Time-varying Expected Consumption Growth and the Cross-sectional Equity Returns

Edward Huayu Fang *

First Version: November 2003
This Version: November 2004

Abstract

This paper explains cross-sectional stock return patterns using a consumption based intertemporal asset-pricing model with two differently priced shocks in the consumption dynamics. Empirically, the two shocks are identified through a VAR specification of the consumption growth and a set of information variables commonly used for forecasting business cycles. Under this specification, strong evidence is found for long-term consumption growth predictability. The model does a superb job in fitting cross-sectional return patterns. In particular, the model explains the size and book-to-market effects better than standard asset-pricing models including the Fama-French three-factor model, which suggests that the size and book-to-market effects are consistent with risks associated with long-run consumption growth opportunities.

*Department of Economics, Duke University, Durham, NC 27708-0120, Email: hf@duke.edu, Phone: 1-919-824-2188. Special thanks to Ravi Bansal, Tim Bollerslev and George Tauchen for their insightful comments and encouragements. I also thank Bjørn Eraker, Ron Gallant, Han Hong, Hui Ou-Yang, Barbara Rossi and all other participants at the Duke University Financial Econometrics lunch group for valuable discussions on the topic. All remaining mistakes are my own.

1 Introduction

Understanding the cross-sectional dispersions in equity returns is a central topic in financial studies. Traditional models suggest that expected returns should be completely determined by the covariances of assets with risk factors. In the case of the Capital Asset Pricing Model (CAPM) by Sharpe (1964) and Linter (1965), the only risk factor is the market portfolio return. In the case of the Consumption-based Capital Asset Pricing Model (C-CAPM) by Breenden (1979), the relevant risk factor is the aggregate consumption growth. While these models have long formed the foundation for modern understanding of asset pricing, empirical research in the last two decades has documented various cross-sectional patterns in stock returns that seriously challenge these models. Two of the most robust and widely studied patterns are the size effect and the book-to-market effect. For example, Fama and French (1992, 1993) document significant dispersions in the average returns of portfolios sorted by firm market capitalization and book-to-market ratio. More importantly, neither the static CAPM nor the traditional C-CAPM is able to provide adequate risk adjustments for the observed return dispersions.[1] The empirical findings lead to active debates on whether the return patterns emerge due to behavior biases or underlying risks.[2]

This paper contributes to the risk-based explanations and identifies systematic risk factors that can explain the cross-sectional return patterns such as the size and the book-to-market effects. In a nutshell, the model is an extension of the traditional C-CAPM. Motivated by an emerging literature on cash-flow models, this paper models time-varying expectation on the aggregate consumption growth in an economy with a non-expected utility function. Importantly, this model structure leads to two differently priced shock components in the aggregate consumption growth in

[1]For more examples, see Basu(1977), Banz(1981) and Shanken (1985).

[2]DeBondt and Thaler (1985) and Lakonishok, Shleifer and Vishny (1994), among others, attribute the book-to-market effect to investors' over-reactions to news. Fama and French (1992, 1993) among others however, argue that the small firms and high book-to-market ratio firms tend to be "distressed" and fundamentally riskier. Hence the observed return dispersions can be justified in terms of risk-return trade-off.

equilibrium. This implies a consumption-based two-beta model for explaining the cross-section of returns. The consumption growth predictability is characterized in a vector autoregressive (VAR) structure together with a set of macroeconomic and financial market variables. The multivariate structure allows the identification of the two shock components in the consumption dynamics. Recursive utility in the form of Epstein-Zin(1989) and Weil(1989) is exploited to derive different prices for the two shocks in equilibrium.

Significant effort has been devoted to the understanding of equity premia in the literature. This paper is related to several strands in the literature and also differs from each of them in important aspects.

Several recent papers have examined asset-pricing implications of aggregate cash flow predictability. For example, Hall (2001), Bansal and Yaron (2004), and Menzly, Santos and Veronesi (2004). In particular, this paper is closely related to Bansal and Yaron (2004) in terms of motivation and theoretical foundation. Bansal and Yaron propose an equilibrium model with a small and persistent predictable component in the aggregate cash flow growth, which as in this paper, leads to two shock components in the aggregate cash flow dynamics. My paper, however, differs from theirs in some important ways. Firstly, Bansal and Yaron calibrate their model to understand time-series properties of the aggregate market. The present paper focuses on explaining the important cross-sectional return puzzles. Secondly, Bansal and Yaron treat the expected aggregate cash flow growth as a latent state variable without estimating it, whereas in my paper the expected consumption growth is modelled and directly estimated using observable information variables. The multivariate predictive structure proposed in this paper allow us to identify the two shock components in the consumption growth, which greatly facilitate the empirical examination of the cross-sectional puzzles.

There has been a recent surge in the use of consumption-base models to explain the cross-sectional return patterns. For example, Lettau and Ludvigson (2002) test a scaled version of the C-CAPM using the log consumption-wealth ratio as the conditioning variable to model the time-varying risk-premium on the consumption beta. Bansal, Dittmar and Lundblad (2002, 2004) model the cash flows of assets and find the exposures of the cash flows to the aggregate consumption have significant bearing on explaining the return dispersions.[3] To date, all works in this category consider only one shock component in the consumption dynamics. This could be due to the assumption of lack of predictability in the consumption growth, time-separable utility or both. To the best of my knowledge, my paper is the first to model two shock components in the consumption dynamics for studying cross-sectional returns.

A number of studies have attempted to explain the cross-sectional return patterns using intertemporal asset-pricing models following Merton (1973). It is standard in this strand of literature to assume return predictability. Campbell(1996) tests an intertemporal model with a market return factor and a hedging factor derived based on market return predictability. More recently, Campbell and Voulteenaho (2004) use a model that has two betas that correspond to "discount news" and "cash-flow news" respectively to explain the size and value effects.[4] My model is distinct from these studies in its focus on the consumption growth predictability. Instead of treating the "cash-flow news" as the residual from return decomposition, I directly model the aggregate cash flow dynamics. The predictability in aggregate cash flow (consumption) and the predictability in return deliver different restrictions in equilibrium as to how economic news affects risks. Consequently, the empirical findings in this paper are sharply different from those based on return predictability. In focusing on the cash flow predictability, this paper provides an alternative perspective for intertemporal asset-pricing modelling.

The main findings of this study are that future consumption growth is strongly

[3]More examples in testing consumption-based models include Hansen and Singleton (1983), Breeden, Gibbons and Litzenberger(1986), Mankiw and Shapiro (1986), Cochrane (1996), Campbell and Cochrane (2000), and Piazzesi, Schneider and Tuzel (2003) among others.

[4]More examples in this class of literature include Campbell and Mei (1993), Brennan, Wang and Xia (2001), and Chan(2003) among others.

predicted by current economic conditions, and the time-variation in the expectation of future growth can explain the size and book-to-market effects. Using 25 size and book-to-market ratio sorted portfolios, I find that the consumption-based two-beta model developed in this paper produces an adjusted R^2 higher than a list of benchmark models including the Fama-French three-factor model. Both the Fama-French factors and portfolio characteristics become insignificant after controlling for the consumption factors. The evidence suggests that the size and book-to-market effects are consistent with risks associated with long-term consumption growth opportunities.

The rest of the paper is organized as follows: Section 2 derives the consumption-based two-beta model; section 3 describes the data and empirical testing methods; section 4 reports empirical results on consumption growth predictability and cross-sectional tests; section 5 performs robustness checks; and section 6 concludes.

2 A Consumption-Based Two-Beta Model

The model in this paper features two shock components in the consumption growth dynamics. The first component, the "current growth shock", is the one-period growth innovation. Essentially, this component is what is captured in the traditional C-CAPM. The second shock component, which is named the "expected growth shock", reflects the revision in the *expectation* of consumption growth in all future periods.[5] The identification of these two shock components and the resulting asset-pricing implications critically depends on two features in the model: 1) the multivariate structure of predictability in the consumption growth; 2) the recursive utility form.

In this section, I first motivate and specify the consumption growth dynamics and define the two types of growth shocks. The model is then solved for the equilibrium prices of the two shocks, which derives a two-beta consumption-based asset pricing model.

[5] The expected growth shock is intimately related to the persistent component in the aggregate cash flow growth examined by Bansal and Yaron (2004).

2.1 Consumption Growth Components

The consumption growth is modelled in a VAR that permits predictability of the growth from a set of information variables. This specification is empirically motivated by the predictability in consumption growth that has been documented in the literature. Early works on consumption predictability include Harvey (1988, 1989b) and Kanel and Stambaugh (1990) among others. More recently, Bansal and Yaron (2004), Bansal, Gallant and Tauchen (2004) propose a specification for the aggregate cash flow growth where the growth has an stochastic conditional expectation which itself follows an AR(1) process. The stochastic expectation on cash flow is treated as a latent state variable in these studies.[6]

This paper uses observable macroeconomic and financial-market information variables to explicitly characterize the consumption growth expectation. The modified specification allows for empirical identification of the two types of growth shocks.

Formally, the joint dynamics of the consumption growth $g_{c,t+1}$ and the information variables x_{t+1} is

$$\begin{bmatrix} g_{c,t+1} \\ x_{t+1} \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \begin{bmatrix} g_{c,t} \\ x_t \end{bmatrix} + \begin{bmatrix} \eta_{c,t+1} \\ \eta_{x,t+1} \end{bmatrix} \tag{1}$$

or, writing $(g_{c,t+1}, x_{t+1})$ as Z_{t+1}, and the coefficient matrix as A, we have

$$Z_{t+1} = AZ_t + \omega_{t+1}$$

The log consumption growth $g_{c,t}$ is the first element in Z_t. x_t is a $K \times 1$ vector of information variables[7]. Let $e1$ be a $(K+1) \times 1$ vector with the first element equal to 1 and all others equal to zero, then $g_{c,t} = e1'Z_t$.

The *current growth shock*, by definition, is the one-period unexpected consumption

[6] A special case for their specification is when the innovation in growth equation and the innovation in the AR(1) equation for the conditional mean are perfectly correlated, in which case the specification reduces to an univariate ARMA(1,1) process.

[7] Details of the information variables will be deferred to the data section

growth. That is,

$$\text{Current Growth Shock:} \quad \eta_{c,t+1} \equiv g_{c,t+1} - E_t[g_{c,t+1}] \tag{2}$$

An important insight is that under the specification of (1), the expectation on future consumption growth is stochastic. To see it more clearly, let's first look at the change of expectation on a given future period growth from time t to $t+1$. By the chain-rule of prediction, we know that at time t, the conditional expectation for the growth in period $t+j$ for $j \geq 1$ is $E_t[g_{c,t+j}] = e1'A^j Z_t$. Moving one-period forward, the conditional expectation at time $t+1$ for the same future period $t+j$ is $E_{t+1}[g_{c,t+j}] = e1'A^{j-1}Z_{t+1}$. The change of expectation from time t to $t+1$ is

$$(E_{t+1} - E_t)[g_{c,t+j}] = e1'A^{j-1}(Z_{t+1} - AZ_t) = e1'A^{j-1}\omega_{t+1} \tag{3}$$

Therefore the revision in expectation on the growth of a future period is stochastic and depends on the VAR parameters and all the innovation terms in the VAR system.

For an infinitely-lived investor, the relevant news is the revision in expectation on all future growth with proper adjustment for time preference. Let ρ be the time-preference parameter[8] and I define the *expected growth shock* to be

$$\text{Expected Growth Shock:} \quad \epsilon_{c,t+1} \equiv (E_{t+1} - E_t)[\sum_{j=1}^{\infty} \rho^j g_{c,t+1+j}] \tag{4}$$

That is, the expected growth shock is the update in investors' expectation of all future discounted growth. As will be shown presently, $\eta_{c,t+1}-$ the *current growth shock* and $\epsilon_{c,t+1}-$ the *expected growth shock*, are the two growth shocks that will be priced differently in equilibrium.

Applying the law of iterative prediction under the VAR specification, i.e. $E_t[Z_{t+j}] = A^j Z_t$, the two growth shocks can be calculated as

$$\begin{aligned} \eta_{c,t+1} &= e_1'\omega_{t+1} & (5) \\ \epsilon_{c,t+1} &= e1'\rho A(I - \rho A)^{-1}\omega_{t+1} & (6) \end{aligned}$$

[8]The time-preference parameter is described in more detail in the equilibrium model in the following subsection

Equation 6 shows taht the expected growth shock, $\epsilon_{c,t+1}$ is a linear combination of the innovations in all the equations in the VAR system. The mapping between the innovation in each individual information variable to the expected growth shock depends nonlinearly on the VAR coefficients. Intuitively, because the investor takes into consideration the dynamics of all the information variables as well as the consumption when she forms her expectation, her revision on the expectation mechanism will reflect news in all the variables as well.

Empirically, the differentiation of the two growth shocks depends on the multivariate structure for consumption growth predictability. If the consumption growth follows a univariate process, for example an AR(1) or a persistent ARMA(1,1) as in Bansal, Dittmar and Lundblad (2002, 2004), the expected growth shock (i.e. $\epsilon_{c,t+1}$) will be a perfectly correlated with the current growth shock (i.e. $\eta_{c,t+1}$).[9] In this case, the two shocks can not be separately identified. The VAR specification, however, implies that the future consumption growth are predicted by variables beyond its own lags, and allows separable identification of the two shocks. In section 4, I will present strong empirical evidence that supports the VAR specification.

2.2 Prices of Consumption Growth Risks

The previous section shows that under the VAR process of consumption growth and information variables, the current growth shock and the expected growth shock are two different shocks. However, for the separation of the shocks to matter for asset-pricing results, asset must have different exposures to the two shocks, and the two shocks must be differently priced in equilibrium. In this subsection, an equilibrium model with non-expected utility is developed to show that in theory the two types of growth shocks are indeed associated with different prices of risk.

Consider a representative investor who maximizes his utility which is assumed to

[9] If the realized consumption growth rate follows an ARMA(1,1) process, then the conditional expected growth will follow an AR(1) with the same conditional innovation as in the realized growth process.

take the recursive form as in Epstein and Zin (1989) and Weil (1989)

$$U(C_t, E_t(U_{t+1}^{1-\gamma})) = \left[(1-\delta)C_t^{\frac{1-\gamma}{\theta}} + \delta(E_t(U_{t+1}^{1-\gamma})^{\frac{1}{\theta}}\right]^{\frac{\theta}{1-\gamma}}$$

where $\theta \equiv \frac{1-\gamma}{1-\frac{1}{\psi}}$. $\gamma > 0$ is the risk-aversion coefficient, and $\psi > 0$ is the intertemporal elasticity of substitution(IES). When $\theta = 1$, equation (7) reduces to the standard time-separable form. In this case, $\gamma = \frac{1}{\psi}$, meaning that the risk-aversion coefficient is restricted to be the inverse of IES. In the more general case of $\theta \neq 1$, the coefficient of risk-aversion is not equal to the reciprocal of IES.

From maximizing (7), the Euler equation for asset i is

$$E_t\left[\left\{\delta\left(\frac{C_{t+1}}{C_t}\right)^{-\frac{1}{\psi}}\right\}^{\theta}\left(\frac{1}{R_{a,t+1}}\right)^{1-\theta} R_{i,t+1}\right] = 1 \tag{7}$$

and in log terms the pricing kernel is

$$m_{t+1} = -\frac{\theta}{\psi}log\delta - \frac{\theta}{\psi}g_{c,t+1} + (\theta-1)r_{a,t+1} \tag{8}$$

where $g_{c,t+1} = log\left(\frac{C_{t+1}}{C_t}\right)$ and $r_{a,t+1} = log\left(\frac{P_{t+1}+C_{t+1}}{P_t}\right)$ are the log consumption growth rate and log aggregate wealth return, respectively. P_t is the the price of a unit claim on the aggregate consumption stream.

Importantly, when $\theta \neq 1$, the pricing kernel is a function of both consumption growth and the aggregate wealth return. This feature is critical for the result of the two consumption growth shocks being differently priced. Note that if $\theta = 1$, the utility reduces to traditional expected utility, in which case the return drops out from the log pricing kernel and the one-period consumption growth serves as a sufficient statistics for the intertemporal marginal rate of substitution. In this case, the time-variation in expected future consumption growth becomes irrelevant for systematic risks. A few recent works have demonstrated the importance of relaxing the reciprocal relationship between the risk aversion coefficient and the IES in order to fit aggregate market regularities such as equity premium, risk free rate, volatility and the leverage effect. See, for example, Bansal and Yaron (2004), and Tauchen (2004). These findings support the assumption of $\theta \neq 1$.

Next, I show that, given that the evolution of the economy is described by the VAR system, the shock to the innovation of the log pricing kernel can be written as a function of the two shock components in consumption growth.

Exploiting the log-linearization method in Campbell and Shiller (1988), the log return of the total wealth can be written as

$$r_{a,t+1} = \kappa_{c,0} + \kappa_{c,1}\nu_{a,t+1} - \nu_{a,t} + g_{c,t+1} \tag{9}$$

where $\nu_{a,t}$ is the log price-consumption ratio and both $\kappa_{c,0}$ and $\kappa_{c,1}$ are constants that depend on the average level of $\nu_{a,t}$.[10]

Since in equilibrium, $r_{a,t+1}$ needs to satisfy the condition that $E_t[exp(m_{t+1} + r_{a,t+1})] = 1$, equation (9) implies that it is possible to solve for the expectation of the log return $r_{a,t+1}$ in an analytic form in terms of the state variables. The relevant state variable is the expected consumption growth which is captured by the set of information variables Z_t. Hence, assume ν_t to be a linear function of Z_t, i.e.

$$\nu_{a,t} = B_0 + B_1' Z_t \tag{10}$$

It can be shown[11]

$$B_1 = (1 - \frac{1}{\psi}) e1' A [I - \kappa_{c,1} A]^{-1}$$

For simplification and to focus on the role of persistent expected growth, homoscedasticity is assumed for the joint distribution of the consumption growth $g_{c,t+1}$ and the aggregate return $r_{a,t+1}$.[12]

[10] $\kappa_{c,0} = log(1 + e^{\bar{\nu}}) - \frac{e^{\bar{\nu}}}{1+e^{\bar{\nu}}}$ and $\kappa_{c,1} = \frac{e^{\bar{\nu}}}{1+e^{\bar{\nu}}}$. Empirically, $\kappa_{c,1}$ is typically less and very close to 1.

[11] See Appendix A for more details in the derivation.

[12] Relaxing the homoscedasticity assumption has two consequences. The first effect of heteroscedasticity is time-varying risk premia on factors. The second effect occurs if the volatility is stochastic, in which case a volatility factor appears. The differences between these two effects are subtle and stressed by Bansal and Yaron (2004) and Tauchen (2004).

With the solution for $\nu_{a,t}$, it is straightforward to write the innovation of $r_{a,t+1}$ as a function of the innovations of the information variables. More specifically,

$$\eta_{r,t+1} \equiv r_{a,t+1} - E_t[r_{a,t+1}] = (1 - \frac{1}{\psi})e1'\kappa_{c,1}A[I - \kappa_{c,1}A]^{-1}\omega_{t+1} + \eta_{c,t+1} \quad (11)$$

It follows that the innovation of the log pricing kernel m_{t+1} is

$$m_{t+1} - E_t[m_{t+1}] \equiv \eta_{m,t+1} = [-\frac{\theta}{\psi} + (\theta-1)]\eta_{c,t+1} + (\theta-1)(1-\frac{1}{\psi})\underbrace{e1'\kappa_{c,1}A[I - \kappa_{c,1}A]^{-1}\omega_{t+1}} \quad (12)$$

The innovation of the log pricing kernel consists of two shocks. The first shock is the current growth shock $\eta_{c,t+1}$. The second shock is contained in the long brace. Comparing this term to the definition in (6), it is easy to recognize that the second shock is exactly the expected growth shock, where the time-preference parameter $\rho = \kappa_{c,1}$. More explicitly, we can write

$$\eta_{m,t+1} = [-\frac{\theta}{\psi} + (\theta - 1)]\eta_{c,t+1} + (\theta - 1)(1 - \frac{1}{\psi})\epsilon_{c,t+1} \quad (13)$$

For the cross-section of asset returns, the following equation needs to hold in the equilibrium.

$$E_t[r_{i,t+1} - r_{f,t+1}] + \frac{\sigma^2_{i,t}}{2} = -Cov_t(m_{t+1}, r_{i,t+1}) \quad (14)$$

$\frac{\sigma^2_{i,t}}{2}$ is a term adjusting for the "Jensen's effect" and the left-hand side of (14) is the relevant measure for the risk premium for asset i. From (13) we see that the risk premium for any asset i depends on two covariances. That is,

$$E_t[r_{i,t+1} - r_{f,t+1}] + \frac{\sigma^2_{i,t}}{2} = \gamma Cov_t(\eta_{c,t+1}, r_{i,t+1}) + (\gamma - \frac{1}{\psi})Cov_t(\epsilon_{c,t+1}, r_{i,t+1}) \quad (15)$$

(15) can be written in terms of betas. Define

$$\beta_{i,\eta} = \frac{Cov(\eta_{c,t+1}, r_{i,t+1})}{\sigma^2_\eta} \quad (16)$$

$$\beta_{i,\epsilon} = \frac{Cov(\epsilon_{c,t+1}, r_{i,t+1})}{\sigma^2_\epsilon} \quad (17)$$

Then (15) can be written as

$$E[r_i - r_f] + \frac{\sigma^2_i}{2} = \gamma\sigma^2_\eta\beta_{i,\eta} + (\gamma - \frac{1}{\psi})\sigma^2_\epsilon\beta_{i,\epsilon} \quad (18)$$

where $\lambda_\eta = \gamma\sigma^2_{\eta,t}$ and $\lambda_\epsilon = (\gamma - \frac{1}{\psi})\sigma^2_{\epsilon,t}$ are the prices of risk for the two betas. (18) is the equilibrium asset-pricing result that will be tested empirically. Betas defined this way can be conveniently obtained as slope coefficients in separate simple regressions of the asset return on the innovations.

Equation (18) forms the basis for the empirical tests in this paper. Importantly, the prices of risk for the two betas in (18) are different, which explains the importance of differentiating the two growth shocks. (18) can be viewed as an extension of the textbook version of C-CAPM. The first beta, $\beta_{i,\eta}$, corresponds to the conventional consumption risk. The second beta, $\beta_{i,\epsilon}$, only appears with the VAR assumption and the recursive structure of the utility function.[13]

Several observations of (18) are warranted. First, the interpretation for $\beta_{i,\eta}$ is standard. Recall that $\eta_{c,t+1}$ is the current growth shock. Since investors prefer to have higher return when consumption is low (i.e., marginal utility of consumption is high) and therefore stocks with negative correlation with the current consumption shock demand a lower risk premium. Second, turning to $\beta_{i,\epsilon}$, this risk factor arises because a long-term investor also cares about future growth opportunities when future growth is predictable. The expected future consumption will affect the investor's current consumption through intertemporal consumption-smoothing. This is why the intertemporal elasticity of substitution enters the price of risk of the second risk factor. In the extreme case when the $\psi = \infty$, a news on future consumption opportunity has one-to-one effect on the current consumption, in which case the expected growth shock has the same price of risk as the current consumption shock. Finally, in a risk-averse world, the risk-aversion coefficient γ is positive. This in principle guarantees a positive price of risk for the current growth shock. The sign of the second price of risk depends on values of γ and ψ. While it is generally agreed that a reasonable value for

[13]Notice the model also incorporates the traditional CAPM as a special case. The news to market return is a linear function of the two growth shocks as shown in (11). Therefore the covariance of the asset return with the market return news,which determines the CAPM beta, is a linear combination of $Cov_t(\eta_{c,t+1}, r_{i,t+1})$ and $Cov_t(\epsilon_{c,t+1}, r_{i,t+1})$.

γ exceeds unity, a reasonable range for ψ remains more contentious. [14] In the case of $\gamma > 1$ and $\psi < 1$, the price of the second beta is guaranteed positive. The positivity and significance of the expected growth risk form important null hypotheses for the following empirical tests.

3 Data and Empirical Methodology

3.1 Data

The data used in this paper is at quarterly frequency and covers 1963.01 to 2002.04.

VAR Data

Following the tradition in the literature, the consumption data used in this paper is the per capita consumption of nondurable goods plus services obtained from the National Income and Product Accounts(NIPA) table on Bureau of Economic Analysis (BEA) web page. The consumption is deflated to real terms by Personal Consumption Expenditures (PCE) index. The consumption growth is measured as the log difference of consumption in two adjacent quarters.

In choosing the information variables to be included in the VAR system (i.e. the elements of x_t), recall that for the separate identification of the two shocks, it is important that the information variables collectively have predictive power beyond the lagged consumption growth. I choose a set information variables mainly under two considerations. Firstly, the variables are theoretically or empirically shown to be related to future growth in the literature. Secondly, I focus on variables that are commonly used for forecasting business cycles and defining investment opportunities to facilitate the interpretations of findings and comparisons with previous literature. As a result the following set of information variables are studied.

[14] For example, Campbell (1999) estimate it to be at around 0.5. Meanwhile, a number of studies argue that it should be well in excess of unity to be consistent with documented empirical regularities, see, for example, Hansen and Singleton (1982), Bansel and Yaron (2004) and Tauchen (2004).

Term spread, denoted $Term_t$. This variable is measured by the difference between yields on a 10-year T-bond and a 3-month T-bill. When an economic downturn is anticipated, the investors will tend to buy more long term bonds and sell short-term bonds. This leads to higher prices and lower yields for the long term bonds relative to short term ones. Therefore, the term spread decreases when future growth is expected to be low.

Inflation, denoted $Infl_t$. This variable is the realized inflation from period $t-1$ to t. It is calculated from the change in PCE index (Year 2000 = 100). Chen, Roll and Ross (1986) show the inflation news is an important macroeconomic risk factor in financial markets.

Risk Free Rate, denoted Rrf_t. This variable is calculated by deflating the nominal risk-free rate(Nrf_t) by $Infl_t$. Nrf_t is measured by compounded returns on one-month T-bill in each quarter. Typically, a lower risk-free rate stimulates investment and leads to higher economic and consumption growth in the future.

Dividend-Yield, denoted Div_t. This is the dividend-yield on the value-weighted CRSP index. Following Bansal, Dittmar and Lundblad (2004), the dividend-yield is calculated by finding the difference between returns including dividends(VWRETD) and returns excluding dividends(VWRETX). I use a trailing 12-month moving-average to remove the seasonality in the dividend-yield following Hodrick and Bollerslev(1992) and Bansal, Dittmar and Lundblad(2004). Many theories suggest the aggregate dividend-yield predict future growth. In a simple discounted cash flow model, a higher current dividend-yield can be attributed either a higher future discount rate or lower time-varying future cash flow growth. Several recent papers have shown that the cash flow growth is predictable by price multiples such as price-dividend ratio or price-earnings ratio.[15] To the extend that the aggregate consumption and the aggregate dividend in the economy are cointegrated, it is reasonable to expect the

[15] Ang(2002) shows the future dividend growth is predicted by dividend-yield. Bansal, Khatchatrian and Yaron (2003) demonstrates that there is more predictability in the earnings growth than in the market returns from the price-dividend ratio.

dividend-yield to be useful in predicting future consumption growth.

The main results reported in this paper are obtained by using the above four information variables. The next two variables are also studied in order to check the robustness of the empirical results.

Default Spread, Def_t, is measured by difference between yields on Moody's rated Baa bonds and Aaa bonds. This variable captures variation in risk-aversion in the market. In anticipation of a bad economic state, investors will flock to higher quality securities and hence bid the their prices and lower their yields. Thus, Def_t is expected to be higher when economic downturn is anticipated.

Dividend-Yield including Repurchases, denoted Div_t^{repu}. The dividends used in this variable include both cash-dividends and share repurchases. The calculation method follows Bansal, Dittmar and Lundblad (2004). Since the 1980s, there has been a surge of using share repurchases as an alternative for paying cash-dividends. This variable tries to capture this potentially important structural change. And empirically, this variable provides a more stationary measure of the dividend-yield.

Table 1 shows the summary statistics of the consumption growth and the information variables. The average consumption growth over the sample period is 0.56% per quarter with a standard deviation of 0.72%. The average $Term_t$ is 1.39%, the average Rrf_t is 0.49% per quarter, the average $Infl_t$ is 0.99% per quarter, and the average Div_t is 0.79% per quarter. Def_t has an average of 1.01%. As expected, Div_t^{repu} is significantly higher than Div_t on average at 1.28% per quarter.

The last 2 columns in the top panel show the first two autocorrelations of each variable. The information variables are generally quite persistent. In particular, Div_t has AR(1) coefficient of 0.96. Confirming earlier empirical findings, Div_t^{repu} behaves much more stationary than Div_t with AR(1) of 0.86. These summary statistics are well in line with those documented in the literature. In the correlation matrix, we see that $g_{c,t}$ has a positive correlation with $Term_t$ and negative correlations with $Infl_t$,

Div_t, and Def_t. Among the information variables, I find the Def_t and the Div_t are quite highly correlated with a correlation coefficient of 53.7%, and both of them are positively correlated with $Infl_t$ with correlations of 39.4% and 69.5%, respectively.

Return Data

Two sets of portfolio returns are studied in this paper. There has been much emphasis on the size and value effects in empirical studies of cross-sectional returns. Returns on the 25 size and book-to-market double-sorted portfolios are the main subject in the paper. The portfolios, which are updated annually at the end of each June, are the intersections of 5 portfolios formed on size (market equity) and 5 portfolios formed on the book-to-market ratio.[16] The size breakpoints for year t are the NYSE market equity quintiles at the end of June of t. Book-to-market for June of year t is the book equity for the last fiscal year end in t-1 divided by market equity at December of t-1. The book-to-market breakpoints are NYSE quintiles. For more details on the construction of the portfolios, see Fama and French (1992, 1993).

Panel A in Table 4 shows the average quarterly returns for the 25 portfolios. The well-known size effect and book-to-market effect are evident. The small-value portfolio has an average return of 3.64%(s.e.=0.03%) and the big-growth portfolio has an average return of 1.31%(s.e.=0.02%). The returns generally exhibit a decreasing trend from portfolios of small firms to big firms, and increasing trend from low book-to-market firms(growth firms) to high book-to-market firms (value firms). An exception is found in the lowest B/M group, where the size effect is obscure.

As a robustness check for the result, a second set of portfolio returns based on portfolios sorted by earning-price ratio and cash-flow to price ratio (in addition to size and book-to-market) are studied.[17]

[16] I thank Kenneth French for generously providing the data.

[17] The return data and portfolio construction details are in Kenneth French's web page.

3.2 Empirical Methods

Testing the model in (18) requires first extracting two types of growth shocks from the VAR system, obtaining assets' exposure to the shocks and estimating the prices of risks. Correspondingly, my empirical method involves three main steps.

In the first step, the VAR system is estimated and the time-series of $\eta_{c,t}$ and $\epsilon_{c,t}$ are obtained. I use GMM to estimate the system of equations simultaneously. Notice that for the VAR system which contains the same independent variables for each equation, there is no efficiency gain by estimating the equations simultaneously rather than separately. GMM will provide exactly the same coefficient estimates as equation-by-equation OLS. GMM, however, provides a convenient way to obtain the heteroscedasticity and autocorrelation consistent standard errors. In my estimation, I use Newey-West weighting matrix with 8 lags. After obtaining the VAR coefficients, $\eta_{c,t}$ and $\epsilon_{c,t}$ can be calculated using formulas in (5) and (6). Note that the time-preference parameter $\kappa_{1,c}$ is not estimated by the VAR system and needs to be estimated separately. Previous studies have argued that $\kappa_{1,c}$ is typically below but very close to 1. Here I follow convention in the literature to set $\kappa_{1,c}$ to 0.99. I also allow $\kappa_{1,c}$ to take different values between $0.96 - -0.99$ and find no significant difference in results.

In the second step, time-series regression of portfolio returns on the two shocks, $\eta_{c,t}$ and $\epsilon_{c,t}$, are separately estimated for each portfolio. This determines the portfolios' exposures to the two risk factors. Specifically, for each portfolio, I estimate

$$r_{i,t} = \alpha_i + \beta_{i,\eta}\eta_{c,t} + u_{i,t} \quad (19)$$

$$r_{i,t} = \phi_i + \beta_{i,\epsilon}\epsilon_{c,t} + \nu_{i,t} \quad (20)$$

where the β's are the factor exposures that coincide with those in equation (18).

The approach of estimating the β's separately in two regressions contrasts with a multivariate beta approach where the β's are jointly estimated in a multivariate regression. Jagannathan and Wang (1998) show that a nonzero risk premium for a factor in a model with univariate betas does not imply a nonzero risk premium on the same factor in the corresponding model with multivariate betas. Therefore, if a theoretical model is in the form of univariate betas, as is the case in this paper, it is misleading to examine the premium for the factor estimated with multivariate betas.

In the third and final step, cross-sectional regression of average excess return on the betas are estimated. Specifically, I estimate the following three equations

$$\bar{r_i} = \lambda_0 + \lambda_1 \beta_{i,\eta} + e_i \tag{21}$$

$$\text{or} \quad \bar{r_i} = \lambda_0 + \lambda_2 \beta_{i,\epsilon} + e_i \tag{22}$$

$$\text{or} \quad \bar{r_i} = \lambda_0 + \lambda_1 \beta_{i,\eta} + \lambda_2 \beta_{i,\epsilon} + e_i \tag{23}$$

where $\bar{r_i}$ is the average quarterly excess return of asset i. Equations (21), (22) and (23) correspond to three subcases of the model with only current growth beta, with only expected growth beta, and with two betas together, respectively. The subcases are estimated in order to test the significance of each β.

It should be noted that the multi-step procedure causes "generated regressors" problem in the estimation. OLS standard errors without adjustment for the generated regressors tend to understate the standard errors of the estimated coefficients. There are two layers of such problem in the estimation procedure. First, the two growth shocks used in the time-series regression of second step is estimated with error from the VAR. Second, another generated-regressors-error exists in the second and third steps because the betas used in the cross-sectional regressions are estimated from the time-series regression in the second step.[18] To deal with this problem, I use two approaches to calculate the standard errors for the cross-sectional coefficients in the main model of this paper. The first approach is conditional on two growth shocks estimated from the first step and combines second and third steps into a one-step GMM estimation following Cochrane (2001). The standard errors are Newey-West

[18]This problem is pervasive for Fama-MacBeth type of 2-step estimations of the factor loadings and prices of risk.

adjusted with 8 lags. The second set of standard errors are obtained by bootstrapping the VAR errors and returns and repeating the 3-step estimations for 10,000 times. Hence, the second approach takes into account both layers of the generate-regressors-errors.

4 Results

4.1 Predictable Consumption Growth

The predictability in consumption growth is one of the premises for the model in this paper. Most of the early empirical works have focused on the sample period before 1990. Empirical research has documented quite different results for pre-1990 sample and the sample includes recent years, suggesting the possibility of some structural changes. See, for example, Ang(2003), and Goyal and Welch(2003). Therefore, in this subsection, the predictability in consumption growth is reexamined with more recent data. Moreover, I use a more complete set of information variables that are commonly used for forecasting business cycles.

The predictive regression is

$$\sum_{j=1}^{k} g_{c,t+j} = \delta_0 + \delta' x_t + e_{t+k} \quad k >= 1 \tag{24}$$

where $g_{c,t+j} = log(C_{t+j}) - log(C_{t+j-1})$ is the one period log consumption growth, and x_t is the vector of information variables. The predictive regression is run over both the full sample from 1963.1 to 2002.4 and a sub-sample from 1963.1 to 1989.4.

Table 2 shows the multiple regression results with $x_t = (Term_t\ Div_t\ Rrf_t\ Infl_t)'$ for a predictive horizon of up to 8 quarters in the future. Significant predictability is found in the pre-1990 sample with this set of information variables. The adjusted R^2 for 1-quarter growth predictability is 30.9%, which reaches 50.6% at 3-quarter horizon and 25.5% at 8-quarter. The results remain qualitatively similar when post-1990 years are included, although with lower adjusted R^2. The adjusted R^2 is 14.8%

for 1-quarter horizon, peaking in 4 quarters at 30.7% and still hovering around 25% 8 quarters in the future. This shows that the list of information variables jointly have strong power in predicting future consumption growth.

Figure 1 plots the expected cumulative future 4-quarter consumption growth. The dates on the horizontal axis correspond to the date when the predictions are made. The vertical grey bars correspond to recessions dated by NBER. The expected growth displays time-variation that corresponds to the business cycle. In particular, a trough in the expected future consumption growth appears in each of the dated recessions, typically the beginning of the recessions. Intuitively, investors foresee lower future consumption growth when a recession is anticipated.

4.2 VAR Results

Table 3 shows the VAR estimation results. The adjusted R^2 for the growth equation increases to 22.9% due to the inclusion of lagged consumption growth. The signs and significance of the coefficients for the information variables are largely the same as those in the predictive regression without the lagged consumption growth.

For the purpose of identifying the two different types of consumption growth shocks, it is important that the set of information variables have predictive power beyond that of the lagged consumption growth in the VAR system. This is indeed the case as an F-test on the joint significance of the information variables are highly significant.

The VAR estimation allows us to infer long-run predictability in the consumption growth, as shown in Hodrick (1992). Two useful statistics for describing long-term predictability are the long-term regression R^2 and the variance ratio. Figure 2 shows the evolution of these two statistics over a 20-year period in the future implied by the VAR estimated in Table 3.[19] In the top panel, the adjusted R^2 appears to increase

[19] Calculations of these two statistics follow Hodrick(1992).

with the predictive horizon for up to 2 years before it starts to slowly decay. However, it still remains at around 10% in the 10-year horizon. The lower panel shows the variance-ratio implied by the VAR. For horizon k, it is calculated as the ratio of the variance of the k -period cumulative growth rates and k times the variance of one period growth. If the growth is i.i.d., then the ratio should be equal to 1. A higher(lower) than unity ratio implies positive(negative) autocorrelation dominates. The figure shows the variance ratio increase to 2.5 in about 5 years and persistently remains above 1. This suggests there is long-term persistent component in the consumption growth. Bootstrap exercises are conducted to evaluate the variation in these implied statistics. The dashed lines in Figure 2 indicate the 97.5%(upper line) and 2.5% (lower line) quantiles of the statistics from 2,500 repetitions.

From the estimated VAR coefficient matrix, the two types of growth shocks can be computed. Figure 3 gives a visual illustration. The variance of the current growth shock and the expected growth shock are 1.49E-5 and 2.97E-5, respectively. This means that the expected growth shock is more volatile than the current growth shock, which is expected because the expected growth shock incorporates innovations from all the information variables besides the innovation of the current growth itself. The 0.21% correlation suggests the two shocks are virtually uncorrelated and represent two very different series. Therefore the VAR structure does a good job in identifying the two shocks.

4.3 Cross-sectional Returns

Now let's turn to the main findings of this study. This subsection first looks at how different portfolios load on the consumption growth risk factors, and then examines whether the different loadings are significantly priced.

Table 4 shows the average cross-sectional portfolio returns together with the portfolios' exposures to the two growth shocks. Each row in the table from left to right represents the size portfolios from small to big in a given book-to-market category.

Each column from top to bottom corresponds to lowest to highest book-market quintiles for a given size category.

The size and book-to-market effects stand out quite significantly in the average returns shown in Panel A. The returns generally increase from top to bottom in each column, consistent with the book-to-market effect. Meanwhile,returns decrease from left to right in each row, consistent with the size effect. Panel B shows the corresponding loadings of each portfolio to the current growth shock. For each row, the betas generally decrease from left to right, which is consistent with the return pattern on the size dimension. But on the book-to-market dimension, the current growth betas tend to decrease from growth stocks to value stocks, which is opposite to the observed return pattern. Panel C reports the loadings to the expected growth shocks. Here the pattern of betas matches closely to that of the returns. The betas generally decreases from left to right in each row, mirroring the size effect, and increases from top to bottom in each column, consistent with the book-to-market effect. The difference in Panels B and C indicate that the expected growth shock is more promising for explaining the cross-sectional return patterns.

To illustrate this point, Figure 6 provides a visual comparison of the patterns for average portfolio returns and exposures to the expected growth shock. The top panel clearly demonstrates the size and book-to-market effects with the height of the bars increasing along the book-to-market dimension from low to high and decrease along size dimension from small to big. In the bottom panel, we can see the exposures to the expected growth shock display very similar patterns.[20] The evidence suggests the return patterns of the 25 portfolios can be explained by their exposures to the expected growth shock.

For comparison purpose, the factor exposures in several benchmark models are also reported. Table 5 shows the betas for the Fama-French 3 factors. There is very

[20] For easiness of viewing, I uniformly add 3 to each of the exposures. This does not change the pattern of the loadings.

weak correlation between average returns and the exposures to the market factor. The SMB factor captures the size effect quite well and the HML factor lines up well with returns on the book-to-market dimension. This is not surprising because the portfolios are constructed based on the same sorting schemes that are used to obtain the factors. However, neither factor can individually capture both effects simultaneously. This suggests both factors are needed together to explain the size and value effects simultaneously.

The next benchmark model is a return-based two-factor model based on Campbell(1996). Campbell(1996) identifies two factors which he calls the "market news factor" and the "hedging factor". The two factors in this model are extracted from a return-based VAR with the same set of information variables used in the consumption VAR.[21] A difference from Campbell (1996), however, is that a proxy of return on human capital is included in the market portfolio return there while here I only use CRSP index return as a proxy for the market return. Since Campbell finds the inclusion of the human-capital return does not affect the results very much, I consider the results from using the CRSP index return as market return to be a reasonable benchmark for comparison.

Panel B and C in Table 6 show the exposures to the first factor, the "market news factor" and the second factor, the "hedging factor", respectively. Notably, the market news betas (Panel B) are positive for all portfolios, and the hedging demand betas are negative for all portfolios (Panel C). Furthermore, the two betas are almost perfectly linearly correlated with a correlation coefficient of 95%. These findings are largely consistent with those in Campbell (1996). Campbell concludes that even after taking into account the hedging demand, the market return news is still the dominant factor, which implies the empirical performance of his model should be very similar to the traditional CAPM in terms of explaining the cross-sectional returns. To verify this, in Panel D of the table, I report the traditional CAPM betas, which are calculated

[21]Results of return-based VAR are available upon request.

as the slope coefficients in time-series regressions of portfolio excess returns on CRSP excess returns. There I indeed find the CAPM betas are very close in terms of both pattern and magnitudes to the first betas in the Campbell two-factor model. The upshot for this analysis is that 1) my approximation to Campbell(1996) successfully replicates the original results, and 2) the model does not perform as well as the two-beta model developed in this paper. Indeed, the Campbell model performs similarly to the traditional CAPM.

To further examine whether the risks measured by these factor loadings are significantly priced, we can look at the cross-sectional regression results. Table 7 reports the cross-sectional regression results for different models. As expected, the current growth beta have no explanatory power for this cross-section of returns but the expected growth beta does a superb job in fitting the returns. The adjusted R^2 with the expected growth beta alone is 81.1%. The price of risk is estimated to be 0.977 and significant at 5% level. When both the current and expected growth betas are included, the adjusted R^2 is 83.3% and the price of risk estimate is 0.990, which is strongly significant with both the GMM standard error (0.258) and the bootstrap standard error (0.445). The coefficient for the expected growth beta is positive and strongly significant. Neither of the traditional CAPM or C-CAPM exhibit significant explanatory power, a result consistent with previous findings. The return-based two-factor model works no better than the traditional CAPM. The only other model that shows significant explanatory power is the Fama-French three-factor model. The adjusted R^2 for this model is 76.4% and the HML beta is positively significant while the SMB beta is positive but not statistically significant.

Figure 6 plots the fitted returns of each model against the actual returns. If the observed returns are consistent with risks measured from the models, the fitted returns and actual returns should line up along a 45 degree line from the origin. It is clear that the consumption-based two-beta model (the upper-left plot) provides a close fit for the return data, similar to the Fama-French model (the lower-right plot).

In comparison, the fitted lines for C-CAPM and CAPM are too flat. The return-based two factor model of Campbell(1996)("+" in the lower left panel) performs similarly to the CAPM.

Furthermore, the consumption-based two-factor model also does a decent job in the fitting the zero-beta rate, which is reflected in the fact that the intercepts in the two-factor model is statistically insignificant. This has been a dimension many previous studies has had considerable difficulty with, see for example, Jagannathan and Wang (1996) and Lettau and Ludvigson (2002).

The fact that the consumption-based two-beta model produces a better fit to the returns of the size and book-to-market portfolios than the SMB and HML factors is very impressive considering that the latter factors are constructed from return differences in extreme portfolios sorted by size and book-to-market. To further explore the relationship between the two models, a cross-sectional regression test is done by putting the factors together. Results are shown in Table 8. It is interesting to find that when the two consumption growth factors are put together with the Fama-French factors, the expected growth beta is still significant as before while neither the SMB nor the HML factor is individually significant now. This suggests the Fama-French factors capture similar economic information as the expected growth factor.

Another test of the model is to regress returns on the two factors together with characteristics. This serves as a good way of detecting spurious factors because, as shown by Kan and Zhang (1997) and Jagannathan and Wang (1998), misspecified factors can not drive out significant firm characteristics. In Table 8, I first reconfirm the significance of the characteristics. Not surprisingly, the lagged size and lagged book-to-market ratios are significant in the cross-sectional regressions before the inclusion of the growth factors, with negative and positive signs respectively. If the two growth factors in the model are misspecified factors, the size and book-to-market should remain significant when the growth factors are added as additional regressors. As shown in Table 8, however, both characteristics lose significance after including the two growth factors in the regression, while the expected growth factor remains strongly positive and precisely estimated. This evidence lend strong support to the claim that the expected growth beta captures exposure to a priced factor rather than a spurious factor.

5 Robustness of Results

In this section, I conduct a battery of robustness checks on the empirical results of the model. Specifically, I check the sensitivity of the results to different choices of information variables included in the VAR specification. In response to the concern on the possible non-stationarity of the dividend-yield, I also try a different measure of the dividend-yield. I further test the model using a broader cross-section of portfolios. Finally, in results that are not reported for the purpose of brevity, I make sure the findings are not significantly altered by using only the pre-1990 sample.

5.1 Sensitivity to Information Variables

There is some concern on how robust the result is with regard to different choices of information variables used to identify the two types of growth shocks. Table 10 shows the cross-sectional regression results from including various combinations of the information variables in the VAR specification. When $Term_t$ is dropped from the VAR, the cross-sectional adjusted R^2 is 61.2%. When $Infl_t$ is dropped, the adjusted R^2 becomes 75.0%. The most significant drop in the cross-sectional R^2 is caused by the exclusion of Div_t, in which case the R^2 is still a respectable 53%. The exclusion of the real risk-free rate Rrf_t or inclusion of the default spread Def_t doesn't affect the cross-sectional results significantly. In all cases examined, the expected growth beta is always positive and statistically significant.

Overall, while each of the information variables contributes to the explanatory power of the model, the significance of the model, especially the significance of the expected growth beta, is quite robust to different choices of information variables.

5.2 Alternative Dividend-Yield Measure

Another common concern is that the persistence in the right-hand-side variables might bias the estimation results. I conduct stationarity test on each variable using Augmented Dicky-Fuller test and find the null of unit-root in the variables are comfortably rejected.[22] Since the stationarity of the dividend-yield (Div_t) is usually the center of debates, to further alleviate the concerns, I use an alternative definition for the dividend-yield, Div_t^{repu}, which includes in the dividends both cash dividends and share repurchases. The autocorrelation coefficients in Table 1 show Div_t^{repu} is a much less persistent variable than Div_t. The last block in Table 10 shows that after replacing Div_t with Div_t^{repu}, the model still produces adjusted R^2 of 68.6% with the expected growth beta being significantly priced.

5.3 Other Portfolios

I also test the model with a broader set of portfolio returns. More specifically, the cross-sectional returns of size (ME_t), book-to-market ratio (B/M_t), earning-to-price ratio, and cashflow-to-price ratio sorted deciles are used for the test. The results are reported in Table 9. The cross-sectional adjusted R^2 for the two-beta model is almost 70% with positively significant price of risk for the expected growth beta (t-value=2.20). The Fama-French three-factor model produces higher adjusted R^2 for this particular set of portfolios but none of the coefficients for the three factors is statistically significant. None of the other benchmark models produce significant results.

In conclusion, tests in this subsection show that the performance of the two-beta model developed in this paper is quite robust.

[22]Results are available upon request.

6 Conclusions

Understanding the cross-sectional equity return dispersions is a central topic in finance and has profound implications for risk management and investment decisions. In this paper, I develop an intertemporal asset-pricing model based on aggregate consumption growth predictability, and study its capacity in explaining some of the documented cross-sectional return patterns. The main contributions of this paper are empirically examining two shock components in the consumption growth and finding that the time-variation in the expected future consumption growth goes a long way in explaining the cross-sectional equity return patterns.

The empirical results show that the model produces superb fits for the cross-sectional returns. In particular, the variation in the expectation of future consumption growth shows up as a very significant risk factor. The covariance risk of the asset with the expected growth shock captures over 80% of the cross-sectional variation in returns of size and book-to-market sorted portfolios. Importantly, the consumption-based two-beta model developed in this paper produces an even better fit to the returns than the Fama-French three-factor model. When used together, the expected growth news factor drives out the Fama-French three factors and size and book-to-market characteristics. The model works substantially better than the traditional (C-)CAPM and, outperforms a model that mimics the model in Campbell (1996). Furthermore, the model exhibits robust performance under a host of stress tests, even when confronted to explain the return patterns of size, book-to-market, earing-to-price, cash-flow-to-price sorted portfolios. The evidence suggests that these cross-sectional return patterns are consistent with risks associated with long-term growth opportunities.

The present model can be extended in several dimensions. First, the model can be extended to include heteroscedasticity in the consumption growth. The current only focuses only on the persistence of the consumption growth and ignores its higher moments variations. With the homoscedastic assumption on consumption growth, the risk premia are constant. Several recent studies suggest fluctuations in economic growth volatility has important asset-pricing implications.[23] When the volatility of economic growth is stochastic, not only will the risk premia will be time-varying, but an additional "volatility factor" also arises. Investigating the model along this dimension is an important extension.

Second, conditional tests of the model can be carried out by allowing the the betas to be time-varying. Time-varying betas can be estimated either by following the rolling-regression technique or from more structured volatility models such as GARCH-in-Mean. Several previous studies argue that size and book-to-market effects are related to business cycle movements (e.g. Ferson and Harvey (1999), Lettau and Ludvigson (2001) and Zhang and Petkova (2003)) or the January effect (e.g. Rogalski and Tinic (1986)). Conditional tests of the model in this paper can potentially shed more light on these issues.

Third, the framework used to identify aggregate cash flow shock components can be easily adapted to identify shock components in asset level cash flows. It is conceivable that an asset's short-term and long-term cash flows have different risk properties and therefore it is interesting to examine how the exposures of different asset-specific cash flow components to the aggregate cash flow growth shocks contribute to the asset's systematic risk. Existing theoretical and empirical works along this line include, among others, Johnson (2002), Bansal, Dittmar and Lundblad (2004), Santos and Veronesi (2004b), and Lettau and Wachter (2004). Extensions on this dimension can possibly help us understand some remaining cross-sectional puzzles such as the momentum effect documented by Jegadeesh and Titman that the present model has limited power in explaining. (1993).[24]

[23]See for example, Bansal and Yaron (2003), Bansal, Khatchatrian and Yaron(2003) and Tauchen(2004).

[24]Fang (2004) finds the momentum effect is closely related to predictable asset-specific cash flow growth.

Finally, the insight that the expected consumption growth shock affects long-term risks motivates designs of hedging mechanism and introduction of new financial markets for better control of the long run economic risks. This opens an important and fruitful avenue for future research.

References

Ang, Andrew, 2002, Characterizing the Ability of Dividend Yields to Predict Future Dividends in Log-Linear Present Value Models, Working Paper, Columbia University.

Bansal, Ravi, Robert Dittmar, and Christian Lundblad, 2004, Consumption, Dividends, and the Cross-Section of Equity Returns, *Journal of Finance*, forthcoming.

Bansal, Ravi, Robert Dittmar, and Christian Lundblad, 2002, Interpreting Risk Premia Across Size, Value, and Industry Portfolios,Working paper, Duke Univeristy.

Bansal, Ravi, Ronald Gallant, and George Tauchen, 2004, Rational Pessimism, Rational Exuberance, and Markets for Macro Risks, Working paper, Duke Univeristy.

Bansal,Ravi, and Amir Yaron, 2004, Risks for the Long Run, *Journal of Finance*, 59, 1481-1509.

Bansal,Ravi, Varoujan Khatchatrian, and Amir Yaron, 2004, Interpretable Asset Markets?, *European Economic Review*, forthcoming.

Banz, Rolf, 1981,The Relationship between Return and Market Value of Common Stocks, *Journal of Financial Economics*, 9, 3-18.

Basu, S., 1981, The Investment Performance of Common Stocks in Relation to Their Price-Earnings Ratios: A Test of the Efficient Market Hypothesis, *Journal of Finance*, 32, 663-682.

Bollerslev, Tim, Robert Hodrick, 1995, Financial Market Efficiency Tests, in M. Hashem Pesaran, and Michael R. Wickens, eds: *Handbook of Applied Econometrics*(Blackwell, Oxford and Malden, MA).

Breeden, Douglas, 1979, An Intertemporal Asset Pricing Model with Stochastic Consumption and Investment Opportunities, *Journal of Financial Economics*, 7, 265-296.

Breeden, Douglas, Michael R. Gibbons, and Robert H. Litzerberger, 1989, Empirical Test of the Consumption-Oriented CAPM, *Journal of Finance*, 44, 231-262.

Brennan, Michael J., Ashley W. Wang, and Yihong Xia, 2001, Intertemporal Capital Asset Pricing and the Fama-French Three-Factor Model , Working Paper, University of Pennsylvania.

Campbell, John, 1991, A Variance Decomposition for Stock Returns, *Economic Journal*, 101, 157-179.

Campbell, John, 1996, Understanding Risk and Return, *Journal of Political Economy*, 104, 298-345.

Campbell, John,and John Cochrane, 2000, Explain the Poor Performance of Consumption-Based Asset Pricing Models, *Journal of Finance*, 55, 2863-2878.

Campbell, John,and Jianping Mei, 1993, What Do Betas Come from? Asset Price Dynamics and the Sources of Systematic Risk, *Review of Financial Studies*, 6, 567-592.

Campbell, John,and Robert Shiller, 1988, Stock Prices, Earnings and Expected Dividends, *Journal of Finance*, 43, 661-676.

Campbell, John, and Tuomo Vuolteenaho, 2004, Bad Beta, Good Beta , *American Economic Review*, forthcoming.

Joseph Chen, Intertemporal CAPM and the Cross-Section of Stock Returns, Working Paper, Marshall School of Business, University of Southern California.

Chen, Nai-Fu, Richard Roll, and Stephan A. Ross, 1986, Economic Forces and the Stock Market, *Journal of Business*, 59, 383-403.

Cochrane, John, 1994, Permanent and Transitory Components of GNP and Stock Prices, *Quarterly Journal of Economics*, 109, 241-265.

Cochrane, John, 1996, A Cross-Sectional Test of An Investment-Based Asset Pricing Model, *Journal of Political Economy*, 104, 574-621.

Cochrane, John, 2001, *Asset Pricing*, Princeton University Press.

Epstein , Lawrence, and Stanley Zin, 1989, Substitution, Risk Aversion, and the Temporal Behavior of Consumption and Asset Returns: A Theoretical Framework, *Econometrica*, 57, 937-969.

Fama, Eugene, and Kenneth French, 1992, The Cross-Section of Expected Stock Returns, *Journal of Finance*, 59, 427-465.

Fama, Eugene, and Kenneth French, 1993, Common Risk Factors in the Returns on Stocks and Bonds, *Journal of Financial Economics*, 33, 3-56.

Fama, Eugene, and James MacBeth, 1973, Risk, Return and Equilibrium: Empirical Tests, *Journal of Political Economy*, 81, 607–636.

Fang, Edward H., 2004, Predictable Cash Flow Growth and the Momentum Effect, Working Paper, Duke University.

Ferson, Wayne, and Campbell Harvey, 1999, Conditioning Variables and the Cross Section of Stock Returns, *Journal of Finance*, 54, 1325-1360.

Goyal, A., and I. Welch, 2003, The Myth of Predictability: Does the Dividend Yield Forecast the Equity Premium?, *Management Science*, 49, 639-654.

Hansen, Lars Peter, and Kenneth Singleton, 1983, Stochastic Consumption, Risk Aversion, and the Temporal Behavior of Asset Returns *Journal of Political Economy*, 91, 249-265.

Harvey, Campbell, 1988, The Real Term Structure and Consumption Growth, *Journal of Financial Economics*, 22, 205-333.

Harvey, Campbell, 1989a, Time-Varying Conditional Covariances in Tests of Asset Pricing Models, *Journal of Financial Economics*, 24, 289-317.

Harvey, Campbell, 1989b, Forecasts of Economic Growth from the Bond and Stock Markets, *Financial Analysts Journal*, Sept-Oct, 38-45.

Jagannathan, Ravi and Zhenyu Wang, 1996, The Conditional CAPM and the Cross-Section of Expected Returns, *Journal of Finance*,51, 3-53.

Jagannathan, Ravi and Zhenyu Wang, 1998, An Asymptotic Theory for Estimating Beta-Pricing Models Using Cross-Sectional Regression, *Journal of Finance*,53, 1285-1309.

Jegadeesh, Narasimhan, and Sheridan Titman, 1993, Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency, *Journal of Finance*, 48, 65-91..

Johnson, Timothy C., Rational Momentum Effects, *Journal of Finance*, 57, 585-608.

Kan, Raymond, and Chu Zhang, 1997, Two-pass Tests of Asset Pricing Models with Useless Factors, *Journal of Finance*, 54, 203-235.

Kandel, Shmuel, and Robert Stambaugh, 1990, Expectations and Volatility of Consumption and Asset Returns, *Review of Financial Studies*, 3, 207-232.

Lakonishok, Josef, Andrei Shleifer, and Robert W. Vishny, 1994, Contrarian Investment, Extrapolation, and Risk, *Journal of Finance*, 49, 1541-1578.

Lettau, Martin, and Sydney Ludvigson, 2001, Resurrecting the (C)CAPM: A Cross-Sectional Test When Risk Premia Are Time-Varying, *Journal of Political Economy*, 109, 1238-1287.

Lettau Martin, and Jessica Wachter, 2004, Why is Long-Horizon Equity Less Risky? A Duration-based Explanation of the Value Premium, NBER Working Paper.

Lintner, John, 1965, Security Prices, Risk, and Maximal Gains from Diversification, *Journal of Finance*, 20, 587-615.

Merton, Robert, 1973, An Intertemporal Capital Asset Pricing Model, *Econometrica* , 41, 867-886.

Menzly, Lior, Tano Santos and Pietro Veronesi, 2004, Understanding Predictability, *Journal of Political Economy*, 112, 1-47.

Piazzesi, Monica, Martin Schneider, and Selale Tuzel, 2003, Housing, Consumption, and Asset Pricing, Working Paper, UCLA.

Petkova, Ralitsa, and Lu Zhang, 2003, Is Value Riskier Than Growth?, Working Paper, University of Rochester.

Rogalski, Richard J., and Seha M. Tinic, 1986, The January Size Effect: Anomaly or Risk Mismeasurement?, *Financial Analyst Journal*, 42, 63-70.

Santos, Tano, and Pietro Veronesi, 2004b, Conditional Betas, NBER Working Paper.

Shanken, Jay, 1985, Multivariate Tests of the Zero-Beta CAPM, *Journal of Financial Economics*, 14, 327-348.

Sharpe, William, 1964, Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk, *Journal of Finance*, 19, 425-442.

Tauchen, George, 2004, Stochastic Volatility in General Equilibrium, Working Paper, Duke University.

Weil, Philippe, 1989, The Equity Premium Puzzle and the Risk-Free Puzzle, *Journal of Monetary Economics*, 24, 401-421.

Appendix A: Derivation of Pricing Kernel as Linear Function of Two Growth Shocks

The dynamics of $g_{c,t}$ is specified by the VAR structure

$$\begin{bmatrix} g_{c,t+1} \\ x_{t+1} \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \begin{bmatrix} g_{c,t} \\ x_t \end{bmatrix} + \begin{bmatrix} \eta_{c,t+1} \\ \eta_{x,t+1} \end{bmatrix} \quad (25)$$

or

$$Z_{t+1} = AZ_t + \omega_{t+1}$$

Z_t has the log consumption growth $g_{c,t}$ as its first element. x_t is a $K \times 1$ vector of information variables. Let $e1$ be a $(K+1) \times 1$ vector with the first element equal to 1 and all others equal to zero, then $g_{c,t} = e1'Z_t$.

Following the log-linearization method in Campbell and Shiller (1988), the log return of the aggregate economy can be written as

$$r_{a,t+1} = \kappa_{c,0} + \kappa_{c,1}\nu_{a,t+1} - \nu_{a,t} + g_{c,t+1} \quad (26)$$

Note that from the Euler equation, the log pricing kernel is

$$m_{t+1} = -\frac{\theta}{\psi} log\delta - \frac{\theta}{\psi} g_{c,t+1} + (\theta - 1)r_{a,t+1} \quad (27)$$

In equilibrium,

$$E_t[exp(m_{t+1} + r_{a,t+1})] = 1 \quad (28)$$

Assuming joint homoscedasticity of $g_{c,t+1}$ and $r_{a,t+1}$, (28) implies

$$E_t[-\frac{\theta}{\psi} g_{c,t+1} + \theta r_{a,t+1}] = \text{constant} \quad (29)$$

Substitute (26) in (29), we get

$$E_t[-\frac{\theta}{\psi} g_{c,t+1} + \theta(\kappa_{c,0} + \kappa_{c,1}\nu_{a,t+1} - \nu_{a,t} + g_{c,t+1})] = \text{constant} \quad (30)$$

For (29) to hold, all term involving the information variables (Z_t) has to exactly cancel out. Conjecture the log price-consumption ratio $\nu_{a,t}$ to be a linear function of Z_t, i.e.

$$\nu_{a,t} = B_0 + B_1' Z_t \quad (31)$$

Substituting (31) into (30) and setting the coefficients in front of the state variables Z_t to be zero yields

$$-\frac{\theta}{\psi} e1'A + \theta(\kappa_{c,1}B_1' + e1')A - \theta B_1' = 0 \quad (32)$$

Solving (32) yields

$$B_1 = (1 - \frac{1}{\psi})e1'A[I - \kappa_{c,1}A]^{-1}$$

B_0 can also be calculated, but for purposes of obtaining innovations, it is irrelevant.

Hence, the innovation of $r_{a,t+1}$ is

$$\eta_{r,t+1} = \kappa_{c,1}B_1'\omega_{t+1} + \eta_{c,t+1}$$

The innovation of the log pricing kernel m_{t+1} is

$$\begin{aligned}\eta_{m,t+1} &= -\frac{\theta}{\psi}\eta_{c,t+1} + (\theta - 1)\eta_{r,t+1} \\ &= [-\frac{\theta}{\psi} + (\theta - 1)]\eta_{c,t+1} + (\theta - 1)(1 - \frac{1}{\psi})e1'\kappa_{c,1}A[I - \kappa_{c,1}A]^{-1} \quad (33)\end{aligned}$$

By definition,

$$\begin{aligned}\text{Current Growth Shock:} \quad \eta_{c,t+1} &= \omega_{1,t+1} \\ \text{Expected Growth Shock:} \quad \epsilon_{c,t+1} &= e1'\kappa_{c,1}A[I - \kappa_{c,1}A]^{-1}\end{aligned}$$

Therefore, the log pricing kernel is a linear function of the two types of consumption growth shocks. That is,

$$\eta_{m,t+1} = -\frac{\theta}{\psi}\eta_{c,t+1} + (\theta - 1)(1 - \frac{1}{\psi})\epsilon_{c,t+1} \quad (34)$$

Table 1: Summary Statistics for VAR Variables

Variables	Means	Std.	Max.	Min.	AR(1)	AR(2)
g_c	0.563	0.718	2.089	-1.137	0.413	0.239
r_m	1.405	8.666	22.839	-26.275	0.033	-0.095
$Term$	1.391	1.860	3.800	-1.430	0.874	0.710
Div	0.787	0.831	1.420	0.271	0.960	0.912
Rrf	0.487	0.736	2.206	-1.144	0.778	0.690
$Infl$	0.994	1.187	2.978	0.060	0.884	0.827
Def	1.009	1.101	2.513	0.353	0.922	0.835
Div^{repu}	1.276	1.425	4.495	0.677	0.858	0.737

Correlations

	g_c	r_m	$Term$	Div	Rrf	$Infl$	Def	Div^{repu}
g_c	1.000	0.166	0.145	-0.155	0.069	-0.338	-0.173	-0.220
r_m		1.000	0.154	-0.108	0.038	-0.154	0.147	-0.131
$Term$			1.000	-0.047	-0.013	-0.330	0.275	0.028
Div				1.000	-0.062	0.695	0.537	0.487
Rrf					1.000	-0.456	0.186	0.541
$Infl$						1.000	0.394	0.257
Def							1.000	0.571
Div^{repu}								1.000

The top panel of the table reports the means and standard deviations of variables. Numbers are in percentages. The bottom panel reports the simple correlations between the variables. Consumption is the real per capita consumption of durable and nondurable goods obtained from the NIPA table on BEA webpage. The consumption growth is measured as the difference of log consumption in two adjacent quarters. $r_{m,t}$ is the CRSP value-weighted index return in excess of the risk-free rate. $Term_t$ is the yield spread between 10-year T-bond and 3-month T-bill. Div_t is the dividend-price ratio for the CRSP stock index where the dividend series is calculated from the differences between the index levels before and after dividend payments and smoothed over the past 12 month. Rrf_t is the quarterly real risk free rate measured by the one-month T-bill rate compounded over the quarter and then deflated by the inflation. $Infl$ is the inflation calculated from the percentage change in the PCE deflator. Def_t is the difference between yields of Baa bond and Aaa bond. Div^{repu} is the dividend-yield taking into account share repurchases.

Table 2: Consumption Growth Prediction

	1963.1–2002.4						1963.1–1989.4					
Horizon	Intercept	$Term_t$	Div_t	Rrf_t	$Infl_t$	Adj. R^2	Intercept	$Term_t$	Div_t	Rrf_t	$Infl_t$	Adj. R^2
$q1$	0.225	0.012	0.554	-0.218	-0.443	0.148	0.262	0.101	0.189	-0.253	-0.413	0.309
	(0.091)	(0.041)	(0.234)	(0.090)	(0.116)	.	(0.082)	(0.039)	(0.319)	(0.082)	(0.125)	.
$q2$	0.475	0.003	1.368	-0.463	-0.970	0.234	0.600	0.152	1.126	-0.585	-1.006	0.424
	(0.167)	(0.074)	(0.436)	(0.166)	(0.192)	.	(0.153)	(0.062)	(0.567)	(0.153)	(0.211)	.
$q3$	0.695	-0.008	2.222	-0.677	-1.503	0.305	0.918	0.187	2.266	-0.899	-1.644	0.522
	(0.230)	(0.103)	(0.604)	(0.229)	(0.253)	.	(0.208)	(0.082)	(0.819)	(0.208)	(0.271)	.
$q4$	0.840	-0.019	2.826	-0.816	-1.902	0.307	1.105	0.227	2.858	-1.081	-2.055	0.506
	(0.303)	(0.134)	(0.727)	(0.301)	(0.317)	.	(0.298)	(0.100)	(1.064)	(0.298)	(0.323)	.
$q5$	0.978	-0.046	3.398	-0.949	-2.249	0.300	1.293	0.241	3.500	-1.264	-2.424	0.482
	(0.401)	(0.165)	(0.883)	(0.398)	(0.385)	.	(0.436)	(0.124)	(1.470)	(0.437)	(0.390)	.
$q6$	1.063	-0.092	3.934	-1.028	-2.586	0.300	1.398	0.212	4.140	-1.364	-2.785	0.461
	(0.5000	(0.193)	(1.025)	(0.496)	(0.454)	.	(0.589)	(0.154)	(1.925)	(0.591)	(0.486)	.
$q7$	1.069	-0.133	4.258	-1.028	-2.798	0.279	1.399	0.175	4.449	-1.358	-3.001	0.416
	(0.600)	(0.222)	(1.115)	(0.595)	(0.547)	.	(0.731)	(0.183)	(2.221)	(0.733)	(0.583)	.
$q8$	1.026	-0.184	4.470	-0.980	-2.909	0.246	1.345	0.122	4.601	-1.298	-3.101	0.354
	(0.712)	(0.257)	(1.319)	(0.707)	(0.664)	.	(0.897)	(0.215)	(2.659)	(0.901)	(0.703)	.

This table reports the results for predicting future consumption growth using current information variables. The dependant variable is the future k-period cumulative consumption growth. The predictive regression is

$$\sum_{j=1}^{k} g_{c,t+j} = \delta_0 + \delta' x_t + e_{t+k} \qquad k >= 1$$

where $g_{c,t+j} = log(C_{t+j}) - log(C_{t+j-1})$ and x_t is the vector of information variables $(Term_t, Div_t, Rrf_t, Infl_t)$. Standard errors are Newey-West adjusted with $L = 10$.

Table 3: VAR Estimations

	$g_{c,t}$	$Term_t$	Div_t	Rrf_t	$Infl_t$	$Adj.\ R^2$
$g_{c,t+1}$	0.299	0.022	0.392	-0.181	-0.311	0.229
	(0.061)	(0.038)	(0.179)	(0.069)	(0.088)	
$Term_{t+1}$	-0.355	0.875	0.373	0.184	-0.144	0.785
	(0.117)	(0.047)	(0.296)	(0.113)	(0.147)	
Div_{t+1}	0.028	-0.003	0.884	0.017	0.053	0.925
	(0.014)	(0.004)	(0.054)	(0.015)	(0.024)	
Rrf_{t+1}	-0.001	0.038	-0.334	0.890	0.223	0.610
	(0.065)	(0.030)	(0.174)	(0.056)	(0.113)	
$Infl_{t+1}$	0.153	-0.044	0.212	0.009	0.837	0.795
	(0.050)	(0.027)	(0.171)	(0.051)	(0.099)	

The table shows the GMM estimates for a first-order VAR model including the log consumption growth rate (g_c), term-spread($Term$), market dividend-price ratio (Div), real risk-free rate (Rrf), and inflation ($Infl$). The VAR is run on demeaned variables without intercepts. The $\bar{R}^2$ is the adjusted-R^2 from equivalent OLS regressions. The weighting matrix for the GMM is Newey-West with $L = 8$.

Table 4: Exposure to the two types of consumption risks for FF25

	ME1	2	3	4	ME5	ME1	2	3	4	ME5
	Average Excess Returns					Std.				
BM1	0.931	1.196	1.251	1.582	1.308	15.259	12.122	10.899	10.584	10.229
2	2.466	2.025	2.137	1.477	1.326	14.029	11.013	10.901	9.116	8.723
3	2.631	2.723	2.166	2.122	1.433	13.302	11.991	10.250	9.347	7.846
4	3.326	2.948	2.607	2.540	1.720	14.152	12.589	11.225	10.716	8.411
BM5	3.637	3.153	3.057	2.721	1.762	15.283	12.993	12.358	11.009	9.764
	β_η					s.e.				
BM1	8.598	6.684	5.378	5.187	3.811	2.769	2.761	2.737	2.700	2.164
2	8.516	5.346	4.634	4.210	2.096	2.322	2.137	2.075	1.969	1.767
3	6.223	4.839	4.168	3.366	2.558	2.144	2.088	1.957	2.015	1.496
4	6.017	4.367	3.543	2.714	1.870	2.063	2.187	2.218	2.302	1.700
BM5	5.995	5.725	4.424	3.947	3.070	2.379	2.477	2.302	2.515	1.753
	β_ϵ					s.e.				
BM1	-1.844	-1.462	-0.721	-0.909	-1.198	2.593	2.402	1.992	1.888	1.547
2	-0.502	-0.583	-0.059	-0.983	-1.435	2.327	2.060	1.975	1.894	1.475
3	0.181	0.137	-0.024	-0.357	-1.568	2.041	1.896	1.788	1.859	1.428
4	0.361	0.248	0.345	0.211	-0.304	2.048	1.902	1.856	1.955	1.529
BM5	0.645	0.136	0.175	-0.051	-0.341	2.133	2.086	1.971	2.099	1.503

Panel A reports the means and standard deviations of the returns (160 quarters) for the 25 size and B/M double-sorted portfolios obtained from Kenneth French's web page. All data are in quarterly. The sample is from 1963.1 to 2002.4. The rest of the table shows the time-series regression estimates of exposures to the two types of innovations obtained from the VAR decomposition. The second panel reports the exposure to the "current growth risk". And third panel reports the exposures to the "expected growth risk". Each row in each panel corresponds to size quintiles from small to big and each column corresponds to B/M quintiles from low to high. The right block of the table shows one-step GMM standard errors of the corresponding exposures in the left panel. All standard-errors are Newey-West adjusted with $L = 8$.

Table 5: Exposure to Fama-French 3 Factors

	ME1	2	3	4	ME5	ME1	2	3	4	ME5
	Average Excess Returns					Std.				
BM1	0.931	1.196	1.251	1.582	1.308	15.259	12.122	10.899	10.584	10.229
2	2.466	2.025	2.137	1.477	1.326	14.029	11.013	10.901	9.116	8.723
3	2.631	2.723	2.166	2.122	1.433	13.302	11.991	10.250	9.347	7.846
4	3.326	2.948	2.607	2.540	1.720	14.152	12.589	11.225	10.716	8.411
BM5	3.637	3.153	3.057	2.721	1.762	15.283	12.993	12.358	11.009	9.764
	β_{MKT}					s.e.				
BM1	1.038	1.075	1.036	1.031	1.016	0.049	0.032	0.027	0.038	0.023
2	0.978	1.000	1.033	1.052	1.021	0.035	0.025	0.033	0.024	0.034
3	0.924	1.003	0.996	1.050	0.926	0.039	0.026	0.030	0.023	0.038
4	0.904	1.021	1.046	1.078	1.005	0.047	0.023	0.035	0.041	0.030
BM5	1.023	1.080	1.055	1.100	1.043	0.037	0.038	0.036	0.050	0.038
	β_{SMB}					s.e.				
BM1	1.455	1.028	0.729	0.369	-0.270	0.068	0.044	0.044	0.066	0.040
2	1.336	0.969	0.584	0.312	-0.225	0.052	0.053	0.042	0.073	0.050
3	1.159	0.764	0.499	0.218	-0.232	0.054	0.041	0.041	0.047	0.050
4	1.112	0.702	0.418	0.202	-0.190	0.059	0.034	0.049	0.046	0.034
BM5	1.195	0.814	0.616	0.407	-0.122	0.049	0.050	0.051	0.066	0.072
	β_{HML}					s.e.				
BM1	-0.411	-0.444	-0.509	-0.504	-0.314	0.085	0.060	0.043	0.050	0.052
2	0.075	0.139	0.165	0.230	0.124	0.048	0.096	0.105	0.132	0.107
3	0.307	0.377	0.467	0.468	0.281	0.051	0.094	0.112	0.108	0.081
4	0.437	0.614	0.694	0.596	0.586	0.039	0.089	0.113	0.080	0.092
BM5	0.730	0.808	0.817	0.746	0.641	0.048	0.048	0.059	0.076	0.063

This table reports the loadings on the Fama-French 3 factors. Panel A reports the means and standard deviations of the returns (160 quarters) for the 25 size and B/M double-sorted portfolios obtained from Kenneth French's web page. All data are in quarterly. The sample is from 1963.1 to 2002.4. The rest of the table shows the time-series regression estimates of exposures to the two types of innovations obtained from the VAR decomposition. The second panel reports the exposure to the "market return factor". The third panel reports the exposures to the "SMB factor". And the fourth panel reports the exposures to the "HML factor". Each row in each panel corresponds to size quintiles from small to big and each column corresponds to B/M quintiles from low to high. The right block of the table shows one-step GMM standard errors of the corresponding exposures in the left panel. All standard-errors are Newey-West adjusted with $L = 8$.

Table 6: Exposure to Market News and Hedge News

	ME1	2	3	4	ME5	ME1	2	3	4	ME5
	Average Excess Returns					Std.				
BM1	0.931	1.196	1.251	1.582	1.308	15.259	12.122	10.899	10.584	10.229
2	2.466	2.025	2.137	1.477	1.326	14.029	11.013	10.901	9.116	8.723
3	2.631	2.723	2.166	2.122	1.433	13.302	11.991	10.250	9.347	7.846
4	3.326	2.948	2.607	2.540	1.720	14.152	12.589	11.225	10.716	8.411
BM5	3.637	3.153	3.057	2.721	1.762	15.283	12.993	12.358	11.009	9.764
	β_a					s.e.				
BM1	1.656	1.576	1.456	1.350	1.041	0.110	0.097	0.084	0.080	0.038
2	1.411	1.280	1.168	1.092	0.918	0.089	0.086	0.068	0.079	0.048
3	1.213	1.126	1.004	0.977	0.755	0.092	0.090	0.087	0.070	0.042
4	1.140	1.040	0.940	0.944	0.749	0.093	0.094	0.093	0.076	0.068
BM5	1.163	1.073	0.991	0.981	0.784	0.105	0.107	0.103	0.105	0.080
	β_h					s.e.				
BM1	-1.418	-1.380	-1.274	-1.184	-0.958	0.130	0.124	0.103	0.087	0.063
2	-1.227	-1.159	-1.051	-1.022	-0.850	0.114	0.094	0.082	0.061	0.057
3	-1.100	-1.030	-0.928	-0.909	-0.698	0.090	0.084	0.079	0.061	0.060
4	-1.035	-0.959	-0.877	-0.875	-0.700	0.087	0.078	0.064	0.069	0.056
BM5	-1.044	-0.971	-0.902	-0.916	-0.723	0.089	0.086	0.091	0.084	0.074
	β_{CAPM}					s.e.				
BM1	1.647	1.556	1.442	1.318	1.032	0.071	0.066	0.058	0.059	0.022
2	1.387	1.269	1.168	1.076	0.907	0.061	0.063	0.052	0.066	0.044
3	1.199	1.126	1.003	0.965	0.757	0.081	0.071	0.074	0.060	0.043
4	1.119	1.044	0.951	0.945	0.748	0.085	0.074	0.077	0.064	0.058
BM5	1.168	1.076	0.983	0.984	0.789	0.084	0.081	0.086	0.083	0.063

This table reports the loadings the two types of return innovations extracted from the return-based VAR. Panel A reports the means and standard deviations of the returns (160 quarters) for the 25 size and B/M double-sorted portfolios obtained from Kenneth French's web page. All data are in quarterly. The sample is from 1963.1 to 2002.4. The rest of the table shows the time-series regression estimates of exposures to the two types of innovations obtained from the VAR decomposition. The second panel reports the exposure to the "market news". The third panel reports the exposures to the "hedging news". And the fourth panel shows the exposures to the CAPM factor. Each row in each panel corresponds to size quintiles from small to big and each column corresponds to B/M quintiles from low to high. The right block of the table shows one-step GMM standard errors of the corresponding exposures in the left panel. All standard-errors are Newey-West adjusted with $L = 8$.

Table 7: Cross-sectional Results for Fama-French 25 Portfolios

	λ_0	λ_η	λ_ϵ	λ_a	λ_h	λ_m	λ_g	λ_{smb}	λ_{hml}	R^2
β_η	**1.957**	0.045	.	.	.	.	.	.	.	-0.032
	(0.704)	(0.145)	.	.	.	.	.	.	.	
	[0.801]	[0.182]	.	.	.	.	.	.	.	
β_ϵ	2.557	.	**0.977**	.	.	.	.	.	.	**0.811**
	(1.891)	.	(0.522)	.	.	.	.	.	.	
	[1.593]	.	[0.391]	.	.	.	.	.	.	
$\beta_\eta \& \beta_\epsilon$	2.221	0.073	**0.990**	.	.	.	.	.	.	**0.833**
	(1.131)	(0.141)	(0.258)	.	.	.	.	.	.	
	[1.665]	[0.235]	[0.445]	.	.	.	.	.	.	
β_a	**2.959**	.	.	-0.709	.	.	.	.	.	0.009
	(1.054)	.	.	(1.044)	.	.	.	.	.	
β_h	**2.993**	.	.	.	0.817	.	.	.	.	0.001
	(1.171)	.	.	.	(1.293)	.	.	.	.	
$\beta_a \& \beta_h$	1.467	.	.	-10.596	-12.402	.	.	.	.	0.022
	(1.190)	.	.	(6.236)	(7.338)	.	.	.	.	
$CAPM$	**2.943**	.	.	.	.	-0.699	.	.	.	0.005
	(1.090)	.	.	.	.	(1.085)	.	.	.	
$CCAPM$	1.460	.	.	.	.	.	0.180	.	.	0.033
	(0.880)	.	.	.	.	.	(0.198)	.	.	
$FF3$	2.717	.	.	.	.	-1.308	.	0.680	**1.444**	**0.764**
	(1.585)	.	.	.	.	(1.463)	.	(0.530)	(0.517)	

This table reports the cross-sectional regression results for Size-B/M double-sorted 25 portfolios. The return data are obtained from Kenneth French's webpage and average returns are taken over the sample of 1963.1-2002.4. The dependant variable in the cross-sectional regressions are the average returns of the 25 portfolios. The betas are obtained from first-step time-series regressions of returns on the risk factors. The GMM standard errors are reported underneath the parameter estimates in parentheses and the bootstrap standard errors (10,000 repetitions) are reported in the brackets. All GMM standard errors are adjusted by Newey-West method with $L = 8$. The adjusted-$R^{2\prime}$s are reported in the last column.

Table 8: Cross-sectional Results for Fama-French 25 Portfolios

	λ_0	λ_η	λ_ϵ	λ_{mkt}	λ_{smb}	λ_{hml}	log(ME)	log(BM)	$\bar{R}^2$
$\beta_\eta, \beta_\epsilon, FF3$	2.707	0.140	**0.663**	-1.105	-0.028	0.747	.	.	0.883
	(2.687)	(0.150)	(0.230)	(3.013)	(1.374)	(0.734)	.	.	
$Size$	**4.268**	.	.	.	.	.	**-0.249**	.	0.187
	(0.832)	.	.	.	.	.	(0.097)	.	
B/M	2.251	.	.	.	.	.	.	**0.861**	0.607
	(0.095)	.	.	.	.	.	.	(0.139)	
$Size + B/M$	**3.696**	.	.	.	.	.	**-0.172**	**0.790**	0.700
	(0.513)	.	.	.	.	.	(0.060)	(0.124)	
$\beta_\eta, \beta_\epsilon, Size$	1.885	0.093	**1.016**	.	.	.	0.030	.	0.825
	(3.183)	(0.236)	(0.442)	.	.	.	(0.214)	.	
$\beta_\eta, \beta_\epsilon, B/M$	2.010	0.102	**0.705**	.	.	.	.	0.397	0.889
	(1.390)	(0.175)	(0.269)	.	.	.	.	(0.386)	
$\beta_\eta, \beta_\epsilon, Size, B/M$	0.503	0.195	**0.786**	.	.	.	0.131	0.446	0.895
	(2.540)	(0.158)	(0.270)	.	.	.	(0.180)	(0.454)	

This table reports the cross-sectional regression results for Size-B/M double-sorted 25 portfolios. The return data are obtained from Kenneth French's webpage and average returns are taken over the sample of 1963.1-2002.4. The dependant variable in the cross-sectional regressions are the average returns of the 25 portfolios. The betas are obtained from first-step time-series regressions of returns on the risk factors. $Size$ is the log market equity of a portfolio and B/M is the log book-to-market ratio. Both characteristics are known before the return period. (For more details see Fama and French (1992).) The GMM standard errors are reported underneath the parameter estimates in parentheses. All GMM standard errors are adjusted by Newey-West method with $L = 8$. The adjusted-$R^{2\prime}$s are reported in the last column.

Table 9: Cross-sectional Results for Size,B/M, E/P, CF/P Portfolios

	λ_0	λ_η	λ_ϵ	λ_a	λ_h	λ_m	λ_g	λ_{smb}	λ_{hml}	$Adj.\ R^2$
β_η	1.335	0.134	.	.	.	.	.	.	.	0.084
	(0.785)	(0.125)	.	.	.	.	.	.	.	
	[0.726]	[0.162]	.	.	.	.	.	.	.	
β_ϵ	2.354	.	**0.685**	.	.	.	.	.	.	**0.611**
	(1.289)	.	(0.336)	.	.	.	.	.	.	
	[1.380]	.	[0.363]	.	.	.	.	.	.	
$\beta_\eta \& \beta_\epsilon$	1.893	0.120	**0.674**	.	.	.	.	.	.	**0.692**
	(1.067)	(0.131)	(0.307)	.	.	.	.	.	.	
	[1.343]	[0.163]	[0.376]	.	.	.	.	.	.	
β_a	2.108	.	.	-0.270	.	.	.	.	.	-0.019
	(1.001)	.	.	(0.956)	.	.	.	.	.	
β_h	2.368	.	.	.	0.579	.	.	.	.	-0.004
	(1.083)	.	.	.	(1.154)	.	.	.	.	
$\beta_a \& \beta_h$	3.715	.	.	12.824	16.048	.	.	.	.	0.228
	(1.913)	.	.	(7.734)	(9.445)	.	.	.	.	
$CAPM$	1.602	.	.	.	.	-0.178	.	.	.	-0.023
	(1.030)	.	.	.	.	(0.982)	.	.	.	
$CCAPM$	0.662	.	.	.	.	.	0.224	.	.	0.188
	(0.930)	.	.	.	.	.	(0.139)	.	.	
$FF3$	-0.298	.	.	.	.	1.365	.	0.629	1.063	**0.891**
	(1.245)	.	.	.	.	(1.292)	.	(0.529)	(0.505)	

This table reports the cross-sectional regression results for 40 decile portfolios sorted independently by size, book-to-market ratio, earning-to-price ratio, cash flow-to-price ratio. The return data are obtained from Kenneth French's web page and average returns are taken over the sample of 1963.1-2002.4. The dependant variable in the cross-sectional regressions are the average returns of the 40 portfolios. The betas are obtained from first-step time-series regressions of returns on the risk factors. The GMM standard errors are reported underneath the parameter estimates in parentheses and the bootstrap standard errors (10,000 repetitions) are reported in the brackets. All GMM standard errors are adjusted by Newey-West method with $L = 8$. The adjusted-$R^{2\prime}$s are reported in the last column.

Table 10: Robustness to Choices of Information Variables

Model	λ_0	λ_η	λ_ϵ	$\bar{R}^2$
$Term, Div, nrf, Def$	2.498	-0.003	**0.872**	0.783
	(0.910)	(0.160)	(0.230)	
$Term, Div, Rrf, Infl, Def$	3.080	0.423	**0.979**	0.739
	(1.033)	(0.185)	(0.260)	
$Term, Div, Rrf, Infl$	2.684	0.072	**0.980**	0.833
	(0.973)	(0.147)	(0.265)	
$Div, Infl, Term$	2.461	0.109	**0.937**	0.836
	(0.962)	(0.132)	(0.246)	
$Div, Rrf, Infl$	1.473	0.087	**1.258**	0.612
	(0.969)	(0.155)	(0.377)	
$Div, Rrf, Term$	2.261	-0.268	**0.677**	0.750
	(0.981)	(0.136)	(0.173)	
$Rrf, Infl, Term$	0.933	-0.205	**0.912**	0.530
	(1.072)	(0.130)	(0.217)	
$Div^{rep}, Rrf, Infl, Term$	1.828	-0.122	**0.793**	0.686
	(0.923)	(0.133)	(0.205)	

The table reports the cross-sectional results for the size and book-to-market ratio sorted 25 portfolios of the two-consumption-beta model with different choices of information variables used for identifying the two types of growth shocks. Specifically,

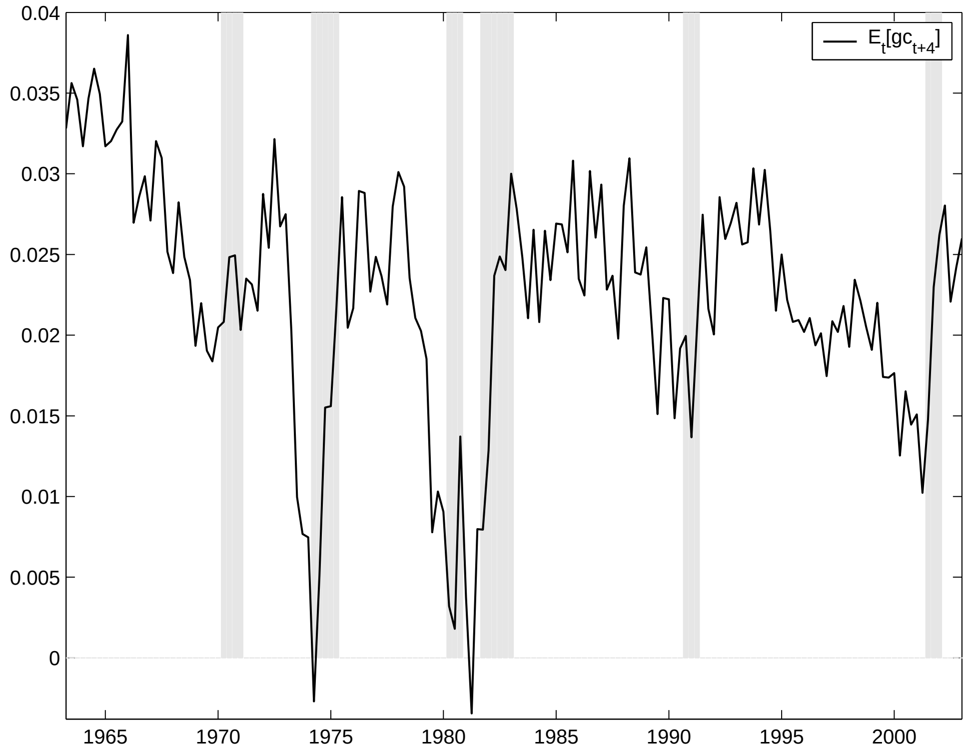
$$\begin{bmatrix} g_{c,t+1} \\ x_{t+1} \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \begin{bmatrix} g_{c,t} \\ x_t \end{bmatrix} + \begin{bmatrix} \eta_{c,t+1} \\ \eta_{x,t+1} \end{bmatrix}$$

where x_t is the set of information variables indicated by the "Model" column. The cross-sectional regression is

$$\bar{r_i} = \lambda_0 + \lambda_1 \beta_{i,\eta} + \lambda_2 \beta_{i,\epsilon} + e_i$$

The estimated coefficients and the adjusted R^2 for the cross-sectional regressions are reported. The standard errors are Newey-West adjusted with $L = 8$.

Figure 1: Time-Variation in Expected Consumption Growth

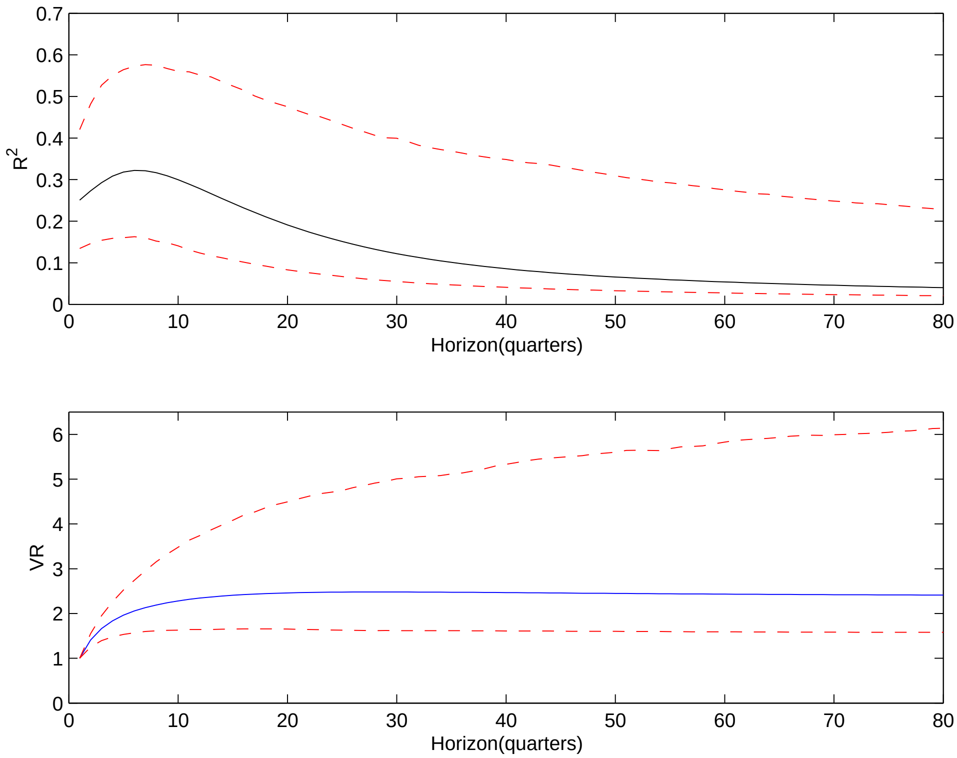


The consumption growth is forecasted by the predictive regression

$$\sum_{j=1}^{4} g_{c,t+j} = \gamma_0 + \gamma' x_t + e_{t+4}$$

where x_t is the vector of information variables $Term_t, Div_t, Rrf_t, Infl_t$ and $g_{c,t+j} = log(C_{t+j}) - log(C_{t+j-1})$. The fitted value of the regression is plotted against date t. The vertical bars correspond to the NBER dated recessions.

Figure 2: Long-run Consumption Growth Predictability Implied by VAR

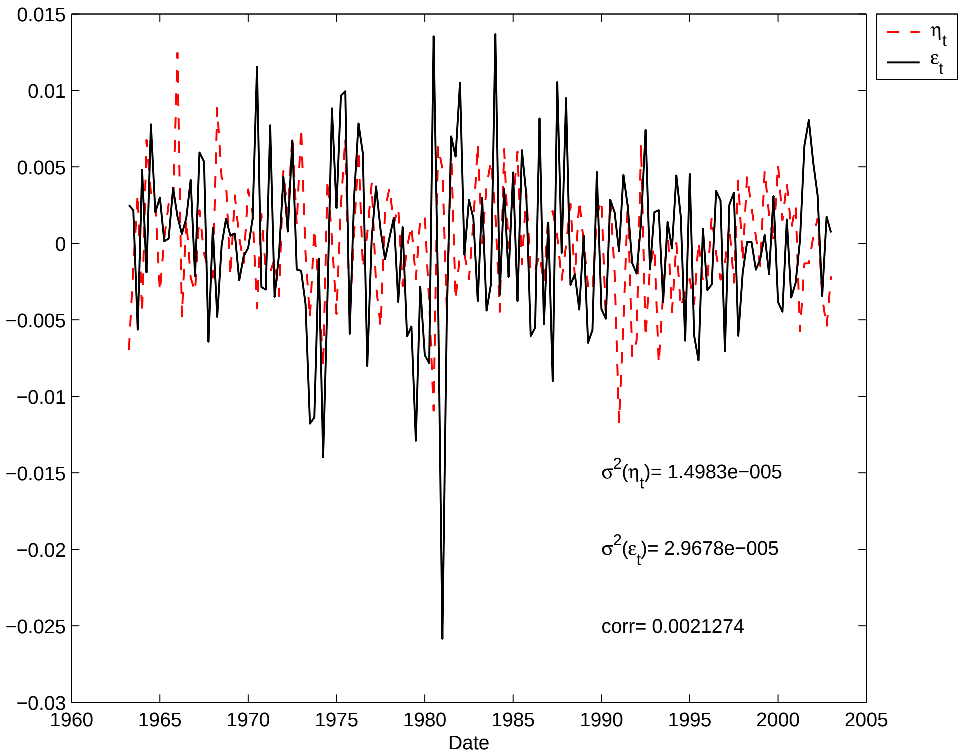


The implied future k-quarter R^2, $R^2(k)$, and variance ratio, $VR(k)$ are calculated following Hodrick (1992). More specifically,

$$
\begin{aligned}
Z_{t+1} &= AZ_t + \omega_{t+1} \\
V &= E(\omega_{t+1}\omega'_{t+1}) \\
C(0) &= \sum_{j=0}^{\infty} A^j V A^{j\prime}; \qquad C(j) = A^j C(0) \\
V_k &= kC(0) + \sum_{j=1}^{k-1} (k-j)[C(j) + C(j)']; \\
W_k &= \sum_{j=1}^{k} (I-A)^{-1}(I-A^j)V(I-A^j)'(I-A)^{-1\prime} \\
R^2(k) &= 1 - \frac{e1'W_k e1}{e1'V_k e1} \\
VR(k) &= \frac{e1'V_k e1}{ke1'C(0)e1}
\end{aligned}
$$

In each panel, the dashed lines correspond to 97.5%(upper) and 2.5%(lower) values from empirical distributions obtained from bootstrap exercises (2500 repetitions) using the estimated parameters in Table 3.

Figure 3: Time-Series of Two Shocks

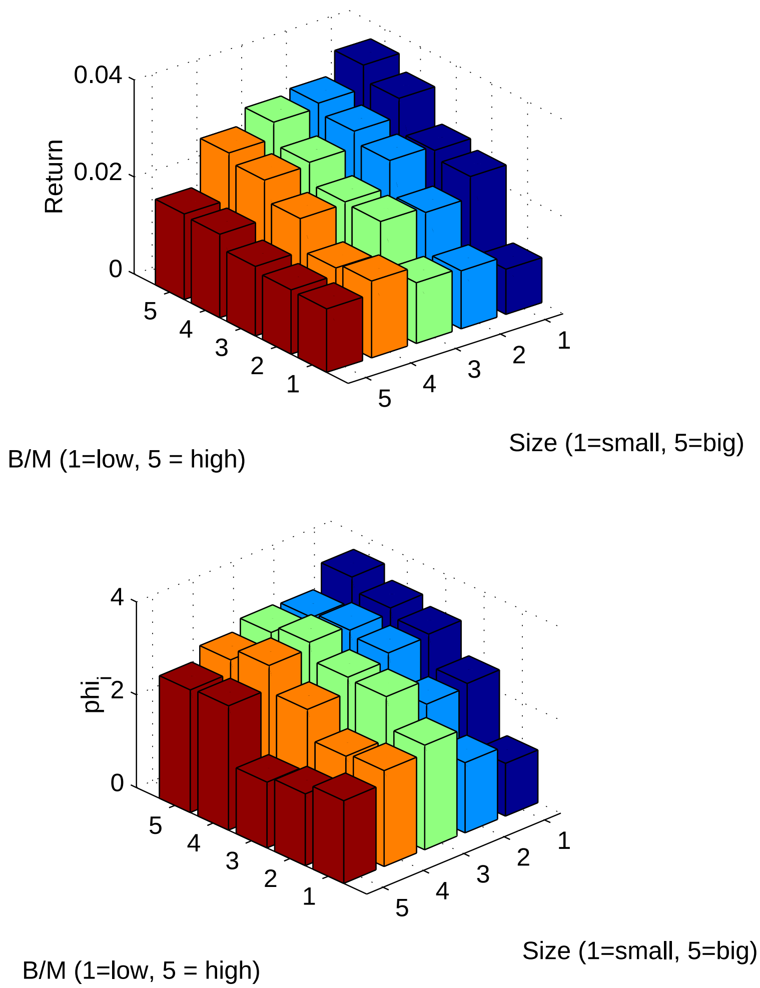


The current growth shock, $\eta_{c,t}$(dashed line) and the expected growth shock $\epsilon_{c,t}$(solid line) are calculated from the estimated VAR coefficients (A) from Table 3. Specifically,

$$\eta_{c,t+1} = g_{c,t+1} - E_t[g_{c,t+1}] = \omega_{1,t+1} \quad (35)$$

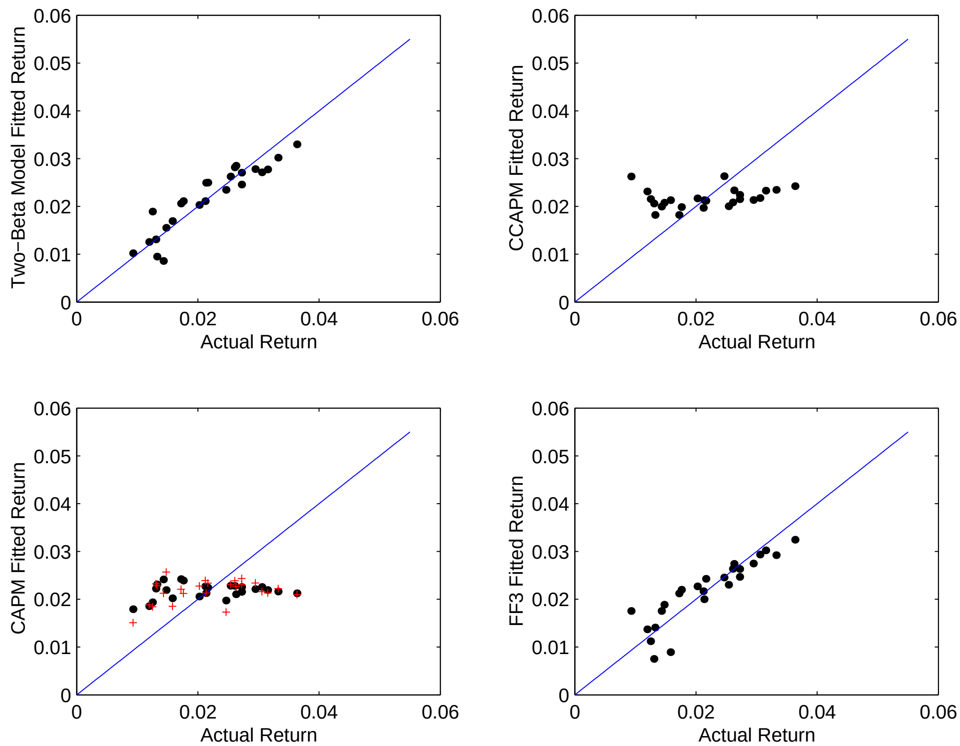
$$\epsilon_{c,t+1} = (E_{t+1} - E_t)[\sum_{j=1}^{\infty} \kappa_{c,1}^{j} g_{c,t+1+j}] = e1'\kappa_{1,c}A(I - \kappa_{1,c}A)^{-1}\omega_{t+1} \quad (36)$$

Figure 4: Pattern of Returns vs. Pattern of Exposures to ϵ_c



The top panel plots the average returns for the size and book-to-market sorted 25 portfolios. For size portfolios, 1 to 5 corresponds small to big. For the book-to-market portfolios, 1 to 5 corresponds to low to high. The bottom panel shows the exposure of each portfolio to the expected growth shock, i.e. β_ϵ. For viewing purposes, 3 is added to each exposure.

Figure 5: Actual vs. Fitted Returns for Fama-French 25 Portfolios



This figure shows the actual excess returns versus fitted excess returns for the Size-B/M 25 portfolios. If the model fits well, then the points should be close to 45° line. The four panels correspond respectively to the consumption-based two-beta model(upper-left), C-CAPM(upper-right), CAPM (lower-left, overlayed by Campbell(1996) two-beta model marked with '+') and Fama-French 3-factor model(lower-right).