Macro Risks and the Term Structure of Interest Rates

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Motivation

- Treasury bond risk premia are time-varying (e.g., Campbell and Shiller, 1991)
- Economic channels of bond return predictability not clear (Bauer and Hamilton, 2017):
  - Only price variables (e.g., yield curve slope) are robust predictors of excess bond returns
  - Macro variables are insignificant predictors

Main Idea and Contribution

- Economic intuition: bond risk premia should be higher in "aggregate supply" (AS) environment than "aggregate demand" (AD) environment as inflation is counter-cyclical in former and pro-cyclical in latter (Fama, 1981)
- Macro risks=second and higher order moments of AD/AS shocks
- Macro risks are robust predictors of excess bond returns

Demand and Supply Shocks

- Consider GDP growth and inflation shocks:
  - $g_{t+1} = E_t[g_{t+1}] + \epsilon^g_{t+1}$
  - $\pi_{t+1} = E_t[\pi_{t+1}] + \epsilon^\pi_{t+1}$
- Model them as functions of "demand" (u^d_t)/"supply" (u^s_t) shocks (Blanchard, 1989):

$$\epsilon^g_{t+1} = \underbrace{\sigma^d_g}_{>0} u^d_{t+1} + \underbrace{\sigma^s_g}_{>0} u^s_{t+1},$$

$$\epsilon^\pi_{t+1} = \underbrace{\sigma^d_\pi}_{>0} u^d_{t+1} - \underbrace{\sigma^s_\pi}_{>0} u^s_{t+1},$$

$$Cov(u^d_{t+1}, u^s_{t+1}) = 0, Var(u^d_{t+1}) = Var(u^s_{t+1}) = 1.$$

Intuition

- If "supply" and "demand" shocks are heteroskedastic, $Cov_t(\epsilon^g_{t+1}, \epsilon^\pi_{t+1})$ will vary over time:

$$Cov_t(\epsilon^g_{t+1}, \epsilon^\pi_{t+1}) = \sigma^d_g \sigma^d_\pi \underbrace{Var_t(u^d_{t+1})}_{\text{macro risk}} - \sigma^s_g \sigma^s_\pi \underbrace{Var_t(u^s_{t+1})}_{\text{macro risk}}$$

- "Demand" shock environment: high $Cov_t(\epsilon^g_{t+1}, \epsilon^\pi_{t+1}) \Rightarrow$ nominal bonds hedge well

- "Supply" shock environment: low $Cov_t(\epsilon^g_{t+1}, \epsilon^\pi_{t+1}) \Rightarrow$ nominal bonds hedge poorly

Identification

- "Demand" and "supply" shocks are not identified in Gaussian framework $\Rightarrow$ use unconditional higher order moments (Lanne, Meitz, and Saikkonen, 2017)

- For example, identification via matching co-skewness moments:

$$E[u_t^g (u_t^\pi)^2] = \sigma_g^d (\sigma_\pi^d)^2 E[(u_t^d)^3] + \sigma_g^s (\sigma_\pi^s)^2 E[(u_t^s)^3],$$
$$E[(u_t^g)^2 u_t^\pi] = (\sigma_g^d)^2 \sigma_\pi^d E[(u_t^d)^3] - (\sigma_g^s)^2 \sigma_\pi^s E[(u_t^s)^3].$$

- Imagine: $E[(u_t^s)^3] \approx 0$ and $E[(u_t^d)^3] < 0$:
  - co-skewness moments admit identification of σ_π^d and σ_g^d
  - if $E[u_t^g (u_t^\pi)^2] < E[(u_t^g)^2 u_t^\pi] \Rightarrow \sigma_\pi^d > \sigma_g^d$

Modeling demand and supply shocks

- Demand and supply shocks modeled using Bad Environment-Good Environment (BEGE) structure (Bekaert and Engstrom, 2017): component models of two 0-mean shocks

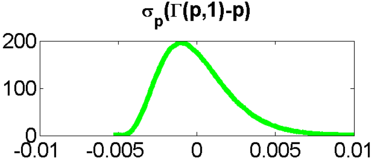
$$\left.\begin{aligned} u^d_{t+1} &= \sigma^d_p \omega^d_{p,t+1} - \sigma^d_n \omega^d_{n,t+1}, \\ u^s_{t+1} &= \sigma^s_p \omega^s_{p,t+1} - \sigma^s_n \omega^s_{n,t+1}, \end{aligned}\right\} \begin{aligned} &\omega_{p,t+1} \text{ - good environment shock} \\ &\omega_{n,t+1} \text{- bad environment shock} \end{aligned}$$

- Shocks follow demeaned gamma distributions:

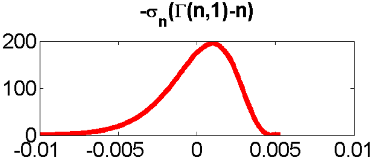
$$\left.\begin{aligned} \omega^d_{p,t+1} &\sim \Gamma(p^d_t, 1) - p^d_t, \\ \omega^d_{n,t+1} &\sim \Gamma(n^d_t, 1) - n^d_t, \\ \omega^s_{p,t+1} &\sim \Gamma(p^s_t, 1) - p^s_t, \\ \omega^s_{n,t+1} &\sim \Gamma(n^s_t, 1) - n^s_t. \end{aligned}\right\} \Gamma(x, y) - \text{gamma distribution with shape parameter x and scale parameter y}$$

Bad Environment-Good Environment structure: Probability density function

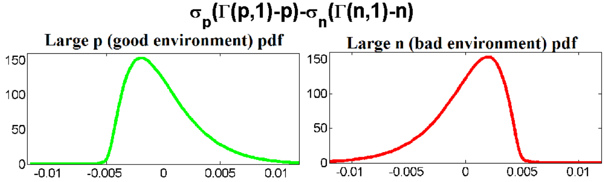
Good component pdf:



Bad component pdf:



Sum pdf:



Time-varying variances

- Shape parameters driven by level shocks (Gourieroux and Jasiak, 2006):

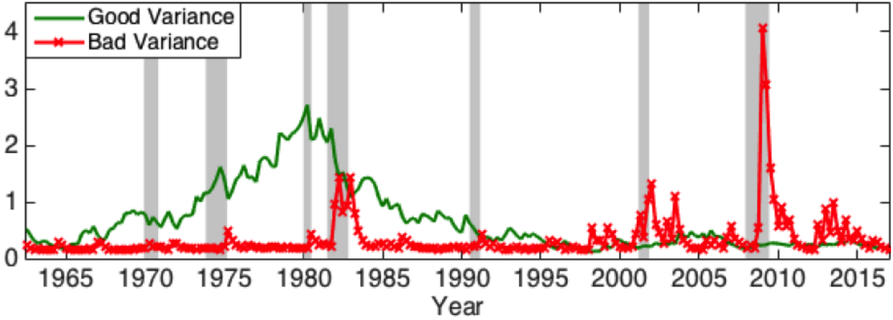
$$p^d_{t+1} = \bar{p}^d + \rho^d_p(p^d_t - \bar{p}^d) + \sigma^d_{pp}\omega^d_{p,t+1}$$

- Similar processes for n^d_{t+1}, p^s_{t+1}, n^s_{t+1}
- **We call** $p^d_t, n^d_t, p^s_t, n^s_t$ **macro risks**:
  - p^d_t/n^d_t = good (positively skewed)/bad (negatively skewed) demand variances
  - p^s_t/n^s_t = good (positively skewed)/bad (negatively skewed) supply variances

Data and Estimation

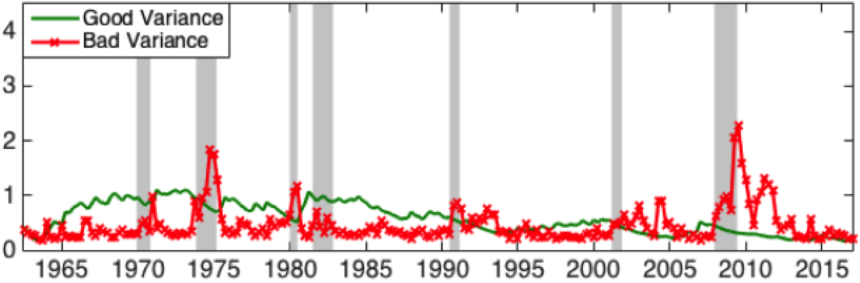
- US quarterly data 1962Q2-2016Q4
- 3 step estimation:
  - Shocks to output growth and inflation: VAR
  - Demand and supply shocks: invert from output growth and inflation shocks after estimating "structural" loadings via GMM using higher order moments **(**3^{rd} **and** 4^{th} **order moments are jointly highly significant and GMM fits them well)**, also allowing for GDP growth and inflation shocks uncorrelated with demand and supply shocks
  - $p_t^d, n_t^d, p_t^s, n_t^s$: approximate maximum likelihood (Bates, 2006)

"Demand" Macro Risks



$$p_t^d = 20.00 + 0.93 \cdot (p_{t-1}^d - 20.00) + 0.98 \cdot \omega_{p,t}^d,$$
$$n_t^d = 0.34 + 0.72 \cdot (n_{t-1}^d - 0.34) + 0.57 \cdot \omega_{n,t}^d.$$

"Supply" Macro Risks



$$p_t^s = 20.00 + 0.99 \cdot (p_{t-1}^s - 20.00) + 0.55 \cdot \omega_{p,t}^s,$$
$$n_t^s = 4.00 + 0.67 \cdot (n_{t-1}^s - 4.00) + 1.25 \cdot \omega_{n,t}^s.$$

Excess Bond Returns and Macro Factors

- Regress future annualized quarterly excess zero-coupon bond returns on macro risks and macro level factors
- Statistical significance is computed using Bauer-Hamilton (2017) bootstrap under the null of no predictability from macro factors
- Macro risks are scaled to unit variance to help interpret regression coefficients

Excess Bond Returns and Macro Factors: Regression Coefficients

	1 year bond	5 year bond
Macro level factors	...	...
p_t^d	-0.87%***	-3.15%***
n_t^d	-0.23%***	-1.66%***
p_t^s	0.40%	0.87%
n_t^s	0.34%	1.45%

Macro level factors: expected aggregate inflation, expected core inflation, expected real GDP growth, unemployment gap

Excess Bond Returns and Macro Factors: Adjusted R^2:s

	1 year bond	5 year bond
3 financial factors	6.66%	7.08%
3 financial factors + macro level factors	9.62%*	7.74%
3 financial factors + macro level factors + macro risks	13.38%***	11.01%***

Financial factors: level, slope, curvature

Realized Bond Return Variances and Macro Factors: Adjusted R^2:s

- Variation in the second moments of bond returns unexplored, although there is a clear return-variance trade-off in Treasury markets (Ghysels et.al., 2014)
- Regressing realized bond return variances on macro risks

	10 year bond
3 financial factors	13.90%
Macro level factors	18.90%
Macro risks	42.67%
3 financial factors + macro level factors	29.37%****
3 financial factors + macro level factors + macro risks	44.08%***

- Macro risks regression coefficients predominantly positive

Conclusions

- Economically intuitive "demand" and "supply" macro risks are robust predictors of excess bond returns
- Work in progress: a term-structure model $\Rightarrow$ more economically motivated than affine term structure models and more tractable than DSGE models