

# Bond Risk Premia in Consumption-based Models

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# Motivation

## Chairman Janet Yellen: large-scale asset purchases December, 2014, Press Conference

*...we're reminding the public that we continue to hold a large stock of assets, and that is tending to push down **term premiums** in longer-term yields.*

## Chairman Ben Bernanke: decomposition March, 2006, New York

*To the extent that the decline in forward rates can be traced to a decline in the **term premium**... the effect is financially stimulative and argues for greater monetary policy restraint... However, if the behavior of long-term yields reflects current or prospective economic conditions, the implications for policy may be quite different-indeed, quite the opposite.*

## Chairman Alan Greenspan: conundrum June, 2005, Beijing

*That improved performance has doubtless contributed to lower inflation-related **risk premiums**, and the lowering of these **premiums** is reflected in significant declines in nominal and real long-term rates. Although this explanation contributes to an understanding of the past decade, I do not believe it explains the decline of long-term interest rates over the past year despite rising short-term rates.*

# Term premium: two models & two channels

- ▶ Gaussian ATSM:
  - ▶ benchmark model
  - ▶ time-varying term premia via **price of risk**
  - ▶ lack micro foundation
- ▶ structural models with recursive preferences
  - ▶ Gaussian: constant term premia
  - ▶ SV: time-varying term premia via **SV**
  - ▶ economic structure imposes restrictions

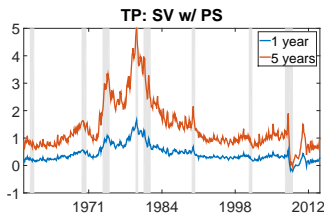
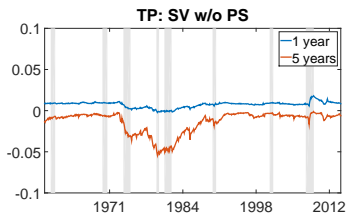
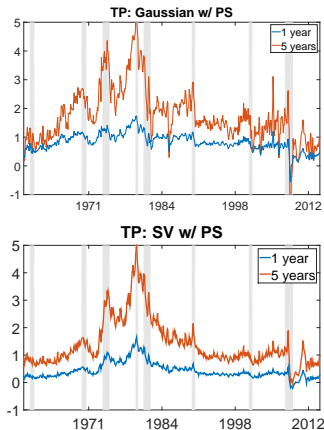
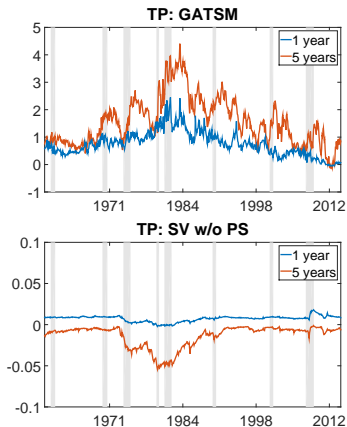
**Goal of this paper:** reconcile the two literatures

# Contributions

- ▶ Introduce a new structural model with recursive preferences
  - ▶ preference shocks  $\rightarrow$  time-varying prices of risk
- ▶ Bridge two literatures on bonds
  - ▶ GATSM and consumption based models.
- ▶ Representative agent's problem must be well-posed
  - ▶ provide conditions guaranteeing a model solution
    - ▶ representative agent cannot be too patient
    - ▶ risk aversion cannot be too large
  - ▶ the geometry of the feasible regions makes estimation challenging

▶ Literature

# Results: term premia



# Outline

- 1 Model
- 2 Estimation
- 3 Results
- 4 Model solution

# Gaussian Model

Agent's problem

$$V_t = \max \left[ (1 - \beta) \Upsilon_t C_t^{1-\eta} + \beta \left\{ \mathbb{E}_t \left[ V_{t+1}^{1-\gamma} \right] \right\}^{\frac{1-\eta}{1-\gamma}} \right]^{\frac{1}{1-\eta}}$$

s.t.  $W_{t+1} = (W_t - C_t) R_{c,t+1}$

Log stochastic discount factor

$$m_{t+1} = \vartheta \ln(\beta) + \vartheta \Delta v_{t+1} - \eta \vartheta \Delta c_{t+1} + (\vartheta - 1) r_{c,t+1},$$

$$m_{t+1}^{\$} = m_{t+1} - \pi_{t+1}$$

where  $\vartheta = \frac{1-\gamma}{1-\eta}$

State variables

$$\Delta c_t = Z'_c g_t, \quad \pi_t = Z'_\pi g_t,$$

$$g_{t+1} = \mu_g + \Phi_g g_t + \Sigma_{0,g} \varepsilon_{g,t+1} \quad \varepsilon_{g,t+1} \sim N(0, I).$$

- ▶ It's a companion form, nesting long-run risk & VARMA.

## Preference shocks

$$\begin{aligned}\Delta v_{t+1} &= Z'_v g_{t+1} + \Lambda_1(g_t) + \Lambda_2(g_t)' \varepsilon_{g,t+1} \\ \Lambda_2(g_t) &= -\eta \Sigma_{0,g}^{-1} (\lambda_0 + \lambda_g g_t)\end{aligned}$$

- ▶  $Z'_v g_{t+1}$ : Albuquerque, Eichenbaum, & Rebelo (2014)
  - ▶ no time-varying price of risk.
- ▶  $\lambda_g \neq 0 \Rightarrow$  **time-varying price of risk/ term premium**



## Sources of risk premia

$$m_{t+1}^{\$} - E_t \left[ m_{t+1}^{\$} \right] = -\lambda_{g,t}^{\$, \prime} \varepsilon_{g,t+1}$$

where the price of risk  $\lambda_{g,t}^{\$}$  is

$$\begin{aligned} \Sigma_{0,g} \lambda_{g,t}^{\$} = & \Sigma_{0,g} \overset{\text{power utility}}{\Sigma'_{0,g}} (\gamma Z_c + Z_\pi) - \kappa_1 \overset{\text{recursive preferences}}{\frac{(\eta - \gamma)}{(1 - \eta)}} \Sigma_{0,g} \Sigma'_{0,g} D_g \\ & - \vartheta \overset{\text{preference shocks}}{\Sigma_{0,g} \Sigma'_{0,g}} Z_v + \eta \vartheta \lambda_0 + \eta \vartheta \lambda_g g_t \end{aligned}$$

- ▶ the price of risk only varies through time if  $\lambda_g \neq 0$ .
- ▶ Campbell & Cochrane (1999): Risk sensitivity function  $\lambda(s_t)$  creates time-varying price of risk

$$m_{t+1} - E_t [m_{t+1}] = -\gamma \sigma_c (1 + \lambda(s_t)) \varepsilon_{c,t+1}$$

- ▶ Our model
  - ▶  $\Lambda_2(g_t)$  is (potentially) a function of any element of the state vector  $g_t$ .
  - ▶ Bond prices are known in closed-form.

## Nominal risk neutral measure $Q^{\$}$

$$g_{t+1} = \mu_g^{Q,\$} + \Phi_g^{Q,\$} g_t + \Sigma_{0,g} \varepsilon_{g,t+1}^{Q,\$}, \quad \varepsilon_{g,t+1}^{Q,\$} \sim N(0, I).$$

where

$$\Sigma_{0,g} \lambda_{g,t}^{\$} = \left( \mu_g - \mu_g^{Q,\$} \right) + \left( \Phi_g - \Phi_g^{Q,\$} \right) g_t$$

Therefore,

$$\Phi_g^{Q,\$} = \Phi_g - \overset{\text{preference shocks}}{\eta \vartheta \lambda_g}$$

- ▶ Same form as a Gaussian ATSM.
- ▶ the price of risk only varies through time if

$$\lambda_g \neq 0 \Rightarrow \Phi_g \neq \Phi_g^{Q,\$}$$

- ▶ Duffee (2002): important feature of the data

# Bond prices

Bond prices

$$P_t^{\$, (n)} = E_t \left[ \exp \left( m_{t+1}^{\$} \right) P_{t+1}^{\$, (n-1)} \right]$$

yields

$$y_t^{\$, (n)} \equiv -\frac{1}{n} \ln \left( P_t^{\$, (n)} \right) = a_n^{\$} + b_{n,g}^{\$, ' } g_t$$

- ▶ Bond loadings are similar to Gaussian ATSMs.
- ▶ They are functions of  $(\beta, \gamma, \psi)$ , where  $\psi = 1/\eta$

▶ Loadings

Consumption-inflation representation

$$y_t^{\$, (n)} = -\ln(\beta) + \frac{\eta}{n} \sum_{j=0}^{n-1} E_t^{\text{Q}, \$} \Delta c_{t+j+1} + \frac{1}{n} \sum_{j=0}^{n-1} E_t^{\text{Q}, \$} \pi_{t+j+1} - \frac{1}{n} \sum_{j=0}^{n-1} E_t^{\text{Q}, \$} \Delta v_{t+j+1} + J.I.$$

# SV model: dynamics

Stochastic volatility process from Creal & Wu (2015 JEconometrics)

$$\begin{aligned}
 g_{t+1} &= \mu_g + \phi_g g_t + \phi_{gh} h_t + \Sigma_{gh} \varepsilon_{h,t+1} + \Sigma_{g,t} \varepsilon_{g,t+1} & \varepsilon_{g,t+1} &\sim N(0, I) \\
 \Sigma_{g,t} \Sigma'_{g,t} &= \Sigma_{0,g} \Sigma'_{0,g} + \sum_{i=1}^H \Sigma_{i,g} \Sigma'_{i,g} h_{it} \\
 h_{t+1} &\sim \text{NCG}(\nu_h, \Phi_h, \Sigma_h) \\
 \varepsilon_{h,t+1} &= h_{t+1} - \text{E}_t[h_{t+1}|h_t]
 \end{aligned}$$

Long run risk

$$\begin{aligned}
 \pi_{t+1} &= \bar{\pi}_t + \varepsilon_{\pi_1,t+1} & \varepsilon_{\pi_1,t+1} &\sim N(0, h_{t,\pi_1}) \\
 \Delta c_{t+1} &= \bar{c}_t + \varepsilon_{c_1,t+1} & \varepsilon_{c_1,t+1} &\sim N(0, h_{t,c_1}) \\
 \bar{\pi}_{t+1} &= \mu_\pi + \phi_\pi \bar{\pi}_t + \phi_{\pi,c} \bar{c}_t + \varepsilon_{\pi_2,t+1} & \varepsilon_{\pi_2,t+1} &\sim N(0, h_{t,\pi_2}) \\
 \bar{c}_{t+1} &= \mu_c + \phi_{c,\pi} \bar{\pi}_t + \phi_c \bar{c}_t + \sigma_{c,\pi} \varepsilon_{\pi_2,t+1} + \varepsilon_{c_2,t+1} & \varepsilon_{c_2,t+1} &\sim N(0, h_{t,c_2})
 \end{aligned}$$

# SV model: preference shock

Preference shock

$$\begin{aligned}\Delta v_{t+1} &= Z'_v g_{t+1} + \Lambda_1 (g_t, h_t) + \Lambda_2 (g_t, h_t)' \varepsilon_{g,t+1} + \Lambda_3 (h_t)' \varepsilon_{h,t+1} \\ \Lambda_2 (g_t, h_t) &= -\eta \Sigma_{g,t}^{-1} (\lambda_0 + \lambda_g g_t + \lambda_{gh} h_t), \quad \Lambda_3 (h_t) = -\lambda_h.\end{aligned}$$

pricing kernel

$$m_{t+1}^{\$} - \text{Et} \left[ m_{t+1}^{\$} \right] = -\lambda_{g,t}^{\$, \prime} \varepsilon_{g,t+1} - \lambda_{h,t}^{\$, \prime} \tilde{\varepsilon}_{h,t+1}$$

risk premium

$$\begin{aligned}\Sigma_{g,t} \lambda_{g,t}^{\$} &= \Sigma_{0,g} \Sigma'_{0,g} (\gamma Z_c + Z_\pi) - \kappa_1 \frac{(\eta - \gamma)}{(1 - \eta)} \Sigma_{0,g} \Sigma'_{0,g} D_g - \vartheta \Sigma_{0,g} \Sigma'_{0,g} Z_v + \eta \vartheta \lambda_0 + \eta \vartheta \lambda_g g_t \\ &\quad + \underbrace{([\gamma Z_c + Z_\pi] \otimes I_G)' \tilde{S}_g h_t}_{\text{power utility}} - \kappa_1 \frac{(\eta - \gamma)}{(1 - \eta)} \underbrace{(D_g \otimes I_G)' \tilde{S}_g h_t}_{\text{recursive preferences}} \\ &\quad - \vartheta \underbrace{(Z_v \otimes I_G)' \tilde{S}_g h_t}_{\text{preference shocks}} + \eta \vartheta \lambda_{gh} h_t + \text{leverage effects} \\ \Sigma_{h,t}^{\prime, -1} \lambda_{h,t}^{\$} &= \Sigma'_{gh} (\gamma Z_c + Z_\pi) - \kappa_1 \frac{(\eta - \gamma)}{(1 - \eta)} \underbrace{(\Sigma'_{gh} D_g + D_h)}_{\text{recursive preferences}} - \vartheta \underbrace{(\Sigma'_{gh} Z_v - \lambda_h)}_{\text{preference shocks}}\end{aligned}$$

# Data

Monthly data from Feb. 1959 to June 2014

## Yields

- ▶ Fama-Bliss zero-coupon yields from CRSP
- ▶ maturities: 3m, 1y, 2y, 3y, 4y, 5y

## Inflation + Population

- ▶ FRED database at St. Louis FRB
- ▶ CPI inflation
- ▶ Civilian population over 16

## Consumption

- ▶ U.S. Bureau of Economic Analysis
- ▶ non-durables + services

# Estimation approach

Step 1: estimate the time series dynamics  $(\theta^{\mathbb{P}}, g_t, h_t)$

- ▶ use MCMC + particle filters → Particle Gibbs sampler. [▶ Details](#)

Step 2: estimate  $\theta^u = (\beta, \gamma, \psi)$  and  $\theta^\lambda$

- ▶ Run a cross-sectional regression on filtered estimates  $\hat{g}_t$  and  $\hat{h}_t$

$$y_t^s = A^s(\theta^u, \theta^\lambda) + B_g^s(\theta^u, \theta^\lambda) \hat{g}_t + B_h^s(\theta^u, \theta^\lambda) \hat{h}_t + \eta_t \quad \eta_t \sim N(0, \Omega)$$

to estimate  $\hat{\zeta}^r = \left( \hat{A}^{s,r}, \text{vec}(\hat{B}_g^{s,r}), \text{vec}(\hat{B}_h^{s,r}) \right)'$

- ▶ We use minimum- $\chi^2$  estimation of Hamilton & Wu (2012 JEconometrics)

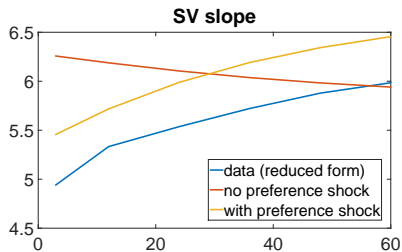
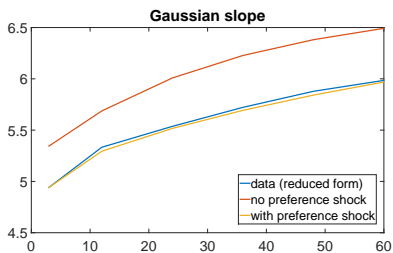
$$\underset{\theta^u, \theta^\lambda}{\text{argmin}} \quad T \left( \hat{\zeta}^r - \zeta(\theta^u, \theta^\lambda) \right)' W \left( \hat{\zeta}^r - \zeta(\theta^u, \theta^\lambda) \right)$$

# Structural parameters

	Gaussian		Gaussian+PS		SV		SV+PS	
$\beta$	1.00		1.00		1.00		1.00	
$\psi$	0.59		1.09		0.61		0.97	
$\gamma$	84.4		416.6		1e-5		1.70	
$\bar{\rho}c$	7.78		5.54		7.06		8.16	
$\Phi_g$	0.95	0.03	0.95	0.03	0.96	0.05	0.96	0.05
	-0.02	0.87	-0.02	0.87	0.00	0.91	0.00	0.91
$\Phi_g^Q$			0.97	0.93			0.98	-0.02
			0.02	0.36			-0.00	0.99
MCS	1330		477		3794		1027	



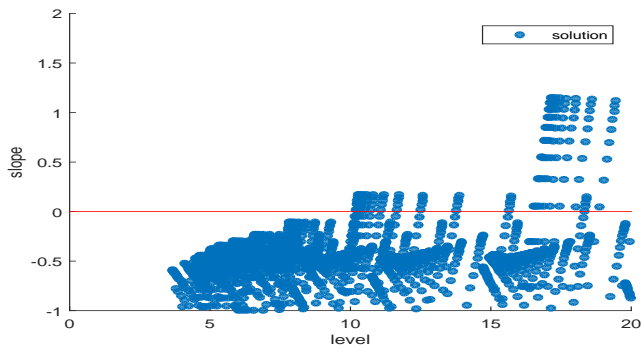
# Unconditional yield curves



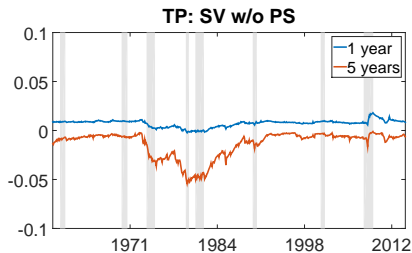
## Why SV is doing worse?

- ▶ SV seems to be more flexible with  $h_t$
- ▶ But there are more moments to match
- ▶ There are only 3 free parameters to match all
- ▶ It's difficult to match both the average level, and slope

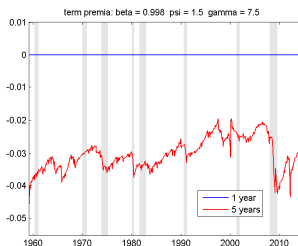
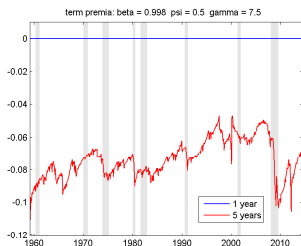
$$\psi = [0, 20]; \beta = [0.6, 1]; \gamma = [0.001, 1100]$$



# Term premia: SV without preference shock



parameters from Bansal & Yaron (2004)



# Comparison with the literature

Tension between fitting macroeconomic variables and yields

- ▶ Macro variables:  $\mathbb{P}$  parameters
- ▶ Cross section of yields:  $\mathbb{Q}$  parameters
- ▶ Term premia: the difference between  $\mathbb{P}$  and  $\mathbb{Q}$

In consumption-based models with recursive preferences,  $\Phi_g = \Phi_g^{\mathbb{Q}}$

- ▶ If we force the model to fit macro variables (*ours*), then
  - ▶  $\Phi_g$  determines the slope is downward
- ▶ If we force the model to fit the upward slope (*literature*), then
  - ▶  $\Phi_g^{\mathbb{Q}}$  determines factor dynamics
  - ▶ macro factors mimic level, slope and curvature of yields

Autocovariance of volatility,  $\Phi_h \neq \Phi_h^{\mathbb{Q}}$ , is not enough to break the tension

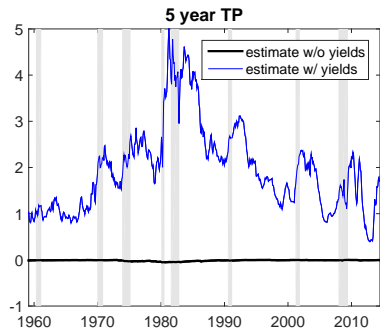
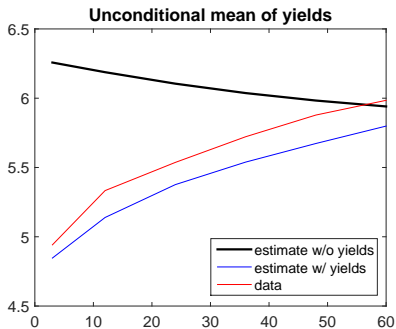
**Preference shock allows  $\Phi_g \neq \Phi_g^{\mathbb{Q}}$**

# Macro factors and yields

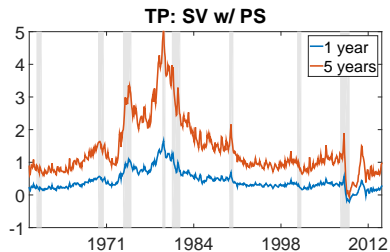
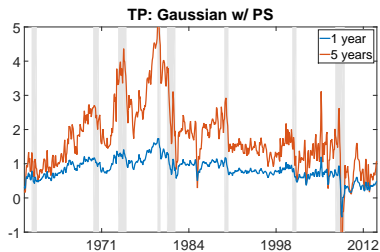
Regression  $R^2$ s of macro factors on yields

	estimates w yields		estimates w/o yields
	w/o m.e.	w/ m.e.	
inflation	1	0.90	0.28
consumption	1	0.99	0.58
inflation V	1	0.66	0.47
consumption V	1	0.87	0.23

# Slope and term premium in SV model



# Adding preference shocks



- ▶ Preference shock breaks the strong tie between  $\mathbb{P}$  and  $\mathbb{Q}$
- ▶ With the preference shock, SV does not add more flexibility for term premia.

## Model solution

- ▶ Step #1: log-linearize  $r_{c,t+1}$  via Campbell & Shiller (1989)

$$r_{c,t+1} = \kappa_0 + \kappa_1 p c_{t+1} - p c_t + \Delta c_{t+1}$$

- ▶ Step #2: guess a solution

$$p c_t = D_0 + D'_g g_t + D'_h h_t$$

- ▶ Step #3: solve the fixed point problem.

$$\bar{p}c = D_0(\bar{p}c) + D'_g(\bar{p}c)' \bar{\mu}_g + D'_h(\bar{p}c)' \bar{\mu}_h$$

- ▶ Step #4: plug the solution into the SDF.
- ▶ **Problem: a solution to the fixed point problem does not always exist.**



# Solution to the fixed point problem

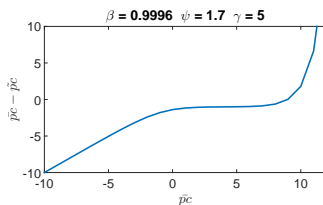
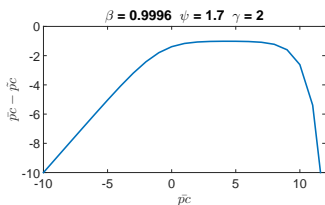
## Proposition

There is a value  $\bar{\beta}(\psi, \gamma, \theta^r)$  such that if  $\beta < \bar{\beta}$ , then there exists a solution for the fixed point problem.

## Sketch of proof

Define  $\tilde{p}\bar{c}(\bar{p}\bar{c}) = D_0(\bar{p}\bar{c}) + D_g(\bar{p}\bar{c})' \bar{\mu}_g + D_h(\bar{p}\bar{c})' \bar{\mu}_h$

The fixed point problem has a solution if  $\bar{p}\bar{c} - \tilde{p}\bar{c}(\bar{p}\bar{c}) = 0$



# Solution to the fixed point problem: Gaussian

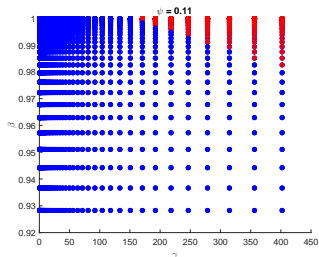
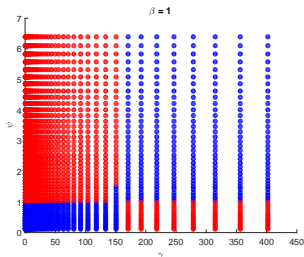
## Corollary

If there is no preference shock, then

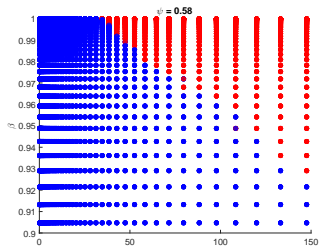
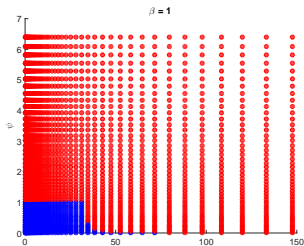
1. If  $Z_1^{\infty'} \mu_g \leq 0$ , then  $\vartheta = \frac{1-\gamma}{1-\eta} < 0$  guarantees the existence of a solution.
2. If  $\beta = 1$ , there is a value  $\bar{\gamma}(\theta^r)$  such that  $\frac{\bar{\gamma}-\gamma}{1-\eta} < 0$  guarantees a solution.
3. For any  $\psi$ ,  $\bar{\beta}$  is monotonic in  $\gamma$ : for  $\psi > 1$ , then  $\frac{d\bar{\beta}}{d\gamma} > 0$ ; for  $\psi < 1$ , then  $\frac{d\bar{\beta}}{d\gamma} < 0$ .

# Model #1: long-run risk, no SV, no preference shock

## Gaussian model



## SV model



# Conclusion

- ▶ Build a new consumption-based asset pricing model
  - ▶ capture realistic dynamics for risk premia
  - ▶ **preference shocks** → flexible time-varying prices of risk
  - ▶ stochastic volatility → time-varying quantity of risk
- ▶ Empirical results:
  - ▶ Flexible time-varying price of risk is key
    - ▶ term premia fluctuate with expected inflation
  - ▶ Term premia from recursive preferences with stochastic volatility are implausible
- ▶ Provide conditions guaranteeing a solution for these models.

# Literature:

## Consumption-based models

- ▶ recursive preferences: *Piazzesi Schneider (07), Le Singleton (10)*
- ▶ recursive preferences + SV: *Bansal Yaron (04), Bansal Gallant Tauchen (07), Bansal Shaliastovich (13),*
- ▶ habit formation: *Wachter (06)*
- ▶ recursive preferences + SV in ICAPM: *Campbell Giglio et al. (14)*
- ▶ recursive preferences + preference shocks: *Albuquerque Eichenbaum Rebelo (14) Schorfheide Song Yaron (14)*

## DSGE models

- ▶ habit formation: *Rudebusch Swanson (08)*
- ▶ recursive preferences: *Rudebusch Swanson (08), van Binsbergen et al. (12), Dew-Becker (14)*
- ▶ solution methods: *Caldara et al. (12)*

# Literature:

## Term premium

- ▶ ATSM: *Duffee (02), Ang Piazzesi (03), Wright (11), Bauer Rudebusch Wu (12)*

## Model solution

- ▶ *Hansen Scheinkman (12), Campbell Giglio et al. (14)*

▶ Back

## Gaussian bond loadings

$$a_n = -\frac{1}{n}\bar{a}_n, b_{n,g} = -\frac{1}{n}\bar{b}_{n,g}$$

$$\begin{aligned}\bar{a}_n^{\$} &= \bar{a}_{n-1}^{\$} + \bar{a}_1^{\$} + (\mu_g - \eta\vartheta\lambda_0 + \Sigma_{0,g}\Sigma'_{0,g} [Z_2 - Z_\pi])' \bar{b}_{n-1,g}^{\$} \\ &\quad + \frac{1}{2}\bar{b}_{n-1,g}^{\$, \prime} \Sigma_{0,g}\Sigma'_{0,g}\bar{b}_{n-1,g}^{\$}\end{aligned}$$

$$\bar{b}_{n,g}^{\$} = (\Phi_g - \eta\vartheta\lambda_g)' \bar{b}_{n-1,g}^{\$} + \bar{b}_{1,g}^{\$}$$

where the initial conditions are

$$\begin{aligned}\bar{a}_1^{\$} &= \ln(\beta) + \bar{\lambda} + (Z_v - \eta Z_c - Z_\pi)' (\mu_g - \eta\vartheta\lambda_0) - \frac{(\vartheta - 1)\vartheta}{2} Z_1' \Sigma_{0,g}\Sigma'_{0,g} Z_1 \\ &\quad + \frac{1}{2} Z_2' \Sigma_{0,g}\Sigma'_{0,g} Z_2 + \frac{1}{2} Z_\pi' \Sigma_{0,g}\Sigma'_{0,g} Z_\pi - Z_2' \Sigma_{0,g}\Sigma'_{0,g} Z_\pi\end{aligned}$$

$$\bar{b}_{1,g}^{\$} = (\Phi_g - \eta\vartheta\lambda_g)' (Z_v - \eta Z_c - Z_\pi)$$

where

$$\begin{aligned}Z_1 &= Z_v + (1 - \eta) Z_c + \kappa_1 D_g \\ Z_2 &= \vartheta Z_v - \gamma Z_c + (\vartheta - 1) \kappa_1 D_g\end{aligned}$$

# Particle Gibbs sampler

For  $j = 1, \dots, M$

$$\begin{aligned}(\mathbf{g}_{1:T}, \mathbf{h}_{0:T})^{(j)} &\sim p\left(\mathbf{g}_{1:T}, \mathbf{h}_{0:T} \mid Y_{1:T}, \theta^{\mathbb{P},(j-1)}\right) \\ \theta^{\mathbb{P},(j)} &\sim p\left(\theta^{\mathbb{P}} \mid Y_{1:T}, \mathbf{g}_{1:T}^{(j)}, \mathbf{h}_{0:T}^{(j)}\right)\end{aligned}$$

- ▶ Draw the state variables using the particle filter, see Andrieu, Doucet, Holenstein (10).
- ▶ Use independence Metropolis-Hastings to draw the parameters  $\theta^{\mathbb{P}}$ .



# Particle Gibbs sampler

For  $t = 1, \dots, T$ , run:

- ▶ For  $j = 2, \dots, J$ , draw from a proposal:  $(h_t^{(j)}) \sim q(h_t | h_{t-1}^{(j)}, y_t, \theta)$ .
- ▶ For  $j = 1, \dots, J$ , calculate the importance weight:

$$w_t^{(j)} \propto \frac{p(y_t | h_t^{(j)}, \theta) p(h_t^{(j)} | h_{t-1}^{(j)}, \theta)}{q(h_t^{(j)} | h_{t-1}^{(j)}, y_t, \theta)}$$

- ▶ For  $j = 1, \dots, J$ , normalize the weights:  $\hat{w}_t^{(j)} = \frac{w_t^{(j)}}{\sum_{j=1}^J w_t^{(j)}}$ .
- ▶ Conditionally resample the particles  $\{h_t^{(j)}\}_{j=1}^J$  with probabilities  $\{\hat{w}_t^{(j)}\}_{j=1}^J$ . In this step, the first particle  $h_t^{(1)}$  always gets resampled and may be randomly duplicated.

Key point: the particle approximation:  $\{\hat{w}_{1:T}, h_{0:T}\}_1^J \approx p(h_{0:T} | y_{1:T}, \theta)$