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

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December 2, 2014

Abstract

We examine the implications of short- and long-run consumption growth fluctuations on the momentum and contrarian profits and the value premium in a unified economic framework. By allowing 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 in generating the momentum and contrarian profits and the value premium. The model also reproduce the size effect, the pairwise correlations between the profitabilities of these investment strategies, and the performance of the standard CAPM and the consumption-based CAPM in explaining these well-documented return behaviors.

JEL Classifications: G12, E44

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

*We thank Torben Andersen, Geert Bekaert, Jonathan Berk, Max Croce (SFS Finance Cavalcade discussant), Eric Ghysels, Kai Li (CICF discussant), Francis Longstaff, Lin Peng, Nick Roussanov, Lukas Schmid, Viktor Todorov, Pietro Veronesi, Fan Yang, Rui Yao, Jianfeng Yu, Irina Zviadadze, and seminar participants at Baruch College, University of Texas at Dallas, the Sixth Annual SoFiE Conference, the 2014 SFS Finance Cavalcade, the 2014 China International Conference in Finance (CICF), and the Asian Finance Association Annual Meetings for helpful comments. All remaining errors are our own.

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1 Motivation

We provide a unified economic framework to explain the widely documented asset return phenomena such as the momentum and contrarian profits and the value premium. While value (growth) firms are similar to loser (winner) firms in terms of their past performance, the profitabilities of these two strategies are strongly negatively correlated. This makes it very challenging for consumption risk models to simultaneously generate the momentum and contrarian profits and the value premium. Our framework builds upon the widely used long-run consumption risk model introduced by Bansal and Yaron (2004) (BY thereafter) and takes into account that firms' dividend growth varies differently to the short-run and long-run consumption growth fluctuations. The setup accommodates the empirical finding that different portfolios constructed on the past return performances and dividend-price ratios exhibit different exposures to the short-run and long-run consumption risks. This allows the asset return behaviors to be explained in an otherwise standard unified framework.

To motivate our economic framework, we first illustrate the relation between the constructed portfolio returns and the short-run and long-run consumption growth fluctuations and then test if the short- and long-run consumption risks can price these constructed portfolios. We decompose the aggregate consumption growth into short- and long-run fluctuations by band-pass filtering.[1] We then regress the returns of 10 book-to-market portfolios, 10 momentum portfolios, and 10 long-term contrarian portfolios on different components of consumption growth variations. Figure 1 plots the exposures of these portfolios to the two components of consumption growth. The left panels of Figure 1 show that at higher frequency (top panels), value firms (portfolio 10) have slightly lower exposure to the consumption growth than the growth firms (portfolio 1), but the

[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). 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.

difference is not statistically significant. In contrast, there is a strong increasing pattern from growth firms to value firms in the exposure to the consumption growth at low frequency (bottom panels). This pattern is consistent with the findings in Parker and Julliard (2005) and Hansen, Heaton, and Li (2008) which document that value portfolios have a higher exposure to the long-run economic shocks than growth portfolios.

For momentum portfolios (the middle panels), the exposure to the consumption growth at high frequency increases almost monotonically from loser firms (portfolio 1) to winner firms (portfolio 10), whereas the pattern at the low frequency is just the opposite. This is consistent with the findings in Bansal, Dittmar, and Lundblad (2005) which demonstrate that the cash flow beta of winner stocks is significantly higher than that of the loser stocks. Lastly, for the contrarian portfolios (the right panels), long-term losers (portfolio 1) have much higher exposure to low frequency consumption growth variation but much lower exposure to high frequency consumption growth variation than long-run winners (portfolio 10). Taking together, the results shown in Figure 1 suggest that if the prices of risk for both high- and low-frequency variation in consumption growth are positive, which is true under standard assumptions of BY and Bansal, Kiku, and Yaron (2012a), the low-frequency consumption risk should be the main driving force for the value premium and contrarian profits, whereas the high-frequency consumption risk should be responsible for momentum profits.[2]

[Insert Figure 1 Here]

We conduct the cross-sectional tests on the value-weighted returns of the constructed portfolios on a two-factor model with the short- and long-run consumption growth fluctuations as the risk factors using the dividend price ratio (DP) to estimate the consumption risk factors.[3] Table 1 shows the the estimated price of risk and the estimated risk premium for the short- and long-run consumption risks. All estimates are positive and significant at the conventional test level with a

[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).

[3]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.

slightly weaker result on the short-term risk premium. The magnitude of the estimated price of risks for the short- and long-run consumption growth fluctuations are also consistent with Bansal and Yaron (2004). We take these findings as evidence for the constructed portfolio returns being related to short- and long-run consumption risks which we focus in our analysis.

[Insert Table 1 Here]

In this paper, we explore the implications for the momentum and contrarian profits and the value premium in an economy with short- and long-run consumption growth risks by specifying firms' cash flow processes that are consistent with these observed empirical patterns.[4] We maintain the specification of BY on the representative agent preference and the consumption process. However, we introduce firms' cash flow processes to accommodate the variation in aggregate dividend growth, the exposures to the short- and long-run consumption growth 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 firm-level dividend growth. Our firm cash flow process is similar to Johnson (2002) but differs in that our firms are subject to time-varying exposures to both temporary growth rate shock and permanent fundamental technological shock.[5] 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. This implies 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.[6] We, however, take a bottom-up

[4]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.

[5]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.

[6]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-

approach and start with firm-level dividend growth processes. In particular, we allow firm cash flow to have time-varying sensitivities to different types of aggregate economic risks. This adds to the richness of firm heterogeneity, accommodates different exposures of the value, momentum and contrarian portfolios to different components of aggregate economic shocks uncovered in data.

In our model, while firm stocks are identical ex ante, they have very different characteristics ex post after the realization of firm specific cash flow shocks. Because it is difficult to calibrate parameters for firm dividend processes from existing studies, we employ a simulated method of moments (SMM) estimation approach to estimate these parameters. We avoid using the cross-sectional average returns of the momentum, contrarian, and value portfolios as matching moments. Instead, we estimate these parameters 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 value-weighted portfolios based on past short- and long-term stock return 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 directly 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 difference in the persistence of the short- and long-run consumption risk exposures played 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

section of stock returns. However, the cash-flow risk has to be very large to generate empirically plausible value premiums, leading to a ''cash-flow risk puzzle".

exposure. Therefore, portfolios sorted by these characteristics should create a large dispersion on the exposure to the long-run risk.

Besides the two persistence variables, our analysis also highlights the importance of the correlation structure between the short- and long-run risk exposure shocks and firm cash flow shock. 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 growth and the short-run consumption risk exposure. 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.

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. 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. Momentum portfolios sorted on the short-term stock return pick up the short-run risk exposure. However, these portfolio sorts do not isolate the risk exposures from one factor to the other: growth firms (firms with a high valuation ratio) also tend to have higher short-term stock return than value firms (firms with a low valuation ratio), implying a negative risk exposure to the short-run risk for the value premium. 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 the momentum profit to consumption shocks (both short-run and long-run) provide a natural explanation for the negative correlation between the profitabilities of these two strategies.

The decomposition of risk exposures also shed 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. Using the sample of observations between January 1931 and December 2011, we find that 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. On the other hand, the market beta varies from 1.10 (0.99) for long-term winners (growth firms) to 1.35 (1.47) for long-term losers (value firms), capturing a large portion of the contrarian profit (value premium). Since both the market portfolio and the consumption growth contain information about the short- and long-run consumption risks, one prediction is that an asset pricing model with both variables as risk factors should notably improve the performance in capturing the cross section of stock returns. We test this prediction in a two-step Fama-MacBeth procedure on 10 momentum, 10 value, and 12 industry portfolios. We find that the two-factor model significantly outperforms one-factor models including the CAPM and the Consumption-CAPM, especially in the post-1963 sample.

Despite the success of our model in reproducing salient features of asset pricing phenomena, one should not simply take it for granted that our flexible 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 are quite different. 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-level 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 short-run 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. Li (2014) focuses on the production side of the economy and studies an investment-based explanation for the value premium and the momentum profit 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) proposes 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. Instead, our paper pursues a consumption-based explanation.[7]

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

[7]Our paper contributes to a large and still growing literature studying the asset pricing implication 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), Croce, Lettau, and Ludvigson (2014), Kiku (2006), among many others.

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

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

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)[8]

[8]See Appendix A-1 for derivation.

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

$$\begin{aligned} pd^i_t = \log(E_t[\exp(\theta\log\delta + (\theta - 1 - \frac{\theta}{\psi})\Delta c_{t+1} + (\theta - 1)(\log(\exp(wc_{t+1}) + 1) - wc_t) \\ + \log(\exp(pd^i_{t+1}) + 1) + \Delta d^i_{t+1})]) \end{aligned} \tag{6}$$

where Δd^i_{t+1} 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 to the consumption growth, there is a small but persistent component in the expected consumption growth which, as shown in BY, helps to explain a wide-range of phenomena in asset prices. Specifically, we have

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

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 specifications in existing studies including possible random walk and mean reverting. 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:

$$\Delta d^i_{t+1} = g_d + \sigma_d \epsilon_{d,t+1} + f^i_t x_t + h^i_t \sigma_c \eta_{t+1} + y^i_{t+1}$$
$$y^i_{t+1} = \rho_y y^i_t + \sigma_y \epsilon^i_{y,t+1} \quad (8)$$

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-variability 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 price and risk premium, are different ex post.

Given that the firm's cash flow exposure to consumption growth 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) which 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 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 next section.

3 Data and Estimation of the Firm Dividend Process

We now describe the sources of data and the SMM procedure. The data used in our empirical analysis are readily available and widely used in finance research. The annual consumption growth 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.[9] 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 on the data from CRSP and COMPUSTAT, and the construction procedure will be 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 of 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,

[9] 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).

the risk aversion γ and the elasticity of intertemporal substitution ψ in the benchmark calibration 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 2. The second group of parameters governs the firm dividend process and are estimated using a simulated method of moments approach detailed below.[10]

[Insert Table 2 Here]

3.1 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 an 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 3. We avoid using the cross-sectional average returns of the value, momentum, and long-term contrarian portfolios as matching mo-

[10]We have also directly estimated the specified firm dividend process using individual firm dividends for a sample of firms with at least 20 years of non-missing dividend growth via the Bayesian Markov Chain Monte-Carlo estimation method. We find qualitatively similar estimates to those reported here, and the result is reported in Online Appendix.

ments. 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.[11] 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 value, momentum, and contrarian investment strategies, we choose the defining characteristics of these strategies as part of our matching moments.[12]

[Insert Table 3 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

[11] We estimate the short-run risk exposure of the momentum winner-minus-loser portfolio following the approach in Bansal, Dittmar, and Lundblad (2005). To obtain the short- and long-run consumption betas, 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. 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.

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

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 2 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%[13] with a standard deviation of 16.22%, very close to the empirical estimates.[14] We find that firm's cash flow exposure to the long-run 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 firm-specific dividend growth rate component is also very persistent ($\rho_y = 0.979$) with a very low conditional volatility ($\sigma_y = 0.0015$).

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

[13]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 equality.

[14]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 many 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.

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 the empirical evidence of Chen, Moise, and Zhao (2009), in which they find that the winner (loser) portfolio has a positive (negative) revision in its cost of equity around the portfolio formation time.

While the overidentification test rejects the model, it does a good job matching the moments of key variables of our interests. The model implied aggregate and cross-sectional moments are reported in Table 4 and Table 5. 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 4 Here]

[Insert Table 5 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 yield 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- 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 contrarian and value portfolios are sorted based on low frequency information, so their returns are sensitive long-run consumption risk, whose exposures are highly 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 6, 7, 8, and 9, respectively.

Table 6 reports the result for the momentum profit. It is well known that momentum and value are "opposite" because value investing takes a long position in the past "losers" and a short position in the past "winners", whereas the momentum 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 6 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 6 Here]

The unconditional CAPM fails to explain the momentum profit. This is particularly true for the equal-weighted returns. The CAPM alpha remains 0.73% or 8.76% annualized after controlling for the market risk factor. This abnormal return 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 4.32% in the simulation versus 4.68% in the data for value-weighted and 1.92% in the simulation versus 8.04% 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 7 Here]

Table 8 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 8 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 in 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 monthly alpha is 0.62% (t-stat = 2.16) for value-weighted returns and 0.16% (t-stat = 0.87) for equal-weighted returns from simulations, as compared with 0.27% (t-stat = 1.37) and 0.83 (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 9. It has been well documented in the literature that small firms have an average return that is higher than big firms, and this firm size premium cannot be captured by the unconditional CAPM.[15] 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 9 Here]

Overall, we find that the economy with long- and short-run consumption risks and a general 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 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 10 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

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

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 10.

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- 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 10. 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 portfolio. This finding is consistent with the empirical motivation in the introduction that momentum, contrarian, and value strategies are loading on differently the short- and long-run fluctuations of the consumption growth.

[Insert Table 10 Here]

The patterns in the dividend shocks and the risk exposures to the short- and long-run consumption risks provide a joint explanation for the profitability of the momentum and contrarian strategies, value and size portfolios. For momentum strategies, short-term winners have high dividend growth in the recent past and high sensitivity to the short-run consumption risk compared to loser firms. The dividend growth is persistent, generating a cash-flow effect; at the same time, the change in sensitivity to short-run risk create a discount effect. For our benchmark calibration, the cash flow effect dominates the discount effect, validating the momentum winners (losers) to have a good (bad) recent performance as well as the dispersion in expected returns. Compared to the long-term winners, growth firms, and big firms, the long-term losers, value firms, and small firms had low dividend growth in the long past; they have high leverage, high sensitivity to the long-run consumption fluctuations, and hence high expected returns.

It is worth highlighting the importance of 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 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, while ignoring the other factor. However, the other risk factor (could be either short- 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 exposures to the market factor follows the direction of the exposures 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 10, 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 our 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.[16] 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 11.[17]

[Insert Table 11 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

[16] This point 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.

[17] 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.

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 11 shows that growth firms have a higher consumption beta than value firms. Similar but weaker finding is also observed for long-term winners versus losers and small versus big firms.

[Insert Table 12 Here]

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 12, 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 12, 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 long-term contrarian profits and the value premium, but negatively with momentum profits. 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 long-term contrarian profits, 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. For example, Jegadeesh and Titman (1993) and Chan, Jegadeesh, and Lakonishok (1996) show that momentum profits are short-lived and the latter documents 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 2-5 years after portfolio formation implied in our model.

Table 13 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 13 Here]

This pattern can be readily understood in our framework. Immediately after portfolio rebalancing, winner firms have a higher exposure to short-run consumption risks 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 long-run consumption risk than loser portfolio due to a lower leverage, and this long-run exposure is very persistent, the effect from 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.[18] 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. 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 14. 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 14 Here]

The CAPM does a decent job in the full sample from 1931 to 2011. As in Panel A of Table 14, 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

[18]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).

portfolio returns (Panel B of Table 14): 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, 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, which tests the overidentification restrictions, 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, so 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.

[Insert Figure 2 Here]

4.6 Sensitivity analysis

In this section, we consider the implication 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 result for this

[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.

sensitivity analysis is reported in Table 15.[20] Specification (0) presents the key variable moments under the benchmark parameterization, and Specifications (1) to (16) report the corresponding moments for alternative parameterizations.

[Insert Table 15 Here]

Specifications (1) and (2) in Table 15 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 risk 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 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

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

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}, long-term losers and value firms tend to have low exposure to the short-run risk and hence their expected return is low 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 that of 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 again dominates that of 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 15 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 15, 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 augmented long-run risk model, long-run risk exposures are highly persistent, so firm characteristics such as long-term stock performance and dividend-price ratio are likely picking up this exposure, so 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 beta 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 contrarian profits and the value premium which 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 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 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 different exposures to the long-run consumption risk. Therefore, the profitability of the momentum, contrarian, and value strategies are compensation for bearing different components of consumption growth fluctuations 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 variation. Therefore, the CAPM provides a stronger explanatory power for the contrarian profit and the value premium than the momentum profit. On the other hand, the consumption growth is mainly driven by the short-run consumption variation, the Consumption-CAPM should better explain the momentum profit than the contrarian profit and the value premium. We find strong evidence for these predictions both in the data and in our simulation.

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: stock-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.

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Table 1: 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 book-to-market portfolios, 10 momentum portfolios, 10 size portfolios, 10 long-term contrarian 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	

Table 2: 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 dividend growth rate	ρ_y	0.979 (0.003)
Conditional volatility of firm dividend growth rate	σ_y	0.0015 (0.0001)
Correl. between shocks to firm dividend growth and exposure to long-run consumption risk	ρ_{fy}	-0.970 (0.122)
Correl. between shocks to firm dividend growth and exposure to short-run consumption risk	ρ_{hy}	0.875 (0.104)

Table 3: 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
Volatility of market excess return	3.375	3.118

Table 4: 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 5: 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 6: 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}	-0.63	-0.14	0.00	-0.02	0.04	0.00	0.05	0.08	0.16	0.32	0.95
	(-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}	-0.74	-0.24	-0.07	-0.02	0.04	0.08	0.15	0.18	0.26	0.43	1.17
	(-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}	-0.17	-0.06	0.02	0.06	0.09	0.10	0.14	0.18	0.20	0.28	0.45
	(-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}	-0.37	-0.22	-0.14	-0.08	-0.03	0.02	0.08	0.15	0.22	0.36	0.73
	(-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 7: Contrarian profits

This table reports the 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}	0.27	0.13	0.21	0.08	0.12	0.07	0.08	0.08	-0.07	-0.11	0.39
	(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}	0.41	0.11	0.08	0.09	0.14	0.09	0.09	0.06	-0.02	-0.27	0.67
	(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}	0.25	0.25	0.22	0.20	0.15	0.18	0.14	0.11	0.04	-0.11	0.36
	(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}	0.06	0.05	0.03	0.02	0.01	0.00	-0.01	-0.02	-0.06	-0.10	0.16
	(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 8: 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}	-0.06	0.02	0.05	-0.02	0.09	0.09	0.07	0.22	0.23	0.21	0.27
	(-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}	-0.44	-0.18	-0.09	0.05	0.08	0.14	0.18	0.21	0.36	0.39	0.83
	(-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}	-0.17	0.07	0.14	0.16	0.23	0.25	0.29	0.32	0.38	0.45	0.62
	(-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}	-0.10	-0.05	-0.03	-0.01	0.01	0.02	0.03	0.04	0.05	0.06	0.16
	(-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 9: 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}	0.33	0.18	0.21	0.18	0.16	0.14	0.13	0.09	0.05	-0.02	0.35
	(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}	0.24	-0.10	-0.05	-0.07	-0.06	-0.03	-0.03	-0.03	-0.03	-0.08	0.32
	(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}	0.42	0.40	0.36	0.34	0.31	0.29	0.27	0.24	0.20	-0.06	0.48
	(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}	0.07	0.05	0.03	0.02	0.01	-0.01	-0.02	-0.03	-0.05	-0.09	0.16
	(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 10: 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. $y \times 100$ is the average stock-level 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 11: 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 in the data), 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 12: 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 annualized 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 13: 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 14: 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 15: 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 dividend-price portfolios, momentum portfolios, and long-term contrarian 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 5% and 95% confidence intervals (the dashed lines). The sample are annual from 1931 to 2011.

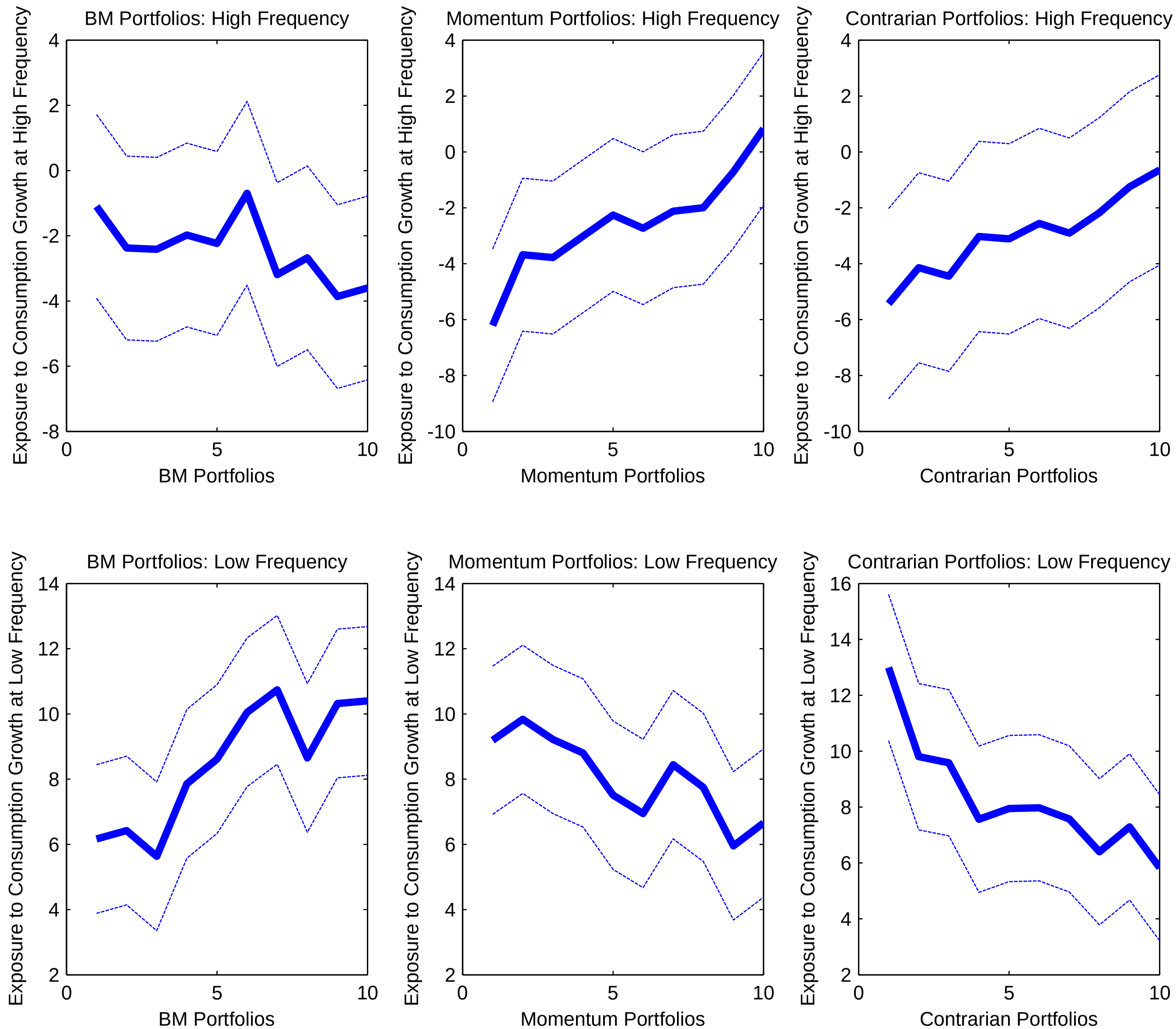
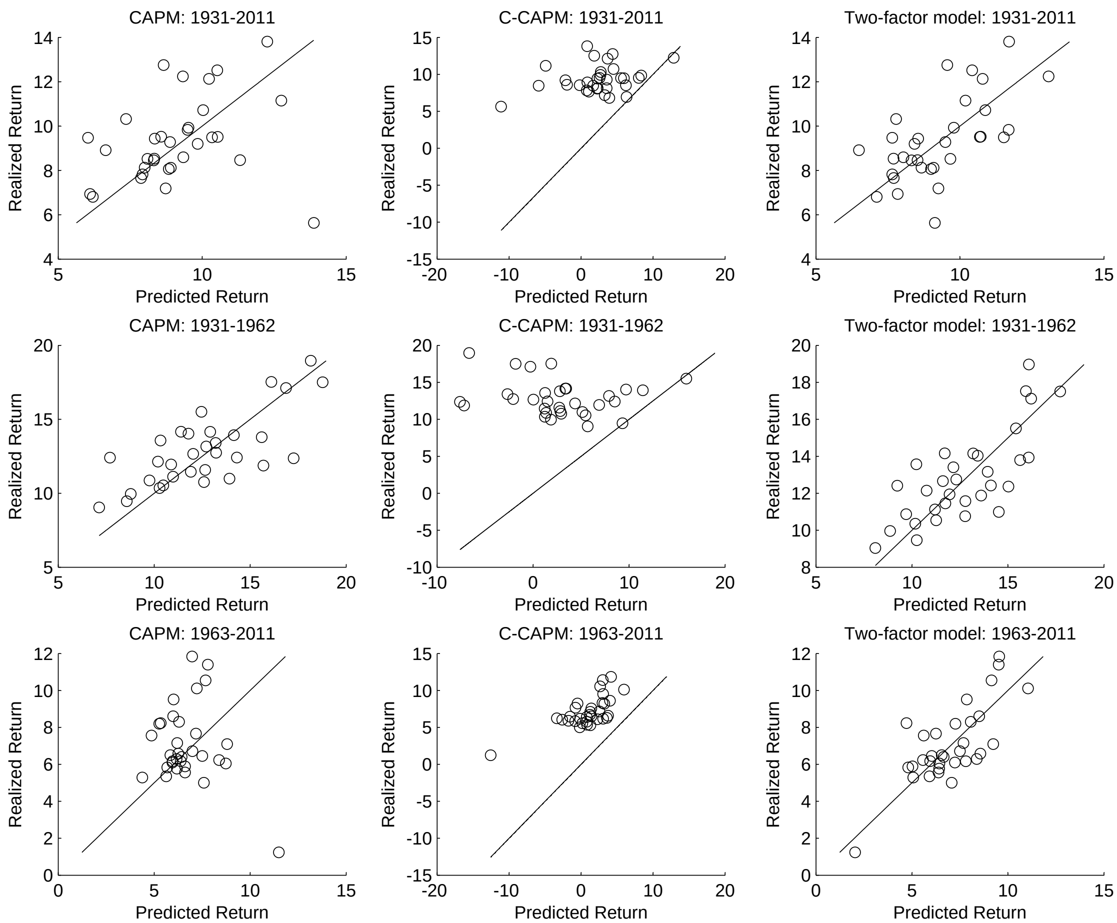


Figure 2: Predicted versus actual returns

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.



Online Appendix for
"Short-run and Long-run Consumption Risks, Dividend Processes and Asset Returns"

1 Bayesian Estimation of the firm-level dividend process

In this section, we complement the simulated method of moments (SMM) estimation by directly estimating the dividend process at the firm level using Baysesian 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 displace strong seasonality, we estimate the process at an annual frequency. We extract the short-run and long-run components of the aggregate consumption growth following Bansal, Kiku and Yaron (2012), and use them as an input of the 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: $g_d \sim N(0.02, 0.25)$, $1/\sigma_d^2 \sim \gamma(1, 0.225)$, $\bar{f} \sim N(4, 1.6)$, $\rho_f \sim Beta(30, 2)$, $1/\sigma_f^2 \sim \gamma(1, 9)$, $\bar{h} \sim N(1, 1.6)$, $\rho_h \sim Beta(2, 4)$, $1/\sigma_h^2 \sim \gamma(1, 12)$, $\rho_y \sim Beta(2, 2)$, $1/\sigma_y^2 \sim \gamma(2, 0.008)$, $\rho_{hy} \sim Unif(-1, 1)$,

$\rho_{fy} \sim Unif(-1, 1)$, 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. The posterior distributions of the estimated parameters are reported in the following table.

Table A1: Parameter distribution from Bayesian MCMC estimation

Variable	Mean	Std	2.50%	Median	97.50%
g_d	0.003	0.008	-0.012	0.003	0.018
σ_d	0.058	0.011	0.044	0.056	0.084
$\bar{f}$	3.830	1.016	2.668	3.568	6.586
ρ_f	0.354	0.060	0.217	0.367	0.443
σ_f	26.970	2.401	22.650	26.910	32.020
$\bar{h}$	0.337	0.857	-1.028	0.325	2.009
ρ_h	0.249	0.103	0.065	0.251	0.412
σ_h	7.957	0.750	6.921	7.747	9.479
ρ_y	0.003	0.002	0.000	0.002	0.008
σ_y	0.240	0.005	0.227	0.241	0.246
ρ_{fy}	-0.908	0.036	-0.948	-0.920	-0.816
ρ_{hy}	0.433	0.250	-0.127	0.486	0.753

2 More sensitivity analysis

In Table A2, we report the result from additional sensitivity analysis. Moments from the benchmark are reported in Specification (0). We consider alternative values for the correlation between shocks to the exposure of long-run consumption growth and firm dividend growth shocks in Specifications (1), (2), and (3), the correlation between shocks to the exposure of short-run consumption growth and firm dividend growth shocks in Specifications (4), (5), and (6), the persistence of exposure to long-run consumption growth in Specifications (7), (8), and (9), the persistence in exposure to short-run consumption growth in Specifications (10), (11), and (12), the standard deviation of aggregate dividend growth shocks in Specifications (13) and (14), the average exposure to long-run risk in (15) and (16), the conditional standard deviation of exposure to long-run risk in (17) and (18), the average exposure to short-run risk in (19) and (20), the conditional standard deviation of exposure to short-run risk in (21) and (22), the persistence in firm-specific dividend growth in (23) and (24), and the conditional standard deviation of firm-specific dividend growth in (25) and (26). 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.

Table A2: Additional sensitivity analysis

Specification	(0)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Parameter		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		-0.97	-0.97	-0.97	0.875	0.875	0.875	0.989	0.989	0.989	0.781	0.781	0.781
Alternative		-0.9	-0.848	-0.5	0.5	0.8	0.95	0.99	0.9	0	0	0.726	0.836
E(MKTVW)	8.20	8.77	8.94	10.92	7.23	8.03	8.26	7.47	13.41	13.75	6.81	8.05	8.71
Std(MKTVW)	25.44	25.91	26.28	28.80	25.36	25.32	25.45	25.14	31.77	32.41	23.30	24.76	26.50
AC1(MKTVW)	0.00	0.00	0.01	0.01	0.00	0.01	0.01	0.01	-0.01	-0.01	0.02	0.01	-0.01
E(MKTEW)	11.66	11.72	11.76	12.02	11.73	11.68	11.65	11.64	12.42	12.65	11.28	11.55	11.85
Std(MKTEW)	28.70	28.82	28.91	29.47	28.84	28.73	28.67	28.65	30.07	30.51	28.01	28.50	29.08
AC1(MKTEW)	0.00	0.00	0.00	0.00	0.00	-0.01	0.00	-0.01	0.00	0.00	0.00	0.00	-0.01
E(rf)	0.90	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	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
E(p-d)	3.12	3.06	3.01	2.79	3.26	3.14	3.10	3.28	2.51	2.49	3.04	3.08	3.20
Std(p-d)	0.25	0.26	0.27	0.30	0.25	0.25	0.25	0.24	0.36	0.37	0.23	0.25	0.27
AC1(p-d)	0.64	0.64	0.65	0.68	0.64	0.64	0.64	0.63	0.73	0.73	0.63	0.64	0.65
Mom	7.54	7.44	7.37	7.77	2.43	6.41	8.62	7.63	8.08	8.59	-2.57	6.07	8.54
Std(Mom)	37.17	36.43	35.99	33.35	25.22	34.28	40.29	37.82	33.00	32.94	8.90	31.36	45.04
Contrarian	5.13	4.64	4.31	2.04	5.49	5.27	5.06	5.59	-1.05	-1.25	6.08	5.44	4.48
Std(Contrarian)	12.50	11.72	11.20	8.55	12.76	12.49	12.48	13.34	3.82	3.91	12.87	12.47	12.91
Value	9.21	8.48	7.86	4.21	10.98	9.45	8.83	10.29	-3.99	-4.41	11.76	9.86	7.84
Std(Value)	26.39	25.13	24.26	19.56	24.91	25.94	26.89	28.06	14.07	14.04	22.80	24.75	29.90
Size	5.72	5.37	4.89	2.50	6.49	5.89	5.68	6.73	-1.11	-1.16	7.46	6.37	5.27
Std(Size)	14.27	13.29	12.50	8.91	14.47	14.26	14.25	15.83	4.90	4.92	14.80	14.18	14.69

Table A2: Additional sensitivity analysis (Continued)

Specification	(0)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)
Parameter		σ_d	σ_d	$\bar{f}$	$\bar{f}$	σ_f	σ_f	$\bar{h}$	$\bar{h}$	σ_h	σ_h	ρ_y	ρ_y	σ_y	σ_y
Benchmark		0.0467	0.0467	5.857	5.857	0.351	0.351	0.008	0.008	4.935	4.935	0.979	0.979	0.0015	0.0015
Alternative		0.0447	0.0487	5.51	6.204	0.317	0.385	-1.417	1.433	4.408	5.562	0.976	0.982	0.0014	0.0016
E(MKTVW)	8.20	8.22	8.18	7.06	9.33	9.22	6.85	7.43	8.94	8.04	8.41	8.58	7.60	8.50	7.84
Std(MKTVW)	25.44	24.91	26.09	24.50	26.84	26.33	24.89	25.10	26.28	24.89	26.22	25.74	26.01	25.63	25.61
AC1(MKTVW)	0.00	0.00	0.00	0.01	0.00	0.00	0.02	0.01	0.01	0.01	0.00	0.01	0.02	0.01	0.01
E(MKTEW)	11.66	11.59	11.68	10.79	12.45	11.82	11.50	10.63	11.76	11.52	11.84	11.66	11.79	11.65	11.68
Std(MKTEW)	28.70	28.15	29.24	27.20	30.29	28.99	28.32	29.58	28.91	28.44	29.08	28.69	28.81	28.68	28.77
AC1(MKTEW)	0.00	0.00	-0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.01	0.00	-0.01	0.00	-0.01
E(rf)	0.90	0.90	0.90	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	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
E(p-d)	3.12	3.10	3.15	3.33	2.97	2.94	3.43	3.34	3.01	3.05	3.23	2.89	3.56	2.99	3.29
Std(p-d)	0.25	0.25	0.26	0.23	0.28	0.27	0.24	0.26	0.27	0.25	0.26	0.26	0.26	0.26	0.25
AC1(p-d)	0.64	0.65	0.63	0.62	0.65	0.66	0.63	0.65	0.65	0.63	0.63	0.64	0.65	0.64	0.64
Mom	7.54	7.48	7.57	7.56	7.39	7.37	7.32	7.51	7.37	6.82	8.09	6.86	7.83	7.08	7.80
Std(Mom)	37.17	37.10	37.25	37.90	36.55	36.25	38.55	37.42	35.99	34.15	40.71	35.70	39.13	36.25	38.15
Contrarian	5.13	5.09	5.19	5.55	4.82	4.27	6.31	5.46	4.31	5.29	5.11	4.62	5.90	4.78	5.57
Std(Contrarian)	12.50	12.41	12.59	13.23	11.85	10.73	14.74	13.20	11.20	12.48	12.58	11.64	13.91	11.87	13.19
Value	9.21	9.15	9.25	9.85	8.64	7.31	11.49	9.71	7.86	9.37	9.08	8.55	9.66	9.06	9.49
Std(Value)	26.39	26.28	26.51	27.51	25.43	23.46	30.12	27.23	24.26	25.47	27.63	25.43	27.87	25.79	27.12
Size	5.72	5.72	5.81	6.28	5.44	4.83	7.24	6.09	4.89	6.01	5.47	5.29	6.66	5.46	6.30
Std(Size)	14.27	14.19	14.36	15.18	13.56	12.24	17.01	14.94	12.50	14.25	14.34	13.23	15.74	13.60	15.06