} \tag{2}$$

where $\theta = \frac{1-\gamma}{1-1/\psi}$, Δc_{t+1} is the consumption growth measured as the first difference in logarithmic consumption, and $r_{a,t+1}$ is the logarithmic return on the consumption claim which can be written as:

$$\begin{aligned} r_{a,t+1} &= \log \left(\frac{W_{t+1} + C_{t+1}}{W_t} \right) \\ &= \log(\exp(wc_{t+1}) + 1) - wc_t + \Delta c_{t+1} \end{aligned} \tag{3}$$

with $wc_t = W_t/C_t$ being the wealth-consumption ratio. In equilibrium, the return r_{t+1} of any security must satisfy the Euler equation

$$E_t[\exp(m_{t+1} + r_{t+1})] = 1 \tag{4}$$

Applying the Euler equation to the consumption claim and the dividend claim, we have the following recursive forms for the wealth-consumption ratio and the price-dividend ratio (denoted by pd_t^i)[7]

$$wc_t = \frac{1}{\theta}\log(E_t[\exp(\theta\log\delta - (\frac{\theta}{\psi} - \theta)\Delta c_{t+1} + \theta(\log(\exp(wc_{t+1}) + 1)))]) \tag{5}$$

$$\begin{aligned} pd_t^i = \log(E_t[\exp(\theta\log\delta + (\theta - 1 - \frac{\theta}{\psi})\Delta c_{t+1} + (\theta - 1)(\log(\exp(wc_{t+1}) + 1) - wc_t) \\ + \log(\exp(pd_{t+1}^i) + 1) + \Delta d_{t+1}^i)]) \end{aligned} \tag{6}$$

where Δd_{t+1}^i is firm i's dividend growth measured as the first difference in logarithmic firm dividend distribution which we discuss in more detail in next subsection.

Next, we discuss the dynamics for the aggregate consumption growth process. The specification of the aggregate consumption growth process is the same as in case (I) of BY. In addition to the i.i.d. short-run shocks (η_{t+1}) to the consumption growth, there is a small but persistent expected consumption growth (x_t) which, as shown in BY, helps to explain a wide-range of phenomena in aggregate asset prices. Specifically, we have

$$\begin{aligned} \Delta c_{t+1} &= g_c + x_t + \sigma_c\eta_{t+1} \\ x_{t+1} &= \rho x_t + \varphi_e\sigma_c e_{t+1} \end{aligned} \tag{7}$$

where g_c and σ_c measures the average consumption growth and volatility of the short-run con-

[7]See Appendix A-1 for derivation.

sumption risk, respectively. The expected consumption growth x_t follows an AR(1) process with a persistence of ρ and conditional volatility of $\varphi_e\sigma_c$. In addition, we assume the short-run consumption shock η_{t+1} and long-run consumption shock e_{t+1} are independent from each other.

2.2 The Firm Dividend Process

One important innovation in our model is the firm dividend process. While aiming to reproduce several salient empirical regularities, we use a general functional form to encompass several specifications in existing studies. In the meantime, we try to maintain the parsimony in our specification to accomplish this objective. With this in mind, we model the firm dividend growth as comprised of three components given below:

$$\begin{aligned} \Delta d^i_{t+1} &= g_d + \sigma_d \epsilon_{d,t+1} + f^i_t x_t + h^i_t \sigma_c \eta_{t+1} + y^i_{t+1} \\ y^i_{t+1} &= \rho_y y^i_t + \sigma_y \epsilon^i_{y,t+1} \end{aligned} \tag{8}$$

The first component, $g_d + \sigma_d \epsilon_{d,t+1}$, governs the aggregate dividend growth, where g_d is the unconditional mean of the aggregate dividend growth process and $\sigma_d \epsilon_{d,t+1}$ represents the short-run innovation in aggregate dividend growth that is un-correlated to the aggregate consumption growth. The second component, $f^i_t x_t + h^i_t \sigma_c \eta_{t+1}$, captures the firm's cash flow co-movement with the aggregate consumption growth. In particular, $f^i_t x_t$ and $h^i_t \sigma_c \eta_{t+1}$ represent components of the firm's cash flow variability due to exposure to the long-run and short-run consumption risks, respectively. For brevity of exposition, we refer to shocks to f^i_t long-run exposure shocks; and shocks to h^i_t short-run exposure shocks. The last term, y^i_{t+1}, captures a firm-specific dividend growth component that is mean-reverting.

We allow the firm's cash flow exposure to the consumption risks (f^i_t and h^i_t) to be time-varying and follow AR(1) processes for simplicity, i.e., $f^i_{t+1} = \rho_f f^i_t + (1-\rho_f)\bar{f} + \sigma_f \epsilon^i_{f,t+1}$ and $h^i_{t+1} = \rho_h h^i_t + (1-\rho_h)\bar{h} + \sigma_h \epsilon^i_{h,t+1}$. We assume that all shocks are independent, except for the correlation between the firm's idiosyncratic cash flow shock with the long-run exposure shock, i.e.,

ρ_{fy}=corr($\epsilon^i_{f,t+1}$, $\epsilon^i_{y,t+1}$), and to the short-run exposure shock, i.e., ρ_{hy}=corr($\epsilon^i_{h,t+1}$, $\epsilon^i_{y,t+1}$). While stocks are identical ex ante, due to firm-specific shocks, their characteristics, including valuation ratio and risk premium, are different ex post.

Given that the firm's cash flow exposure to consumption risks (f^i_t and h^i_t) are time-varying, our specification above is in fact very general and nests a wide range of specifications on firm dividend processes used in other studies including Bansal, Kiku, and Yaron (2012b) and also captures the main features of the firm dividend growth process in Johnson (2002). Our firm dividend process also differs from that used in Lettau and Wachter (2007) and Santos and Veronesi (2010) who model shares of individual firm dividend as a fraction of aggregate dividend. This effectively restricts the heterogeneity of firm cash flow risk to move in tandem with the aggregate cash flow variability at any point in time. From that perspective, our firm dividend process specification accommodates a broader and richer structure of a firm's cash flow responses to different types of the aggregate economic risks. Because of the flexible nature of our firm dividend process specification, there are few parameter values governing the dividend process readily available for a calibration analysis. To uncover these parameter values, we use a simulated method of moments (SMM) approach to formally estimate our economic model. We discuss the details of our estimation in the next section.

3 Data and Estimation of the Firm Dividend Process

3.1 Data

The data used in our empirical analysis are readily available and widely used in finance research. The annual consumption data is from National Income and Product Account (NIPA). Following the consumption-based asset pricing literature, we define consumption as the non-durable goods minus clothing and footwear plus service.[8] The returns for book-to-market, size, momentum, long-term contrarian, Fama-French industry portfolios, as well as the standard risk factors such as the market return are from Kenneth French's Web site. Self-constructed portfolios are based

[8]To be specific, consumption is calculated as non-durable (Row 8 of NIPA Table 2.3.5 divided by Row 25 of NIPA Table 2.4.4) minus clothing and footwear (Row 10 of NIPA Table 2.3.5 divided by Row 30 of NIPA Table 2.4.4) plus services (Row 13 of NIPA Table 2.3.5 divided by Row 47 of NIPA Table 2.4.4).

on the data from CRSP and COMPUSTAT, and the construction procedure is discussed in more detail when needed. The benchmark sample is from January 1931 to December 2011, where the starting point is restricted by the availability of the return data for constructing the long-term contrarian portfolios.

Following the convention of the long-run risk literature, we model the representative agent's decision at a monthly frequency and then annualize the moments of variables of interests in order to compare with the empirical data. To facilitate comparison of our results to those in existing literature, we separate the parameters into two groups. The first group of parameters are chosen to match the moments of aggregate variables in the time series. Since the economy from the aggregate perspective is identical to case (I) of BY, we use the parameters in BY as a guidance. For instance, the risk aversion γ and the elasticity of intertemporal substitution ψ in the benchmark parameterization are set to 10 and 1.5, respectively, exactly the same as in BY. The subjective discount rate is set to 0.9994, which is used to match the level of risk-free rate. The mean consumption growth and volatility parameters g_c and σ_c determine the first and second moments of aggregate consumption growth, and we choose the value of 0.0015 and 0.0078, respectively, to match the data. The long-run consumption growth component is small but very persistent. We set its conditional volatility relative to short-run risk and its persistence very close to values in BY at 0.044 and 0.98, respectively. The benchmark parameter values for this group are summarized in the top panel of Table 1. The second group of parameters governs the firm dividend process and are estimated using a simulated method of moments approach detailed below.

[Insert Table 1 Here]

3.2 SMM Estimation of the Firm Dividend Process

The general specification of our firm dividend process makes it difficult to calibrate using parameter values from existing studies. We therefore estimate the parameters governing firm dividend process given by equation (8). We follow Duffie and Singleton (1993), Smith (1993), and Gourieroux, Monfort, and Renault (1993) and employ a simulated method of moments (SMM) estimation on these parameters.

In particular, holding the values of the first group of parameters, we search for the optimal values of the set of parameters governing the firm dividend process Γ given by

$$\Gamma = \{g_d, \sigma_d, \bar{f}, \rho_f, \sigma_f, \bar{h}, \rho_h, \sigma_h, \rho_y, \sigma_y, \rho_{hy}, \rho_{fy}\}' \tag{9}$$

by matching 25 empirical moments, which are listed in Table 2. We avoid using the cross-sectional average returns of the momentum, and long-term contrarian, and valuation ratio portfolios as matching moments. Instead, we estimate the parameters of the dividend process using firm characteristics and aggregate moments, and explore the asset pricing implications of this model using these estimated parameter values. This approach mitigates the concern that the parameters of the dividend process are directly implied by returns on the target portfolios.

Specifically, to capture the short-run and long-run consumption risk exposures, we include the long-run consumption betas for the contrarian loser-minus-winner portfolio and the value-minus-growth portfolio, as well as the short-run consumption beta for the momentum winner-minus-loser portfolio. We estimate the short-run risk exposure of the momentum winner-minus-loser portfolio following the approach in Bansal, Dittmar, and Lundblad (2005). We estimate the long-run risk exposures of the contrarian loser-minus-winner portfolio and the value-minus-growth portfolio by regressing the long-term portfolio real dividend growth on the long-term real aggregate consumption growth.[9] At the aggregate level, we include the mean and standard deviation of aggregate dividend growth rate, the aggregate log(P/D) ratio, and the equity premium. These moments can help pin down the values of the parameters governing the aggregate dividend process. Given our interest in the momentum, contrarian, and value investment strategies, we choose the defining characteristics of these strategies as part of our matching moments.[10]

[9]We regress the portfolio log real dividend growth onto the trailing 8-quarter moving average of log real aggregate consumption growth, and the coefficient on the consumption growth term is our proxy for the short-run risk exposure. To obtain the long-run consumption betas, since the long-run risk is small but persistent, its exposures for the value-minus-growth portfolio and contrarian loser-minus-winner portfolio can be approximately estimated from the long-run overlapping regression. For each portfolio, we calculate the portfolio 20-year moving average of log real dividend growth rate, and the univariate regression coefficient of this cumulative dividend growth on the 20-year moving average of the log real aggregate consumption growth is our estimate for the long-run risk exposure.

[10]We include dividend yield (DP), short-term past return ($R_{t-6\to t-2}$), and long-term past return ($R_{t-60\to t-13}$)

[Insert Table 2 Here]

Denote Ψ^A as the vector of these moments in the actual data, and $\Psi^S(\Gamma)$ as the vector of these moments from the simulated data. The parameter vector (Γ) are then estimated from the following minimization problem:

$$\hat{\Gamma} = \arg\min_{\Gamma} [\Psi^S(\Gamma) - \Psi^A]' W [\Psi^S(\Gamma) - \Psi^A] \tag{10}$$

where W is the weighting matrix. Intuitively, the coefficients for the firm dividend process are chosen to minimize the weighted average of squared deviations of moments from the data. The SMM estimation requires that for a set of parameter values, we find the optimal solution to the dynamic model. Unlike standard long-run risk models that can be solved using log-linearization approximation, our model contains a non-linear term $f_t^i x_t$, so we solve the model numerically. For consumption and dividend claims, we first calculate the valuation ratios (wc_t and pd_t^i) using equations (5) and (6) by value function iterations. We then simulate 100 samples with each sample representing 972 months and 1,000 firms. The detail of the numerical method is described in Appendix A-2. Following Bloom (2009), we solve the above minimization problem using an annealing algorithm to find the global minimum. We also start with different initial guesses for Γ and find that the estimates are very robust and insensitive to the initial guesses.

The bottom panel of Table 1 reports the result from the SMM estimation. The estimated parameter values for the aggregate dividend growth $g_d = -0.0038$ and $\sigma_d = 0.0467$, implying an average growth rate of aggregate dividend of 1.296%[11] with a standard deviation of 16.22%, very close to the empirical estimates.[12] We find that firm's cash flow exposure to the long-run

of the value and growth portfolios (Portfolio 10 and 1 for the dividend price decile portfolios), the momentum winner and loser portfolios (Portfolio 10 and 1 for momentum decile portfolios), and the contrarian winners and losers portfolios (Portfolio 10 and 1 for the long-term contrarian portfolios) for $3 \times 6 = 18$ moment conditions for portfolio characteristics.

[11]Note that g_d is no longer equal to the average monthly dividend growth because the cross-sectional distribution of dividend process changes the unconditional mean of aggregate dividend growth due to the Jensen's inequality.

[12]Chen (2009) documents that, depending on whether monthly dividends are reinvested or not, the accumulated annual market dividend volatility can range from 11.8% to 14.7% for the 1926-2005 sample. In this paper, we measure annual aggregate dividend growth using the reinvestment strategy, so its volatility is higher than some other works in the literature, including Bansal and Yaron (2004). Since our focus is on the cross section, our main result is essentially the same if we estimate the model using the aggregate dividend growth data without reinvestment.

risk is very persistent (ρ_f=0.989) with a conditional volatility of long-run risk exposure σ_f at 0.351. In the meantime, the persistence of firm's cash flow exposure to the short-run risk is much lower at $\rho_h = 0.781$ with a higher conditional volatility ($\sigma_h = 4.935$). The estimated persistence and conditional volatility of firm-specific dividend growth rate component are $\rho_y = 0.979$ and $\sigma_y = 0.0015$, respectively.

Our estimation results show that the correlation between the firm's cash flow shock and its exposure to the long-run consumption risk, i.e., ρ_{fy}, is negative at -0.970 while the correlation between the firm's idiosyncratic cash flow shock and its exposure to the short-run consumption risk, i.e., ρ_{hy}, is positive at 0.875. Both coefficients have low standard errors indicating that our estimates are quite precise. Intuitively, the estimated negative correlation between firm specific dividend shocks and long-run exposure shocks can be understood by a firm's leverage effect. As stock price falls due to negative cash flow shocks, the fixed operating cost represents a larger portion of total cost of production, driving up the operating leverage. In addition, if a firm is financed by both equity and debt, the financial leverage will also increase. Both leverage effects imply a larger sensitivity to the aggregate long-run growth shocks, and this can be captured by a negative correlation between $\epsilon^i_{f,t+1}$ and $\epsilon^i_{y,t+1}$. The estimated positive correlation between the firm specific dividend shocks and short-run exposure shocks is consistent with a real option effect as studied in Sagi and Seasholes (2007). Sagi and Seasholes (2007) argue that firms that performed well in the recent past are better poised to exploit their growth options. Because these options are risky assets that now account for a larger fraction of firm value, such firms are riskier. From this perspective, our result provides an empirical estimation of this real option effect quantitatively using the portfolio-level data. This positive correlation is also consistent with the empirical evidence of Chen, Moise, and Zhao (2009), who find that the winner (loser) portfolio has a positive (negative) revision in its cost of equity around the portfolio formation time.[13]

While the overidentification test rejects the model, it does a good job matching the moments

[13] As a robustness check, we have also directly estimated the firm dividend process using firm-level dividend data for a sample of firms with at least 20 years of non-missing dividends by applying the Bayesian Markov Chain Monte-Carlo (MCMC) estimation method. We find similar estimates to those reported here and the details are discussed in Appendix A-3.

of key variables of our interests. The model implied aggregate and cross-sectional moments are reported in Table 3 and Table 4. Overall, these parameter values imply an average equity premium of 8.20% with a standard deviation of 25.44% per year for value-weighted market return, and an average equity premium of 11.66% with a standard deviation of 28.70% for equal-weighted market return. The observed counterparts in the data are well within the confidence interval from the simulated data. In addition, autocorrelation of the market return from simulation is found to be very close to zero.

[Insert Table 3 Here]

[Insert Table 4 Here]

The simulated portfolios from the model have both qualitatively and quantitatively similar dividend yield, past short-term and long-term return performances as in the data. For instance, the short-term return (month $t-6$ to $t-2$) of the momentum winner (loser) portfolio is 58.1% (-30.8%) in the simulation, and 51.5% (-27.6%) in the data. For the long-term contrarian strategy, the long-term return (month $t-60$ to $t-13$) of the loser (winner) portfolio is -57.4% (338.2%) in the simulation, and -47.3% (315.2%) in the data. For the value strategy, the dividend yield for the high (low) dividend-price portfolio is 0.159 (0.026) from the simulation, compared with 0.104 (0.015) in the actual data. In addition, the model is capable of capturing several salient empirical features. First, stocks with high dividend yield tend to have a low past long-term performance. This is consistent with the finding in Fama and French (1996) that the high-minus-low (HML) factor is able to capture the long-term contrarian premium. Second, stocks with a high dividend yield also have a low past short-term performance. A good past performance drives up the stock price and lowers the dividend yield. Third, momentum portfolios pick up the short-term past performance, but the difference in the long-term performance between winner and loser portfolios is small. Similarly, the long-term contrarian portfolios capture the long-term performance, but there is no strong difference in their short-term performance between the two extreme portfolios. We discuss the intuitions of these patterns in Section 4.3.

4 Results and Discussions

In this section, we discuss the implications of short-run and long-run consumption risks for the cross section of stock returns. We start by comparing the momentum and contrarian profits, the value premium, and the size effect implied by the model with their observed counterparts in the data. We also explore the performance of the unconditional CAPM using the simulated data. In Section 4.2, we examine the difference in economic forces driving these premiums. In particular, we find that momentum portfolios are sorted based on more recent and high frequency information, so they are more exposed to the short-run consumption risk, whose exposures move at a higher frequency. However, the long-term contrarian and value portfolios are sorted based on low frequency information, so their returns are sensitive to the long-run consumption risk, whose exposures are persistent and moving at a lower frequency. This difference has implications for the performance of the CAPM and Consumption-CAPM, as well as the correlations between the momentum profit, the contrarian profit, the value premium, and the size premium, which we explore in Section 4.3. In Section 4.4, we explore the dynamics of momentum profits and show that our parsimonious model is capable of reproducing the short life of the momentum profitability. We test a two-factor model with the market return and consumption growth as risk factors in Section 4.5. Finally, we conduct sensitivity analysis on the values of key parameters in Section 4.6.

4.1 Portfolio Returns

This section compares our model implied momentum and contrarian profits, value premium, size premium and the CAPM test results to their counterparts in actual data. We report our findings for the momentum profit, the contrarian profit, the value premium, and the size premium in Tables 5, 6, 7, and 8, respectively.

Table 5 reports the result for the momentum profit. It is well known that momentum and value are "opposite" because momentum investing takes a long position in the past "winners" and a short position in the past "losers", whereas value investing does the opposite. Nevertheless, both strategies make considerable profits. Our model is capable of generating a positive momentum profit at the same time of maintaining a positive value premium. Table 5 shows that the average value-weighted excess return of the simulated loser portfolio is 4.15%, which is 7.35% lower than the simulated winner portfolio. The result for equal-weighted returns is very similar, albeit higher (7.71% momentum profit). These findings are consistent with the empirical counterparts in the data, where the momentum profit is 6.97% for the value-weighted returns, and 6.96% for the equal-weighted returns.

[Insert Table 5 Here]

The unconditional CAPM fails to explain the momentum profit. This is particularly true for the equal-weighted returns. The CAPM alpha remains 8.78% per year after controlling for the market risk factor. This abnormal return spread is even bigger than the return spread (7.71%) between the winner and loser portfolios. This can also be seen from the pattern of market betas. The market beta for the loser portfolio is 1.02 and higher than the winner portfolio 0.91, qualitatively consistent with what is found in the data (1.43 versus 0.86) for equal-weighted returns.

The contrarian profit for the value-weighted returns is 5.07% in the simulation versus 6.48% in the data. While the contrarian profit remains very sizable for the equal-weighted returns at 5.07% in the simulation, it is lower than its counterpart in the data (15.05%). The result is consistent with the low (high) average CAPM betas for long-term winners (losers) both in the simulation (0.89 versus 0.98 for valued-weighted returns and 0.82 versus 1.12 for equal-weighted returns) and in the data (1.10 versus 1.35 for valued-weighted returns and 0.86 versus 1.42 for equal-weighted returns).

However, the unconditional CAPM is not capable of explaining the contrarian profit. The annualized abnormal return for the contrarian strategy based on the CAPM alpha is 4.30% in the simulation versus 4.63% in the data for value-weighted and 1.96% in the simulation versus 8.07% in the data for equal-weighted return. This suggests that the spread in the market beta is not large enough to capture the return spread.

[Insert Table 6 Here]

Table 7 shows that the model produces a large value premium. For the value weighted returns, the average excess return increases monotonically from growth firms (4.69%) to value firms (14.52%), and the implied average value premium is 9.83%, which is slightly higher than the empirical value of 6.91%. For the equal weighted returns, our simulated value premium is about 9.09% per year, which is smaller than 15.39% for the empirical counterpart.

[Insert Table 7 Here]

When the unconditional CAPM tests are performed on these portfolios, we find that market risk exposures are going in the right direction in capturing the value premium. Specifically, the market beta increases from 0.85 for growth firms to 1.12 for value firms in the value-weighted returns, and increases from 0.64 to 1.30 for equal-weighted returns. The patterns are very similar in the data for our sample period, where growth firms have a low market beta of 0.99 versus 1.47 for value firms for the value-weighted (0.88 versus 1.32 for equal-weighted) returns. Despite the pattern in the market betas, the abnormal return spread between value firms and growth firms remains positive. The annualized CAPM alpha is 7.46% (t-stat = 2.16) for value-weighted returns and 1.90% (t-stat = 0.87) for equal-weighted returns from simulations, as compared with 3.25% (t-stat = 1.37) and 9.91 (t-stat = 4.30), respectively, in the data.

While not imposed as moment conditions for different size portfolios in our SMM estimation, we now explore the model prediction on the firm size effect, and the result is reported in Table 8. It has been well documented in the literature that small firms earn a higher average return than big firms, and this firm size premium cannot be captured by the unconditional CAPM.[14] Consistent with the empirical data, the simulated size premium is more than 5% per year. Small firms have a higher exposure to the market factor, but the average CAPM alpha for the small-minus-big portfolio remains large and positive. Therefore, even though we do not include information from size-sorted portfolios in the SMM estimation, the model with the estimated parameter values can still well capture the salient features of stock returns along this dimension.

[Insert Table 8 Here]

[14]See, for example, Banz (1981), Reinganum (1981), Keim (1983), and Fama and French (1992).

Overall, we find that the economy with short-run and long-run consumption risks and a general but parsimonious firm dividend process is capable of jointly producing the economically sizable momentum and contrarian profits, value premium, firm size premium, and the performance of the unconditional CAPM. Even though firms are identical ex ante, firm dividend processes generate different firm characteristics ex post after realization of firm specific shocks. By sorting on different firm characteristics, the model has different predictions on firm future returns. We will explore this mechanism in more detail in the next section.

4.2 Risk Exposures

Our economic framework has two priced risk factors: the short-run and the long-run consumption risks. Any portfolio sorting that generates a spread in average returns must be due to the heterogeneity in compensation for either short-run or long-run risk, or both. In this section, we take a closer look at the risk exposures of the momentum, contrarian, value, and size strategies documented in the previous section.

Table 9 presents several characteristics for these momentum, contrarian, dividend-price, and firm size portfolios from the model simulation. The first row of each panel reports the average dividend growth rate at the time of portfolio formation. Consistent with existing literature, growth firms and past winners (both short-term and long-term) have higher firm-level dividend growth rate y than value firms and past losers. However, while both past short-term and long-term winners have high dividend growth rate, the former has high average returns but the latter has low average returns. Thus, dividend growth rate is not a clean proxy for risk exposures. As such, we explore the patterns of two components of dividend growth at month t: the short-term changes in dividend growth (i.e., the cumulative change between $t-6$ and $t-2$), and the long-term changes in dividend growth (i.e., the cumulative change between $t-60$ and $t-13$), as reported in the second and third row of each panel in Table 9.

The decomposition implies that the momentum portfolios show a strong pattern for the short-term dividend growth with the winners having a higher short-term dividend growth than the losers. But their long-term dividend growth pattern is much weaker. On the other hand, the long-term contrarian, dividend-price, and firm size portfolios have a large spread in the long-term dividend growth, but the pattern for the short-term dividend growth is weak. Specifically, long-term winners, growth firms, big firms have a higher long-term dividend growth than long-term losers, value firms, and small firms. Based on our estimated correlation between dividend growth shocks and short-run and long-run exposure shocks, these findings imply that long-term winners, growth firms, and big firms should have a lower exposure to the long-run consumption risk than long-term losers, value firms, and small firms, whereas short-term winners should have a higher exposure to the short-run consumption risk than the short-term losers. This is confirmed in the last two rows of each panel in Table 9. Indeed, the spread in the exposures to the long-run risk is 3.39 (7.32 versus 3.93), 7.27 (9.42 versus 2.15), and 3.87 (7.74 versus 3.87) for the contrarian, dividend-price, and size portfolios, respectively, and the spread in the exposures to the short-run risk is 12.00 for the momentum portfolios. This finding is consistent with the empirical evidence in the introduction that momentum, contrarian, and value strategies load differently on the high- and low-frequency fluctuations of the consumption growth.

[Insert Table 9 Here]

The patterns in the dividend shocks and the risk exposures to the short-run and long-run consumption risks provide a joint explanation for the profitability of the momentum and contrarian strategies, value and size portfolios. Short-term winners have high dividend growth in the recent past. The positive dividend shock realizations induce a persistent increase in their future cash flow, while the positive correlation between the firm dividend shock and the short-run risk exposure creates a higher discount rate. Our estimated parameter values indicate that the cash flow effect dominates the discount effect, giving rise to the high realized returns as well as high expected returns for these firms (momentum winners). The same channel explains the low expected returns for momentum losers experiencing negative dividend shock realizations. On the other hand, compared to the long-term winners, growth firms, and big firms, firms with poor long-term performance, low valuation ratios, and small market capitalization had low dividend growth in the long past; they have high leverage, high exposure to the long-run consumption fluctuations, and hence high expected returns.

It is worth highlighting the difference in the persistence of the short-run and long-run risk exposures. The short-run risk exposure is relatively short-lived, whereas the long-run risk exposure is persistent. Intuitively, momentum portfolios are sorted on the stock performance in the past several months, so they should pick up the less persistent component of the risk exposures, that is, the exposure to the short-run consumption risk. On the other hand, sorting variables such as the long-term performance, dividend-price ratio, and firm size are persistent and therefore picking up the more persistent components of the risk exposures. Portfolios sorted by these characteristics should create a large dispersion on the long-run risk exposure. The divergence in the persistence of these two betas facilitate the model reproducing the coexistence of these phenomena in the cross-sectional stock returns.

4.3 CAPM, Consumption-CAPM, and Strategy Return Correlations

So far, we have only focused on the main contributing risk factor for the profitability of the momentum, contrarian, value, and firm size strategies. However, the other risk factor (could be either short-run or long-run risk depending on the strategy) provides important clues to the findings in asset pricing tests, such as the failure of the CAPM. For instance, for momentum profits, past short-term winners have a higher exposure to the short-run risk than past losers, but the pattern of the long-run risk exposure is exactly the opposite, because winners on average have a lower leverage than losers. Since the equity premium is mainly driven by the long-run risk, the exposure to the market factor follows the direction of the exposure to the long-run risk, generating a higher market beta for losers than winners. In the meantime, the long-term contrarian and value strategies are profitable because they load on the long-run consumption risk. However, as shown in Table 9, long-term losers and value firms in fact have a lower exposure to short-run consumption risk than long-term winners and growth firms. This is because, given a positive correlation coefficient for ρ_{hy}, positive dividend shocks on long-term winners and growth firms tend to increase the firm's exposure to short-run risk, which predicts an expected return that is opposite to finding a positive contrarian profit and value premium. In our model, both short-run and long-run risks positively contribute to the equity premium, so the market factor alone is not capable of capturing the contrarian profit and the value premium.

The same argument also works for Consumption-CAPM. The consumption growth is mainly driven by the short-run consumption variations, so we expect that momentum portfolios are more correlated with consumption growth than portfolio sorted on long-term contrarian, valuation ratio, and firm size that are more exposed to the long-run consumption shocks.[15] To test this, we regress the value-weighted excess returns of the momentum, the contrarian, the valuation ratio, and the firm size portfolios on the time series of consumption growth, and report the results in Table 10.[16]

[Insert Table 10 Here]

Consistent with Figure 1, the consumption beta shows a strong pattern and increases monotonically from the loser to winner momentum portfolio. In the data and in the model, a 1% increase in the consumption growth corresponds to a 3.97%-6.50% increase in the average return for the winner portfolios and 2.40%-3.43% decrease in the average return for the loser portfolios. The difference in short-run consumption risk exposures between winner and loser portfolios are both economically and statistically significant, and explains more than 20% of the time series variation of the momentum profit in the data and almost 40% in the model. On the other hand, the pattern of consumption betas for the contrarian, valuation ratio, and size portfolios are weak. If anything, Table 10 shows that growth firms have a higher consumption beta than value firms. Similar but weaker findings are also observed for long-term winners versus losers and small versus big firms.

[Insert Table 11 Here]

[15] A similar argument is also made in Colacito and Croce (2011) who show that a decomposition of the short-run and long-run components of consumption risk can explain a wide range of international finance puzzles, including the high correlation of international stock markets, despite the lack of correlation of fundamentals.

[16] To save space, we only report the results from value-weighted returns for the Consumption-CAPM in this section and the two-factor model analysis in Section 4.5. The results from equal-weighted returns are qualitatively similar.

The difference in exposures to the short-run and long-run consumption risks also provides insights on the correlation between the momentum and contrarian profits, the value premium, and the size premium. As shown in the first panel of Table 11, the correlation between the momentum profit and the value premium is -0.40 for the value-weighted returns, and -0.48 for the equal-weighted returns. The correlation between the contrarian profit and the value premium is 0.64 for the value-weighted returns and 0.80 for the equal-weighted returns. These patterns are reproduced in our model. As reported in the second panel of Table 11, our model predicts a negative correlation between the momentum profit and the value premium of -0.38 for the value-weighted returns, and -0.44 for the equal-weighted returns, and a positive correlation between the contrarian profit and the value premium of 0.53 for value-weighted returns, and 0.74 for the equal-weighted returns.

The correlation between the momentum and contrarian profits from the model is also on average similar to that in the data. In addition, the model generates a quantitatively similar result for the correlations between the size premium and the profitability of the other three investment strategies. Specifically, the size premium comoves positively with the contrarian profit and the value premium, but negatively with the momentum profit. These results lend strong support to our discussions on the risk exposures. The momentum profit has a positive sensitivity to the short-run risk, but a negative sensitivity to the long-run risk. On the other hand, the contrarian profit, value premium, and size premium load positively on the long-run risk, but negatively on the short-run risk. Therefore, a shock to consumption (either long-run or short-run) induces opposite responses of the momentum profit and the contrarian profit, value premium, and size premium, giving rise to a negative correlation between them.

4.4 Dynamics of Momentum Profits

Existing literature documents that the momentum profit is also short-lived (Jegadeesh and Titman (1993)). Chan, Jegadeesh, and Lakonishok (1996) show that the winner-minus-loser return is 15.4% per annum on average at the one-year horizon, but is close to zero during the second and the third year after portfolio formation. Our analysis above indicates that the momentum strategies are closely related to the exposure to the short-run consumption risk. Since the latter is short-lived, it may have implications for the dynamics of the momentum profit documented in existing studies. To accomplish this goal, we examine the profitability of buy-and-hold momentum portfolios from 1 to 12 months and 2 to 5 years after portfolio formation implied in our model.

Table 12 reports the buy-and-hold monthly returns for each of the first 12 months and annual returns for 2 to 5 years of the momentum portfolios using simulated data from our model. Consistent with the existing literature, momentum profits are short-lived. In particular, the average return spread between the winner and loser portfolios remains positive up to the seventh month after the portfolio rebalancing, and then reverses. From the second year to the fifth year after portfolio sorts, the loser portfolio in fact consistently has a higher return than the winner portfolio, generating the momentum reversal.

[Insert Table 12 Here]

This pattern can be readily understood in our framework. Immediately after portfolio rebalancing, winner firms have a higher exposure to the short-run consumption risk than loser firms. This large spread in the short-run risk beta explains the immediate momentum profit. However, this short-run risk exposure is not persistent. After about seven to eight months, the difference in the short-run risk beta between winners and losers are much smaller. At the same time, because winners have a lower exposure to the long-run consumption risk than losers due to a lower leverage, and this long-run risk exposure is very persistent, the effect from the long-run risk will dominate that of the short-run risk, giving rise to a reversal in the momentum profitability.

4.5 A Two-factor Model

In our model with both long- and short-run consumption risks, the long-run innovation to consumption growth is small but persistent, but it is able to explain a large fraction of the variation in market returns. On the other hand, the short-run innovation is the major component for the consumption growth.[17] Therefore, we expect a significant improvement in a two-factor model with both the market factor and the consumption growth over a one-factor model such as the CAPM and the Consumption-CAPM.[18] In this section, we compare the performance of the three models using a two-stage Fama-MacBeth procedure.

We use as the test assets the 10 book-to-market portfolios, 10 momentum portfolios, and 12 Fama-French industry portfolios from Kenneth French's Web site. In the first stage (time series), we regress the portfolio excess returns on the risk factor(s), generating the factor risk exposure(s). In the second stage (cross-section), the average portfolio returns are regressed onto the risk exposures without intercept, and the estimated coefficient(s) are the factor risk premium(premia). The estimation results from the second stage is reported in Table 13. As a robustness check, we split the full sample into pre- and post-1963 subperiods. The starting year of 1963 is conventional in majority of the literature studying the US stock market.

[Insert Table 13 Here]

The CAPM does a decent job in the full sample from 1931 to 2011. As in Panel A of Table 13, the mean absolute error (MAE) for the 32 portfolios is 1.46% per year, and the estimated price of risk for the market portfolio is 8.78% per year, close to the sample average of market risk premium. The Consumption-CAPM fails to capture most of the cross-sectional variations in portfolio returns: the MAE is more than 7% per year, and the OLS-R^2 is -416.83%.[19] However, we still have an estimate of the risk premium in consumption growth of 3.24% per year, and it is statistically different from zero. When both the market and consumption growth are included,

[17]It should be noted that the model includes three aggregate factors. Besides the short-run and long-run consumption variations, the aggregate dividend growth is also a factor. However, as assumed in Bansal, Kiku, and Yaron (2012a), this factor does not correlate with consumption shocks. Therefore, it does not contribute to the risk premium. Similar argument is used in Lettau and Wachter (2007).

[18]The two-factor model can also be motivated by economic models with social status concerns, e.g., Bakshi and Chen (1996) and Roussanov (2010).

[19]The OLS-R^2 follows the definition from Jagannathan and Wang (1996) and Lettau and Ludvigson (2001):

$$R^2 = \frac{Var_c(\bar{R}_i) - Var_c(\bar{e}_i)}{Var_c(\bar{R}_i)}$$

where $\bar{R}_i$ represents the time-series average of the return to portfolio i, $Var_c(\cdot)$ is the cross-sectional variance, and $\bar{e}_i$ is the average price error for portfolio i. The cross-sectional R^2 can be negative because we impose the zero-intercept restriction in the second-stage regression.

we find a large improvement in the explanatory power. The MAE decreases to 1.18% per year from 1.46% from the CAPM, and the OLS-R^2 increases from -36.53% to 34.06%. Even though this model is rejected under the J_T statistic for the overidentification restriction test, the estimated risk premia are reasonable at 9.27% per year for the market factor and 1.2% per year for consumption risk and statistically significant (t-stat = 4.12 and 2.37, respectively).

When we follow the same procedure on the two subsamples, we find very similar results. In both subsamples, the two-factor model outperforms both the CAPM and the Consumption-CAPM by producing much higher OLS-R^2 and smaller MAE. Note that the CAPM is doing a better job in the earlier subsample, and the estimated price of risk for the consumption growth is statistically insignificant from zero. However, the point estimate is very stable across subsamples. The model performances can also be visually compared in Figure 2, where we plot the average portfolio returns against the model predicted returns. These plots show that the observations are much better aligned to the 45-degree lines in our two-factor model than those from the CAPM and Consumption-CAPM, and the improvement is most striking in the post-1963 sample.[20]

[Insert Figure 2 Here]

We also compare the two-stage Fama-MacBeth regression results for 40 portfolios (10 momentum, 10 contrarian, 10 book-to-market or dividend-price ratio, and 10 size portfolios) between the simulated data and the empirical data.[21] Overall, we find that the cross-sectional test results using the simulated data are very similar to those using the empirical data, providing further support to our model for the cross-sectional stock returns. The better performance of the two-factor model is consistent with the findings in Roussanov (2014) who compares the conditional one-factor consumption CAPM with a two-factor consumption-based model augmented with an aggregate wealth growth factor. Roussanov (2014) finds that covariances of portfolio returns with long-run consumption growth generate small and insignificant pricing errors in asset pricing tests.

[20] In Appendix A-4, we estimate an alternative two-factor model using the General Method of Moments (GMM) with short-run and long-run consumption risks as the risk factors. The estimated price of risk are broadly consistent with those used in Bansal and Yaron (2004).

[21] The results are reported in the Online Appendix.

4.6 Sensitivity Analysis

In this section, we consider the implications of alternative parameterizations on the cross section of stock returns. In particular, we change parameter values one at a time based on the benchmark parameterization, and explore how moments of key variables change accordingly. The results for this sensitivity analysis are reported in Table 14.[22] Specification (0) presents the key moments under the benchmark parameterization, and Specifications (1) to (16) report the corresponding moments for alternative parameterizations.

[Insert Table 14 Here]

Specifications (1) and (2) in Table 14 change the agent's risk aversion. As shown in BY and Bansal, Kiku, and Yaron (2012a), the price of risk for the short-run risk component is the risk aversion coefficient γ, and the price of risk for the long-run risk component is $(\gamma - \frac{1}{\psi})\frac{k_1}{1-k_1\rho}$, where k_1 is a number less than but very close to 1. Therefore, an increase in γ increases the price of risk for both the short-run and long-run consumption risks, and we should expect a larger equity premium, momentum profit, and value premium. This is indeed confirmed in Specification (1). When risk aversion coefficient increases to 15 from the benchmark value of 10, the value-weighted equity premium goes up to 10.2% per year, whereas the momentum profit and the value premium increase to 11.46% and 13.60% per year from 7.54% and 9.21% in the benchmark model, respectively. If we reduce the risk aversion to 5 (Specification (2)), the corresponding equity premium, momentum profit and value premium fall down to 5.13%, 3.71%, and 4.02%, respectively.

The elasticity of intertemporal substitution (EIS) affects the price of the long-run consumption risk, but not the short-run consumption risk. As such, both the equity premium and the value premium should increase with EIS, but momentum profit, which loads mainly on the short-run risk, should be barely affected. Specifications (3) and (4) report the cases when EIS is changed to 2 and 0.5. In the latter situation, the equity premium reduces by more than 50% to 3.51% per year, whereas the value premium goes down by 12% to 8.07%. On the other hand, the momentum profit stays almost the same in both specifications as in the benchmark. Therefore, even though

[22] In the Online Appendix, we report results from additional sensitivity analysis.

the value of EIS exerts a large influence on the aggregate market such as the equity premium, its effect on the cross section of stock returns is much weaker.

Specifications (5) and (6) assume a lower and higher correlation in absolute value between firm dividend shocks and the long-run exposure shocks ρ_{fy}. When ρ_{fy} is increased by two standard deviations to -0.726 in Specification (5), a positive firm dividend shock induces a smaller decrease in the long-run risk exposure, and we find that the average contrarian profit and value premium are reduced to 3.41% and 6.55% due to a lower leverage, whereas the momentum profit remains almost the same. Conversely, we observe an increase in the contrarian profit and value premium when we change ρ_{fy} to -0.99 in Specification (6). In the extreme case of a zero correlation between firm dividend shocks and long-run exposure shocks (Specification (7)), the average momentum profit becomes 8.12%, but the contrarian profit and the value premium are now negative (-1.12% and -0.18%, respectively). Without a strong negative correlation ρ_{fy}, lower exposures of long-term losers and value firms to the short-run risk lead to their lower expected returns compared with long-term winners and growth firms.

The prediction is the opposite when we change the parameter value for the correlation between firm dividend shocks and the short-run exposure shocks ρ_{hy} (Specifications (8), (9), and (10)). A two-standard deviation decrease in ρ_{hy} leads to a lower momentum profit and a higher contrarian profit and value premium. When ρ_{hy} is set to zero (Specification (10)), short-term losers have a higher leverage and a higher exposure to long-run consumption risk than short-term winners. Therefore, the momentum profit becomes negative (-3.41%), whereas the contrarian profit and value premium are now 6.07% and 13.45%. On the other hand, when ρ_{hy} is increased to 0.99 (Specification (9)), a positive dividend shock induces a higher exposure to short-run consumption risk. In this case, we have a stronger momentum profit (9.34%) but weaker contrarian profit(4.89%) and value premium (8.74%).

To examine the impact of the persistence in the long-run risk exposure ρ_f, we examine two standard deviation changes in this parameter value in Specifications (11) and (12). The direct effect from an increase in ρ_f is that the dispersion in f in the cross section is greater, since the unconditional dispersion is related to the persistence of the underlying process. This increases the magnitude of the contrarian profit and value premium but reduces that of the momentum profit. The result in Specification (12) shows that the contrarian profit and value premium indeed goes up to 7.42% and 14.4%. However, the momentum profit also increase from 7.54% to 7.76%. How could the momentum strategy become even more profitable when the opposing force is stronger? In fact, there is an indirect effect underlying the portfolio sorting: by increasing the persistence of the long-run risk exposures, the difference in the frequencies/persitences of short-run and long-run risk exposures becomes more substantial. Therefore, momentum portfolios are less affected by the low-frequency leverage effect and the momentum strategy becomes more profitable. In this specification, the indirect effect dominates the direct effect, indicating a slightly stronger momentum profit.

When ρ_f is reduced to 0.95 in Specification (13), the direct effect is that unconditional dispersion in f is smaller, so we expect the value premium to be weaker. However, as ρ_f gets smaller, sorting variables such as dividend-price ratio has less discerning ability of differentiating the exposures to the short-run and long-run risks. Therefore, the high dividend-price ratio portfolio includes more short-term losers, and the low dividend-price ratio portfolio contains more short-term winners. This indirect effect strengthens the direct effect, so the value premium now becomes even negative (-2.61%). In contrast, the direct and indirect effects offset each other for the momentum sort, so the average momentum profitability does not deviate much from the benchmark specification.

The last three specifications of Table 14 explore the effect of the persistence of the short-run risk exposures ρ_h on asset prices with Specifications (14) and (15) corresponding to two standard deviation changes in this parameter value. The direct and indirect effects discussed above also apply here. By increasing ρ_h (Specification (15)), we expect a larger dispersion in the short-run risk exposure in the cross section and a higher momentum profit. However, a higher ρ_h also reduces the difference in the frequencies between the short-run and long-run exposures. The two effects offset each other for the momentum strategy, generating an about 26.5% increase in momentum profit to 9.54%; These effects enhance each other for the value strategy, so the value premium is 42% smaller than that in the benchmark specification. In contrast, when we decrease ρ_h to 0.5

in Specification (16), these two effects strengthen each other (in a negative way) for momentum strategies, and a momentum investor can make an average return of only 1.39%, whereas a value investor can now enjoy an average return of 11.25%.

The result from the Specification (11)-(16) in Table 14, again, highlights the importance of the divergence in the persistence of short-run and long-run risk exposures in reproducing a coexistence of the positive momentum and contrarian profit, and value premium. Portfolio sorting variables with a certain persistence (or frequency range) contain relevant information regarding the risk exposures of similar persistence (or frequency range). In our model, long-run risk exposures are persistent, so firm characteristics such as long-term stock performance and dividend-price ratio are likely picking up this exposure. The average returns of the investment strategies based on these characteristics are mainly compensation for the long-run risk exposures. On the other hand, short-run consumption risk exposure is not persistent, so the short-term past stock performance contains information regarding the short-run risk exposures. Therefore, momentum profits are closely related to short-run consumption risk.

5 Conclusion

We provide a unified framework to explain several widely documented asset return phenomena including the momentum and long-term contrarian profits and the value premium. These asset return behaviors are known to be difficult to explain in risk-based economic models. Building upon the long-run risk model by Bansal and Yaron (2004), we introduce firms' dividend processes that are motivated by empirical findings on the exposures of the momentum, contrarian, and value investment strategies to short-run and long-run components of consumption growth fluctuations, and also build upon existing studies linking firm dividend processes to the momentum profit (Johnson (2002)) and the value premium (Lettau and Wachter (2007) and Santos and Veronesi (2010)). We find that this otherwise standard model goes a long way towards reproducing important phenomena in the cross section of stock returns including the momentum and long-term contrarian profits, the value premium, and the size effect.

The key insight in our model is the disentanglement of the risk exposures of different investment strategies to the short-run and long-run consumption risks. We demonstrate that portfolios sorted by the short-term stock returns have very different exposures to the short-run consumption risk. On the other hand, portfolios sorted on variables such as the past long-term stock returns and valuation ratios (e.g, book-to-market, dividend-price ratio) have a large dispersion in the long-run consumption risk exposure. Therefore, the profitability of the momentum, contrarian, and value strategies are compensation for bearing different components of consumption risks at different horizons. Our model is capable of generating the coexistence of the momentum and contrarian profits, the value premium and the size effect.

Besides the unconditional profitability of these strategies, our model also sheds light on the performance of standard asset pricing tests such as the CAPM and the consumption-CAPM in explaining these return phenomena. For instance, the market portfolio is mainly governed by the long-run consumption fluctuation. Therefore, the CAPM provides a stronger explanatory power for the long-term contrarian profit and the value premium than the momentum profit. On the other hand, the aggregate consumption growth is mainly driven by the short-run consumption fluctuation, so the Consumption-CAPM should better explain the momentum profit than the long-term contrarian profit and the value premium. We find strong evidence for these predictions both in the data and in our simulation.

While our otherwise standard intertemporal asset pricing model offers joint explanations for widely documented asset pricing phenomena such as momentum, contrarian, value, and size premium effects, there are a few limitations of our model. For instance, our firm-level dividend process takes a reduced form, but a deeper understanding of the underlying drivers for the dividend process is important and requires a full specification of a firm's decisions. A dynamic general equilibrium model with firm's financing, investment, and hiring decisions and real frictions (in the spirit of Gomes, Kogan, and Zhang (2003), for instance) can be potentially fruitful along this dimension. There are also other cross-sectional stock return phenomena, such as the gross profitability premium documented in Novy-Marx (2013), which may require additional dimension of heterogeneity to reconcile its coexistence with the value premium. Kogan and Papanikolaou

(2013) take an important step by highlighting the difference between the profitability of assets-in-place and that of growth options. It would be interesting for future studies to explore the relation of this heterogeneity and the firm-level dividend process and its implications for asset pricing.

Appendix

A-1 Valuation Ratios

With the no-arbitrage condition, the return on consumption claim must satisfy the following equation:

$$\begin{aligned}
E_t[\exp(m_{t+1} + r_{a,t+1})] &= E_t[\exp(\theta \log \delta - \frac{\theta}{\psi}\Delta c_{t+1} + \theta(\log(\exp(wc_{t+1}) + 1) - wc_t + \Delta c_{t+1}))] \\
&= E_t[\exp(\theta \log \delta - (\frac{\theta}{\psi} - \theta)\Delta c_{t+1} + \theta(\log(\exp(wc_{t+1}) + 1) - wc_t))] \\
&= 1
\end{aligned} \tag{1}$$

Rearranging the terms in the previous equation, we have

$$wc_t = \frac{1}{\theta}\log(E_t[\exp(\theta \log \delta - (\frac{\theta}{\psi} - \theta)\Delta c_{t+1} + \theta(\log(\exp(wc_{t+1}) + 1)))]) \tag{2}$$

Similarly for dividend claim, the return on an individual stock i is

$$\begin{aligned}
r^i_{d,t+1} &= \log\left(\frac{P^i_{t+1} + D^i_{t+1}}{P^i_t}\right) \\
&= \log(\exp(pd^i_{t+1}) + 1) - pd^i_t + \Delta d^i_{t+1}
\end{aligned} \tag{3}$$

and

$$\begin{aligned}
E_t[\exp(m_{t+1} + r^i_{d,t+1})] = E_t[\exp(\theta \log \delta - \frac{\theta}{\psi}\Delta c_{t+1} + (\theta - 1)(\log(\exp(wc_{t+1}) + 1) - wc_t + \Delta c_{t+1}) \\
+ \log(\exp(pd^i_{t+1}) + 1) - pd^i_t + \Delta d^i_{t+1})] = 1
\end{aligned} \tag{4}$$

So the recursive form for the valuation ratio of the dividend claim is:

$$pd^i_t = \log(E_t[\exp(\theta \log \delta + (\theta - 1 - \frac{\theta}{\psi})\Delta c_{t+1} + (\theta - 1)(\log(\exp(wc_{t+1}) + 1) - wc_t) + \log(\exp(pd^i_{t+1}) + 1) + \Delta d^i_{t+1})]) \tag{5}$$

A-2 Numerical Solution

Our long-run risk model is solved through value function iterations. There is one state variable in solving the valuation ratio for consumption claims: the long-run expected consumption growth x_t, and three additional state variables in solving the valuation ratio for dividend claims: firm-level dividend growth y^i_t, the exposure to short-run consumption risk h^i_t, and the exposure to long-run consumption risk f^i_t. We discretize x_t into 5 grids, and y^i_t, h^i_t, and f^i_t into 3 grids individually. Since the valuation ratios are smooth in the state space, the result is very robust to finer grids.

With the grids set up, we iterate the value functions by calculating the right-side of the valuation ratio equations (5) and (6), until the difference in the valuation ratio from the previous iteration is smaller than a pre-specified convergence tolerance. Numerical integrations are estimated by Gaussian-Hermite quadratures. After the valuation ratios are solved, we simulate 100 artificial samples with each representing 972 months and 1,000 firms.

A-3 Bayesian Estimation of Firm Dividend Process

To provide robustness check on the simulated method of moments (SMM) estimation, we also directly estimate the dividend process at the firm level using Bayesian Markov Chain Monte Carlo (MCMC) method. The advantage of this approach is that we can avoid stock returns and portfolio formations, and conduct the estimation using only the information about firm-level dividend and aggregate consumption.

Since both consumption and dividend growth show strong seasonality, we estimate the process at annual frequency. We extract the short-run and long-run components of the aggregate consumption growth following Bansal, Kiku, and Yaron (2012b), and use them as inputs in our

Bayesian MCMC estimation. For the dividend growth, we include firms with at least 20 annual observations of (non-missing) dividend growth, so that firms that pay no dividend are excluded from our sample. The final sample is an unbalanced panel with 360 firms and 10,677 firm-year observations.

There are 12 parameters governing the firm-level dividend process: g_d, σ_d, $\bar{f}$, ρ_f, σ_f, $\bar{h}$, ρ_h, σ_h, ρ_y, σ_y, ρ_{hy}, ρ_{fy}. Our choice of the prior distributions are described as follows: $g_d \sim N(0.02, 0.25)$, $1/\sigma_d^2 \sim \gamma(1, 0.0225)$, $\bar{f} \sim N(4, 1.6)$, $\rho_f \sim Beta(30, 2)$, $1/\sigma_f^2 \sim \gamma(1, 9)$, $\bar{h} \sim N(1, 1.6)$, $\rho_h \sim Beta(2, 4)$, $1/\sigma_h^2 \sim \gamma(1, 12)$, $\rho_y \sim Beta(2, 2)$, $1/\sigma_y^2 \sim \gamma(2, 0.008)$, $\rho_{hy} \sim Unif(-1, 1)$, $\rho_{fy} \sim Unif(-1, 1)$, where N represents a normal distribution, γ a gamma distribution, $Beta$ a beta distribution, and $Unif$ a uniform distribution. Note we do not use a very strong prior for these parameters, so that posterior distributions are mainly driven by the firm-level dividend processes and their correlation with short-run and long-run consumption fluctuations. We run 200,000 simulations and discard the first 30,000 to get past any initial transients.

To make comparison to monthly SMM estimates feasible and take into account the finite sample bias, we use Monte-Carlo simulations to find the monthly parameter values for firm dividend process so that their annual counterparts match the MCMC estimates after aggregating monthly variables to annual frequency. The results are reported in Panel B of Table A1. We focus on the key parameters that we explicitly discussed in the main text. For ease of comparison, we also reported the corresponding SMM estimates for these parameters in Panel A of Table A1. The values in brackets represent 95% confidence interval for each estimate, respectively. On the monthly basis, the MCMC estimated autocorrelation for the short-run consumption risk exposure (ρ_h) is 0.909. This is slightly more persistent than the SMM estimate of 0.781. However, the 95% confidence intervals for the MCMC and the SMM estimation overlapped. The standard deviation of the short-run risk exposure measured by (σ_h) are 3.498 for MCMC and 4.935 for SMM with overlapping confidence intervals. For the autocorrelation on the long-run consumption risk exposure (ρ_f), while the annual estimate from MCMC is 0.354, the corresponding monthly estimate is 0.933. This is comparable to the monthly SMM estimate of 0.989.

The MCMC estimated standard deviation of the long-run risk exposure (σ_f) is larger than the SMM estimate (10.779 versus 0.351). There are data-related reasons that contributed to the difference. First, the long-run consumption risk is estimated using annual data from 1931 and 2011 by projecting the future one-year consumption growth rate on log(DP) and real risk-free rate. While this being a reasonable approach, it may also introduce the measurement error in the long-run consumption risk variable used in our MCMC estimation. Second, while in reality firms' dividend policy is affected by firm specific situations, our MCMC estimation in Panel B does not take into consideration the firm fixed effect. We now explicitly address these two considerations and the resulting MCMC estimates are reported in Panel C and Panel D.

Panel C of Table A1 reports the monthly MCMC estimates after taking into consideration a measurement error that is comparable to annual consumption growth standard error. The monthly MCMC estimate for the standard deviation of the long-run consumption risk exposure (σ_f) reduced to 1.061. This is much closer to the monthly SMM estimate shown in Panel A. In the meantime, the other estimates remained comparable to the estimated counterparts by the SMM. Finally, in Panel D of Table A1, we consider both the measurement error on long-run consumption risk and firm fixed effect on its dividend growth. Our monthly MCMC estimate for the standard deviation of the long-run consumption risk exposure (σ_f) further reduced to 0.316, a value very similar to the SMM estimate. The other monthly MCMC estimates also are much closer to their respective SMM counterparts (0.894 versus 0.781 for ρ_h, 5.039 versus 4.935 for σ_h, and 0.963 versus 0.989 for ρ_f).

Overall, our SMM-based estimation results reported in the paper are broadly consistent with the Markov Chain Monte-Carlo estimation when we make the comparison on the same monthly frequency. As a result, our firm dividend growth model has empirical support from firm-level dividend data.

A-4 Estimation of the price of risk for short-run and long-run consumption risks

We conduct the cross-sectional tests on the value-weighted returns of the constructed portfolios on a two-factor model associated with the consumption risks. The risk factors are estimated using the dividend price ratio (DP) and represent the short-run and long-run consumption growth fluctuations.[23] Table A2 shows the estimated price of risk and the estimated risk premium for the short-run and long-run consumption risks. All estimates are positive and significant at the conventional test level with a slightly weaker result on the short-term risk premium. The magnitude of the estimated price of risks for the short-run and long-run consumption growth fluctuations are also consistent with Bansal and Yaron (2004).

[23] Specifically, we follow Bansal, Kiku, and Yaron (2012b) and regress aggregate consumption growth at year $t+1$ on the natural logarithm of the aggregate dividend price ratio and real risk-free rate at year t to extract the expected consumption growth.

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Table 1: Parameters

This table summarizes the parameter values in the benchmark model. The model is solved at a monthly frequency and the moments of variables of interest are annualized to compare with their counterparts in data. Panel A lists the parameters that are guided by the existing literature, and the parameters in Panel B are estimated via simulated method of moments, with the standard errors reported in parentheses.

Parameter	Symbol	Value
Literature guided parameters		
Relative risk aversion	γ	10
Elasticity of intertemporal substitution	ψ	1.5
Subjective discount factor	β	0.9994
Consumption growth rate	g_c	0.0015
Conditional volatility of consumption growth rate	σ_c	0.0078
Persistence of long-run consumption risk	ρ	0.98
Conditional volatility of long-run risk relative to short-run risk	φ_e	0.044
Estimated parameters		
Aggregate dividend growth parameter	g_d	-0.0038 (0.0007)
Conditional volatility of aggregate dividend growth	σ_d	0.0467 (0.0020)
Average long-run risk exposure parameter	$\bar{f}$	5.857 (0.347)
Persistence of long-run risk exposure	ρ_f	0.989 (0.001)
Conditional volatility of long-run risk exposure	σ_f	0.351 (0.034)
Average short-run risk exposure parameter	$\bar{h}$	0.008 (1.425)
Persistence of short-run risk exposure	ρ_h	0.781 (0.055)
Conditional volatility of short-run risk exposure	σ_h	4.935 (0.527)
Persistence of firm-specific dividend growth rate	ρ_y	0.979 (0.003)
Conditional volatility of firm-specific dividend growth rate	σ_y	0.0015 (0.0001)
Correl. between shocks to firm-specific dividend growth and long-run exposure shocks	ρ_{fy}	-0.970 (0.122)
Correl. between shocks to firm-specific dividend growth and short-run exposure shocks	ρ_{hy}	0.875 (0.104)

Table 2: Moments in SMM estimation

This table reports the 25 moments used in the simulated method of moments estimation from the data and from the simulation. These moments include the dividend price ratio (DP), short-term cumulative return in the formation period (month $t-6$ to $t-2$) and long-term cumulative return in the formation period (month $t-60$ to $t-13$) for the momentum loser portfolio, momentum winner portfolio, contrarian loser portfolio, contrarian winner portfolio, growth portfolio, value portfolio, the short-run risk exposure for the momentum winner-minus-loser portfolio, the long-run risk exposure for the contrarian loser-minus-winner portfolio and the value-minus-growth portfolio, the mean and standard deviation of aggregate dividend growth, the equity premium, and the average log aggregate price-dividend ratio. We simulate 100 samples with each sample representing 972 months and 1,000 firms. The cross-simulation average annualized moments are reported.

Moments	Data	Model
Average DP of momentum losers	0.017	0.078
Average DP of momentum winners	0.019	0.064
Average DP of contrarian losers	0.008	0.117
Average DP of contrarian winners	0.028	0.041
Average DP of growth portfolio	0.015	0.026
Average DP of value portfolio	0.104	0.160
Average short-term returns of momentum losers	-0.276	-0.306
Average short-term returns of momentum winners	0.515	0.576
Average short-term returns of contrarian losers	0.047	0.067
Average short-term returns of contrarian winners	0.038	0.043
Average short-term returns of growth portfolio	0.074	0.116
Average short-term returns of value portfolio	0.030	0.013
Average long-term returns of momentum losers	0.392	0.747
Average long-term returns of momentum winners	0.386	0.615
Average long-term returns of contrarian losers	-0.473	-0.570
Average long-term returns of contrarian winners	3.152	3.335
Average long-term returns of growth portfolio	1.055	1.931
Average long-term returns of value portfolio	0.563	-0.113
Short-run risk exposure of momentum winner-minus-loser portfolio	8.875	9.048
Long-run risk exposure of contrarian loser-minus-winner portfolio	5.024	3.379
Long-run risk exposure of value-minus-growth portfolio	6.591	7.243
Average aggregate dividend growth	1.255	1.296
Volatility of aggregate dividend growth	16.189	16.219
Average market excess return	7.982	8.391
Average log aggregate price-dividend ratio	3.375	3.118

Table 3: Aggregate variables in the time series

This table reports aggregate moments generated from the real data and simulated data. We simulate 100 samples with each sample representing 972 months and 1,000 firms. The cross-simulation median annualized moments are reported.

Moments	Data	Median	2.5%	5%	95%	97.5%
Average consumption growth (%)	1.93	1.98	0.52	0.62	2.90	3.21
Volatility of consumption growth (%)	2.93	2.84	2.28	2.37	3.48	3.51
AC(1) of consumption growth	0.49	0.48	0.24	0.29	0.64	0.64
Aggregate dividend growth(%)	1.25	1.08	-4.94	-4.29	7.19	9.29
Volatility of aggregate dividend growth (%)	16.19	16.18	13.22	13.46	19.39	20.04
AC(1) of dividend growth	0.21	0.41	0.20	0.24	0.58	0.59
Average annual market value-weighted excess returns (%)	7.98	8.20	2.29	3.07	14.47	15.14
Annual standard deviation of value-weighted market excess returns(%)	19.83	25.44	20.71	21.42	35.96	48.02
AC(1) coefficient of annual value-weighted market excess returns	-0.08	0.00	-0.25	-0.21	0.23	0.27
Average annual market equal-weighted excess returns (%)	13.85	11.66	5.17	5.53	17.39	19.18
Annual standard deviation of equal-weighted market excess returns(%)	30.91	28.70	23.61	24.76	35.97	36.44
AC(1) coefficient of annual equal-weighted market excess returns	-0.04	0.00	-0.23	-0.22	0.20	0.23
Average risk-free rate (%)	0.86	0.90	-0.16	0.01	1.64	1.75
Volatility of risk-free rate (%)	0.97	1.24	0.86	0.95	1.62	1.65
AC(1) of risk-free rate	0.65	0.83	0.68	0.69	0.90	0.91
Expected aggregate log price-dividend ratio	3.37	3.12	3.01	3.03	3.23	3.25
Volatility of aggregate log price-dividend ratio	0.45	0.25	0.19	0.19	0.34	0.44
AC(1) coefficient of aggregate log price-dividend ratio	0.88	0.64	0.39	0.44	0.81	0.83

Table 4: Portfolio characteristics

This table reports the cross-sectional characteristics in the momentum, contrarian, and dividend-price (DP) portfolios from real data and simulated data. Following Fama and French (1988), we calculate dividend yield in June of each year as the total dividends paid from July of previous year to June of this year per dollar of equity in June of this year. We calculate momentum at month t as the cumulative return between month $t-6$ and $t-2$ to avoid the microstructure issues. Long-term performance at month t is defined as the cumulative return between month $t-60$ and $t-13$. For the simulation of the model, we simulate 100 samples with each sample representing 972 months and 1,000 firms. The cross-simulation average annualized moments are reported.

Data

Mom Port.	Los	2	3	4	5	6	7	8	9	Win
DP	0.017	0.027	0.032	0.035	0.037	0.037	0.036	0.035	0.031	0.019
$R_{t-6\to t-2}$	-0.276	-0.148	-0.078	-0.025	0.022	0.069	0.122	0.187	0.284	0.515
$R_{t-60\to t-13}$	0.392	0.470	0.498	0.496	0.504	0.510	0.521	0.513	0.493	0.386

Con Port.	Los	2	3	4	5	6	7	8	9	Win
DP	0.008	0.022	0.030	0.036	0.039	0.040	0.040	0.039	0.035	0.028
$R_{t-6\to t-2}$	0.047	0.050	0.053	0.052	0.051	0.050	0.051	0.051	0.047	0.038
$R_{t-60\to t-13}$	-0.473	-0.183	0.026	0.211	0.391	0.586	0.819	1.139	1.666	3.152

DP Port.	Lo	2	3	4	5	6	7	8	9	Hi
DP	0.015	0.023	0.029	0.035	0.041	0.047	0.053	0.062	0.076	0.104
$R_{t-6\to t-2}$	0.074	0.065	0.063	0.060	0.051	0.050	0.047	0.047	0.046	0.030
$R_{t-60\to t-13}$	1.055	0.875	0.752	0.688	0.625	0.548	0.532	0.499	0.534	0.563

Model

Mom Port.	Los	2	3	4	5	6	7	8	9	Win
DP	0.071	0.076	0.077	0.078	0.078	0.078	0.077	0.076	0.074	0.068
$R_{t-6\to t-2}$	-0.308	-0.193	-0.124	-0.064	-0.006	0.054	0.121	0.201	0.314	0.581
$R_{t-60\to t-13}$	0.745	0.613	0.575	0.550	0.538	0.534	0.537	0.539	0.557	0.624

Con Port.	Los	2	3	4	5	6	7	8	9	Win
DP	0.117	0.099	0.090	0.083	0.077	0.071	0.065	0.059	0.052	0.041
$R_{t-6\to t-2}$	0.066	0.064	0.062	0.061	0.060	0.058	0.057	0.053	0.051	0.043
$R_{t-60\to t-13}$	-0.574	-0.358	-0.192	-0.028	0.149	0.354	0.608	0.955	1.518	3.382

DP Port.	Lo	2	3	4	5	6	7	8	9	Hi
DP	0.026	0.039	0.047	0.055	0.063	0.072	0.083	0.095	0.114	0.159
$R_{t-6\to t-2}$	0.073	0.066	0.063	0.060	0.058	0.056	0.054	0.052	0.049	0.043
$R_{t-60\to t-13}$	1.954	1.118	0.832	0.645	0.503	0.383	0.271	0.168	0.053	-0.114

Table 5: Momentum profits

This table reports the momentum profits from real and simulated data. For the real data, the momentum at time t is defined as the cumulative return between month $t-6$ and $t-2$ to avoid the microstructure issues. Portfolios sorted by momentum are then held for the month $t+1$. The sample is from January 1931 to December 2011. The momentum portfolios from simulated data are sorted using the exactly same strategy as in the real data. We simulate 100 samples with each sample representing 972 months and 1,000 firms. The cross-simulation average annualized moments are reported for the mean, standard deviation, CAPM α, CAPM β, and CAPM R^2. Newey-West t-stats given in parentheses control for heteroscedasticity and autocorrelation.

Data

VW	Los	2	3	4	5	6	7	8	9	Win	W-L
Mean	4.37	8.14	9.08	8.47	8.34	7.86	7.89	8.15	9.00	11.34	6.97
Std	34.13	27.00	24.54	23.06	20.63	20.45	18.81	18.74	19.11	22.20	27.95
α^{CAPM}	-7.53	-1.65	-0.03	-0.24	0.47	0.01	0.66	1.00	1.97	3.87	11.40
	(-4.09)	(-1.27)	(-0.03)	(-0.27)	(0.61)	(0.02)	(0.97)	(1.35)	(2.19)	(2.92)	(4.37)
β^{CAPM}	1.56	1.28	1.20	1.14	1.03	1.03	0.95	0.94	0.92	0.98	-0.58
	(20.74)	(19.90)	(21.39)	(21.27)	(29.86)	(34.27)	(38.20)	(46.46)	(24.65)	(16.11)	(-4.44)
$R^2(\%)$	73.56	79.55	83.44	86.30	88.11	89.14	89.47	87.94	81.99	68.44	15.24

EW	Los	2	3	4	5	6	7	8	9	Win	W-L
Mean	8.87	12.00	12.24	12.54	11.87	11.85	11.91	12.23	12.74	15.84	6.96
Std	39.33	32.01	27.96	27.19	24.19	23.35	21.74	21.94	21.64	24.83	27.02
α^{CAPM}	-8.94	-2.86	-0.83	-0.19	0.54	0.90	1.81	2.16	3.11	5.15	14.09
	(-6.65)	(-2.88)	(-1.02)	(-0.25)	(0.68)	(1.24)	(2.52)	(2.84)	(3.48)	(4.40)	(6.39)
β^{CAPM}	1.43	1.19	1.05	1.02	0.91	0.88	0.81	0.81	0.77	0.86	-0.57
	(32.60)	(27.43)	(41.02)	(25.23)	(39.81)	(36.65)	(48.27)	(37.57)	(23.35)	(17.69)	(-7.49)
$R^2(\%)$	86.88	91.25	92.57	92.92	92.92	92.99	91.54	89.19	83.88	78.44	29.48

Model

VW	Los	2	3	4	5	6	7	8	9	Win	W-L
Mean	4.15	6.00	7.17	7.80	8.32	8.55	9.08	9.81	10.14	11.50	7.35
Std	30.58	28.30	27.45	27.03	26.86	26.81	27.12	27.72	28.98	33.34	42.51
α^{CAPM}	-2.08	-0.70	0.28	0.72	1.12	1.25	1.63	2.21	2.34	3.31	5.39
	(-0.73)	(-0.30)	(0.15)	(0.39)	(0.62)	(0.72)	(0.94)	(1.17)	(1.17)	(1.26)	(1.13)
β^{CAPM}	0.77	0.83	0.85	0.87	0.89	0.90	0.92	0.94	0.96	1.02	0.25
	(20.87)	(27.16)	(30.82)	(34.54)	(36.77)	(38.30)	(38.58)	(38.15)	(35.29)	(28.16)	(3.82)
$R^2(\%)$	35.69	48.13	54.18	58.86	61.96	63.69	65.00	64.90	62.08	52.26	2.10

EW	Los	2	3	4	5	6	7	8	9	Win	W-L
Mean	6.57	8.48	9.47	10.16	10.74	11.26	11.84	12.50	13.13	14.28	7.71
Std	31.61	28.99	27.86	27.14	26.68	26.43	26.42	26.70	27.59	30.81	37.20
α^{CAPM}	-4.40	-2.65	-1.67	-0.95	-0.32	0.28	0.96	1.76	2.61	4.38	8.78
	(-2.29)	(-2.12)	(-1.88)	(-1.58)	(-0.81)	(0.78)	(1.81)	(2.12)	(2.06)	(2.00)	(2.15)
β^{CAPM}	1.02	1.03	1.03	1.03	1.02	1.01	1.00	0.99	0.97	0.91	-0.11
	(40.71)	(63.36)	(89.96)	(133.13)	(204.80)	(234.86)	(149.57)	(92.09)	(58.35)	(31.75)	(-2.04)
$R^2(\%)$	69.28	84.64	91.62	95.91	98.15	98.48	96.62	91.87	82.38	58.19	0.73

Table 6: Long-term contrarian profits

This table reports the long-term contrarian profits from real and simulated data. For the real data, long-term contrarian portfolio returns in the real data are from Kenneth French's Web site. The sample is from January 1931 to December 2011. In the simulated data, the long-term performance at time t is defined as the cumulative return between month $t-60$ and $t-13$. We simulate 100 samples with each sample representing 972 months and 1,000 firms. The cross-simulation average annualized moments are reported for the mean, standard deviation, CAPM α, CAPM β, and CAPM R^2. Newey-West t-stats given in parentheses control for heteroscedasticity and autocorrelation.

					Data						
VW	Los	2	3	4	5	6	7	8	9	Win	L-W
Mean	13.53	11.22	11.30	8.97	9.54	8.43	8.77	8.62	6.89	7.05	6.48
Std	30.71	27.16	24.00	21.32	21.52	19.79	20.35	19.75	20.04	22.33	22.38
α^{CAPM}	3.27	1.53	2.50	0.96	1.40	0.88	0.97	0.99	-0.82	-1.36	4.63
	(1.70)	(1.04)	(2.09)	(1.05)	(1.66)	(1.16)	(1.34)	(1.37)	(-1.10)	(-1.35)	(1.83)
β^{CAPM}	1.35	1.27	1.15	1.05	1.07	0.99	1.02	1.00	1.01	1.10	0.24
	(17.59)	(13.01)	(17.34)	(19.25)	(18.24)	(29.18)	(25.08)	(42.72)	(36.44)	(22.67)	(2.03)
R^2(%)	67.59	77.05	81.30	85.36	86.66	88.21	88.93	90.16	89.69	85.91	4.14
EW	Los	2	3	4	5	6	7	8	9	Win	L-W
Mean	22.54	15.75	14.18	13.17	13.29	11.67	11.80	11.41	10.10	7.49	15.05
Std	39.71	30.97	28.14	25.62	24.82	22.72	22.99	22.92	22.63	24.40	27.78
α^{CAPM}	4.88	1.27	0.95	1.06	1.63	1.02	1.03	0.73	-0.22	-3.19	8.07
	(3.09)	(1.29)	(1.14)	(1.48)	(2.23)	(1.36)	(1.44)	(0.97)	(-0.27)	(-2.84)	(3.33)
β^{CAPM}	1.42	1.16	1.06	0.97	0.93	0.85	0.86	0.86	0.83	0.86	0.56
	(25.05)	(24.80)	(28.44)	(31.83)	(31.59)	(51.78)	(47.81)	(32.71)	(18.65)	(11.86)	(4.88)
R^2(%)	83.78	92.61	93.65	94.62	93.41	92.98	92.91	91.97	88.13	81.06	26.77

					Model						
VW	Los	2	3	4	5	6	7	8	9	Win	L-W
Mean	10.99	10.80	10.32	9.99	9.39	9.65	9.12	8.59	7.71	5.92	5.07
Std	29.50	28.75	28.32	28.05	27.56	27.27	26.83	26.40	25.92	25.23	24.36
α^{CAPM}	3.03	3.00	2.62	2.34	1.84	2.16	1.74	1.30	0.52	-1.26	4.30
	(1.62)	(1.61)	(1.44)	(1.30)	(1.06)	(1.23)	(1.01)	(0.76)	(0.28)	(-0.95)	(1.71)
β^{CAPM}	0.98	0.96	0.95	0.95	0.93	0.93	0.91	0.90	0.89	0.89	0.09
	(36.77)	(36.93)	(37.74)	(38.38)	(38.93)	(39.24)	(39.12)	(38.67)	(40.14)	(42.18)	(2.81)
R^2(%)	62.58	63.19	63.56	64.22	64.46	65.02	64.94	65.30	66.79	70.99	2.17
EW	Los	2	3	4	5	6	7	8	9	Win	L-W
Mean	12.88	12.33	11.88	11.58	11.22	10.91	10.55	10.03	9.23	7.81	5.07
Std	29.40	28.43	27.78	27.25	26.70	26.15	25.57	24.84	23.94	22.15	12.40
α^{CAPM}	0.78	0.58	0.38	0.28	0.14	0.05	-0.07	-0.28	-0.66	-1.18	1.96
	(1.53)	(1.35)	(0.96)	(0.75)	(0.38)	(0.14)	(-0.21)	(-0.72)	(-1.44)	(-1.86)	(1.89)
β^{CAPM}	1.12	1.09	1.06	1.04	1.02	1.00	0.98	0.95	0.91	0.82	0.30
	(158.99)	(191.98)	(208.48)	(227.61)	(231.50)	(232.17)	(218.31)	(191.85)	(152.05)	(97.02)	(21.00)
R^2(%)	97.38	98.03	98.29	98.46	98.49	98.45	98.29	97.87	96.88	92.83	38.48

Table 7: The value premium

This table reports the value premium from real and simulated data. For the real data, the returns of book-to-market portfolios are from Kenneth French's Web site. The sample is from January 1931 to December 2011. The value premium is defined using dividend-price ratio from the simulation. We simulate 100 samples with each sample representing 972 months and 1,000 firms. The cross-simulation average annualized moments are reported for the mean, standard deviation, CAPM α, CAPM β, and CAPM R^2. Newey-West t-stats given in parentheses control for heteroscedasticity and autocorrelation.

Data

VW	Low	2	3	4	5	6	7	8	9	Hi	H-L
Mean	6.77	7.56	7.65	7.85	8.58	9.29	9.46	11.59	12.29	13.68	6.91
Std	19.60	18.84	18.24	21.09	19.60	21.68	23.25	24.49	26.36	32.77	23.35
α^{CAPM}	-0.77	0.19	0.56	-0.30	1.10	1.03	0.82	2.59	2.72	2.48	3.25
	(-1.00)	(0.31)	(0.91)	(-0.39)	(1.29)	(1.16)	(0.76)	(2.19)	(1.97)	(1.32)	(1.37)
β^{CAPM}	0.99	0.97	0.93	1.07	0.98	1.08	1.13	1.18	1.25	1.47	0.48
	(50.29)	(51.73)	(40.56)	(25.14)	(30.85)	(23.01)	(17.93)	(15.15)	(21.95)	(14.72)	(4.13)
$R^2(\%)$	89.68	92.72	91.56	90.25	88.20	88.00	83.45	81.79	79.66	70.71	14.86

EW	Low	2	3	4	5	6	7	8	9	Hi	H-L
Mean	5.76	8.61	9.83	12.21	12.60	13.42	14.44	15.62	18.66	21.15	15.39
Std	25.07	23.45	23.24	24.82	24.40	24.67	25.81	27.61	30.49	36.66	24.86
α^{CAPM}	-5.22	-2.19	-1.05	0.56	0.94	1.66	2.13	2.55	4.35	4.68	9.91
	(-4.22)	(-2.77)	(-1.61)	(0.84)	(1.86)	(2.97)	(3.60)	(3.48)	(4.82)	(3.49)	(4.30)
β^{CAPM}	0.88	0.87	0.87	0.93	0.94	0.94	0.99	1.05	1.15	1.32	0.44
	(13.63)	(21.53)	(23.89)	(50.90)	(49.72)	(68.83)	(45.33)	(31.94)	(26.46)	(22.29)	(4.04)
$R^2(\%)$	81.25	89.79	92.90	93.26	96.81	96.13	96.30	94.87	93.41	85.40	20.58

Model

VW	Low	2	3	4	5	6	7	8	9	Hi	H-L
Mean	4.69	7.84	8.91	9.47	10.48	10.96	11.66	12.28	13.20	14.52	9.83
Std	24.38	24.94	26.04	26.96	27.84	28.90	30.01	31.21	32.76	35.56	33.33
α^{CAPM}	-2.09	0.89	1.64	1.97	2.79	3.05	3.50	3.89	4.52	5.37	7.46
	(-1.50)	(0.53)	(1.03)	(1.19)	(1.61)	(1.70)	(1.84)	(1.93)	(2.07)	(2.17)	(2.16)
β^{CAPM}	0.85	0.87	0.90	0.93	0.95	0.98	1.00	1.03	1.07	1.12	0.27
	(39.91)	(40.39)	(40.20)	(40.50)	(39.75)	(39.20)	(37.70)	(36.74)	(35.17)	(32.38)	(6.08)
$R^2(\%)$	69.14	67.97	67.27	66.64	65.53	64.15	62.84	61.43	59.39	55.92	6.26

EW	Low	2	3	4	5	6	7	8	9	Hi	H-L
Mean	5.74	8.03	9.20	9.99	10.80	11.42	12.10	12.75	13.58	14.83	9.09
Std	19.80	21.76	23.25	24.55	25.78	27.06	28.40	29.86	31.74	35.10	26.39
α^{CAPM}	-1.19	-0.63	-0.31	-0.17	0.09	0.18	0.32	0.43	0.58	0.70	1.90
	(-1.00)	(-0.86)	(-0.58)	(-0.42)	(0.24)	(0.52)	(0.77)	(0.79)	(0.81)	(0.67)	(0.87)
β^{CAPM}	0.64	0.80	0.88	0.94	0.99	1.04	1.09	1.14	1.20	1.30	0.66
	(45.64)	(90.54)	(135.17)	(187.90)	(230.75)	(238.78)	(212.58)	(174.55)	(139.96)	(102.22)	(25.55)
$R^2(\%)$	69.77	90.25	95.45	97.61	98.42	98.52	98.10	97.21	95.75	92.50	42.59

Table 8: Firm size effect

This table reports the firm size effect from real and simulated data. For the real data, size portfolio returns in the real data are from Kenneth French's Web site. The sample is from January 1931 to December 2011. In the simulated data, the firm size is measured by market capitalization. We simulate 100 samples with each sample representing 972 months and 1,000 firms. The cross-simulation average annualized moments are reported for the mean, standard deviation, CAPM α, CAPM β, and CAPM R^2. Newey-West t-stats given in parentheses control for heteroscedasticity and autocorrelation.

					Data						
VW	Sma.	2	3	4	5	6	7	8	9	Big	S-B
Mean	15.13	12.88	12.76	11.91	11.44	10.96	10.46	9.64	8.81	6.82	8.30
Std	35.56	31.04	28.37	26.37	25.20	24.03	22.69	21.53	20.44	17.59	26.40
α^{CAPM}	3.98	2.16	2.46	2.20	1.87	1.66	1.59	1.13	0.65	-0.22	4.20
	(1.83)	(1.32)	(1.89)	(1.83)	(2.03)	(2.01)	(2.18)	(1.89)	(1.50)	(-0.61)	(1.74)
β^{CAPM}	1.46	1.41	1.35	1.27	1.26	1.22	1.16	1.12	1.07	0.92	0.54
	(13.06)	(21.82)	(21.69)	(25.26)	(29.63)	(33.22)	(40.94)	(51.14)	(65.83)	(117.74)	(4.61)
$R^2(\%)$	59.50	72.18	79.76	82.06	87.38	90.61	92.50	94.75	96.47	96.99	14.66
EW	Sma.	2	3	4	5	6	7	8	9	Big	S-B
Mean	19.97	14.12	13.34	12.21	11.59	11.18	10.42	9.62	8.98	7.10	12.87
Std	38.44	32.55	29.38	27.37	26.00	24.73	23.29	22.20	21.22	19.02	28.92
α^{CAPM}	2.94	-1.21	-0.63	-0.79	-0.69	-0.37	-0.38	-0.42	-0.41	-0.95	3.89
	(2.17)	(-1.51)	(-1.03)	(-1.34)	(-1.15)	(-0.56)	(-0.55)	(-0.54)	(-0.45)	(-0.92)	(1.83)
β^{CAPM}	1.36	1.23	1.12	1.04	0.98	0.93	0.87	0.80	0.75	0.65	0.72
	(18.66)	(32.99)	(49.18)	(60.36)	(73.78)	(63.38)	(46.62)	(33.00)	(28.09)	(26.86)	(8.07)
$R^2(\%)$	83.12	93.86	95.85	95.57	94.56	92.47	91.08	86.60	83.03	75.92	40.79

					Model						
VW	Sma.	2	3	4	5	6	7	8	9	Big	S-B
Mean	13.68	13.12	12.53	12.11	11.63	11.22	10.82	10.35	9.60	7.14	6.54
Std	30.16	28.80	27.84	27.12	26.46	25.85	25.18	24.43	23.55	23.40	19.23
α^{CAPM}	5.06	4.75	4.36	4.08	3.74	3.46	3.22	2.93	2.39	-0.67	5.73
	(2.91)	(3.03)	(2.94)	(2.91)	(2.79)	(2.71)	(2.62)	(2.52)	(2.20)	(-1.78)	(2.87)
β^{CAPM}	1.06	1.03	1.01	0.99	0.97	0.96	0.94	0.91	0.89	0.98	0.09
	(43.75)	(46.78)	(48.74)	(50.53)	(51.76)	(53.94)	(55.09)	(56.86)	(58.51)	(208.81)	(4.01)
$R^2(\%)$	69.16	71.58	72.92	74.10	75.05	76.04	76.89	77.85	78.92	97.87	5.53
EW	Sma.	2	3	4	5	6	7	8	9	Big	S-B
Mean	13.47	12.63	12.02	11.59	11.09	10.68	10.27	9.78	9.08	7.81	5.66
Std	30.72	28.98	27.98	27.23	26.55	25.91	25.22	24.45	23.53	21.94	14.15
α^{CAPM}	0.85	0.65	0.42	0.29	0.06	-0.08	-0.19	-0.34	-0.61	-1.04	1.88
	(1.44)	(1.41)	(1.05)	(0.78)	(0.19)	(-0.23)	(-0.53)	(-0.86)	(-1.27)	(-1.56)	(1.62)
β^{CAPM}	1.17	1.11	1.07	1.04	1.02	0.99	0.96	0.93	0.89	0.81	0.35
	(156.90)	(190.97)	(214.62)	(228.56)	(233.22)	(228.79)	(215.05)	(188.63)	(149.13)	(98.06)	(24.20)
$R^2(\%)$	96.86	97.85	98.25	98.44	98.49	98.42	98.19	97.67	96.42	92.03	42.02

Table 9: Dividend dynamics and risk exposures

This table reports the dividend dynamics and risk exposures of the momentum portfolios, contrarian portfolios, dividend-price portfolios, and size portfolios from simulated data. We simulate 100 samples with each sample representing 972 months and 1,000 firms. The cross-simulation mean are reported. y is the firm-specific dividend growth rate, which is scaled by 100 times for convenience of exposition. $\Delta y(l)$ is the cumulative change in y between $t-60$ and $t-13$. $\Delta y(s)$ is the cumulative change in y between $t-6$ and $t-2$. f is the exposure to long-run consumption shocks. h is the exposure to short-run consumption shocks.

Mom Port.	Los	2	3	4	5	6	7	8	9	Win
$y \times 100$	-0.26	-0.22	-0.17	-0.13	-0.08	-0.02	0.04	0.12	0.23	0.49
$\Delta y(l)$	1.59	0.46	0.04	-0.19	-0.35	-0.45	-0.48	-0.46	-0.34	0.18
$\Delta y(s)$	-3.08	-1.89	-1.25	-0.73	-0.27	0.19	0.66	1.20	1.90	3.27
f	6.25	6.31	6.26	6.18	6.09	5.97	5.83	5.64	5.35	4.68
h	-5.62	-3.55	-2.41	-1.45	-0.60	0.28	1.18	2.25	3.61	6.38

Con Port.	Los	2	3	4	5	6	7	8	9	Win
$y \times 100$	-0.54	-0.35	-0.24	-0.15	-0.07	0.02	0.11	0.22	0.36	0.64
$\Delta y(l)$	-8.29	-5.13	-3.42	-2.03	-0.78	0.47	1.78	3.26	5.16	8.98
$\Delta y(s)$	0.00	0.00	-0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
f	7.32	6.87	6.57	6.32	6.08	5.83	5.56	5.24	4.82	3.93
h	-0.16	-0.10	-0.08	-0.03	-0.02	0.02	0.06	0.08	0.12	0.20

DP Port.	Lo	2	3	4	5	6	7	8	9	Hi
$y \times 100$	1.09	0.64	0.42	0.23	0.07	-0.08	-0.24	-0.42	-0.64	-1.07
$\Delta y(l)$	9.34	5.56	3.61	2.05	0.67	-0.67	-2.07	-3.62	-5.56	-9.31
$\Delta y(s)$	0.27	0.15	0.10	0.05	0.01	-0.02	-0.06	-0.10	-0.16	-0.24
f	2.15	3.68	4.46	5.07	5.62	6.15	6.69	7.29	8.03	9.42
h	1.19	0.70	0.44	0.24	0.07	-0.09	-0.26	-0.45	-0.68	-1.07

Size Port.	Sma	2	3	4	5	6	7	8	9	Big
$y \times 100$	-0.43	-0.27	-0.18	-0.10	-0.04	0.03	0.09	0.17	0.27	0.46
$\Delta y(l)$	-3.41	-2.12	-1.40	-0.83	-0.30	0.20	0.74	1.35	2.13	3.65
$\Delta y(s)$	-0.06	-0.03	-0.03	-0.02	-0.01	0.00	0.01	0.03	0.04	0.07
f	7.74	7.01	6.62	6.30	6.02	5.74	5.45	5.11	4.69	3.87
h	-0.27	-0.17	-0.12	-0.07	-0.03	0.02	0.08	0.12	0.20	0.33

Table 10: Consumption-CAPM: Time series regression

This table reports the test result of Consumption-CAPM on the value-weighted returns of the momentum, contrarian, dividend-price (or book-to-market), and size portfolios from both real and simulated data. We simulate 100 samples with each sample representing 972 months and 1,000 firms. The cross-simulation mean are reported for the C-CAPM β and C-CAPM R^2. Newey-West t-stats given in parentheses control for heteroscedasticity and autocorrelation.

Data

Mom Port.	Los	2	3	4	5	6	7	8	9	Win	W-L
β^{CCAPM}	-3.43	-1.82	-0.67	-0.60	0.52	0.69	1.10	1.92	2.47	3.97	7.40
	(-1.56)	(-1.23)	(-0.67)	(-0.49)	(0.52)	(0.64)	(1.22)	(2.61)	(3.49)	(3.80)	(3.58)
$R^2(\%)$	3.21	1.61	0.33	0.29	0.28	0.46	1.44	4.02	5.95	10.73	20.11

Con Port.	Los	2	3	4	5	6	7	8	9	Win	L-W
β^{CCAPM}	-1.45	-0.52	-0.85	-0.04	-0.33	0.07	0.40	0.44	1.58	1.43	-2.88
	(-0.82)	(-0.31)	(-0.68)	(-0.03)	(-0.26)	(0.06)	(0.33)	(0.46)	(1.76)	(1.49)	(-1.65)
$R^2(\%)$	0.72	0.13	0.61	0.00	0.09	0.01	0.14	0.18	2.48	1.43	4.13

BM Port.	Lo	2	3	4	5	6	7	8	9	Hi	H-L
β^{CCAPM}	1.02	0.33	0.24	0.71	1.10	2.58	0.83	1.14	0.56	0.26	-0.75
	(1.12)	(0.45)	(0.32)	(0.64)	(0.93)	(2.73)	(0.68)	(0.87)	(0.40)	(0.15)	(-0.46)
$R^2(\%)$	1.00	0.14	0.08	0.47	1.10	5.40	0.53	0.84	0.19	0.03	0.43

Size Port.	Sma	2	3	4	5	6	7	8	9	Big	S-B
β^{CCAPM}	0.89	0.94	0.26	0.67	0.68	0.74	0.45	0.02	0.49	1.24	-0.34
	(0.45)	(0.58)	(0.17)	(0.53)	(0.58)	(0.70)	(0.41)	(0.02)	(0.51)	(1.66)	(-0.18)
$R^2(\%)$	0.22	0.33	0.03	0.23	0.28	0.36	0.14	0.00	0.23	1.92	0.06

Model

Mom Port.	Los	2	3	4	5	6	7	8	9	Win	W-L
β^{CCAPM}	-2.40	-1.01	-0.26	0.43	1.21	1.62	2.37	2.99	4.20	6.50	8.90
	(-2.44)	(-1.04)	(-0.29)	(0.41)	(1.19)	(1.68)	(2.34)	(2.99)	(4.10)	(5.59)	(7.05)
$R^2(\%)$	7.44	2.55	1.56	1.70	3.13	4.67	8.17	11.75	19.31	31.47	39.69

Con Port.	Los	2	3	4	5	6	7	8	9	Win	L-W
β^{CCAPM}	1.90	1.83	1.96	1.87	1.94	1.95	1.91	1.88	1.99	2.06	-0.16
	(1.67)	(1.73)	(1.87)	(1.80)	(1.88)	(1.94)	(1.97)	(1.97)	(2.15)	(2.27)	(-0.18)
$R^2(\%)$	4.70	5.08	5.57	5.28	5.63	5.72	5.85	5.84	6.65	7.43	1.59

DP Port.	Lo	2	3	4	5	6	7	8	9	Hi	H-L
β^{CCAPM}	2.51	2.01	1.90	1.70	1.76	1.51	1.51	1.39	1.12	0.75	-1.76
	(2.88)	(2.25)	(1.94)	(1.63)	(1.62)	(1.37)	(1.26)	(1.12)	(0.83)	(0.51)	(-1.28)
$R^2(\%)$	10.96	7.19	6.11	4.87	4.80	3.56	3.19	2.79	2.33	1.76	3.17

Size Port.	Sma	2	3	4	5	6	7	8	9	Big	S-B
β^{CCAPM}	1.84	1.89	1.89	1.90	1.93	1.92	1.95	1.99	1.94	2.20	-0.36
	(1.56)	(1.69)	(1.77)	(1.82)	(1.92)	(1.97)	(2.05)	(2.20)	(2.24)	(2.52)	(-0.41)
$R^2(\%)$	4.38	4.76	5.12	5.40	5.82	5.90	6.34	6.94	7.30	8.87	1.73

Table 11: Correlation for the profitability of momentum, contrarian, value, and size strategies

This table reports the correlation coefficients between momentum profits (Mom), long-term contrarian profits (Con), the value premium (Value), and size premium (Size), calculated as value-weighted (VW) and equal-weighted (EW), from the real data and the model. The data sample is monthly from January 1931 to December 2011. For the model, we simulate 100 samples with each sample representing 972 months and 1,000 firms. The cross-simulation average moments are reported.

Data

VW	Mom	Con	Value	Size	EW	Mom	Con	Value	Size
Mom	1.00	-0.31	-0.40	-0.38	Mom	1.00	-0.54	-0.48	-0.57
Con	-0.31	1.00	0.64	0.65	Con	-0.54	1.00	0.80	0.86
Value	-0.40	0.64	1.00	0.70	Value	-0.48	0.80	1.00	0.77
Size	-0.38	0.65	0.70	1.00	Size	-0.57	0.86	0.77	1.00

Model

VW	Mom	Con	Value	Size	EW	Mom	Con	Value	Size
Mom	1.00	-0.12	-0.38	-0.27	Mom	1.00	-0.16	-0.44	-0.27
Con	-0.12	1.00	0.53	0.54	Con	-0.16	1.00	0.74	0.78
Value	-0.38	0.53	1.00	0.79	Value	-0.44	0.74	1.00	0.86
Size	-0.27	0.54	0.79	1.00	Size	-0.27	0.78	0.86	1.00

Table 12: Dynamics of momentum profits

This table reports the buy-and-hold monthly returns for each of the first 12 months and annual returns for 2 to 5 years of momentum portfolios from simulations. We simulate 100 samples with each sample representing 972 months and 1,000 firms. The cross-simulation mean are reported.

	m1	m2	m3	m4	m5	m6	m7	m8	m9	m10	m11	m12	y2	y3	y4	y5
Los.	0.55	0.63	0.70	0.75	0.79	0.82	0.85	0.86	0.88	0.89	0.90	0.91	12.41	12.53	12.51	12.60
2	0.70	0.76	0.80	0.83	0.86	0.88	0.90	0.91	0.91	0.92	0.93	0.93	12.61	12.66	12.63	12.66
3	0.79	0.82	0.85	0.87	0.88	0.90	0.91	0.92	0.93	0.93	0.93	0.93	12.58	12.65	12.65	12.64
4	0.84	0.86	0.87	0.89	0.90	0.90	0.92	0.92	0.93	0.93	0.93	0.93	12.53	12.59	12.57	12.55
5	0.89	0.90	0.90	0.91	0.91	0.92	0.92	0.92	0.92	0.93	0.93	0.93	12.42	12.45	12.47	12.49
6	0.93	0.93	0.92	0.92	0.92	0.92	0.92	0.92	0.92	0.91	0.91	0.92	12.30	12.29	12.36	12.35
7	0.98	0.97	0.95	0.94	0.92	0.92	0.92	0.91	0.91	0.91	0.90	0.91	12.13	12.11	12.17	12.21
8	1.03	0.99	0.97	0.94	0.93	0.92	0.91	0.90	0.90	0.89	0.89	0.89	11.87	11.89	11.97	12.01
9	1.09	1.04	0.99	0.96	0.93	0.91	0.90	0.88	0.88	0.87	0.86	0.86	11.45	11.51	11.61	11.71
Win.	1.18	1.09	1.02	0.95	0.91	0.88	0.85	0.83	0.81	0.80	0.79	0.78	10.49	10.58	10.76	10.95
W-L	0.63	0.46	0.32	0.20	0.12	0.06	0.00	-0.04	-0.07	-0.09	-0.11	-0.13	-1.92	-1.94	-1.75	-1.66

Table 13: Cross-sectional regressions with market returns and consumption growth

This table reports the cross-sectional tests on the value-weighted returns of 32 portfolios—10 book-to-market portfolios, 10 momentum portfolios, and 12 Fama-French industry portfolios from Kenneth French's Web site. The tested models include CAPM, Consumption-CAPM, and a two-factor model with market return (MKT) and consumption growth (ConG) as the risk factors. The data is annual from 1931 to 2011. The tests are implemented on the full sample and two subsamples 1931-1962 and 1963-2011. For each model, the estimated risk premia, mean absolute error (MAE), p-value for the J_T tests, and the OLS-R^2 are reported. Newey-West t-stats given in parentheses control for heteroscedasticity and autocorrelation.

Panel A: 1931-2011

	CAPM	C-CAPM	MKT+ConG
MKT	8.78		9.27
	(3.89)		(4.12)
ConG		3.24	1.20
		(2.78)	(2.37)
MAE	1.46	7.01	1.18
$p(J_T)$	0.00	0.13	0.00
R^2 (%)	-36.53%	-416.83%	34.06%

Panel B: 1931-1962

	CAPM	C-CAPM	MKT+ConG
MKT	11.46		11.93
	(2.73)		(2.88)
ConG		4.05	1.03
		(1.84)	(1.06)
MAE	1.56	10.06	1.35
$p(J_T)$	0.00	0.00	1.00
R^2 (%)	28.36%	-539.11%	50.99%

Panel C: 1963-2011

	CAPM	C-CAPM	MKT+ConG
MKT	6.95		7.34
	(2.78)		(2.90)
ConG		1.55	1.12
		(3.16)	(2.75)
MAE	1.82	6.14	1.11
$p(J_T)$	0.00	0.00	0.00
R^2 (%)	-71.37%	-23.88%	55.01%

Table 14: Sensitivity analysis

This table reports the moments for variables of interest from simulations of the model under alternative parameterizations. We change one parameter each time from the benchmark case, as highlighted in the first two rows of the table. Moments from the benchmark are reported in Specification (0). We consider alternative values for the relative risk aversion in Specifications (1) and (2), the elasticity of intertemporal substitution in Specifications (3) and (4), the correlation between shocks to the exposure of long-run consumption growth and firm dividend growth shocks in Specifications (5), (6), and (7), the correlation between shocks to the exposure of short-run consumption growth and firm dividend growth shocks in Specifications (8), (9), and (10), the persistence of exposure to long-run consumption growth in Specifications (11), (12), and (13), the persistence in exposure to short-run consumption growth in Specifications (14), (15), and (16). We report the mean, standard deviation, and the first-order autocorrelation coefficient of market excess returns (both value-weighted and equal-weighted), risk-free rate, log price-dividend ratio, the profitability to momentum, contrarian, value, and size strategies. We simulate 100 samples with each sample representing 972 months and 1,000 firms. The cross-simulation median annualized moments are reported.

Specification	(0)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Parameter		γ	γ	ψ	ψ	ρ_{fy}	ρ_{fy}	ρ_{fy}	ρ_{hy}	ρ_{hy}	ρ_{hy}	ρ_f	ρ_f	ρ_f	ρ_h	ρ_h	ρ_h
Benchmark		10	10	1.5	1.5	-0.970	-0.970	-0.970	0.875	0.875	0.875	0.989	0.989	0.989	0.781	0.781	0.781
Alternative		15	5	2	0.5	-0.726	-0.99	0	0.667	0.99	0	0.987	0.991	0.95	0.671	0.891	0.5
E(MKTVW)	8.20	10.20	5.13	8.89	3.51	9.46	8.05	13.24	7.73	8.44	6.28	9.74	5.18	13.01	7.97	10.03	7.33
Std(MKTVW)	25.44	25.50	27.30	26.20	21.14	27.13	25.40	32.82	25.29	25.43	24.53	26.89	25.34	31.13	24.32	30.09	23.61
AC1(MKTVW)	0.00	0.02	0.00	0.00	0.02	0.02	0.01	0.00	0.01	0.01	-0.01	0.00	0.02	-0.01	0.01	-0.01	0.01
E(MKTEW)	11.66	15.54	6.85	12.35	6.57	11.86	11.64	12.42	11.70	11.64	11.88	11.75	11.72	12.23	11.48	12.30	11.36
Std(MKTEW)	28.70	27.42	31.16	29.67	22.26	29.12	28.68	30.25	28.77	28.65	28.97	28.90	28.72	29.76	28.36	30.00	28.15
AC1(MKTEW)	0.00	0.01	-0.01	0.00	0.02	0.00	0.00	0.00	-0.01	0.00	0.00	0.00	-0.01	0.00	0.00	-0.01	0.00
E(rf)	0.90	0.34	1.47	0.36	4.88	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90
Std(rf)	1.24	1.24	1.24	0.93	3.72	1.24	1.24	1.24	1.24	1.24	1.24	1.24	1.24	1.24	1.24	1.24	1.24
AC1(rf)	0.83	0.83	0.83	0.83	0.83	0.83	0.83	0.83	0.83	0.83	0.83	0.83	0.83	0.83	0.83	0.83	0.83
E(p-d)	3.12	2.87	4.07	3.13	3.02	2.92	3.14	2.61	3.19	3.09	3.52	2.86	4.41	2.53	3.06	3.44	3.03
Std(p-d)	0.25	0.24	0.29	0.26	0.20	0.28	0.25	0.36	0.25	0.25	0.25	0.27	0.26	0.35	0.24	0.31	0.24
AC1(p-d)	0.64	0.64	0.67	0.65	0.58	0.65	0.64	0.71	0.64	0.64	0.64	0.67	0.68	0.72	0.63	0.66	0.64
Mom	7.54	11.46	3.71	7.55	7.45	7.48	7.51	8.12	4.72	9.34	-3.41	7.09	7.76	7.42	4.77	9.54	1.39
Std(Mom)	37.17	36.76	37.82	37.21	37.02	34.91	37.45	31.22	29.81	42.07	20.36	35.84	40.93	33.38	26.62	57.78	16.56
Contrarian	5.13	6.53	3.20	5.19	4.64	3.41	5.30	-1.12	5.39	4.89	6.07	4.13	7.42	-0.33	5.66	2.67	5.82
Std(Contrarian)	12.50	10.49	16.45	12.46	12.87	10.16	12.70	7.51	12.57	12.48	13.60	10.31	17.28	3.76	12.54	16.29	12.73
Value	9.21	13.60	4.02	9.33	8.07	6.55	9.36	-0.18	10.21	8.74	13.45	6.37	14.40	-2.61	10.29	5.32	11.25
Std(Value)	26.39	24.51	29.30	26.32	26.85	22.44	26.78	15.68	25.35	27.16	25.58	22.40	34.81	14.15	23.96	39.38	23.05
Size	5.72	8.70	3.07	5.80	5.16	3.92	5.97	-0.20	6.11	5.68	7.55	3.72	9.91	-0.69	6.54	4.00	6.93
Std(Size)	14.27	13.59	15.73	14.23	14.60	11.16	14.59	6.36	14.34	14.28	15.40	10.63	21.98	4.92	14.21	16.98	14.39

Figure 1: Exposures to consumption risk at high and low frequencies

This figure plots the exposure of momentum, long-term contrarian, and dividend-price portfolios to the growth rate of non-durable consumption and services at both high and low frequencies. Portfolio returns are from Kenneth French's Web site. The times series of returns and consumption growth are filtered using the band pass filter developed in Christiano and Fitzgerald (2003), and the exposures in the figures are the coefficients of univariate regression of filtered returns on the filtered consumption growth. High frequencies range from 2-year to 8-year period, while low frequencies range from 20-year to 70-year period. The figure displays the point estimates (the solid lines) and the 95% confidence intervals (the dashed lines). The sample are annual from 1931 to 2011.

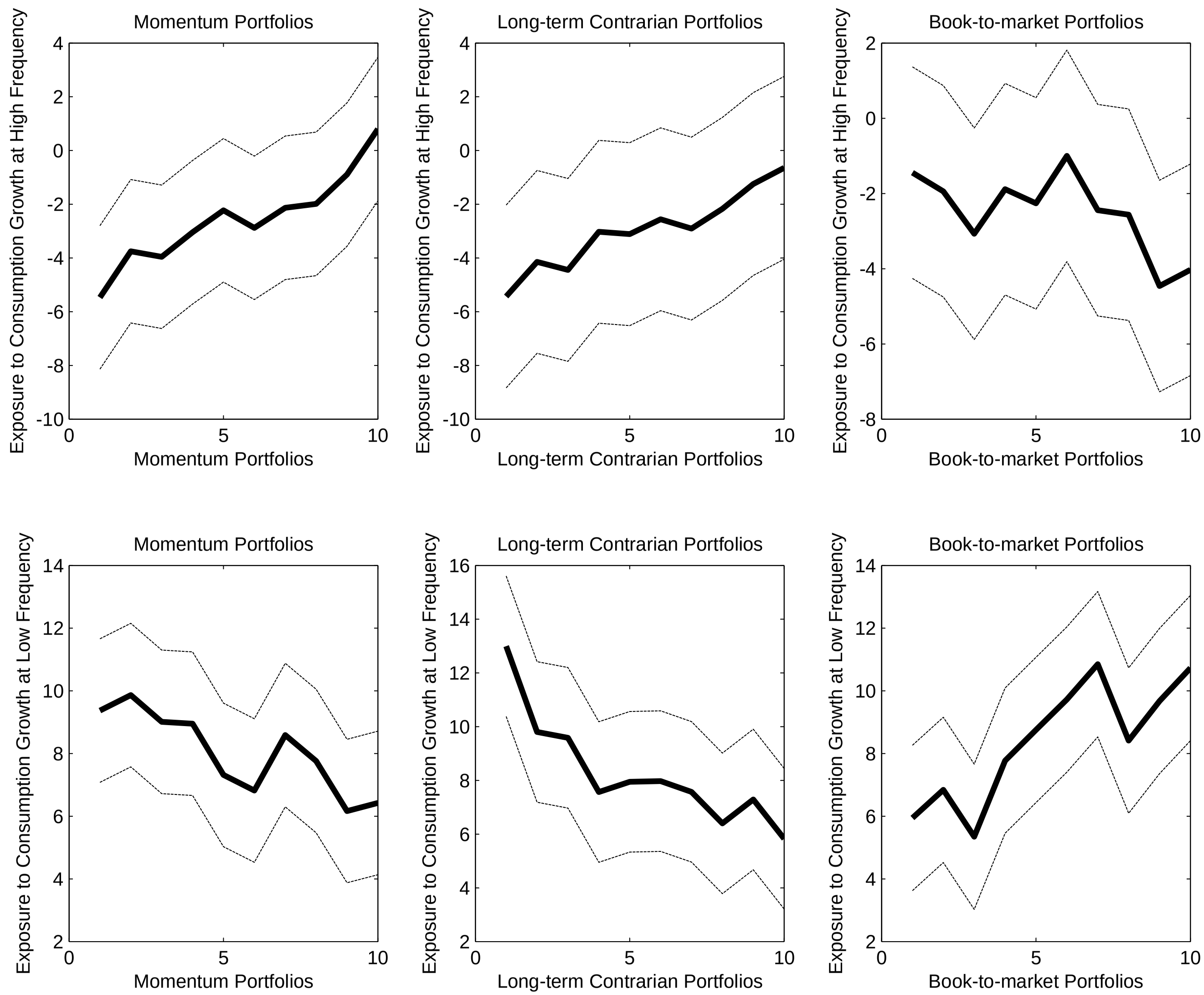

Figure 2: Predicted versus actual returns

This figure compares the model predicted returns with the actual returns for 32 portfolios–10 book-to-market portfolios, 10 momentum portfolios, and 12 Fama-French industry portfolios from Kenneth French's Web site. The tested models include CAPM, Consumption-CAPM, and a two-factor model with market return (MKT) and consumption growth (ConG) as the risk factors. The data is annual from 1931 to 2011. The tests are implemented on the full sample and two subsamples 1931-1962 and 1963-2011.

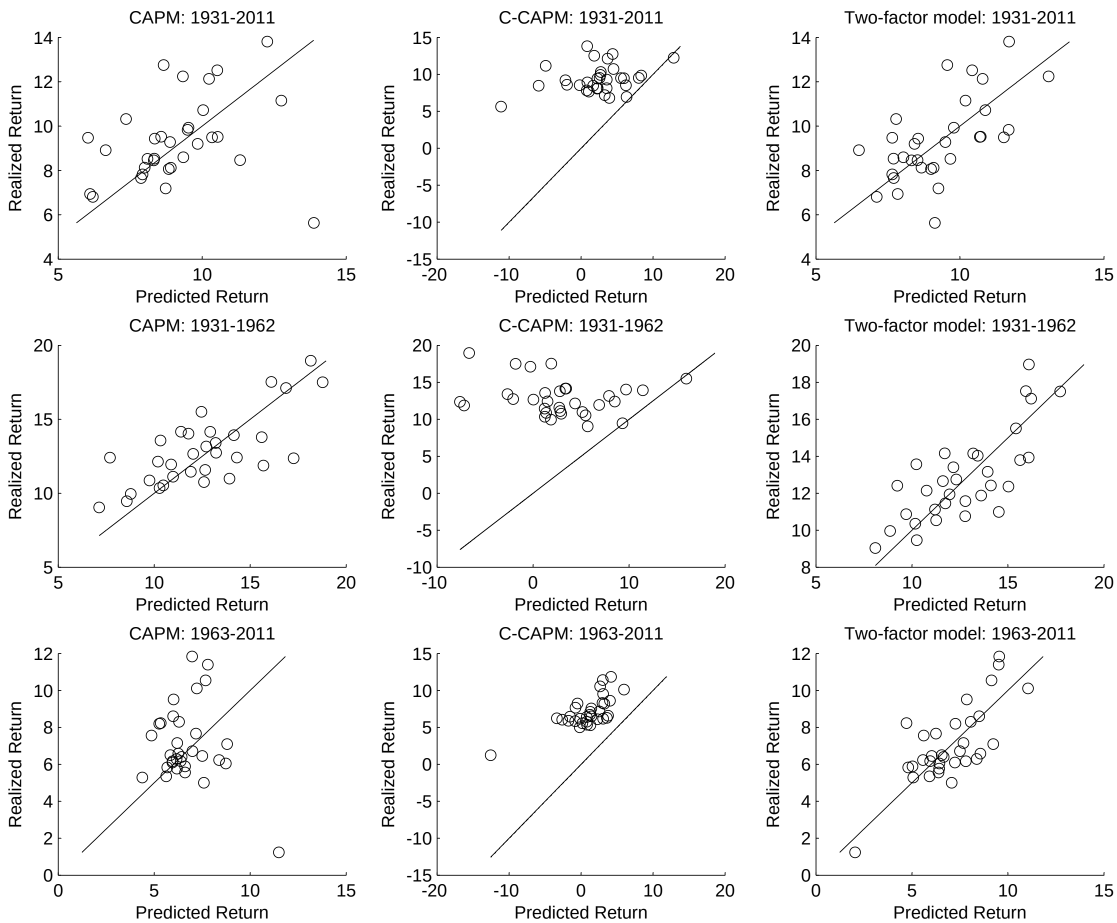

Table A1: MCMC estimated parameters

This table compares the parameter values from alternative estimations. For each parameter in ρ_h, σ_h, ρ_f, and σ_f, we report the point estimate with 95% confidence intervals. SMM corresponds to the estimate from the simulated method of moments. MCMC1 corresponds to the Bayesian Markov Chain Monte-Carlo estimation with no measurement errors or firm-fixed effects. MCMC2 corresponds to the Bayesian Markov Chain Monte-Carlo estimation with measurement errors in long-run consumption risks. MCMC3 corresponds to Bayesian Markov Chain Monte-Carlo estimation with both measurement errors in long-run consumption risks and firm-fixed effect. All parameters are converted into monthly frequencies for convenience of comparison.

Panel A: SMM estimation

ρ_h	σ_h	ρ_f	σ_f
0.781	4.935	0.989	0.351
[0.671, 0.891]	[3.881, 5.989]	[0.987, 0.991]	[0.283, 0.419]

Panel B: MCMC1:
No measurement error or firm-fixed effect

ρ_h	σ_h	ρ_f	σ_f
0.909	3.498	0.933	10.779
[0.833, 0.944]	[3.042, 4.167]	[0.898, 0.949]	[9.053, 12.798]

Panel C: MCMC2:
Measurement errors in long-run consumption risks

ρ_h	σ_h	ρ_f	σ_f
0.921	4.752	0.947	1.061
[0.854, 0.954]	[4.215, 5.445]	[0.920, 0.960]	[0.920, 1.218]

Panel D: MCMC3:
Measurement errors in long-run consumption risks + firm-fixed effect

ρ_h	σ_h	ρ_f	σ_f
0.894	5.039	0.963	0.316
[0.848, 0.926]	[4.300, 5.972]	[0.911, 0.987]	[0.271, 0.370]

Table A2: Cross-sectional regressions with short-run and long-run consumption risks

This table reports the cross-sectional tests on the value-weighted returns of 10 momentum portfolios, 10 long-term contrarian portfolios, 10 book-to-market portfolios, 10 size portfolios, and 30 Fama-French industry portfolios from Kenneth French's Web site. The tested model is a two-factor model with short-run (SRR) and long-run (LRR) consumption risks as the risk factors. The data is annual from 1931 to 2011. We follow Bansal, Kiku, and Yaron (2012b) and regress aggregate consumption growth rate at year $t+1$ on log(DP) and real risk-free rate at year t to extract the expected consumption growth. The estimated risk prices (bs), the estimated risk premia (λs), mean absolute error (MAE), p-value for the J_T tests, and the OLS-R^2 are reported. Newey-West t-statistics given in parentheses control for heteroscedasticity and autocorrelation.

	Coefficient	t-statistic
b_{SRR}	25.74	(1.61)
λ_{SRR}	0.63	(1.25)
b_{LRR}	211.27	(2.35)
λ_{LRR}	0.34	(2.30)
MAE	1.52	
$p(J_T)$	1.00	
$R^2(\%)$	0.14	