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):

\[ \epsilon^g_{t+1} = \sigma^d_g u^d_{t+1} + \sigma^s_g u^s_{t+1}, \quad \sigma^d_g, \sigma^s_g > 0 \]
\[ \epsilon^\pi_{t+1} = \sigma^d_\pi u^d_{t+1} - \sigma^s_\pi u^s_{t+1}, \quad \sigma^d_\pi, \sigma^s_\pi > 0 \]

\[ \text{Cov}(u^d_{t+1}, u^s_{t+1}) = 0, \text{Var}(u^d_{t+1}) = \text{Var}(u^s_{t+1}) = 1. \]
Intuition

If "supply" and "demand" shocks are heteroskedastic, $\text{Cov}_t(\varepsilon^g_{t+1}, \varepsilon^\pi_{t+1})$ will vary over time:

$$\text{Cov}_t(\varepsilon^g_{t+1}, \varepsilon^\pi_{t+1}) = \sigma^d \sigma^d \text{Var}_t(u^d_{t+1}) - \sigma^s \sigma^s \text{Var}_t(u^s_{t+1})$$

"Demand" shock environment: high $\text{Cov}_t(\varepsilon^g_{t+1}, \varepsilon^\pi_{t+1}) \Rightarrow$ nominal bonds hedge well

"Supply" shock environment: low $\text{Cov}_t(\varepsilon^g_{t+1}, \varepsilon^\pi_{t+1}) \Rightarrow$ nominal bonds hedge poorly
Identification

"Demand" and "supply" shocks are not identified in Gaussian framework ⇒ 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 \( \sigma_\pi^d \) and \( \sigma_g^d \)
- if \( E[u_t^g (u_t^\pi)^2] < E[(u_t^g)^2 u_t^\pi] \) ⇒ \( \sigma_\pi^d > \sigma_g^d \)
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

\[
\begin{align*}
\omega_{p,t+1}^d &= \sigma_p^d \omega_{p,t+1}^d - \sigma_n^d \omega_{n,t+1}^d, \\
\omega_{n,t+1}^d &= \sigma_p^s \omega_{p,t+1}^s - \sigma_n^s \omega_{n,t+1}^s,
\end{align*}
\]

- Shocks follow demeaned gamma distributions:

\[
\begin{align*}
\omega_{p,t+1}^d &\sim \Gamma(p_t^d, 1) - p_t^d, \\
\omega_{n,t+1}^d &\sim \Gamma(n_t^d, 1) - n_t^d, \\
\omega_{p,t+1}^s &\sim \Gamma(p_t^s, 1) - p_t^s, \\
\omega_{n,t+1}^s &\sim \Gamma(n_t^s, 1) - n_t^s.
\end{align*}
\]

\[
\left\{ \begin{array}{l}
\gamma_{p,t+1}^d - \text{good environment shock} \\
\gamma_{n,t+1}^d - \text{bad environment shock}
\end{array} \right\}
\]

\[
\Gamma(x, y) - \text{shape parameter } x \text{ and scale parameter } y
\]
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):
  \[ p_{t+1}^d = \bar{p}^d + \rho_p (p_t^d - \bar{p}^d) + \sigma_{pp} \omega_{p,t+1} \]

- Similar processes for \( n_{t+1}^d, p_{t+1}^s, n_{t+1}^s \)

- **We call** \( p_t^d, n_t^d, p_t^s, n_t^s \) **macro risks:**
  - \( p_t^d/n_t^d = \text{good (positively skewed)/bad (negatively skewed) demand variances} \)
  - \( p_t^s/n_t^s = \text{good (positively skewed)/bad (negatively skewed) supply variances} \)
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 (3rd and 4th 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

\[ p^s_t = 20.00 + 0.99 \cdot (p^s_{t-1} - 20.00) + 0.55 \cdot \omega^s_{p,t}, \]
\[ n^s_t = 4.00 + 0.67 \cdot (n^s_{t-1} - 4.00) + 1.25 \cdot \omega^s_{n,t}. \]
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

<table>
<thead>
<tr>
<th>Macro level factors</th>
<th>1 year bond</th>
<th>5 year bond</th>
</tr>
</thead>
<tbody>
<tr>
<td>$p^d_t$</td>
<td>-0.87%***</td>
<td>-3.15%***</td>
</tr>
<tr>
<td>$n^d_t$</td>
<td>-0.23%***</td>
<td>-1.66%***</td>
</tr>
<tr>
<td>$p^s_t$</td>
<td>0.40%</td>
<td>0.87%</td>
</tr>
<tr>
<td>$n^s_t$</td>
<td>0.34%</td>
<td>1.45%</td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th></th>
<th>1 year bond</th>
<th>5 year bond</th>
</tr>
</thead>
<tbody>
<tr>
<td>3 financial factors</td>
<td>6.66%</td>
<td>7.08%</td>
</tr>
<tr>
<td>3 financial factors +</td>
<td>9.62%*</td>
<td>7.74%</td>
</tr>
<tr>
<td>macro level factors</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3 financial factors +</td>
<td>13.38%***</td>
<td>11.01%***</td>
</tr>
<tr>
<td>macro level factors +</td>
<td></td>
<td></td>
</tr>
<tr>
<td>macro risks</td>
<td></td>
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</tbody>
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Financial factors: level, slope, curvature
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

<table>
<thead>
<tr>
<th>Model</th>
<th>Adjusted $R^2$s</th>
</tr>
</thead>
<tbody>
<tr>
<td>3 financial factors</td>
<td>13.90%</td>
</tr>
<tr>
<td>Macro level factors</td>
<td>18.90%</td>
</tr>
<tr>
<td>Macro risks</td>
<td>42.67%</td>
</tr>
<tr>
<td>3 financial factors + macro level factors</td>
<td>29.37%****</td>
</tr>
<tr>
<td>3 financial factors + macro level factors</td>
<td>44.08%***</td>
</tr>
</tbody>
</table>

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 more economically motivated than affine term structure models and more tractable than DSGE models.