

Forecasting stock returns with a structural estimate of risk aversion

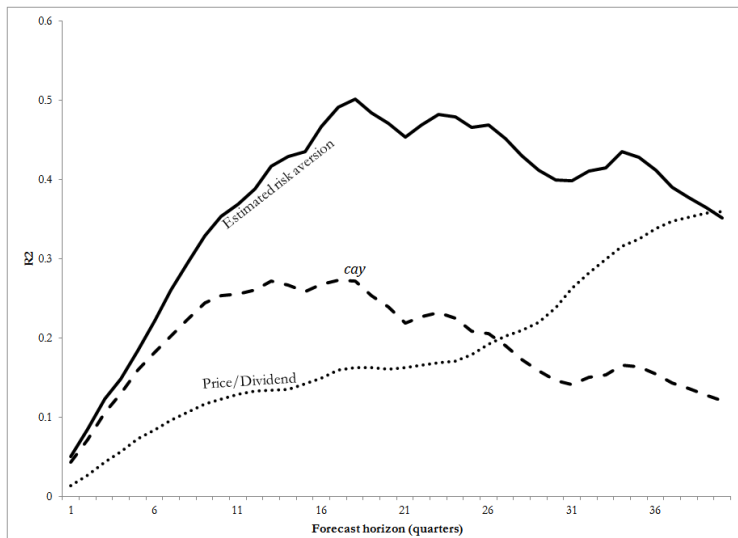
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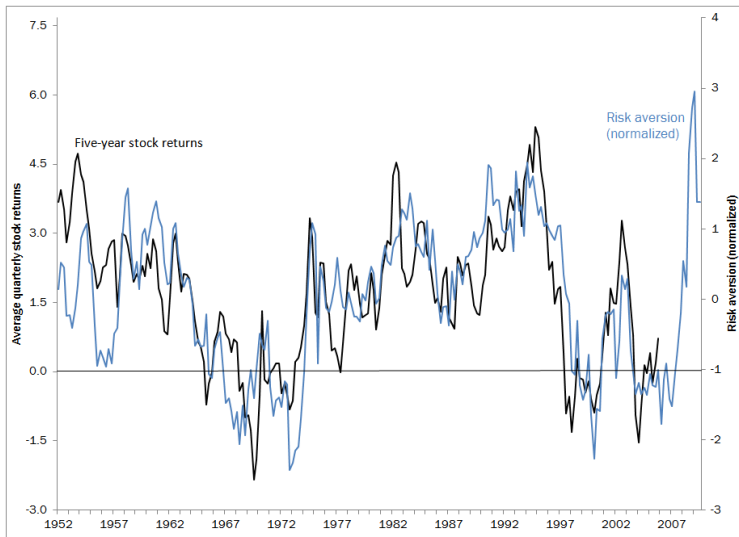
Harvard

11/8/2011

- Thanks for coming
- Section of my job market paper on forecasting returns
- Most of this is covered in the appendix

The basic result





Introduction

- Estimated risk aversion comes from a model
- It forecasts stock returns embarrassingly well
- Discuss today whether this is right

- 1 The model
- 2 Basic forecasting regressions
- 3 Out-of-sample results
- 4 Robustness to parameter choices

- Epstein–Zin preferences with time-varying risk aversion

$$V_t = \left\{ (1 - \beta) C_t^{1-\rho} + \beta \left[E_t V_{t+1}^{1-\alpha_t} \right]^{\frac{1-\rho}{1-\alpha_t}} \right\}^{\frac{1}{1-\rho}}$$
$$\alpha_t = (1 - \phi) \bar{\alpha} + \phi \alpha_{t-1} - \lambda \left(\log V_t^A - E_{t-1} \log V_t^A \right)$$

Motivated from a model with habit formation

- If we can measure the history of V_t^A , can measure α_t .

Measuring risk aversion

- Define the *Wealth Portfolio* as the asset that pays C_t as its dividend
- For Epstein-Zin preferences,

$$W_t = V_t^{1-\rho} C_t^\rho / (1 - \beta)$$

intuitively, $W = V / MU_C$

$$V_t \propto W_t (W_t / C_t)^{\frac{\rho}{1-\rho}}$$

\implies With V_t , we can calculate risk aversion

$$\alpha_{t+1} = (1 - \phi) \bar{\alpha} + \phi \alpha_t - \lambda \log \left(V_{t+1}^A / E_t V_{t+1}^A \right)$$

- Check for whether the assumed process for α_t fits returns

Measuring risk aversion

$$\alpha_t = (1 - \phi) \bar{\alpha} + \phi \alpha_{t-1} - \lambda \left(\frac{1}{1 - \rho} \Delta w c_{t-j} + \Delta c_{t-j} - \overline{\Delta w} \right)$$

$$\alpha_t = \bar{\alpha} - \lambda \sum_{j=0}^{\infty} \phi^j \left(\frac{1}{1 - \rho} \Delta w c_{t-j} + \Delta c_{t-j} - \overline{\Delta w} \right)$$

Calibrate ρ and ϕ ; $\rho = 2/3$; $\phi = 0.96$ (half-life = 17 quarters)

Ignore $\bar{\alpha}$ and λ

Measuring risk aversion

$$\alpha_t = (1 - \phi) \bar{\alpha} + \phi \alpha_{t-1} - \lambda \left(\Delta w_t + \frac{\rho}{1 - \rho} \Delta w c_t - \overline{\Delta w} \right)$$

- How do we measure $\overline{\Delta w}$?
- If the model is true, full-sample mean should work
 - Could also regress Δw_t on α_t or $w c_t$
- Or, for $E_{t-1} \Delta w_t$ use sample mean of Δw_j for $j < t$
 - Should this matter versus full-sample mean?
 - Just a level shift in α_t

Relationship with the wealth/consumption ratio

$$\alpha_t = \bar{\alpha} - \lambda \sum_{j=0}^{\infty} \phi^j \left(\frac{1}{1-\rho} \Delta w c_{t-j} + \Delta c_{t-j} - \overline{\Delta w} \right)$$

$$\phi \sum_{j=0}^{\infty} \phi^j \Delta x_{t-j} = x_t - (1-\phi) \sum_{k=0}^{\infty} \phi^k x_{t-k}$$

- α_t overweights recent innovations to wc
- Similar to detrending wc_t (effect is small)

- Two methods:
 - Measure consumption and wealth
 - Using innovations to the level of technology as innovations to V_t

- Financial wealth from flow of funds; labor income from the BEA
- Suppose

$$\begin{aligned}w_t &= \chi f_t + (1 - \chi) h_t \\h_t &= i_t + \mu_t\end{aligned}$$

- w_t wealth; f_t financial wealth; h_t human wealth; i_t labor income; μ_t stationary error
 - Everything in logs
- Observe f_t and i_t ,

$$w_t = \chi f_t + (1 - \chi) i_t + (1 - \chi) \mu_t$$

- Under balanced growth (or looser theories) consumption and wealth are cointegrated
 - Stationary consumption growth and discount rates
- Suppose $c_{ND,t} = \eta c_t + \zeta_t$

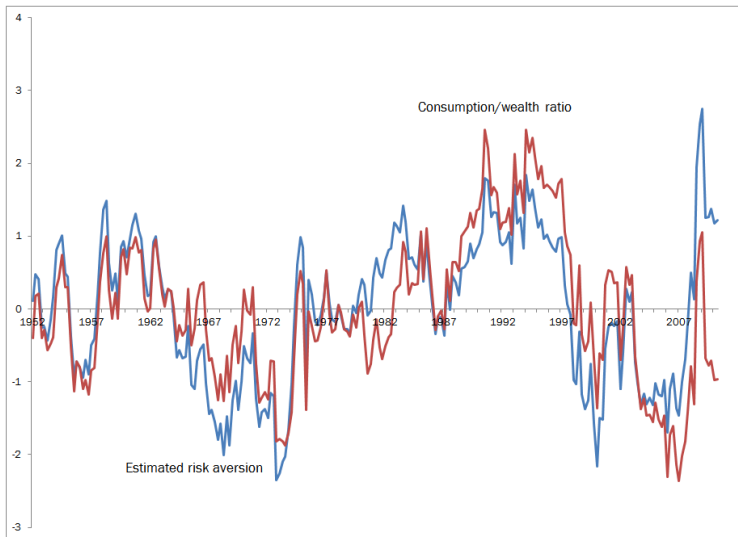
$$\begin{aligned} c_t - w_t &= \varepsilon_t \\ \eta^{-1} c_{ND,t} - \chi f_t - (1 - \chi) i_t &= \underbrace{\varepsilon_t + (1 - \chi) \mu_t + \eta^{-1} \zeta_t}_{\text{stationary}} \end{aligned}$$

- Estimate the cointegrating vector for c_t , f_t , and i_t
- χ is then identified (as long as η is unconstrained)
- Lettau and Ludvigson (2001) call residual *cay*

Figure 4. Value, raw and linearly detrended



Note: Household value (lifetime utility) is measured using data on wealth and consumption from Sydney Ludrigson's website. The thin line is the absolute level of value (left-hand axis); the thick line is value linearly detrended. Both variables are measured in logs. Grey bars are NBER-dated recessions



Out-of-sample testing

- Compare my forecast and *cay* to a constant-mean forecast
- Under the null (no predictability), RMSE is lower for constant mean than anything else
- Need to adjust for this difference
- Clark and McCracken (2001, 2005); Clark and West (2007)

Out-of-sample testing

- Estimate VECM on data 0 to t
- Construct $\hat{\alpha}$
- On data up to date t , estimate $b_{1,t}$ and $\varepsilon_{t,j}$ as

$$\begin{aligned}r_{k,k+j} &= b_0 + b_{1,t}\hat{\alpha}_k \\ \varepsilon_{t,j}^{\hat{\alpha}} &\equiv r_{t,t+j} - b_0 - b_{1,t}\hat{\alpha}_t\end{aligned}$$

- Use $\varepsilon_{t,j}^{\hat{\alpha}}$ to construct OOS test statistics, $1 \leq j \leq 20$

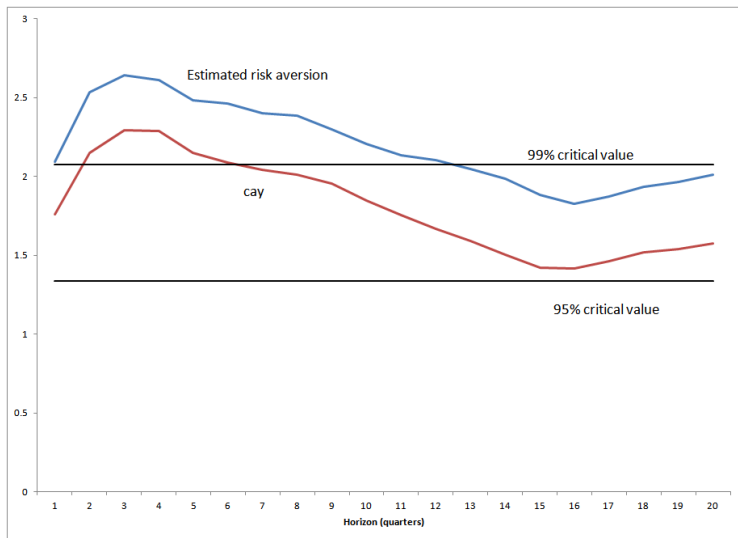
Out-of-sample testing

- Denote $\varepsilon_{t,j}^{iid}$ as error from a constant-mean model for returns
- $\varepsilon_{t,j}^{iid}$ is encompassed by $\varepsilon_{t,j}^{\hat{\alpha}}$
- Test statistic is

$$\begin{aligned}f_{t,j} &= \left(\varepsilon_{t,j}^{iid}\right)^2 - \left(\left(\varepsilon_{t,j}^{\hat{\alpha}}\right)^2 - \left(\varepsilon_{t,j}^{iid} - \varepsilon_{t,j}^{\hat{\alpha}}\right)^2\right) \\ &= 2\varepsilon_{t,j}^{iid} \left(\varepsilon_{t,j}^{iid} - \varepsilon_{t,j}^{\hat{\alpha}}\right) \\ OOS_j &= \frac{(T - R)^{-1/2} \sum_{t=R}^T f_{t,j}}{S(f_{t,j})}\end{aligned}$$

where $S(f_{t,j})$ is a long-run variance estimate

Out-of-sample test statistics



$$r_t = b_0 + b_1\alpha_{t-1} + \varepsilon_t$$

- Finite sample results for OLS assume $E_t\varepsilon_t\alpha_{t-j} = 0 \forall j$
- We can only assume $E_t\varepsilon_t\alpha_{t-j} = 0 \forall j > 0$
- Innovations to r_t are correlated with innovations to α_t
 - Good news lowers risk aversion
- Asymptotically, OLS is consistent; biased in small samples
 - See also Mankiw and Shapiro (1986); Cavanagh, Elliott, and Stock (1995)

- Suppose consumption and wealth follow random walks; returns i.i.d.

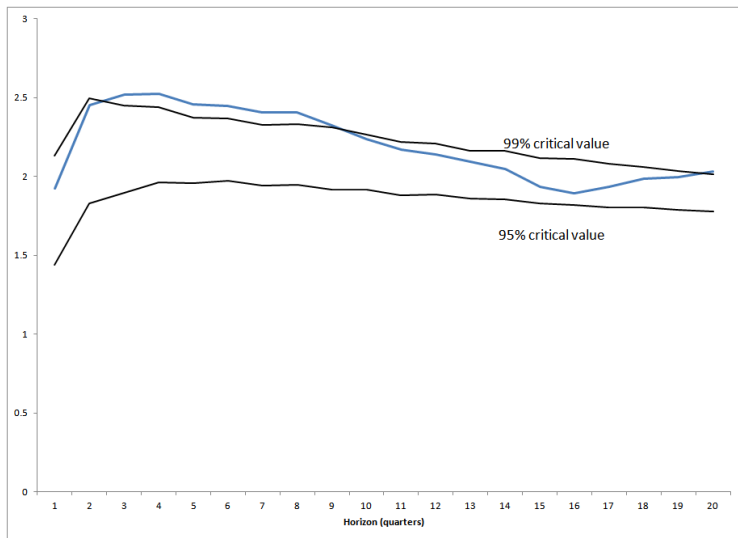
$$\Delta f_t = \varepsilon_{f,t}$$

$$\Delta i_t = \varepsilon_{i,t}$$

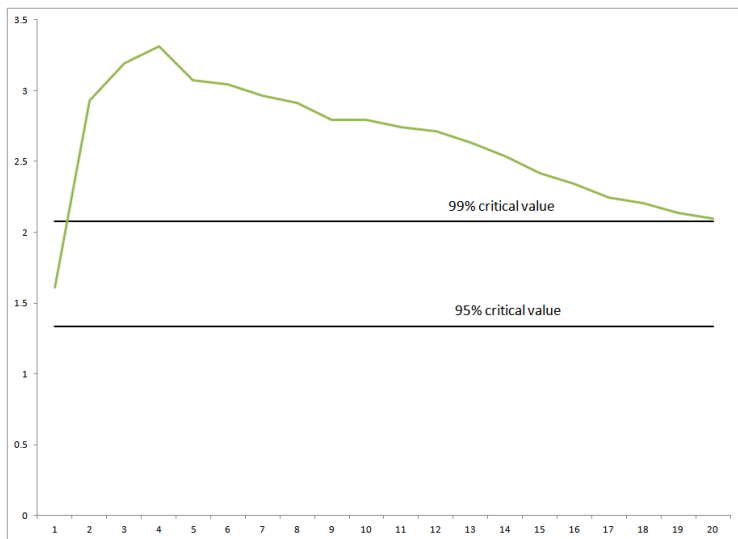
$$\Delta c_t = \varepsilon_{c,t}$$

- 1 Draw bootstrap samples of $\{\varepsilon_{f,t}, \varepsilon_{i,t}, \varepsilon_{c,t}, r_t\}$
 - 2 Estimate vecm
 - 3 Construct α_t^{boot}
 - 4 Calculate OOS test statistics
- Hard test: lots of estimation error

Bootstrapped critical values



Estimated risk aversion versus cay



- Everything up to here fixes ϕ and ρ exogenously
- ρ from micro evidence and aggregate facts
- ϕ might have look-ahead bias
- Look at R^2 for varying values of ρ and ϕ

Varying persistence of risk aversion

ϕ^4	1q	5q	10q	20q
0.7	0.04	0.17	0.31	0.40
0.75	0.04	0.19	0.33	0.43
0.8	0.05	0.21	0.36	0.47
<i>0.85</i>	<i>0.06</i>	<i>0.23</i>	<i>0.39</i>	<i>0.49</i>
0.9	0.06	0.25	0.41	0.50
0.95	0.07	0.27	0.43	0.48
0.99	0.07	0.27	0.42	0.43
<i>cay</i>	0.05	0.18	0.27	0.28

- Robust to any beliefs about ϕ

Varying EIS

<i>EIS</i>	1q	5q	10q	20q
10	0.05	0.21	0.35	0.50
3	0.05	0.22	0.38	0.52
1.5	<i>0.06</i>	<i>0.023</i>	<i>0.39</i>	<i>0.49</i>
1.1	0.05	0.20	0.33	0.38
2/3	0.01	0.03	0.05	0.01
1/5	0.01	0.04	0.06	0.19
1/10	0.01	0.06	0.09	0.24
<i>cay</i>	0.05	0.18	0.27	0.28

- Need $EIS > 1$
- Common result in this literature

Risk aversion measured from technology growth

