

Risks For the Long Run: Estimation and Inference*

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Abstract

Recent work by Bansal and Yaron (2004) on Long Run Risks suggests that these fundamental economic risks can account for the cross-section of asset returns. In this paper we develop methods to estimate their equilibrium model by exploiting the asset pricing Euler Equations. Using an empirical estimate for the long run risk component we demonstrate that the Long Run Risk model can capture quite well both the time and cross sectional variation in returns. The model generates relatively small pricing errors for the equity premium as well as the ‘value’ and ‘size’ premium. We show that time aggregation effects—that is, a mismatch in the sampling and the agent’s decision interval leads to significant biases in the estimates for risk aversion and the elasticity of intertemporal substitution. Our evidence suggests that accounting for these biases is important for interpreting the magnitudes of the preference parameters and the economic implications of the model for asset prices.

Preliminary and Incomplete

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1 Introduction

An elegant approach to evaluate the empirical plausibility of an asset pricing model is to exploit its asset pricing Euler equation restrictions using the Generalized Method of Moment (GMM) estimation technique (e.g., Hansen and Singleton (1982)). This approach provides a convenient way to impose the model restrictions on asset payoffs and estimate the model parameters. In recent work Bansal and Yaron (2004) develop a Long Run Risk (LRR) asset pricing model and suggest it can empirically account for differences in expected returns across assets. The motivation for this paper is to evaluate the LRR model along these dimensions using Euler Equation based estimation methods. *A priori* it is not entirely clear how to proceed with such an estimation as the intertemporal marginal rate of substitution in this model, based on the Epstein and Zin (1989) and Weil (1989) preferences, incorporates the return on the consumption asset which is not directly observed by the econometrician. In this paper we present methods for estimating models with these preferences exploiting Euler Equations and a GMM estimator. Using these methods we explore if the Long Run Risks (LRR) model has empirical support; we find considerable empirical support for the model at plausible preference configurations. Our evidence suggests that the investor concerns about long run risks are empirically important for understanding asset returns. Our estimation also highlights the importance of time aggregation in consumption in drawing inferences about the magnitudes of preference parameters.

To make estimation feasible in the LRR model we exploit the dynamics of aggregate consumption growth and the model's Euler restrictions to solve for the unobserved return on the claim over the future consumption stream. The LRR model proposed in Bansal and Yaron (2004) has three risk sources (state variables) in the aggregate consumption dynamics: (i) high frequency or short run risks in consumption, (ii) low frequency or long run movements in consumption, and (iii) fluctuations in consumption uncertainty, i.e., consumption volatility risk. We derive expressions for the Intertemporal Marginal Rates of Substitution (IMRS) in terms of these risk sources for a wide range of risk aversion and intertemporal substitution parameters. We document that our methods for characterizing the model's pricing kernel are very accurate. Earlier work by Epstein and Zin (1991) also pursues the strategy of exploiting the Euler Equation-GMM method for estimation; however, they assume that the return on the consumption asset coincides with the observed value weighted market return. This premise, we show, can distort the estimated preferences and lead to false rejections of

the model.

Following the work of Bansal and Yaron (2004) on long run risks, Bansal, Dittmar, and Lundblad (2005), Hansen, Heaton, and Li (2005), Bansal, Gallant, and Tauchen (2005), Kiku (2006), and Malloy, Moskowitz, and Vissing-Jorgensen (2004), Lettau and Ludvigson (2005), also explore its implication for asset returns. However, these papers, unlike the focus of this paper, do not evaluate the empirical plausibility of the LRR model from the perspective of the Euler Equation-GMM based estimation approach.

Exploiting the methods we develop, our Euler Equation-GMM based estimation of the LRR model shows that: (i) The long run risk component is highly persistent, displays fluctuations that are correlated with business cycles, and is economically and statistically significantly predictable by theoretically motivated variables, (ii) In the cross section, assets with large mean returns (e.g., value and small assets) are more sensitive to innovations in the long run risk variable; that is, these returns have larger betas with respect to the long run risk component while having negligible dependence on the betas constructed for short horizon consumption innovations; (iii) the model is not rejected by the overidentifying restrictions. The pricing errors for the various assets we consider seem small and plausible. In the annual data, the estimated risk aversion is in excess of twenty while estimates for the IES are less than one. We show, however, that after accounting for time aggregation effects, the most likely value for the population risk aversion and IES are closer to 10 and 2 respectively.

Time aggregation plays an important role in interpreting our estimates and evidence. The decision interval of the agent and the frequency with which an econometrician observes consumption data need not coincide. In the context of the LRR model, if consumption data is observed only on a coarser interval (e.g., annual), while the decision interval of the agent is on a finer interval (e.g., monthly), then the estimates of the risk aversion will be much larger than their true value, while the estimates of the IES will be lower than their true values, and typically less than one. This effect is important as much of the earlier evidence, indeed, finds estimates that are in the region of high risk aversion and low IES (see Campbell (1993), Hall (1988)). Our evidence indicates that much of the earlier evidence and the associated views regarding low values of IES and high risk aversion could simply be an artifact of time aggregation effects in estimation.

In sum, the evidence in this paper shows that the long run risk model is quite capable in quantitatively pricing the time series and cross section of returns, and doing so with plausible

parameter estimates. These parameter estimates can be quite difficult to precisely estimate using annual data. They tend to produce a somewhat misspecified model that leads to preference parameter estimates that are biased towards what is often found in the literature.

The paper continues as follows: Section 2 presents the model and its testable restrictions. Section 3 presents the data, while Section 4 provides the results of our empirical analysis. Section 5 presents Monte-Carlo evidence regarding time aggregation. Section 6 provides concluding remarks.

2 Model

In this section we specify a model based on Bansal and Yaron (2004). The underlying environment is one with complete markets and the representative agent has Epstein and Zin (1989) type preferences which allow for the separation of risk aversion and the elasticity of intertemporal substitution. Specifically, the agent maximizes her life-time utility, which is defined recursively as,

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

where C_t is consumption at time t , $0 < \delta < 1$ reflects the agent's time preferences, γ is the coefficient of risk aversion, $\theta = \frac{1-\gamma}{1-\frac{1}{\psi}}$, and ψ is the elasticity of intertemporal substitution (IES). Utility maximization is subject to the budget constraint,

$$W_{t+1} = (W_t - C_t) R_{c,t+1}, \quad (2)$$

where W_t is the wealth of the agent, and $R_{c,t}$ is the return on all invested wealth.

Consumption and dividends have the following joint dynamics:

$$\begin{aligned} \Delta c_{t+1} &= \mu_c + x_t + \sigma_c \eta_{t+1} \\ x_{t+1} &= \rho x_t + \varphi_e \sigma_e e_{t+1} \\ \sigma_{t+1}^2 &= \bar{\sigma}^2 + \nu(\sigma_t^2 - \bar{\sigma}^2) + \sigma_w w_{t+1}, \end{aligned} \quad (3)$$

where Δc_{t+1} is the growth rate of log consumption. As in the long run risks model of

Bansal and Yaron (2004) (BY), $\mu_c + x_t$ is the conditional expectation of consumption growth, and x_t is a small but persistent component that captures long run risks in consumption growth. The parameter ρ determines the persistence in the conditional mean of consumption growth, $\mu_c + x_t$. For parsimony, as in Bansal and Yaron (2004), we have a common time-varying volatility in consumption, which, as shown in their paper, leads to time-varying risk premia. The unconditional variance of consumption is $\bar{\sigma}^2$ and ν governs the persistence of the volatility process.

As in Epstein and Zin (1989), it is easily shown that, for any asset j , the first order condition yields the following asset pricing Euler condition,

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

where m_{t+1} is the log of the intertemporal marginal rate of substitution and $r_{j,t+1}$ is the log of the gross return on asset j .

2.1 Estimation Feasibility

It can be shown that with the Epstein and Zin (1989) preferences, the log of the Intertemporal Marginal Rate of Substitution (IMRS), m_{t+1} , is

$$m_{t+1} = \theta \log \delta - \frac{\theta}{\psi} \Delta c_{t+1} + (\theta - 1) r_{c,t+1}, \quad (5)$$

where $r_{c,t+1}$ is the continuous return on the consumption asset. As this return is unobservable and endogenous to the model we need to solve for it using the consumption dynamics. Epstein and Zin (1991) circumvent the unobservability of $r_{c,t+1}$ by equating it with the observed market return, $r_{m,t+1}$. Bansal and Yaron (2004) explicitly solve for this return given the consumption dynamics.

To solve for the return on wealth we use the log-linear approximation for the continuous return on the wealth portfolio, namely,

$$r_{c,t+1} = \kappa_0 + \kappa_1 z_{t+1} + \Delta c_{t+1} - z_t, \quad (6)$$

where $z_t = \log(P_t/C_t)$ is log price to consumption ratio (the valuation ratio corresponding

to a claim that pays consumption) and the κ 's are log linearization constants with κ_0 and κ_1 being,

$$\kappa_1 = \frac{\exp(\bar{z})}{1 + \exp(\bar{z})}, \quad (7)$$

$$\kappa_0 = \log(1 + \exp(\bar{z})) - \kappa_1 \bar{z}, \quad (8)$$

and \bar{z} is the mean of the log price-consumption ratio.

To derive the time series for $r_{c,t+1}$ we require a solution for log price-consumption ratio, which we conjecture follows, $z_t = A_0 + A_1 x_t + A_2 \sigma_t^2$. The solution for the A 's depends on all the preference parameters and the parameters that govern the state variables. Given this solution and the solution for the κ 's, which are also endogenous to the model, one can create the return to the consumption asset.

For notational ease let the state variables for the model be $Y_t' = [1 \quad x_t \quad \sigma_t^2]$, and $\mathbf{A}' = [A_0 \quad A_1 \quad A_2]$, then the solution for $z_t = \mathbf{A}'Y_t$, where¹

$$\mathbf{A}' = \left[A_0 \quad \frac{1-\frac{1}{\psi}}{1-\kappa_1\rho} \quad -\frac{(\gamma-1)(1-\frac{1}{\psi})}{2(1-\kappa_1\nu)} \left[1 + \left(\frac{\kappa_1\varphi_e}{1-\kappa_1\rho} \right)^2 \right] \right]. \quad (9)$$

As the A 's depend on κ 's and hence on the average price-consumption ratio, \bar{z} , a solution to the system is fixed on \bar{z} . That is, to solve for the κ_1 and κ_0 one needs the numerical solution for \bar{z} , which satisfies

$$\bar{z} = \mathbf{A}(\bar{z})\bar{Y}. \quad (10)$$

This is quite easy to implement in practice.

Given the solution for z_t , the IMRS, in terms of the state variables and innovations can be stated as

$$m_{t+1} = \mathbf{\Gamma}'Y_t - \mathbf{\Lambda}'\zeta_{t+1} \quad (11)$$

where the three sources of risks are

$$\zeta'_{t+1} = \left[\sigma_t \eta_{t+1} \quad \sigma_t e_{t+1} \quad \sigma_w w_{t+1} \right] \quad (12)$$

¹The expression for A_0 , as well as for Γ_0 in equation (13), is given in the Appendix.

and the three dimensional vectors $\mathbf{\Gamma}$ and $\mathbf{\Lambda}$, follow

$$\mathbf{\Gamma}' = \left[\Gamma_0 \quad -\frac{1}{\psi} \quad -(\gamma - 1)(\gamma - \frac{1}{\psi})\frac{1}{2} \left[1 + \left(\frac{\kappa_1 \varphi_e}{1 - \kappa_1 \rho} \right)^2 \right] \right] \quad (13)$$

and

$$\mathbf{\Lambda}' = \left[\gamma \quad \left(\gamma - \frac{1}{\psi} \right) \frac{\kappa_1 \varphi_e}{1 - \kappa_1 \rho} \quad -(\gamma - 1)(\gamma - \frac{1}{\psi}) \frac{\kappa_1}{2(1 - \kappa_1 \rho)} \left[1 + \left(\frac{\kappa_1 \varphi_e}{1 - \kappa_1 \rho} \right)^2 \right] \right]. \quad (14)$$

Note that equation (11) for the pricing kernel has an approximation error emanating from the linear approximation around the theoretical value of average price to consumption ratio. We show that this approximation error is quite small and does not materially affect the results.

Given the expression for (11), it immediately follows that the risk premium on any asset j is

$$E_t[r_{j,t+1} - r_{f,t} + 0.5\sigma_{t,r}^2] = \sum_{i=1}^3 \lambda_i \sigma_{i,t}^2 \beta_{i,j} \quad (15)$$

where $\beta_{i,j}$ is the beta with respect to the i^{th} risk source of ζ_{t+1} for asset j , and λ_i is the i^{th} entry of $\mathbf{\Gamma}$.

2.2 Special Case: IES=1

The IES is a critical parameter in the Long Run Risk Model. Many papers specialize the Epstein and Zin (1989) preferences to the case in which IES is set to one (e.g., Giovannini and Weil (1989), Tallarini (2000), Hansen, Heaton, and Li (2005), Hansen and Sargent (2006)). This has great analytical convenience in certain situations. It is important to note that while the value function of the representative agent displays a discontinuity at IES=1, our *estimation methodology* nests the case of IES=1 in a continuous fashion. Namely, the IMRS components as given in (11) adjust in continuous way as one takes the limit of the IES parameter to one. Specifically, as is well known, in the IES=1 case the price-consumption ratio, z , is constant and is determined by δ . A virtue of our approach of approximating the return, $r_{c,t+1}$, and accounting for the dependence of the approximating constants (i.e., κ_0 , κ_1) on all the model parameters, is that the pricing kernel is continuous in IES. That is,

$$\lim_{\psi \rightarrow 1} \kappa_1 = \delta \quad \lim_{\psi \rightarrow 1} \mathbf{\Gamma}' = \mathbf{\Gamma}'(\psi = 1, \kappa_1 = \delta) \quad \lim_{\psi \rightarrow 1} \mathbf{\Lambda}' = \mathbf{\Lambda}'(\psi = 1, \kappa_1 = \delta) \quad (16)$$

Evaluating the pricing kernel (11) under the above restrictions gives exactly the same solution as in Giovannini and Weil (1989), Tallarini (2000) and Hansen, Heaton, and Li (2005). Thus, this approach does not confine the econometrician to prespecified value of the IES. That is, in estimation the IES is a free parameter.

2.3 Time Aggregation and Finite Sample Effects on Estimation

Time aggregation, in our context, arises when the sampling frequency of the data is different from the decision interval of the agent. For example, the data may be sampled at an annual frequency while the decision interval may be monthly. This aggregation effect, we show, has the effect of distorting the parameter estimates and consequently the interpretation of the model implications. While it is well known that time aggregation can have important implications for asset pricing (e.g., Heaton (1993), Heaton (1995)), it has, as shown below, particularly severe quantitative effects in our model due to the persistence in the long run risk component.

In our case time aggregation effects emanate from two sources. First, the monthly consumption is replaced by annual consumption $C_t^a = \sum_{j=1}^{12} C_{t-j}$, where C_{t-j} corresponds to month j consumption in year t . To avoid any ambiguity regarding the frequency of a given variable, we denote annual variables with superscript a . Second, with annual data the estimates of monthly x_t are replaced by annual estimates x_t^a , which are obtained from annual consumption growth. This latter feature, as we show below, will also distort the measure of the persistence in the x_t process, and consequently the market price of risks. More precisely, the econometrician would estimate

$$m_{t+1}^a = \mathbf{\Gamma}^a Y_t^a - \mathbf{\Lambda}^a \zeta_{t+1}^a. \quad (17)$$

Recall, the risk compensation for the long run risk on a monthly frequency is λ_e

$$\lambda_e \sigma_t^2 = \left(\gamma - \frac{1}{\psi} \right) \frac{\kappa_1 \varphi_e}{1 - \kappa_1 \rho} \sigma_t^2. \quad (18)$$

The 'effective risk aversion', λ_e , is highly sensitive to the risk aversion parameter γ , as well as the parameter ρ governing the persistence of the long run component x_t . If the true decision interval of the agent is monthly but the econometrician uses annual data, then ρ^a is

much smaller than ρ , and this tends to make the market price of risk on an annual frequency smaller for any given risk aversion and IES parameters. For example, as we show below, a monthly model in which ρ is 0.982 yields an annual (via time aggregation) ρ^a of only 0.68. The fact that the annualized volatility multiplying this effective risk premia, σ_t , is about 12 times that of the monthly volatility is still not enough to compensate for the reduction in effective risk aversion due to the smaller annual persistence coefficient. Thus, to achieve the desired risk premia, and to offset the reduction in 'effective risk aversion', the econometrician estimates a very large risk aversion even though the true risk aversion is much smaller.

The message from this is simple but important. Time aggregation and the appropriate decision interval can have critical effects for deducing the appropriate risk aversion parameter. Note, that these potential effects would be absent in a model that focuses on *i.i.d* consumption growth, in which case the long run piece is absent and time aggregation essentially does not effect the estimation of γ via λ_η .

In addition to the time-aggregation effects, another channel that tends to push the risk aversion to a larger magnitude is the finite sample bias in estimating ρ . It is well known, see Kendall (1954), that the persistence parameter in a standard AR(1) process is biased downwards – this again tends to lower the market price of long run risks and hence estimation, to match the risk premium, tends to push the risk aversion higher. We provide, via simulations, a decomposition of the magnitude of the effects that arise solely due to time aggregation and due to finite sample bias.

2.4 Pricing Kernel Approximation Error

In our empirical work, we rely on the approximate analytical solutions of the model presented above and discussed in more details in the Appendix. In this section, we evaluate the accuracy of the log-linear approximation by comparing the approximate analytical solution for the price to consumption ratio to its numerical counterpart. The magnitude of the approximation error in the price-consumption ratio allows us to assess the reliability of the log-linear analytical solution for the stochastic discount factor, and consequently, model implications based on log-linear approximation.

Notice first that the value function in the Epstein-Zin preferences is given by,

$$V_t = (1 - \delta)^{\frac{\psi}{\psi-1}} W_t (W_t/C_t)^{\frac{1}{\psi-1}}, \quad (19)$$

i.e., the life-time utility of the agent, normalized by the level of either consumption or wealth, is proportional to the wealth to consumption ratio. Hence, the solution to the wealth-consumption ratio (or, alternatively, price to consumption) based on the log-linearization of the wealth return in equation (6) will determine the dynamics of the value function. Recall also that the evolution of the IMRS (see equation (5)), through the return on wealth, depends on the valuation of the consumption claim. Thus, the log-linear solution for the IMRS, as well, hinges on the accuracy of the log-linear approximation of the price-consumption ratio.

To solve the model numerically, we use the approach proposed by Tauchen and Hussey (1991). This method is based on a discrete representation of the conditional density of the state variables, x and σ^2 . In particular, we solve the pricing equation by approximating the integral in (4) by a finite sum using the Gauss-Hermite quadrature. Note that the resulting solutions, in their turn, are subject to an approximation error. In order to minimize this error and ensure the high quality of the benchmark numerical solutions, we use sufficiently large number of grid points in the quadrature rule.² In addition, for simplicity in this exercise we shut-off the channel of time-varying consumption volatility. Aside from this restriction, we evaluate the numerical and log-linear analytical solutions using the same parametrization of consumption growth dynamics that we subsequently employ in our simulation experiment (see Section 5 and Panel A of Table VI). Our benchmark calibration of preferences is $\delta = 0.9989$, $\gamma = 10$ and $\psi = 2$; however, we also consider alternative combinations of risk aversion and IES parameters.

Overall, we find that log-linear analytical solutions are remarkably close to the numerical results. In particular, for risk aversion of 10 and IES of 2, the numerical and analytical mean(volatility) of the log price to consumption ratio are 4.724 (0.0318) and 4.716 (0.0321) respectively.³ Thus, the approximation error, expressed as a percentage of the corresponding numerical value, is about 0.17% for the mean and 0.86% for the standard deviation of the log price-consumption ratio. As the elasticity of intertemporal substitution decreases to 0.5, the

²Specifically, we discretize the dynamics of the expected growth component, x_t , using 100-point rule. We find that increasing the number of grid points leads to virtually identical numerical results.

³All the numbers reported in this section are in monthly terms.

percentage error falls to about 0.02% for \bar{z} and 0.42% for σ_z . Although the approximation somewhat deteriorates as the magnitude of risk aversion increases, the deviation between analytical and numerical solutions remains quite small. For example, holding IES at 2 and varying risk aversion between 5 and 15 results in 0.03%–0.51% error band for the mean and 0.17%–2.17% for the standard deviation of the log price-consumption ratio.

As discussed above, the dynamics of the price to consumption ratio has a direct bearing on the time-series properties of the IMRS. The fairly small approximation error in the price-consumption ratio, that we document, guarantees the accuracy of the pricing implications of the log-linearized solutions. Indeed, we find that approximate analytical and numerical solutions deliver very similar quantitative implications along all dimensions of the model, including levels and variances of the risk-free rate, price-dividend ratios, returns on consumption and dividend claims, and the pricing kernel.⁴ This evidence confirms that empirical findings that we present below are robust to the log-linear approximation of the model.

3 Data

In this paper we use data on consumption and asset prices for the time period from 1930 till 2002 — the longest available sample. We take the view that this sample better represents the overall variation in asset and macro economic data. Importantly, this long sample also helps in achieving more reliable statistical inference. In addition, annual data is less prone to measurement errors that arise from seasonalities and other measurement problems highlighted in Wilcox (1992). The decision interval of the agent is assumed to be monthly which is motivated by standard payment cycles and is a common assumption in the literature. It is fairly straightforward to assume a different decision frequency (e.g., weekly or quarterly); however, this change will not alter the empirical findings in a significant manner.

In our empirical tests, we employ portfolios with opposite size and book-to-market characteristics that are known to provide investors with different premia over the years. In addition, our asset menu comprises the aggregate stock market portfolio and a proxy of a risk-less asset. The construction of portfolios is standard (see Fama and French (1993)). In particular, for the size sort, we allocate individual firms across 10 portfolios according

⁴For brevity, the detailed evidence is not reported here (it is yet available upon request).

to their market capitalization at the end of June of each year. Book-to-market deciles are likewise re-sorted at the end of June by ranking all the firms into 10 portfolios using their book-to-market values as of the end of the previous calendar year. NYSE breakpoints are used in both sorts. For each portfolio, including the aggregate market, we construct value-weighted monthly returns as well as per-share price and dividend series as in Campbell and Shiller (1988), Bansal, Dittmar, and Lundblad (2005), and Hansen, Heaton, and Li (2005). Monthly data are then time-aggregated to an annual frequency and converted to real using the personal consumption deflator. Panel A of Table I provides descriptive statistics for returns, dividend growth rates and price-dividend ratios for the five portfolios of interest — small and large (i.e., firms in the top and bottom market capitalization deciles), growth and value (firms with the lowest and highest book-to-market ratios, respectively), and the aggregate stock market. The first column illustrates the well-known size and value premia. Over the sample period, small stocks have outperformed large firms by about 5.9%; the spread in returns on value and growth firms has averaged about 6.4%. Both high book-to-market and small firms have experienced higher growth rate of dividends and have been much more volatile than their corresponding counterparts. The bottom line of Panel A reports the mean and the standard deviation of the risk-free rate. The real interest rate is constructed by subtracting the 12-month expected inflation from the annualized yield on the 3-month Treasury bill taken from the CRSP treasury files.

Finally, we take seasonally adjusted per-capita data on real consumption and gross domestic product (GDP) from the NIPA tables available on the Bureau of Economic Analysis website. Aggregate consumption is defined as consumer expenditures on non-durables and services. Summary statistics of consumption and GDP growth rates are presented in Panel B of Table I. Growth rates are constructed by taking the first difference of the corresponding log series. In addition, Panel B displays the mean and the standard deviation of the default premium measured as the difference in yields on Baa and Aaa corporate bonds published by the Board of Governors of the Federal Reserve System.

4 Empirical Findings

Estimating and testing equation (4) involves computing the pricing kernel in equation (11). To achieve this we require to specify the dynamics of consumption growth rate and x_t . An

econometrician who relies on the long risk model but relies on an annual data and decision interval will focus on annual consumption growth rates, $\Delta c_{t+1}^a \equiv \log(C_t^a/C_{t-1}^a)$, and the long run risk component, x_t^a .

An approach to estimate these components and risk factors in the annual data is to first specify a VAR which includes consumption growth and other predictive variables such as the price-dividend ratio, the risk-free rate, the default premium, etc. Specifically, let $Y_t^a = [\Delta c_t^a, v_t^a]$ where v_t^a is an $n - 1 \times 1$ vector of predictive variables.⁵ Assume that,

$$Y_{t+1}^a = BY_t^a + \Upsilon_{t+1}^a, \quad (20)$$

where B is an $n \times n$ matrix and Υ_{t+1}^a is a vector of residuals. Let ι_j be a row vector of zeros with one in j^{th} column. The persistent component, x_t^a , equals the conditional expectation of consumption growth which under the specification above is

$$x_t^a = \iota_1 BY_t^a.$$

Further, the innovation to consumption growth, which corresponds to high frequency shock is

$$\eta_{t+1}^a = \iota_1 \Upsilon_{t+1}^a.$$

The long run risk shock, e_{t+1}^a , is extracted by fitting an AR(1) to x_t^a , that is

$$x_{t+1}^a = \rho^a x_t^a + e_{t+1}^a$$

Given the dynamics of x_t^a and shocks η_{t+1}^a and e_{t+1}^a , the pricing kernel in (11) is computable for any configuration of preference parameters.

In principle, the volatility component can be estimated by adding a standard GARCH specification for Υ_{t+1}^a , but given the annual data and for other reasons discussed further below we only use the long run component in specifying consumption growth dynamics.⁶

⁵To simplify the notation, all the variables in equation (20) are de-meaned from the outset.

⁶In general, the above VAR can be augmented by the variance equation as in Bansal and Yaron (2004) model described in Section 2. In particular, the variance of consumption growth can be measured by taking an absolute value of consumption residuals, and, similarly to x^a , its dynamics can be modelled via a simple first-order autoregressive process. This would allow us to estimate the exposure of asset returns to volatility risks, $\beta_{w,j}^a$, and evaluate the market price of fluctuating economic uncertainty. Although feasible, this specification will unlikely yield a reliable estimate of the volatility component and its time-series behavior

4.1 What is X?

Table II provides the VAR in equation (20) for extracting x_t^a . In predicting consumption growth, we use a two-year moving average of lagged consumption growth, the log of consumption to GDP ratio, as well as other typical asset pricing predictive variables. Specifically, we use the price-dividend ratio of the aggregate market portfolio, the short interest rate, and the default premium. The price-dividend ratio rises, as theory predicts, when x_t^a rises. In addition, when consumption is above GDP it is predicted to revert back towards GDP's level. Finally, both the default premium and risk-free rate affect x_t^a in a significant way. There are two key features of Table II. First, consumption growth is highly predictable with an adjusted R^2 of 37%. Figure 1 provides the time series of x_t^a plotted along with realized consumption growth and NBER recessions. It is clear that this variable is relatively slow moving and captures features of the business cycle. Recessions are clearly associated with a decline in x_t^a . Together, this evidence clearly shows that the data is far from an *i.i.d* view for consumption growth. Second, the persistence parameter, ρ^a , is quite large at 0.67, implying an approximate monthly persistence of $0.67^{1/12} = 0.968$.

4.2 Returns and Betas

Before continuing on to formally estimating the model, we provide preliminary evidence linking the returns, betas, and market price of risk as described in equation (15). In order to derive the betas we use the following strategy. We first estimate the expected return for a given asset, $\bar{r}_{j,t+1}^a$, by projecting the asset return on lagged realized and expected growth of consumption, Δc_t and x_t respectively, as well as its own lagged dividend growth and price-dividend ratio. Given the innovations η_{t+1}^a and e_{t+1}^a , described above, and the innovations to the asset return, $u_{r,j,t+1}^a = r_{j,t+1}^a - \bar{r}_{j,t+1}^a$, we compute the asset's betas with respect to various consumption risks. Specifically, the long-run consumption beta is measured as $\beta_{e,j}^a \equiv \frac{\text{Cov}(e_{t+1}^a, u_{r,j,t+1}^a)}{\text{Var}(e_{t+1}^a)}$, while the exposure of asset returns to transient risks in consumption is

given a low sampling frequency of the data in hand. Therefore, in our empirical work, we abstract from time-varying uncertainty and focus primarily on the pricing of short- and long-run risks in consumption level. However, the volatility component is needed for matching salient features of annualized asset market data when in Section 5 we calibrate a monthly long run risk model and time aggregate it to annual frequency. We find that in the simulated annual data, as in the actual data, it is difficult to detect the presence of the volatility component.

constructed as $\beta_{\eta,j}^a \equiv \frac{\text{Cov}(\eta_{t+1}^a, u_{r,j,t+1}^a)}{\text{Var}(\eta_{t+1}^a)}$.

The cross-sectional prices of risks are estimated by regressing mean returns on the two betas, i.e.,

$$\bar{R}_j^a = \lambda_0^a + \lambda_\eta^a \beta_{\eta,j}^a + \lambda_e^a \beta_{e,j}^a + \epsilon_j^a \quad (21)$$

To expand the degrees of freedom, in the cross-sectional regression we employ the full asset menu consisting of 10 size and 10 book-to-market sorted portfolios plus the aggregate stock market. We find that the price of short-run consumption risks, although positive, is not significantly different from zero. In particular, $\hat{\lambda}_\eta^a = 0.33$ (SE=0.252). In contrast, the market price of low-frequency fluctuations in consumption is both positive and significant: $\hat{\lambda}_e^a = 0.58$ (SE=0.092). Together, the consumption betas explain about 50% of the cross-sectional variation in risk premia. It is worthy to note, though, that the predictive ability in the cross-section is entirely attributed to the long-run beta. Table III provides the betas for the five returns we consider. There is a clear link between average returns on these assets and their exposures to long-run risk as measured by β_e^a . In particular, note that value and growth portfolios have a β_e^a of 15.3 and 10.4 respectively reflecting the ‘value premium’; in a similar fashion the long run β ’s for small and big firms are 16.4 and 9.1 respectively, reflecting the effect of size. Finally, the table also provides the standard CCAPM betas, β_{ccapm}^a . It is quite evident that average returns are not well captured by these traditional betas, giving rise to the well documented failure of the CCAPM.

4.3 Euler Equation Estimation Evidence

This section provides the main results of our paper. The vector of structural parameters we seek to estimate includes the preference and technology parameters governing the dynamics for consumption. We utilize an annual version of equation (4) for the five asset returns: the risk-free rate, market return, value and growth, large and small firm portfolios in estimating this parameter vector. Table IV provides the estimates of the structural parameters based on the Euler equations for the Long Run Risk model for several alternative GMM weighting matrices. In the first panel, we use the identity matrix. In the second panel, we use the diagonal of the inverse of the returns’ covariance matrix which gives more weight to assets with lower volatility. The third panel describes the optimal covariance matrix. Each of these panels provides the structural parameters regarding preferences, namely, IES, and risk

aversion (ψ , and γ), where we pre-set the time discount rate, δ , to 0.9989¹². In addition, we provide the average pricing error for each of the returns, and the J test for overidentifying restrictions.

The results are quite illuminating. For the identity matrix, risk aversion is above 27 and the IES is 0.6. For the inverse of the covariance return matrix, the results are similar; risk aversion is 23, and IES is 0.7. In both cases the standard errors for the IES and risk aversion are quite large. For the optimal weighting matrix the GMM procedure leads to similar estimates for the preference parameters, and the model again can not be rejected at standard significance levels.⁷ The main feature of the results is the fact that the model prices assets quite well. Formally the model is not rejected as the overidentifying restrictions have p-values above 0.2 for all alternative weighting matrices. Moreover, the pricing errors are quite small. The largest pricing error is only 0.059 for the return on the portfolio of small stocks when using the optimal weighting matrix. For comparison, Table V provides similar results for the more restrictive case of time separable CRRA preferences. As is well known, these preferences have more difficulty in pricing assets. The model's overidentifying restriction test is rejected when the weighting matrix used is the returns covariance matrix, and is only marginally significant for the other two weighting matrices (a p-value of 12%). Moreover, the pricing errors are substantially larger for the CRRA preferences. In particular, the maximal pricing error (for small portfolio) is now around 22%, while there are other two digit pricing errors. Perhaps, the most apparent discrepancy in statistical fit between the CRRA preferences and the LRR model is the pricing errors of a portfolio of Value minus Growth, and Small minus Large. While the t-statistics on these two pricing errors are insignificant for the LRR model, they are statistically rejected for the CRRA model.

Finally, our results are robust to alternative use of instruments. In results that are not reported here, we use more elaborate system of instruments to capture potential important variation in conditional moments. For example, adding lagged consumption growth, or risk free rate or market return as instruments, leads to similar large (above twenty) risk aversion estimates.

In sum, our model shows that once the return to wealth is appropriately accounted for, the Long Run Risk Model can account quite well for both the time series and cross sectional

⁷The results are quite similar when we use the continuously updated weighting matrix, as in Hansen, Heaton, and Yaron (1996), to those using the inverse of the covariance matrix of returns.

variation in returns. A concerning open issue is the fact that the IES seems to be below one and risk aversion is quite large. This parameter configuration in simulations of the Long Run Risk model is likely to produce data features which are counterfactual. This consequently raises an important issue in terms of interpreting the empirical evidence documented in the data in this paper and in earlier work. In the remaining sections we address this issue by highlighting the effects of time aggregation. In particular, we show that even if the population risk aversion is low and the IES is larger than one, the GMM when contaminated by time aggregation effects will produce estimates, as in our case above, of high risk aversion and low IES. More specifically, we write down a *monthly* Long Run Risk Model of the type specified in equation (3) and show that time aggregation to *annual* data leads to downward bias in the estimated IES and an upward bias in the estimated risk aversion, while maintaining the ability to price annual asset returns.

5 Decision Interval and Time Aggregation

In this section we examine the effects the decision interval and time aggregation have on the economic plausibility of the Long Run Risk model and the interpretation of structural parameters. In particular, we wish to assess how time aggregation affects the estimation procedure utilized in the previous section. To do so we calibrate a monthly version of the Long Run Risk model and then time aggregate the data to construct simulated annual variables counterpart to their observed data.

5.1 Consumption, Dividends, and Asset Returns

To complete the specification of the model, we need, in addition to the consumption dynamics already given in (3), to specify the dividend dynamics of each asset j ,

$$\Delta d_{j,t+1} = \mu_d + \phi_j x_t + \pi_j \sigma_t \eta_{t+1} + \varphi_j \sigma_t u_{d,j,t+1} \quad (22)$$

where $\Delta d_{j,t+1}$ is the dividend growth rate of portfolio j . In addition, we assume that all shocks are *i.i.d* normal and are orthogonal to each other, although we allow for cross-sectional correlations in dividend news, $u_{d,j,t+1}$. Dividends have a levered exposure to the persistent component in consumption, x_t , which is captured by the parameter ϕ_j . In addition, we

allow the *i.i.d* consumption shock η_{t+1} to influence the dividend process, and thus serve as an additional source of risk premia. The magnitude of this influence is governed by the parameter π_j .⁸ In essence, save for this addition, the dynamics are similar to those in Bansal and Yaron (2004). The model is assumed to have a monthly decision interval and the parameters governing the consumption and dividend dynamics are given in Panels A of Table VI and VII respectively. Throughout we use a risk aversion parameter of 10 and an IES value of 2.

We simulate from the monthly consumption and dividend dynamics specified in equations (3) and (22). We construct the appropriate time aggregated C_t^a and D_t^a level series and then construct their annual growth rates. Panel B of Table VI provides Monte-Carlo evidence regarding the annual time series of consumption growth. Specifically, we simulate the model with 876 months which results in 73 annual observations as in our data set. We replicate this over 500 simulations. The last two columns in Table VI are the median and standard deviation respectively of annual consumption growth across these simulations. The table clearly shows that the model successfully matches the mean, standard deviation, and autocorrelation of annual consumption growth.

Panel A of Table VII provides the parameters governing the dividend dynamics for the five assets we consider. Panel B of this table, provides information regarding the mean, standard deviation of dividend growth and its correlation with consumption growth from the data and the model. Again, the model's statistics are based on the median and standard deviation across the 500 Monte-Carlo simulations. By and large, the model's output matches quite well with the data. The correlations between consumption and dividend growth are essentially indistinguishable from their point estimates in the data. The data and the model's mean dividend growth rates are all within standard error of each other. More importantly, the ranking across the four assets of interest is maintained. The volatility of dividend growth is matched very precisely (and within one standard error) for the market, growth and large portfolios. For the small and value portfolios the model's median volatility is quite smaller than that implied by the data. However, these two portfolios' extreme volatility are driven by few data points. Our approach is to be more conservative with respect to these volatility numbers while ensuring the model generates average returns that are comparable to what is observed in the data.

⁸Note that this type of specification is isomorphic to one in which $\pi_j = 0$ but the correlation between η_{t+1} and $u_{d,j,t+1}$ is non-zero.

Table VIII provides the data and model predictions for the mean and volatility of the return as well as the level of the price dividend ratio for each asset. Again, the model replicates quite well all of these statistics. The data is well within one standard error of the model estimates. In particular, note that the model is able to generate the ‘size’ and ‘value’ premium.

5.2 GMM Estimation and Time Aggregation

Equipped with plausible model-generated data for returns, we use GMM on the annual simulated data and test equation (4) in an analogous fashion to the estimation procedure we used for the observed data. Table IX provides the distribution of risk aversion and IES estimates, as well as the $J-Stat$ and p-values across the 500 simulations. This table provides several important implications. First, the mean of the risk aversion and IES estimates across simulations is quite close to those estimated directly on the annual data in Table IV. This holds true for the different weighting schemes used. Noteworthy is the fact that the mean risk aversion is large and is between 17 (for the optimal weighting matrix) and 19 (for the identity weighting matrix). Figure 2 provides a histogram of the risk aversion estimates using the optimal and identity weighting matrix; the dispersion and right skewness are apparent. Moreover, the mean estimates for the IES are all less than 1. Recall, these simulations are based on a model in which risk aversion is 10 and the IES is 2. Thus, time aggregation leads to severe downward bias in IES and quite significant upward bias in risk aversion. Further, note that the model is not rejected by the overidentifying restrictions. In fact the mean $J-Stat$ is quite close to that estimated by the data in Table IV which is well within the 90% confidence interval generated by the simulations.

Table X provides analogous estimates for risk aversion, the IES, and $J-Stat$ when the moment conditions specialize the utility function to power utility as in Table V. The risk aversion estimates are larger than those for the Epstein and Zin (1989) preferences in Table IX. Figure 2 also provides the histogram of risk aversion estimates across simulations for the power utility preferences. The distribution is large and seem to be somewhat bimodal with a mass at small and very large risk aversion levels. The model is rejected based on the mean $J-Stats$ and the pricing errors deteriorate substantially relative to the case of Epstein-Zin preferences. In this respect the results of imposing the power utility restriction are similar to those estimated in the data as seen in comparing Tables IV and V.

Together, Tables IX-X remarkably replicate the results in Tables IV-V, providing additional support in favor of the model proposed and estimated. A natural question to ask is why the IES is estimated with a downward bias while risk aversion is estimated with an upward bias? The answer hinges on time aggregation. As explained in section 2.3 time aggregation (in conjunction with stochastic volatility) reduces the persistence of the monthly x_t process and therefore the ability of the model to generate risk premia.

In Table XI we isolate the time aggregation effects from those of having a finite sample by estimating the model using a very long annual sample. The top two rows in this table provide the persistence ρ^a of x_t^a and the R^2 of consumption growth process. It is clear that even in a very long sample the autocorrelation in x_t^a is obviously lower than that of x_t but more surprisingly is also quite lower than that of ρ^{12} . That is the long sample's autocorrelation is 0.70 while the monthly's model autocorrelation (0.982) raised to the power of 12 is 0.80. Finally, the median estimate for ρ in finite samples is 0.65 (the 5% and 95% quintiles are 0.34 and 0.85 respectively), which shows that finite sample contributes to another small reduction in the persistence of the long run component. Based on this long sample, the remaining panels of this table provide the GMM estimates of risk aversion and IES for the three alternative weighting matrices. Specifically, risk aversion is around 13-14 (relative to a true population value of 10) and the IES is around 0.7 relative to a population of value 2. Note, however, that the p-values of the overidentifying restrictions of the model are significantly and uniformly rejected across the various weighting matrices. This information compared to the results in Table IX shows that finite sample properties are, to a large degree, responsible for the non rejection results of the model.

As emphasized in section 2.3 risk aversion and persistence play complementary roles in contributing to risk premia. To generate risk premia while compensating for the downward bias in persistence, as just shown above, the estimated risk aversion is increased relative to its true value. This larger risk aversion has an adverse effect in lowering the risk free rate through the precautionary effect term. To compensate for that, the IES is lowered. This is demonstrated by the fact that in the simulations the correlation between γ and μ/ψ , the non precautionary term of the risk free rate, is 0.60. Together, this evidence underscores the importance of sampling frequency and the potential consequences of extracting preferences from time aggregated data.

Epstein and Zin (1991) pursue a GMM estimation approach but in evaluating the pricing

kernel in equation (5) replace the return on the consumption claim $r_{c,t+1}$ with the observed value weighted NYSE stock market return. In Table XII we use our simulated data to estimate the model with a pricing kernel based on the market return. The estimated risk aversion is quite low. This, to a large extent, is due to the large volatility induced into the pricing kernel by the volatile market return. Finally, and most importantly, the table clearly shows that the model’s overidentifying restrictions are overwhelmingly rejected. Finite sample experiments also lead to vast rejection of the model. The implication of this experiment is that deriving the appropriate return on consumption is critical for appropriately assessing the LRR model.

6 Conclusions

This paper establishes a practical method for obtaining the long run risk component – an essential ingredient of the Long Run Risk model proposed in Bansal and Yaron (2004). Using this we are able to empirically construct the unobservable return on total wealth, a required input in pricing assets when using the Epstein and Zin (1989) preferences. The Long Run Risk model is quite successful at capturing the time series and cross-sectional variation in returns. The model prices assets quite well including the ‘value’ and ‘size’ premium. A calibrated version of the model generates the equity premium, volatility of the market return, and the mean and volatility of the risk free rate as well as the returns on several portfolios and their price-dividend ratios. In using the model as a data generating process we show that time aggregation leads to downward biased estimates of the IES and upward bias in risk aversion — and to estimates of similar magnitude to the levels estimated using the observed data. Together, this information provides strong evidence in favor of the long run risk model, while at the same time reconciling why often the literature had found large values of risk aversion and small values of the IES.

7 Appendix

To derive asset prices we use the IMRS together with consumption and dividend dynamics given in (3) and (22). The Euler condition in equation (4) implies that any asset j in this economy should satisfy the following pricing restriction,

$$E_t \left[\exp \left(\theta \ln \delta - \frac{\theta}{\psi} \Delta c_{t+1} + (\theta - 1) r_{c,t+1} + r_{j,t+1} \right) \right] = 1, \quad (23)$$

where $r_{j,t+1} \equiv \log(R_{j,t+1})$ and $r_{c,t+1}$ is the log return on wealth. Notice that the solution to (23) depends on time-series properties of the unobservable return r_c . Therefore, we first substitute $r_{j,t+1} = r_{c,t+1}$ and solve for the return on the aggregate consumption claim; after that, we present the solution for the return on a dividend-paying asset.

7.1 Consumption Claim

We start by conjecturing that the logarithm of the price to consumption ratio follows, $z_t = A_0 + A_1 x_t + A_2 \sigma_t^2$. Armed with the endogenous variable z_t , we plug the approximation $r_{c,t+1} = \kappa_0 + \Delta c_{t+1} + \kappa_1 z_{t+1} - z_t$ into the Euler equation above. The solution coefficients, A 's, can now be easily derived by collecting the terms on the corresponding state variables. In particular,

$$\begin{aligned} A_0 &= \frac{1}{1 - \kappa_1} \left[\log \delta + \kappa_0 + \left(1 - \frac{1}{\psi} \right) \mu_c + \kappa_1 A_2 (1 - \nu) \bar{\sigma}^2 + \frac{\theta}{2} \left(\kappa_1 A_2 \sigma_w \right)^2 \right] \\ A_1 &= \frac{1 - \frac{1}{\psi}}{1 - \kappa_1 \rho} \\ A_2 &= - \frac{(\gamma - 1) \left(1 - \frac{1}{\psi} \right)}{2 (1 - \kappa_1 \nu)} \left[1 + \left(\frac{\kappa_1 \varphi_e}{1 - \kappa_1 \rho} \right)^2 \right] \end{aligned} \quad (24)$$

For more details, see the the appendix in Bansal and Yaron (2004).

Notice that the derived solutions depend on the approximating constants, κ_0 and κ_1 , which, in their turn, depend on the unknown mean of the price to consumption ratio, \bar{z} . In order to solve for the price of the consumption asset, we first substitute expressions for κ 's

(equations (7) and (8)) into the expressions for A 's and solve for the mean of the price to consumption ratio. Specifically, \bar{z} can be found by numerically solving a fixed-point problem:

$$\bar{z} = A_0(\bar{z}) + A_2(\bar{z})\bar{\sigma}^2 ,$$

where the dependence of A 's on \bar{z} is given above.

The solution for the price-consumption ratio, z_t , allows us to write the pricing kernel as a function of the evolution of the state variables and the model parameters,

$$m_{t+1} = \Gamma_0 + \Gamma_1 x_t + \Gamma_2 \sigma_t^2 - \lambda_\eta \sigma_t \eta_{t+1} - \lambda_e \sigma_t e_{t+1} - \lambda_w \sigma_w w_{t+1} , \quad (25)$$

where

$$\begin{aligned} \Gamma_0 &= \log \delta - \frac{1}{\psi} \mu_c - (\theta - 1) \left[A_2 (1 - \nu) \bar{\sigma}^2 + \frac{\theta}{2} (\kappa_1 A_2 \sigma_w)^2 \right] \\ \Gamma_1 &= -\frac{1}{\psi} \\ \Gamma_2 &= (\theta - 1) (\kappa_1 \nu - 1) A_2 \end{aligned} \quad (26)$$

and

$$\begin{aligned} \lambda_\eta &= \gamma \\ \lambda_e &= (1 - \theta) \kappa_1 A_1 \varphi_e = (\gamma - \frac{1}{\psi}) \frac{\kappa_1 \varphi_e}{1 - \kappa_1 \rho} \\ \lambda_w &= (1 - \theta) \kappa_1 A_2 = -(\gamma - 1) (\gamma - \frac{1}{\psi}) \frac{\kappa_1}{2(1 - \kappa_1 \rho)} \left[1 + \left(\frac{\kappa_1 \varphi_e}{1 - \kappa_1 \rho} \right)^2 \right] \end{aligned} \quad (27)$$

Note that λ 's represent market prices of transient (η_{t+1}), long-run (e_{t+1}) and volatility (w_{t+1}) risks respectively. For more detailed discussion see Bansal and Yaron (2004).

7.2 Dividend Paying Assets

The solution coefficients for the valuation ratio of a dividend-paying asset j can be derived in a similar fashion as for the consumption asset. In particular, the price-dividend ratio for

a claim to dividends, $z_{j,t} = A_{0,j} + A_{1,j}x_t + A_{2,j}\sigma_t^2$, where

$$\begin{aligned}
A_{0,j} &= \frac{1}{1 - \kappa_{1,j}} \left[\Gamma_0 + \kappa_{0,j} + \mu_{d_j} + \kappa_{1,j}A_{2,j}(1 - \nu)\bar{\sigma}^2 + \frac{1}{2} \left(\kappa_{1,j}A_{2,j} - \lambda_w \right)^2 \sigma_w^2 \right] \\
A_{1,j} &= \frac{\phi_j - \frac{1}{\psi}}{1 - \kappa_{1,j}\rho} \\
A_{2,j} &= \frac{1}{1 - \kappa_{1,j}\nu} \left[\Gamma_2 + \frac{1}{2} \left((\pi_j - \lambda_\eta)^2 + (\kappa_{1,j}A_{1,j}\varphi_e - \lambda_\epsilon)^2 \right) \right]
\end{aligned} \tag{28}$$

It follows then that the innovation into the asset return is given by,

$$r_{j,t+1} - E_t[r_{j,t+1}] = \varphi_j \sigma_t u_{j,t+1} + \beta_{\eta,j} \sigma_t \eta_{t+1} + \beta_{e,j} \sigma_t e_{t+1} + \beta_{w,j} \sigma_w w_{t+1} , \tag{29}$$

where the asset's betas are defined as,

$$\begin{aligned}
\beta_{\eta,j} &= \pi_j \\
\beta_{e,j} &= \kappa_{1,j}A_{1,j}\varphi_e \\
\beta_{w,j} &= \kappa_{1,j}A_{2,j}
\end{aligned}$$

The risk premium for any asset is determined by the covariation of the return innovation with the innovation into the pricing kernel. Thus, the risk premium for $r_{j,t+1}$ is equal to the asset's exposures to systematic risks multiplied by the corresponding risk prices,

$$\begin{aligned}
E_t(r_{j,t+1} - r_{f,t}) + 0.5\sigma_{t,r_j}^2 &= -Cov_t(m_{t+1} - E_t(m_{t+1}), r_{j,t+1} - E_t(r_{j,t+1})) \\
&= \lambda_\eta \sigma_t^2 \beta_{\eta,j} + \lambda_e \sigma_t^2 \beta_{e,j} + \lambda_w \sigma_w^2 \beta_{w,j}
\end{aligned}$$

7.3 IES=1

When $\psi = 1$, the log of the IMRS is given in terms of the value function normalized by consumption, $vc_t = \log(V_t/C_t)$,

$$m_{t+1} = \log \delta - \gamma \Delta c_{t+1} + (1 - \gamma)vc_{t+1} - \frac{1 - \gamma}{\delta} vc_t$$

Conjecturing that $vc_t = B_0 + B_1x_t + B_2\sigma_t^2$ and using the evolution of vc_t :

$$vc_t = \frac{\delta}{1-\gamma} \log E_t \left[\exp\{(1-\gamma)(vc_{t+1} + \Delta c_{t+1})\} \right],$$

the solution coefficients are given by,

$$B_0 = \frac{\delta}{1-\delta} \left[\mu + B_2(1-\nu)\bar{\sigma}^2 + \frac{1}{2}(1-\gamma)(B_2\sigma_w)^2 \right]$$

$$B_1 = \frac{\delta}{1-\delta\rho} \tag{30}$$

$$B_2 = -(\gamma-1) \frac{\delta}{2(1-\delta\nu)} \left[1 + \left(\frac{\delta\varphi_e}{1-\delta\rho} \right)^2 \right] \tag{31}$$

As above, the pricing kernel can be expressed in terms of underlying preference parameters, state variables and systematic shocks,

$$m_{t+1} = \Gamma_0 + \Gamma_1x_t + \Gamma_2\sigma_t^2 - \lambda_\eta\sigma_t\eta_{t+1} - \lambda_\epsilon\sigma_t\epsilon_{t+1} - \lambda_w\sigma_w w_{t+1} \tag{32}$$

where:

$$\Gamma_0 = \log \delta - \mu - (1-\gamma) \left[\frac{1}{\delta} B_2(1-\nu)\bar{\sigma}^2 + \frac{1}{2}(1-\gamma)(B_2\sigma_w)^2 \right] \tag{33}$$

$$\Gamma_1 = -1$$

$$\Gamma_2 = -\frac{(\gamma-1)^2}{2} \left[1 + \left(\frac{\delta\varphi_e}{1-\delta\rho} \right)^2 \right]$$

and

$$\lambda_\eta = \gamma \tag{34}$$

$$\lambda_\epsilon = (\gamma-1) \frac{\delta\varphi_e}{1-\delta\rho}$$

$$\lambda_w = -(\gamma-1)^2 \frac{\delta}{2(1-\delta\rho)} \left[1 + \left(\frac{\delta\varphi_e}{1-\delta\rho} \right)^2 \right]$$

Finally, note that in the IES=1 case, the wealth-to-consumption ratio is constant, namely, $\frac{W_t}{C_t} = \frac{1}{1-\delta}$. The price-to-consumption ratio, therefore, is equal $\frac{P_t}{C_t} = \exp(\bar{z}) = \frac{\delta}{1-\delta}$. Consequently, the parameter of the log-approximation of the log-wealth return,

$$\kappa_1 = \frac{\exp(\bar{z})}{1 + \exp(\bar{z})} = \frac{\frac{\delta}{1-\delta}}{1 + \frac{\delta}{1-\delta}} = \delta.$$

Plugging $\kappa_1 = \delta$ and $\psi = 1$ into equations (25), (26) and (27), yields exactly equation (32), (33) and (34). It then follows that

$$\lim_{\psi \rightarrow 1} \kappa_1 = \delta \quad \lim_{\psi \rightarrow 1} \Gamma' = \Gamma'(\psi = 1, \kappa_1 = \delta) \quad \lim_{\psi \rightarrow 1} \Lambda' = \Lambda'(\psi = 1, \kappa_1 = \delta) \quad (35)$$

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Table I
Summary Statistics

Panel A: Asset Data

	Returns		Div Growth		Log(P/D)	
	Mean	StdDev	Mean	StdDev	Mean	StdDev
Size Portfolios						
Small	0.134	0.34	0.066	0.27	4.07	0.62
Large	0.076	0.19	0.003	0.11	3.30	0.43
B/M Portfolios						
Growth	0.070	0.22	-0.003	0.16	3.71	0.62
Value	0.134	0.33	0.047	0.29	3.42	0.68
Market	0.083	0.20	0.007	0.11	3.33	0.46
Risk-free Rate	0.008	0.01				

Panel B: Predictive Variables

	Mean	StdDev
Consumption Growth	0.020	0.022
GDP Growth	0.022	0.051
Default Spread	0.012	0.007

Panel A of Table I presents descriptive statistics for returns, dividend growth rates and logarithms of price-dividend ratios of size and book-to-market sorted portfolios, and the aggregate stock market. Small and large portfolios represent firms in the top and bottom market capitalization deciles, growth and value correspond to the lowest and highest book-to-market decile. Returns are value-weighted, dividends and price-dividend ratios are constructed on the per-share basis, growth rates are measured by taking the first difference of the logarithm of dividend series. The bottom line of Panel A reports the mean and the standard deviation of the annualized yield on the 3-month Treasury bill. Panel B presents sample statistics for the per-capita consumption of nondurables and services, gross domestic product (GDP), and the default premium. The latter is defined as the difference in yields on Baa and Aaa corporate bonds. All asset and macro data are real, sampled on an annual frequency and cover the period from 1930 to 2002.

Table II
Predictability of Consumption Growth

Predictor	Estimate	t-stat
2-yr Moving Ave of Cons Growth	0.445	2.90
Log(Cons/GDP)	-0.070	-2.52
Default Spread	1.912	3.62
Short Interest Rate	-0.116	-2.09
Log(P/D)	0.019	2.30
$\bar{R}^2 = 0.37$		

Table II presents predictability evidence for consumption growth. The second column reports estimated regression coefficients from projecting consumption growth onto lagged predictive variables. The corresponding t-statistics are calculated using the Newey-West variance-covariance estimator with 4 lags. The data employed in the regression are annual and span the period from 1930 to 2002.

Table III
Consumption Betas

	Mean Ret	β_{η}^a	β_e^a	β_{ccapm}^a
Small	0.134	0.51	16.40	0.71
Large	0.076	2.22	9.10	0.69
Growth	0.070	2.65	10.69	0.82
Value	0.134	0.90	15.30	0.14
Market	0.083	2.28	10.40	0.59

Table III presents mean returns and consumption betas for firms in the lowest and highest deciles of size and book-to-market sorted portfolios — small and large, and growth and value, respectively, as well as the aggregate stock market. Consumption betas are calculated as the covariation between consumption news and innovations in asset returns scaled by the variance of the corresponding consumption shock. β_{η}^a represents the exposure of returns to transient shocks in consumption, β_e^a measures risks related to long-run fluctuations in consumption. Short-run consumption innovations are constructed by removing the conditional mean from the realized growth in consumption, where the former is modelled according to Table II. Long-run consumption risks are extracted by fitting an AR(1) process to the expected growth component. Innovations in returns are constructed using a log-linear approximation of returns and estimated VAR(1)-dynamics for dividend growth rates and price-dividend ratios. The frequency of the data is annual, the sample covers the period from 1930 to 2002.

Table IV
Estimation Evidence: Long Run Risk Model

	Panel A: W = Identity		Panel B: W = diag{Var(R)} ⁻¹		Panel C: W = Optimal	
<i>Parameter</i>	Estimate	SE	Estimate	SE	Estimate	SE
RA	27.70	8.67	22.89	7.37	22.25	6.89
IES	0.59	2.57	0.70	2.67	0.80	3.02
<i>Asset</i>	PrError	t-stat	PrError	t-stat	PrError	t-stat
Small	0.038	0.30	0.054	0.53	0.059	0.59
Large	-0.020	-0.18	-0.009	-0.11	-0.004	-0.05
Growth	-0.032	-0.29	-0.020	-0.24	-0.015	-0.19
Value	0.021	0.18	0.037	0.40	0.042	0.46
Market	-0.018	-0.16	-0.006	-0.07	-0.001	-0.01
Risk-Free	0.012	0.09	0.000	0.00	0.003	0.03
Small-Large	0.058	1.33	0.063	1.45	0.063	1.45
Value-Growth	0.052	1.62	0.057	1.82	0.057	1.83
<i>J-stat</i>	5.60		5.28		5.93	
<i>p-value</i>	0.23		0.26		0.20	

Table IV presents GMM estimates of Long Run Risk model: the risk aversion parameter (RA) and the elasticity of intertemporal substitution (IES). Three vertical panels summarize estimation results for different weighting schemes: the identity matrix (A), the inverse of the diagonal of the variance-covariance matrix of returns (B) and the optimal weighting matrix (C). The asset menu consists of firms with small and large market capitalization, low and high book-to-market ratio (growth and value, respectively), aggregate stock market and the risk-free rate. Average pricing errors and their t-statistics are presented for each asset. The bottom two lines report J-statistics for overidentifying restrictions and the corresponding p-values. The data employed in the estimation are annual and cover the period from 1930 to 2002.

Table V
Estimation Evidence: CRRA Preferences

	Panel A: W = Identity		Panel B: W = diag{Var(R) ⁻¹ }		Panel C: W = Optimal	
<i>Parameter</i>	Estimate	SE	Estimate	SE	Estimate	SE
RA	4.07	1.35	42.86	7.71	2.51	0.75
<i>Asset</i>	PrError	t-stat	PrError	t-stat	PrError	t-stat
Small	0.072	1.38	0.220	0.32	0.104	1.91
Large	-0.017	-0.70	-0.007	-0.02	0.013	0.61
Growth	-0.021	-0.83	-0.036	-0.08	0.009	0.37
Value	0.044	1.24	0.134	0.22	0.075	2.03
Market	-0.009	-0.40	0.009	0.02	0.021	0.96
Risk-Free	-0.081	-2.99	-0.003	-0.01	-0.054	-2.87
Small-Large	0.089	2.02	0.227	1.18	0.090	2.01
Value-Growth	0.065	2.54	0.170	1.19	0.066	2.55
<i>J-stat</i>	8.64		12.14		8.64	
<i>P-value</i>	0.12		0.03		0.12	

Table V presents GMM estimates of the parameter of risk aversion (RA) for CRRA preferences. Three vertical panels summarize estimation results for different weighting schemes: the identity matrix (A), the inverse of the diagonal of the variance-covariance matrix of returns (B) and the optimal weighting matrix (C). The asset menu consists of firms with small and large market capitalization, low and high book-to-market ratio (growth and value, respectively), aggregate stock market and the risk-free rate. Average pricing errors and their t-statistics are presented for each asset. The bottom two lines report J-statistics for overidentifying restrictions and the corresponding p-values. The data employed in the estimation are annual and cover the period from 1930 to 2002.

Table VI
Consumption Growth Dynamics

Panel A: Calibration of Monthly Consumption Growth

μ_c	ρ	φ_e	$\bar{\sigma}$	ν	σ_w
0.0015	0.982	0.042	0.0054	0.98	0.0000068

Panel B: Dynamics of Annual Consumption Growth

Statistic	— Data —	— Model —
$E[\Delta c]$	1.96 (0.34)	1.72 (0.57)
$\sigma(\Delta c)$	2.21 (0.38)	2.28 (0.38)
$AC(1)$	0.44 (0.13)	0.47 (0.13)

Panel A of Table VI summarizes the calibration of parameters that govern the dynamics of monthly consumption growth:

$$\begin{aligned}
 \Delta c_{t+1} &= \mu_c + x_t + \sigma_t \eta_{t+1} \\
 x_{t+1} &= \rho x_t + \varphi_e \sigma_t e_{t+1} \\
 \sigma_{t+1}^2 &= \bar{\sigma}^2 + \nu(\sigma_t^2 - \bar{\sigma}^2) + \sigma_w w_{t+1}
 \end{aligned}$$

Panel B reports the mean, the volatility and the first-order autocorrelation of annual consumption growth. “Data” column presents summary statistics of observed per-capita consumption of non-durables and services over the period from 1930 till 2002. Numbers in parentheses are robust standard errors calculated using the Newey-West variance-covariance estimator with 4 lags. The entries reported in “Model” column are based on 500 simulated samples, each with 876 months, time-aggregated to 73 annual observations. Model-implied statistics represent the median and the standard deviation (in parentheses) of the corresponding statistics across simulations.

Table VII
Dividend Growth Dynamics

Panel A: Calibration of Monthly Dividend Growth Rates

Asset	μ_d	ϕ	π	φ
Small	0.0055	4.7	0.5	5.0
Large	0.0015	2.3	3.3	5.7
Growth	0.0015	1.9	3.6	7.1
Value	0.0040	4.4	1.9	5.2
Market	0.0015	2.3	3.8	5.4

Panel B: Dynamics of Annual Dividend Growth Rates

Asset	Statistic	— Data —		— Model —	
Small	$E[\Delta d]$	6.57	(4.15)	6.49	(2.66)
	$\sigma(\Delta d)$	27.2	(4.19)	11.1	(1.81)
	$Corr(\Delta c, \Delta d)$	0.44	(0.09)	0.43	(0.13)
Large	$E[\Delta d]$	0.34	(1.09)	1.67	(2.08)
	$\sigma(\Delta d)$	10.5	(1.69)	12.0	(1.64)
	$Corr(\Delta c, \Delta d)$	0.50	(0.15)	0.55	(0.11)
Growth	$E[\Delta d]$	-0.26	(1.65)	1.77	(2.20)
	$\sigma(\Delta d)$	16.3	(1.94)	14.0	(2.07)
	$Corr(\Delta c, \Delta d)$	0.47	(0.10)	0.47	(0.12)
Value	$E[\Delta d]$	4.67	(3.40)	4.73	(2.68)
	$\sigma(\Delta d)$	28.6	(3.61)	11.5	(1.83)
	$Corr(\Delta c, \Delta d)$	0.51	(0.07)	0.57	(0.11)
Market	$E[\Delta d]$	0.74	(1.18)	1.63	(2.04)
	$\sigma(\Delta d)$	11.0	(1.92)	12.1	(1.64)
	$Corr(\Delta c, \Delta d)$	0.60	(0.14)	0.61	(0.10)

Panel A of Table VII presents the calibration of monthly dividend growth rates for the cross-section of assets:

$$\Delta d_{j,t+1} = \mu_{d_j} + \phi_j x_t + \pi_j \sigma_t \eta_{t+1} + \varphi_j \sigma_t u_{d,j,t+1}$$

The asset menu comprises small and large market capitalization firms, growth and value portfolios that represent low and high book-to-market firms respectively, and the aggregate stock market. Panel B reports the mean and the volatility of dividend growth rates, as well as their correlation with consumption growth. “Data” column presents summary statistics of the per-share dividend series observed over 1930-2002 time period. Numbers in parentheses are robust standard errors calculated using the Newey-West variance-covariance estimator with 4 lags. The entries reported in “Model” column are based on 500 simulated samples, each with 876 months, time-aggregated to 73 annual observations. Model-implied statistics represent the median and the standard deviation (in parentheses) of the corresponding statistics across simulations.

Table VIII
Asset Pricing Implications

Asset	Statistic	— Data —		— Model —	
Small	$E(R)$	13.45	(4.18)	13.04	(3.16)
	$\sigma(R)$	33.9	(3.84)	28.6	(4.25)
	$E(pd)$	4.07	(0.15)	3.68	(0.10)
Large	$E(R)$	7.58	(2.19)	7.68	(2.27)
	$\sigma(R)$	19.1	(1.79)	18.3	(2.84)
	$E(pd)$	3.30	(0.10)	3.21	(0.05)
Growth	$E(R)$	7.01	(2.40)	6.69	(2.40)
	$\sigma(R)$	21.6	(1.89)	19.8	(3.16)
	$E(pd)$	3.71	(0.15)	3.54	(0.04)
Value	$E(R)$	13.37	(3.03)	12.63	(3.08)
	$\sigma(R)$	33.1	(3.89)	26.7	(3.97)
	$E(pd)$	3.42	(0.15)	3.17	(0.09)
Market	$E(R)$	8.27	(2.10)	7.90	(2.26)
	$\sigma(R)$	20.1	(1.88)	18.7	(2.86)
	$E(pd)$	3.33	(0.11)	3.15	(0.05)
Risk-Free Rate	$E(R)$	0.76	(0.27)	1.06	(0.29)
	$\sigma(R)$	1.12	(0.22)	0.89	(0.17)

Table VIII presents asset pricing moments for five equity portfolios and the risk-free rate. Small and large are portfolios of firms with low and high market capitalization, growth and value correspond to the top and the bottom book-to-market deciles. $E(R)$, $\sigma(R)$ and $E(pd)$ denote expected returns, return volatilities and means of log price-dividend ratios respectively. “Data” column presents summary statistics of the observed annual data that span the period from 1930 to 2002. Numbers in parentheses are robust standard errors calculated using the Newey-West variance-covariance estimator with 4 lags. The entries reported in “Model” column are based on 500 simulated samples, each with 876 months, time-aggregated to 73 annual observations. Model-implied statistics represent the median and the standard deviation (in parentheses) of the corresponding statistics across simulations.

Table IX
Simulation Evidence: Long Run Risk Model

		Mean	5%	50%	95%
Panel A: W = Identity	<i>RA</i>	19.11	8.56	17.51	39.16
	<i>IES</i>	0.56	0.16	0.41	1.06
	<i>J-stat</i>	5.90	1.95	5.83	9.51
	<i>P-value</i>	0.26	0.05	0.21	0.75
Panel B: W = $\text{diag}\{\text{Var}(\mathbf{R})^{-1}\}$	<i>RA</i>	17.55	7.77	15.95	33.44
	<i>IES</i>	0.57	0.18	0.54	1.00
	<i>J-stat</i>	6.11	1.60	5.94	9.99
	<i>P-value</i>	0.27	0.04	0.20	0.81
Panel C: W = Optimal	<i>RA</i>	16.74	7.31	15.17	31.08
	<i>IES</i>	0.96	0.18	0.67	2.53
	<i>J-stat</i>	5.95	2.06	5.85	9.49
	<i>P-value</i>	0.26	0.05	0.21	0.72

Table IX presents the distribution of GMM estimates of the Long Run Risk Model, J-statistics for overidentifying restrictions and the corresponding p-values. RA and IES denote risk aversion and the elasticity of intertemporal substitution respectively. Three horizontal panels summarize estimation results for different weighting schemes: the identity matrix (A), the inverse of the diagonal of the variance-covariance matrix of returns (B) and the optimal weighting matrix (C). The asset menu consists of firms with small and large market capitalization, low and high book-to-market ratio, aggregate stock market and the risk-free rate. The entries are based on 500 simulated samples, each with 876 months, time-aggregated to 73 annual observations.

Table X
Simulation Evidence: CRRA Preferences

		Mean	5%	50%	95%
Panel A: W = Identity	<i>RA</i>	33.41	2.79	36.82	75.67
	<i>J-stat</i>	7.30	2.54	7.39	11.93
	<i>P-value</i>	0.27	0.04	0.19	0.77
Panel B: W = diag{Var(R) ⁻¹ }	<i>RA</i>	50.35	0.14	54.17	80.45
	<i>J-stat</i>	23.61	4.27	13.95	75.48
	<i>P-value</i>	0.09	0.00	0.02	0.51
Panel C: W = Optimal	<i>RA</i>	18.06	1.74	12.95	53.23
	<i>J-stat</i>	8.68	4.45	8.92	11.81
	<i>P-value</i>	0.16	0.04	0.11	0.49

Table X presents the distribution of the GMM estimate of the risk aversion parameter (RA) of CRRA preferences, J-statistics for overidentifying restrictions and the corresponding p-values. Three horizontal panels summarize estimation results for different weighting schemes: the identity matrix (A), the inverse of the diagonal of the variance-covariance matrix of returns (B) and the optimal weighting matrix (C). The asset menu consists of firms with small and large market capitalization, low and high book-to-market ratio, aggregate stock market and the risk-free rate. The entries are based on 500 simulated samples, each with 876 months, time-aggregated to 73 annual observations.

Table XI
Simulation Evidence: Time Aggregation and Long Run Risk Model

Long Sample		
X-properties :	ρ	0.70
	R^2	0.44
Panel A:	<i>RA</i>	15.09
W = Identity	<i>IES</i>	0.36
	<i>P-value</i>	0.00
Panel B:	<i>RA</i>	13.38
W = $\text{diag}\{\text{Var}(\mathbf{R})^{-1}\}$	<i>IES</i>	0.43
	<i>P-value</i>	0.00
Panel C:	<i>RA</i>	13.15
W = Optimal	<i>IES</i>	0.69
	<i>P-value</i>	0.00

Table XI presents the GMM estimates of the Long Run Risk Model, J-statistics for overidentifying restrictions and the corresponding p-values for a long simulation. RA and IES denote risk aversion and the elasticity of intertemporal substitution respectively. Three horizontal panels summarize estimation results for different weighting schemes: the identity matrix (A), the inverse of the diagonal of the variance-covariance matrix of returns (B) and the optimal weighting matrix (C). The asset menu comprises firms with small and large market capitalization, low and high book-to-market ratio, aggregate stock market and the risk-free rate, as well as an asset that pays aggregate consumption each period. The entries are based on a sample with 10,000 annual observations.

Table XII
Simulation Evidence: Pricing Kernel based on Market Return

Long Sample		
Panel A:	<i>RA</i>	1.63
W = Identity	<i>IES</i>	1.68
	<i>P-value</i>	0.00
Panel B:	<i>RA</i>	0.59
W = Optimal	<i>IES</i>	0.70
	<i>P-value</i>	0.00

Table XII presents the GMM estimates of the Long Run Risk Model, J-statistics for overidentifying restrictions and the corresponding p-values for a pricing kernel in which the market return $r_{m,t}$ is used instead of the return on consumption, $r_{c,t}$. The model and estimation are based on monthly frequency. RA and IES denote risk aversion and the elasticity of intertemporal substitution respectively. Three horizontal panels summarize estimation results for different weighting schemes: the identity matrix (A), the inverse of the diagonal of the variance-covariance matrix of returns (B) and the optimal weighting matrix (C). The asset menu comprises firms with small and large market capitalization, low and high book-to-market ratio, aggregate stock market and the risk-free rate, as well as an asset that pays aggregate consumption each period. The entries are based on a sample with 120,000 monthly observations.

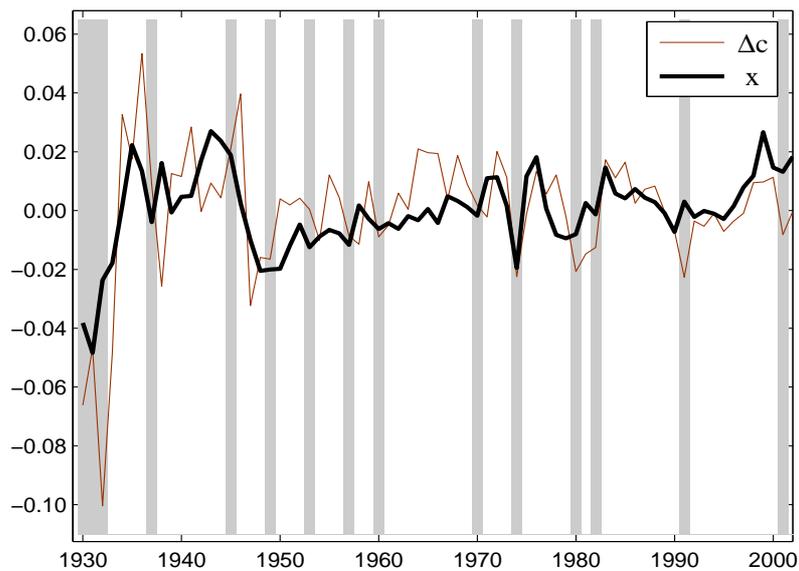
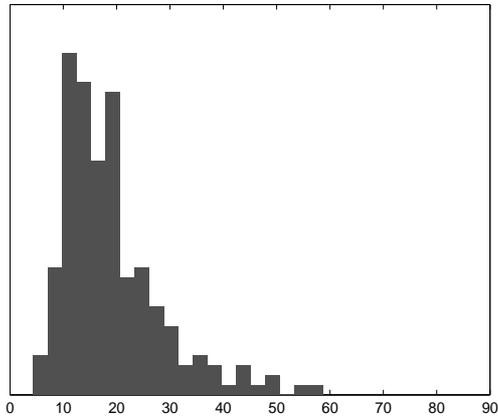
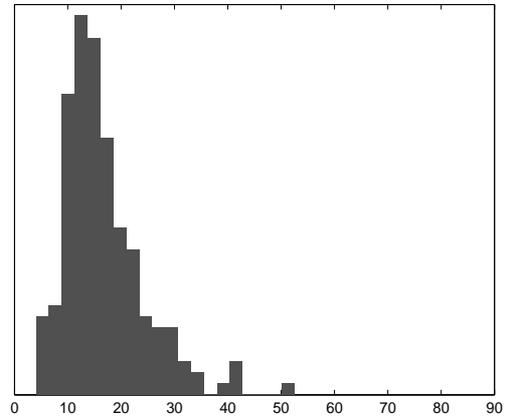


Figure 1. Realized and Expected Growth of Consumption

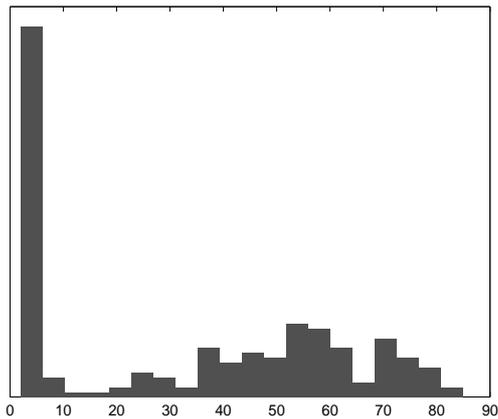
Figure 1 plots time series of realized (thin red line) and expected (thick black line) growth in consumption. Consumption is defined as the per-capita expenditure on non-durables and services. The expected consumption growth is constructed according to the predictability evidence presented in Table II. The data are real, sampled on an annual frequency and cover the period from 1930 to 2002. Shaded areas correspond to NBER-dated recessions.



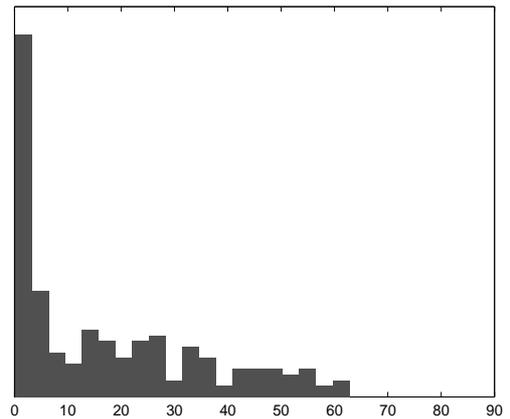
(a) EZ Preferences, $W = \text{Identity}$



(b) EZ Preferences, $W = \text{Optimal}$



(c) CRRA Preferences, $W = \text{Identity}$



(d) CRRA Preferences, $W = \text{Optimal}$

Figure 2. Histogram of the RA Estimate

Figure 2 displays the monte carlo distribution of the GMM estimate of the parameter of risk aversion. In the top panel, (a) and (b), moment conditions are based on Epstein and Zin (1989) preferences, the bottom figures, (c) and (d) correspond to CRRA preferences. Plots on the left are based on the identity weight matrix, the right column presents histograms for the optimal GMM matrix. The figures are based on 500 simulated samples, each with 876 months, time-aggregated to 73 annual observations.