

# Term Structure of Asset Prices and Returns

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# Motivation

- The largest challenge to representative agent models comes from evidence about the term structure of expected returns.
- In an endowment economy, representative agent models have two key components:
  - ① An equilibrium-based SDF which prices all assets of the economy
  - ② An exogenously specified CF process for a given asset
- The empirical evidence implicitly suggests which features these two components must possess.

# Contributions of this paper

- 1 Introduces evidence on term structure of **average log excess returns** for US government bonds, foreign-currency bonds, inflation protected bonds, dividend yields.
- 2 Identifies features that allow affine asset pricing models to be consistent with this evidence
- 3 Introduces the idea of **co-entropy** to compute log excess returns in non-normal environments
- 4 Shows that the empirical evidence is consistent with and implies certain features within an equilibrium asset pricing model

# Definitions

- Cash flow  $d_t$  with growth rate  $g_{t,t+n} = \frac{d_{t+n}}{d_t}$  over  $n$  periods.
  - ▶ Analyze **zero coupon claims** to  $g_{t,t+n}$  with price  $p_{t,n}$
  - ▶ Yield:  $y_{t,t+n} = -\frac{1}{n} \log p_{t,n}$
  - ▶ Hold-to-maturity  $n$ -period log return:  
$$\log R_{t,t+n} = \log(g_{t,t+n}/p_{t,n}) = \log g_{t,t+n} + ny_{t,t+n}$$
- Term spread of average per-period returns:  
$$\frac{1}{n} E[\log R_{t,t+n}] - E[\log R_{t,t+1}] = E[y_{t,t+n} - y_{t,t+1}]$$
- Define per-period excess holding return:  
$$\log RX_{t,t+n} = \frac{1}{n} (\log R_{t,t+n} - \log R_{t,t+n}^f)$$
- **Average difference in log RX = difference in average term spreads!**  
$$E(\log RX_{t,t+n} - \log RX_{t,t+1}) = E(y_{t,t+n} - y_{t,t+1}) - E(y_{t,t+n}^f - y_{t,t+1}^f)$$

We only need to compute the average excess return for  $n = 1$  and then propagate it across horizons using the yields.

# Log excess returns

- Change in averages with horizon tracks the difference between term spreads of the USD bond yield curve and the asset's yield curve.
  - ▶ Returns are difficult to calculate over long horizons, number of observations decrease mechanically
  - ▶ Yields are available every period, do not require CF observations
- Natural relation with entropy of SDF. Log excess returns vs sharpe ratios
- Complements evidence on term structure of risk premia, and connects evidence across the different horizons in a more transparent way
  - ▶ *Binsbergen et al. 2012, Belo et al. 2015*

# Table 1: One period average excess returns

- Quarterly log excess returns: difference of log gross returns between asset and 3 month bond
- Large cross sectional dispersion in returns: 1.36% per quarter
- Short term excess returns are non-normal

## Table 2: Yields and departures from US term structure

- US term structure shape
- Difference in term spread relative to US nominal curve



# Figure 1: Term structure of excess returns

- $E(\log RX_{t,t+n} - \log RX_{t,t+1}) = E(y_{t,t+n} - y_{t,t+1}) - E(y_{t,t+n}^f - y_{t,t+1}^f)$
- Excess returns decline with horizon except for dividend strips
- Large cross-sectional differences in excess returns, increase with horizon (persistence of asset yields vs. interest rates)

# What determines level and shape of the term structure?

Tension between shape and level of US nominal term structure:

- Average level of excess returns (**large**) gives a lower bound on the largest risk premium in the economy  $\iff$  entropy of SDF
- How the yield term spread changes with horizon (**small**) gives an upper bound on horizon dependence. This bounds entropy

Can apply this logic to other assets:

- Redefine pricing kernel as the product of the USD pricing kernel and the cashflow growth of a given asset.
- Term structure driven by differences between USD curve and asset specific yields  $\rightarrow$  **infer empirically plausible cashflow dynamics for each asset**

Will quantitatively characterize this tension using an affine term structure model.

# Matching empirical evidence with an affine model

- ① How can we match shape?
  - Let expected cashflow growth depend on two state variables. One which also effects the expected consumption growth, i.e. the "L.R. risk" component, and one which is asset specific.
  - generates **cross sectional differences in cashflow persistence**, allows cashflow to have different persistence than pricing kernel
- ② How can we match level?
  - The pricing kernel and cashflow growth process should have **non-normal coincident iid** jumps. Resolves tension between level and shape of yield curve, generates realistic risk premia.

# Implications for rep agent endowment economy models

Can reverse-engineer rep agent model with recursive preferences to have a similar functional form of the transformed pricing kernel. **Highlights how certain features of the data translate into an equilibrium model.**

- ① Volatility, rather than variance, of consumption growth  $AR(1)$ 
  - ▶ generates upward sloping yield curves
- ② Consumption growth features iid jump
  - ▶ resolves tension between level and shape in generating realistic risk premia
- ③ Expected cashflow growth depends on two state variables, one similar to traditional LR risk component, and the other asset specific
  - ▶ allows differences in persistence to match shape of term structure

# Related Literature

- Interaction between cashflow and kernel at infinite horizon
  - ▶ *Hansen 2012, Hansen et al. 2008*
  - ▶ In contrast, this paper relies on finite horizon evidence to characterize transition in log excess returns
- Value premium in the cross-section of equities
  - ▶ *Lettau and Wachter 2007*
  - ▶ These papers confront a different set of facts that do not have explicit horizon dependence, make different modeling choices.
- Impact of jumps
  - ▶ *Merton 1976, Backus et al. 2011*
  - ▶ The ability of jumps to explain asset risk premia

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# Entropy

## Definition (Khinchin axioms and Shannon Entropy)

Let  $X$  be a random variable with density  $p$ , the Shannon Entropy

$$H(p) = -\mathbb{E}_t [\log p]$$

is the unique (up to normalization) function from  $\Delta(X)$  to  $\mathbb{R}$  that satisfies the Khinchin Axioms: continuity, expandability, additivity and maximality for the uniform distribution.

## Definition (Relative Entropy (a.k.a. Kullback-Leibler divergence))

Let  $p_{t,t+1} = p(x_{t+1}|x_t)$  be the transition state transition density, and  $p_{t,t+n} = \prod_{j=1}^n p(x_{t+j}|x_{t+j-1})$ . The *relative entropy* of the risk-adjusted distribution is defined as

$$L_t \left( \frac{\tilde{p}_{t,t+n}}{p_{t,t+n}} \right) = \log \mathbb{E}_t \left[ \frac{\tilde{p}_{t,t+n}}{p_{t,t+n}} \right] - \mathbb{E}_t \left[ \log \left( \frac{\tilde{p}_{t,t+n}}{p_{t,t+n}} \right) \right]$$

while  $\tilde{p}_{t,t+n}$  is the same transition density under the risk neutral measure.

# Entropy

## Definition (Conditional Entropy)

$$L_t(M_{t,t+n}) = \log \mathbb{E}_t [M_{t,t+n}] - \mathbb{E}_t [\log M_{t,t+n}]$$



# Entropy

## Definition (Conditional Entropy)

$$L_t(M_{t,t+n}) = \log \mathbb{E}_t [M_{t,t+n}] - \mathbb{E}_t [\log M_{t,t+n}]$$

Linkage:  $M_{t,t+n} = q_{t,t+n} \frac{\tilde{p}_{t,t+n}}{p_{t,t+n}}$  where  $q_{t,t+n} := \mathbb{E}_t [M_{t,t+n}] = R_{t,t+1}^f$  is the price of an  $n$ -period bond.

# Entropy

## Definition (Conditional Entropy)

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## Proposition (Entropy Bound)

The pricing equation  $\mathbb{E}_t [M_{t,t+1} R_{t,t+1}] = 1$  implies

$$\mathbb{E} \left[ \log R_{t,t+1} - \log R_{t,t+1}^f \right] \leq \mathbb{E} [L_t(M_{t,t+1})]$$

## Proof.

Apply Jensen's inequality to the pricing equation

$$\mathbb{E}_t [\log M_{t,t+1}] + \mathbb{E}_t [\log R_{t,t+1}] \leq 0$$

add  $L_t(M_{t,t+1})$  to both sides and take unconditional expectation. □

# Cumulant Generating Function

## Definition (Cumulant Generating Function)

$$k_t(s; \log(X_{t+1})) = \log \mathbb{E}_t \left[ e^{s \log X_{t+1}} \right]$$

Linkage:

$$\begin{aligned} L_t(M_{t,t+1}) &= k_t(1; \log M_{t,t+1}) - \mathbb{E}_t [\log M_{t,t+1}] \\ &= \frac{\kappa_{2,t}(\log M_{t,t+1})}{2!} + \underbrace{\sum_{j=3}^{\infty} \frac{\kappa_{j,t}(\log M_{t,t+1})}{j!}}_{\text{Nonnormalpart}} \end{aligned} \quad (1)$$

where  $\kappa_{j,t}(X) := \frac{\partial^j}{\partial s^j} k_t(s; X)|_{s=0}$  and  $k_t(s; X) = \sum_{j=1}^{\infty} \kappa_{j,t}(X) \frac{s^j}{j!}$ .

# Coentropy

## Definition (Coentropy)

$$C(X_1, X_2) = L(X_1 X_2) - L(X_1) - L(X_2)$$

### Relation to CGFs:

$$k(s_1, s_2) = \log \mathbb{E} \left[ e^{s_1 \log X_1 + s_2 \log X_2} \right] = \sum_{j=1}^{\infty} \sum_{p=0}^j \frac{\kappa^{j-p,p}}{j!} \frac{j!}{p!(j-p)!} s_1^{j-p} s_2^p$$

where  $\kappa^{i,j} = \frac{\partial^{i+j}}{\partial s_1^i \partial s_2^j} k(s_1, s_2) \big|_{s_1=s_2=0}$  is the joint cumulant.

$$C(X_1, X_2) = \underbrace{\kappa^{1,1}}_{\text{log-normal}} + \underbrace{\sum_{j=3}^{\infty} \sum_{p=1}^{j-1} \frac{\kappa^{j-p,p}}{p!(j-p)!}}_{\text{higher-order joint cumulants}}$$

**Intuition:** Coentropy focuses on the joint distribution of two r.v. by removing all the terms pertaining to the respective marginal distributions.

# Horizon dependence

## Proposition (Horizon dependence and bond yield)

Assuming stationarity,  $\mathbb{E} [\log M_{t,t+1}] = \mathbb{E} [\log M_{s,s+1}]$ ,  $\forall s$ , we have  
 $\mathcal{H}_m(n) := \mathcal{L}_m(n) - \mathcal{L}_m(1) = -\mathbb{E} [y_{t,t+n}^f - y_{t,t+1}^f]$  where  
 $\mathcal{L}_m(n) = \frac{1}{n} \mathbb{E} [L_t(M_{t,t+n})]$  and  $y_{t,t+n}^f = -\frac{1}{n} \log q_{t,t+n}$  is the yield

Intuition: If  $M_{t,t+1}$  are iid, then  $\mathbb{E} [L_t(M_{t,t+n})] = n \mathbb{E} [L_t(M_{t,t+1})]$ . So  $\mathcal{H}_m(n)$  measures the departure from the iid case which is observed in data.

## Proof.

$$\begin{aligned} L_t(M_{t,t+n}) &= \log \mathbb{E}_t [M_{t,t+n}] - \mathbb{E}_t [\log M_{t,t+n}] \\ L_t(M_{t,t+n}) &= \log q_{t,t+n} - \mathbb{E}_t \left[ \sum_{j=1}^n \log M_{t+j-1,t+j} \right] \\ \mathcal{L}_m(n) &= \frac{1}{n} \mathbb{E} [\log q_{t,t+n}] - \mathbb{E} [\log M_{t,t+1}] \text{ by stationarity} \\ \mathcal{H}_m(n) &= -\mathbb{E} [y_{t,t+n}^f - y_{t,t+1}^f] \text{ by } y_{t,t+n}^f = -\frac{1}{n} \log q_{t,t+n} \end{aligned}$$



Implication: Increasing yield curve  $\Rightarrow$  negative horizon dependence.

# Excess Return and Coentropy

Proposition ((log) risk premium and expected (log) excess return)

$$\log \mathbb{E}_t [R_{t,t+1}] - \log R_{t,t+1}^f = -C_t(M_{t,t+1}, R_{t,t+1})$$

$$\mathbb{E}_t [\log R - \log R^f] = L_t(M) - L_t(MR) = -L_t(R) - C_t(M, R)$$

Proof.

$$\begin{aligned} C_t(M, R) &= \log \mathbb{E}_t [MR] - \mathbb{E}_t [\log(MR)] - (\log \mathbb{E}_t [M] - \mathbb{E}_t [\log M]) \\ &\quad - (\log \mathbb{E}_t [R] - \mathbb{E}_t [\log R]) \\ &= -\log \mathbb{E}_t [R] - \log \mathbb{E}_t [M] \\ &\quad + (\mathbb{E}_t [\log R] + \mathbb{E}_t [\log M] - \mathbb{E}_t [\log(MR)]) \\ &= -\log \mathbb{E}_t [R] + \log R^f \end{aligned}$$

$$L_t(M) - L_t(MR) = \log \mathbb{E}_t [M] + \mathbb{E}_t [\log MR] - \mathbb{E}_t [\log M] - \log \mathbb{E}_t [MR] \quad (2)$$

□

# Example

**Example 1:**  $\log M_{t,t+1} = \log \beta + a_0 w_{t+1} + a_1 w_t$  with  $w_t$  i.i.d. standard normal

- $L_t(M_{t,t+1}) = \frac{a_0^2}{2}$
- $\log M_{t,t+n} = ns \log \beta + a_0 w_{t+n} + (a_0 + a_1) \sum_{j=1}^{n-1} w_{t+j} + a_1 w_t$
- $k_t(s; \log M_{t,t+n}) = ns \log \beta + (n-1)s^2 \frac{(a_0+a_1)^2}{2} + s^2 \frac{a_0^2}{2} + sa_1 w_t$
- $\log q_{t,t+n} = k_t(1; \log M_{t,t+n})$
- $y_{t,t+1}^f = -\log q_{t,t+1} = -\log \beta - a_0^2/2 - a_1 w_t$
- $\mathcal{H}_m(n) = \frac{n-1}{n} \frac{(a_0+a_1)^2 - a_0^2}{2}$

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- $k_t(s; \log M_{t,t+n}) = ns \log \beta + (n-1)s^2 \frac{(a_0+a_1)^2}{2} + s^2 \frac{a_0^2}{2} + sa_1 w_t$
- $\log q_{t,t+n} = k_t(1; \log M_{t,t+n})$
- $y_{t,t+1}^f = -\log q_{t,t+1} = -\log \beta - a_0^2/2 - a_1 w_t$
- $\mathcal{H}_m(n) = \frac{n-1}{n} \frac{(a_0+a_1)^2 - a_0^2}{2}$

Tension: volatility of  $y_{t,t+1}^f$  pins down  $a_1 \Rightarrow$  level of  $y_{t,t+1}^f$  determines  $a_0 \Rightarrow$  need to match  $\mathcal{H}_m(n)$  simultaneously.



## Example: Coentropy

**Example 2:** Let  $\log(X)|J=j \sim \mathcal{N}(j\mu, j\Delta)$  where  $J \sim \text{Poi}(\omega)$  and  $\Delta = (\delta_{ij})_{ij} \in \mathbb{R}^{2 \times 2}$  is a 2 dimensional symmetric positive definite matrix.

- $k(s) = \omega(e^{s^\top \mu + \frac{1}{2}s^\top \Delta s} - 1)$
- $L(X_i) = \omega(e^{\mu_i + \frac{1}{2}\delta_{ii}} - 1) - \omega\mu_i$
- $L(X_1 X_2) = \omega(e^{\mu_1 + \mu_2 + \frac{1}{2}(\delta_{11} + \delta_{11} + 2\delta_{12})} - 1) - \omega(\mu_1 + \mu_2)$
- $C(X_1, X_2) = \omega(e^{\mu_1 + \mu_2 + \frac{1}{2}(\delta_{11} + \delta_{11} + 2\delta_{12})} - e^{\mu_1 + \frac{1}{2}\delta_{11}} - e^{\mu_2 + \frac{1}{2}\delta_{22}} + 1)$
- $\text{Cov}(\log X_1, \log X_2) = \sum_{j=0}^{\infty} (\mu_1 \mu_2 + \delta_{12}) j \frac{\omega^j e^{-\omega}}{j!} = (\mu_1 \mu_2 + \delta_{12}) \mathbb{E}[J]$

## Example: Coentropy

**Figure:** Coentropy and covariance:  $\mu_1 = \mu_2 = -0.5$ ,  $\Delta = \frac{1}{\omega} \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$ . The  $\frac{1}{\omega}$  term is to ensure the variance doesn't vary with  $\omega$ .

## Term Structure of assets

Let  $\hat{M}_{t,t+1} = M_{t,t+1}g_{t,t+1}$  be a transformed pricing kernel, we have

$$q_{t,t+n} = \mathbb{E}_t [M_{t,t+1}g_{t,t+1}q_{t+1,t+n}] = \mathbb{E}_t [\hat{M}_{t,t+1}q_{t+1,t+n}]$$

### Definition (Excess Return)

$$\log RX_{t,t+n} = \frac{1}{n}(\log R_{t,t+n} - \log R_{t,t+n}^f)$$

### Proposition

$$\mathbb{E}_t [\log RX_{t,t+n} - \log RX_{t,t+1}] = \mathcal{H}_m(n) - \mathcal{H}_{\hat{m}}(n)$$

### Proof.

$$\mathbb{E}_t [\log RX_{t,t+n} - \log RX_{t,t+1}] =$$

$$\mathbb{E}_t [y_{t,t+n} - y_{t,t+n}^f] - \mathbb{E}_t [y_{t,t+1} - y_{t,t+1}^f] =$$

$$\mathbb{E}_t [y_{t,t+n} - y_{t,t+1}] - \mathbb{E}_t [y_{t,t+n}^f - y_{t,t+1}^f] = -\mathcal{H}_{\hat{m}}(n) + \mathcal{H}_m(n)$$

□

# Simplified KLV Model

## Setup

$$\begin{cases} \log M_{t,t+1} = \log \beta + \theta_m^\top x_t - \lambda_t^2/2 + \lambda_t w_{t+1} \\ \log g_{t,t+1} = \log \gamma + \theta_g^\top x_t + \eta_0 w_{t+1} \\ x_{t+1} = \Phi x_t + w_{t+1} e \end{cases} \quad (3)$$

where  $x_t = (\mathbf{x}_{1,t}, x_{2,t})^\top$ ,  $\lambda_t = \lambda_0 + \lambda_1 \mathbf{x}_{1,t}$ ,  $\theta_m = (\theta_{m1}, 0)^\top$ ,  $\Phi = \text{diag}(\phi_1, \phi_2)$  and  $\{w_t\}$  is i.i.d. normal.

**Conditional Entropy**  $L_t(M_{t,t+1}) = (\lambda_0 + \lambda_1 x_{1,t})^2/2$

**Entropy**  $\mathcal{L}_m(1) = \frac{1}{2} \left( \lambda_0^2 + \frac{\lambda_1^2}{1-\phi^2} \right)$

# Simplified KLV Model: Bond Price

## Bond Price

- 1 Suppose  $q_{t,t+n} = A_n + B_n x_t$
- 2  $q_{t,t+n} = \mathbb{E}_t \left[ e^{\log \beta + \theta_m^\top x_t - \lambda_t^2 / 2 + \lambda_t w_{t+1}} e^{A_{n-1} + B_{n-1}(\Phi x_t + w_{t+1} e)} \right]$
- 3 Match the coefficient of  $x_t$

$$\begin{cases} B_n = \theta_m^\top + B_{n-1} \Phi + B_{n-1} [\lambda_1 e, 0] \\ A_n = \log \beta + \lambda_0 B_{n-1}^\top e + \frac{1}{2} (B_{n-1}^\top e)^2 \end{cases}$$

- 4  $q_{t,t+1} = \mathbb{E}_t \left[ e^{\log \beta + \theta_m^\top x_t - \lambda_t^2 / 2 + \lambda_t w_{t+1}} \right] = e^{\log \beta + \theta_m^\top x_t}$

- 5 
$$\begin{cases} B_n = \theta_m^\top (I - \Phi^*)^{-1} (I - \Phi^{*n}); \Phi^* = \Phi + [\lambda_1 e, 0] \\ A_n = n \log \beta + \lambda_0 \sum_{j=0}^{n-1} B_j^\top e + \frac{1}{2} \sum_{j=0}^{n-1} (B_j^\top e)^2 \end{cases}$$

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- 3 Match the coefficient of  $x_t$

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- 4  $q_{t,t+1} = \mathbb{E}_t \left[ e^{\log \beta + \theta_m^\top x_t - \lambda_t^2 / 2 + \lambda_t w_{t+1}} \right] = e^{\log \beta + \theta_m^\top x_t}$

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**Horizon Dependence**  $\mathcal{H}_m(n) = \frac{1}{n} \left[ \lambda_0 \sum_{j=0}^{n-1} B_j^\top e + \frac{1}{2} \sum_{j=0}^{n-1} (B_j^\top e)^2 \right]$

# Simplified KLV Model: Transformed Pricing Kernel

## Transformed Pricing Kernel and its Horizon Dependence

- $\log \hat{M}_{t,t+1} = \log \hat{\beta} + \hat{\theta}_m^\top x_t - \hat{\lambda}_t^2/2 + \hat{\lambda}_t w_{t+1}$  where
  - ▶  $\log \hat{\beta} = \log \beta + \log \gamma + \lambda_0 \eta_0 + \frac{\eta_0^2}{2}$
  - ▶  $\hat{\theta}_m^\top = (\theta_{m1} + \theta_{g1} + \eta_0 \lambda_1, \theta_{g2})$
  - ▶  $\hat{\lambda}_0 = \lambda_0 + \eta_0, \hat{\lambda}_t = \hat{\lambda}_0 + \lambda_1 x_{1,t}$
- $\mathcal{H}_{\hat{m}}(n) = \frac{1}{n} \left[ \hat{\lambda}_0 \sum_{j=0}^{n-1} \hat{B}_j^\top e + \frac{1}{2} \sum_{j=0}^{n-1} (\hat{B}_j^\top e)^2 \right]$ 
  - ▶  $\hat{B}_n = \hat{\theta}_m^\top (I - \Phi^*)^{-1} (I - \Phi^{*n})$

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# Calibration of KLV

## US nominal bonds

- Short rate,  $y_{t,t+1}^f = -\log q_{t,t+1} = -\log \beta - \theta_{m1} x_{1t} \rightarrow$  match empirical **short rate std dev and autocorrelation**  $\rightarrow \theta_{m1}, \phi_1$
- Match empirical **average of term spread**  $y_{t,t+40}^f - y_{t,t+1}^f$  using duality of horizon dependence and average term spread  $\rightarrow \lambda_0$
- Match empirical **level** of yield curve  $\rightarrow \beta$
- Match maturity dependence of term spread with **curvature of yield curve**  $\rightarrow \lambda_1$

# Calibration of KLV

FX bonds and equity dividend strips

- Assume  $\theta_{g1} = -\theta_{m1} - \lambda_1 \eta_0$
- One-period yield  $y_{t,t+1} = -\log \hat{\beta} - \theta_{g2} x_{2t} \rightarrow$  match empirical **std dev and autocorrelation**  $\rightarrow \theta_{g2}, \phi_2$
- Match empirical **average of term spread**  $\rightarrow \eta_0$
- Match empirical **level** of one-period yield  $\rightarrow \gamma$

# KLV results

- Contrary to literature, FX rates are not random walks
- The domestic and foreign pricing kernels are not symmetric

In KLV lognormal setting,

$$\begin{aligned}\mathbb{E}_t [\log RX_{t,t+1}] &= -\frac{1}{2}\text{var}_t (\log RX_{t,t+1}) - \text{cov}_t (\log M_{t,t+1}, \log RX_{t,t+1}) \\ &= -\frac{\eta_0^2}{2} - (\lambda_0 + \lambda_1 x_{1t}) \eta_0\end{aligned}$$

The unconditional average excess returns  $-\frac{\eta_0^2}{2} - \lambda_0 \eta_0$  **do not match** the data after calibration for the other moments!

# KLTV results

## KLV Extension I: iid normal shocks

Idea: iid terms affecting both SDF and cashflow growth do not affect term spreads.

$$\begin{cases} \log M_{t,t+1} = \log \beta + \theta_m^\top x_t - \lambda_t^2/2 + \lambda_t w_{t+1} + \lambda_2 \varepsilon_{t+1} \\ \log g_{t,t+1} = \log \gamma + \theta_g^\top x_t + \eta_0 w_{t+1} + \eta_2 \varepsilon_{t+1} \\ x_{t+1} = \Phi x_t + w_{t+1} e \end{cases} \quad (4)$$

This yields,

$$\text{var} \log RX_{t,t+1} = \eta_0^2 \left[ 1 + \lambda_1^2 (1 - \phi_1^2)^{-1} \right] + \eta_2^2 \rightarrow \eta_2$$

$$\mathbb{E} [\log RX_{t,t+1}] = -\frac{\eta_0^2}{2} - \frac{\eta_2^2}{2} - \lambda_0 \eta_0 - \lambda_2 \eta_2 \rightarrow \lambda_2$$

$\lambda_2$  (unique loading on the SDF) varies in the cross-section – failure

## KLV Extension II: iid Poisson shocks

$$\begin{cases} \log M_{t,t+1} = \log \beta + \theta_m^\top x_t - \lambda_t^2/2 + \lambda_t w_{t+1} + \lambda_2 z_{t+1}^m \\ \log g_{t,t+1} = \log \gamma + \theta_g^\top x_t + \eta_0 w_{t+1} + \eta_2 z_{t+1}^g \\ x_{t+1} = \Phi x_t + w_{t+1} e \end{cases} \quad (5)$$

Here,  $z^g$  and  $z^m$  are both compound Poisson processes (with **coincident jumps**) with arrival rate  $\omega$  and jump size distribution  $\mathcal{N}(\mu_m, \delta_m^2)$  and  $\mathcal{N}(\mu_d, \delta_g^2)$ , respectively.

## KLV Extension II: iid Poisson shocks

Define  $\mathcal{C}_{mg}(n) = n^{-1} \mathbb{E} [C_t (M_{t,t+n}, g_{t,t+n})]$ .

Hence,

$$\mathcal{C}_{mg}(n) - \mathcal{C}_{mg}(1) = \mathcal{H}_{\widehat{m}}(n) - \mathcal{H}_m(n) - \mathcal{H}_g(n)$$

Horizon dependence  $\mathcal{H}$  for any of  $\{\widehat{m}, m, g\}$  is not affected by any iid shocks! This gives,

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$$\mathcal{C}_{mg}(1) = \lambda_0 \eta_0 + k_z(\lambda_2, \eta_2) - k_z(\lambda_2, 0) - k_z(0, \eta_2)$$

$$\text{where, } k_z(s_1, s_2) = \omega \left( e^{s_1 \mu_m + s_2 \mu_g + \frac{1}{2} (s_1^2 \delta_m^2 + s_2^2 \delta_g^2)} - 1 \right)$$



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But the entropy differs now:

$$\mathcal{L}_m(1) = \frac{\lambda_0^2}{2} + \frac{\lambda_1^2}{2} (1 - \phi_1^2)^{-1} - \omega \lambda_2 \mu_m + \omega \left( e^{\lambda_2 \mu_m + \frac{1}{2} \lambda_2^2 \delta_m^2} \right)$$

We also get  $\mathcal{C}_{mg}(n)$  and  $\mathcal{L}_m(n)$ .

# Calibration of KLV Extn II

- Normalize  $\lambda_2 = \eta_2 = 1$ .
- Use CI2 model from ? to get *reasonable*  $\omega, \mu_m, \delta_m$
- 

$$\mathbb{E} [\log RX_{t,t+1}] = -\frac{\eta_0^2}{2} - \lambda_0 \eta_0 - k_z(\lambda_2, \eta_2) + k_z(\lambda_2, 0) + \omega \eta_2 \mu_g \rightarrow \mu_g$$
$$\text{var} \log RX_{t,t+1} = \eta_0^2 \left( 1 + \lambda_1^2 (1 - \phi_1^2)^{-1} \right) + \eta_2^2 \omega (\mu_g + \delta_g^2) \rightarrow \delta_g$$

## KLV Extn II: iid Poisson shocks

### Results:

- Covariance and coentropy vary significantly
- Variance and autocorrelation of simulated cash-flows (*not matched in calibration*) line up with the data
- Equity premium (infinite portfolio of strips) is matched as well
- Further analysis: non-normality in SDF largely drives the risk-premium BUT needs the non-normality in cash flow (even if it's small) to get any traction



# A Representative Agent Model

# References