

# Robust Identification of Investor Beliefs

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# Motivation

Behavioral “distortions” and “ambiguity aversion” are **compelling** in environments for which uncertainty is **complex** and speculation about the future is **challenging**

## ▷ WHAT?

- We propose and justify a **data** and **model-based** method for deducing market beliefs
- We construct bounds on **expectations** of unknown future aggregates captured as a nonlinear expectation

## ▷ WHY?

- They provide a formal way to address the **public** and **private sector** interest in market perceptions
- They serve as a **diagnostic** for models in which asset prices are represented with distorted beliefs

# Two observations

Asset prices are:

- ▷ REVEALING: forward-looking and serve as barometers for market beliefs
- ▷ CHALLENGING:
  - entangle beliefs and risk aversion
  - data are sparse along some important dimensions

# Two approaches

We could:

- ▷ impose **rational expectations** and explore “exotic” or “ad hoc” models with time-varying risk aversion
- ▷ model beliefs that are **distorted** (relative to rational expectations) justified by a) psychology or b) ambiguity aversion with moderate risk aversion

We speak to this **second approach**:

*We bound private sector beliefs by limiting how much these beliefs conflict with the probabilities implied by historical evidence.*

# Our method

- ▷ presume that a dynamic model is **misspecified** under rational expectations
- ▷ correct this misspecification, we allow for beliefs to differ and to be “**distorted**” (from rational expectations)
- ▷ limit the alternative probabilities using statistical measures of “**divergence**” that capture the magnitude of the distortion
- ▷ derive **bounds** on the beliefs that are consistent with the observed asset prices and survey evidence

# Basic formulation

- ▷ Moment equations under rational expectations:

$$\mathbb{E} [f(X, \theta) \mid \mathfrak{A}] = 0.$$

where the function  $f$  captures the parameter dependence ( $\theta$ ) along with variables ( $X$ ) observed by the econometrician.

- ▷ A typical asset pricing example:

$$\mathbb{E}(SRet - \mathbf{1}_n | \mathfrak{A}) = 0$$

where  $Ret$  is a vector of returns,  $S$  is the stochastic discount factor (SDF),  $\mathfrak{A}$  denote the investor information set.

For simplicity, I will drop the parameter dependence but comment later on how unknown parameters can be included.

# Market beliefs

We consider **conditional moment restrictions** of the form:

$$\widetilde{\mathbb{E}}[f(X) \mid \mathfrak{A}] = \mathbb{E}[Nf(X) \mid \mathfrak{A}] = 0.$$

where  $N \geq 0$  and  $\mathbb{E}(N \mid \mathfrak{A}) = 1$ .

The random variable  $N$  provides a flexible change in the probability measure.  $N$  captures how the rational expectations are altered by market beliefs.

- ▷ each  $N$  is a “**belief distortion**”
- ▷  $N$  **not uniquely identified!**

General applicability to dynamic, stochastic, general equilibrium models.

# Two Applications

- ▷ long-term risk-neutral pricing

$$S = (Ret^h)^{-1}$$

where  $Ret^h$  is the limiting holding period return on a long-term bond

- ▷ unitary relative risk aversion in recursive utility

$$S = (Ret^w)^{-1}$$

where  $Ret^w$  is the one-period return on the wealth portfolio



# Digression 1

For recursive utility,

▷ The SDF ratio is:

$$\frac{S_{t+1}}{S_t} = \beta \left( \frac{C_{t+1}}{C_t} \right)^{-\rho} \left( \frac{V_{t+1}}{R_t} \right)^{\rho-1} \left( \frac{V_{t+1}}{R_t} \right)^{1-\gamma}.$$

▷ The return on wealth is:

$$Ret_{t+1}^w = \beta^{-1} \left( \frac{V_{t+1}}{R_t} \right)^{1-\rho} \left( \frac{C_{t+1}}{C_t} \right)^{\rho}.$$

**Observation:** for  $\gamma = 1$ ,  $(Ret_{t+1}^w)^{-1}$  is the one-period stochastic discount factor ratio

## Digression 2

For long-term approximation, consider the eigenvalue problem:

$$\mathbb{E} \left[ \left( \frac{S_{t+1}}{S_t} \right) e^s(X_{t+1}) \mid \mathfrak{A}_t \right] = \exp(\eta^s) e^s(X_t)$$

▷ Limiting holding-period return is

$$Ret_{t+1}^h = \exp(-\eta^s) \left[ \frac{e^s(X_{t+1})}{e^s(X_t)} \right]$$

▷ One-period transition for the long-term risk neutral probability:

$$N_{t+1} = \left( \frac{S_{t+1}}{S_t} \right) \left[ \frac{e^s(X_{t+1})}{e^s(X_t)} \right] \exp(-\eta^s)$$

**Observation:**  $\frac{S_{t+1}}{S_t} = N_{t+1} (R_{t+1}^h)^{-1}$ .

# Proportional risk premia

The **proportional risk premia** from the perspective of the altered probability is:

$$\log \mathbb{E} (NRet \mid \mathfrak{A}) + \mathbf{1}_n \log \mathbb{E} (NS \mid \mathfrak{A}) .$$

- ▷ The first term is the logarithm **altered expectation** of  $Ret$
- ▷ The second term is the negative of the logarithm of the **risk-free return**

Our methods allow us to compare the rational expectations version of the risk compensations to bounds on these proportional compensations as implied by market data.

# Dynamic recursive formulation

- ▷ **environment**: Baseline probability triple  $(\Omega, \mathfrak{G}, P)$  used to govern the data generation
- ▷ **alternative probability measure**  $Q$
- ▷ **conditioning information**: let  $\mathfrak{A}_t$  denote the date  $t$  information (sigma algebra) where  $\mathfrak{A}_t \subset \mathfrak{A}_{t+1}$

Recall:  $Q_t$  and  $P_t$  are the restrictions of  $Q$  and  $P$  to  $\mathfrak{A}_t$

# Alternative probabilities

- ▷ consider probabilities  $Q$  for which there exists an  $N = \{N_{t+1} : t = 0, 1, \dots\} \geq 0$  where  $N_{t+1}$  is in the date  $t + 1$  information set and satisfies:

$$\int B_t dQ_t = \int \mathbb{E}(N_{t+1} B_{t+1} \mid \mathfrak{A}_t) dQ_t$$

for bounded stochastic process  $B$

- ▷ form

$$M_T = \prod_{t=1}^T N_t$$

where  $\mathbb{E}(M_T B_T \mid \mathfrak{A}_0)$  is the conditional expectation of  $B_T$  under  $Q$ .

Note:  $N_{t+1}$  distorts the **one-period transition probabilities** between dates  $t$  and  $t + 1$ .

# Conditional Divergence

We use the **conditional** version of  $\phi$  divergence as an important **building block**:

$$\mathbb{E} [\phi(N_{t+1}) \mid \mathfrak{A}_t]$$

for a strictly convex function  $\phi$  defined on  $(0, \infty)$  with  $\phi(1) = 0$ .

▷ by Jensen's Inequality,

$$\mathbb{E} [\phi(N_{t+1}) \mid \mathfrak{A}_t] \geq 0.$$

▷ leading example:

$$\phi(n) = n \log n$$

which is conditional relative entropy or Kullback-Leibler divergence.

# Equivalent representation

Construct a function  $\psi$  such that

$$n\psi\left(\frac{1}{n}\right) = \phi(n).$$

Observations:

- ▷  $\psi$  is also strictly convex with  $\psi(1) = 0$
- ▷  $\psi$  satisfies

$$\mathbb{E}\left[N_{t+1}\psi\left(\frac{1}{N_{t+1}}\right) \mid \mathfrak{A}_t\right] = \mathbb{E}[\phi(N_{t+1}) \mid \mathfrak{A}_t]$$

- ▷ for Kullback-Leibler

$$\psi(n) = -\log n$$

# Intertemporal divergence

$$\mathcal{R}(N) = \lim_{T \rightarrow \infty} \frac{1}{T} \mathbb{E} \left[ M_T \sum_{t=1}^T \psi \left( \frac{1}{N_t} \right) \mid \mathfrak{A}_0 \right]$$

Observations:

- ▷ by the Law of Large Numbers for stationary, ergodic processes:

$$\int \psi \left( \frac{1}{N_{t+1}} \right) dQ_{t+1} = \int \mathbb{E} [\phi(N_{t+1}) \mid \mathfrak{A}_t] dQ_t.$$

where  $Q$  is the probability measure implied by  $N$ .

- ▷ Divergence depends on  $N_{t+1}$  and  $Q_t$  which are linked via the stationarity restriction.



# Problem of interest

For a given function  $g$ , we solve:

$$\inf_{N \geq 0} \lim_{t \rightarrow \infty} \frac{1}{T} \mathbb{E} \left[ M_T \sum_{t=1}^T g(X_t) \middle| \mathfrak{A}_0 \right]$$

subject to the constraints

$$\mathcal{R}(N) \leq \kappa$$

$$\mathbb{E}[N_{t+1} f(X_{t+1}) \mid \mathfrak{I}_t] = 0$$

$$\mathbb{E}[N_{t+1} \mid \mathfrak{I}_t] = 1$$

$$M_{t+1} = N_{t+1} M_t$$

Impose additional restrictions to ensure implied probability measures satisfy the Law of Large Numbers.

# Solution

Three steps:

- i) introduce a **nonnegative multiplier** to enforce the constraint  $\mathcal{R}(N) \leq \kappa$  and solve the problem for alternative values of this multiplier,
- ii) use a **martingale decomposition** of the objective to produce a recursive representation of the multiplier problem,
- iii) solve this problem using **recursive methods** familiar from dynamic programming.

# Step one

Solve

$$\inf_{N \geq 0} \lim_{t \rightarrow \infty} \frac{1}{T} \mathbb{E} \left( M_T \left[ \sum_{t=1}^T g(X_t) + \xi \psi \left( \frac{1}{N_t} \right) \right] \middle| \mathfrak{A}_0 \right) - \xi \kappa$$

subject to the constraints

$$\mathbb{E}[N_{t+1} f(X_{t+1}) \mid \mathfrak{I}_t] = 0$$

$$\mathbb{E}[N_{t+1} \mid \mathfrak{I}_t] = 1$$

$$M_{t+1} = N_{t+1} M_t$$

where  $\xi \geq 0$  is a Lagrange multiplier

Taking the supremum over  $\xi$  enforces the divergence constraint.

# Martingale decomposition

Recursion: find a real number  $\mu$  and a stochastic process  $v$  such that

$$\mathbb{E} \left( N_{t+1} \left[ g(X_{t+1}) + \xi \psi \left( \frac{1}{N_{t+1}} \right) + v_{t+1} \right] \mid \mathfrak{A}_t \right) - \mu - v_t = 0$$

Observe that

$$\sum_{t=1}^T \left[ g(X_{t+1}) + \xi \psi \left( \frac{1}{N_{t+1}} \right) \right] - T\mu + v_T - v_0$$

is martingale under  $\mathbb{Q}$ .

## Step three

Recursion: find a number  $\mu$  and a process  $v$  such that

$$\inf_{N_{t+1} \geq 0} \mathbb{E} \left( N_{t+1} \left[ g(X_{t+1}) + \xi \psi \left( \frac{1}{N_{t+1}} \right) + v_{t+1} \right] \mid \mathfrak{A}_t \right) - \mu - v_t = 0$$

subject to

$$\mathbb{E} [N_{t+1} f(X_{t+1}) \mid \mathfrak{A}_t] = 0$$

$$\mathbb{E} (N_{t+1} \mid \mathfrak{A}_t) = 1$$

Compute using dynamic programming methods.

# Nonlinear expectation

We represent restricted belief distortions by an alternative **nonlinear expectation**.  $\mathbb{K}$  maps bounded functions  $g$  into real numbers and satisfies:

- i) if  $g_2 \geq g_1$ , then  $\mathbb{K}(g_2) \geq \mathbb{K}(g_1)$ .
- ii) if  $g$  constant, then  $\mathbb{K}(g) = g$ .
- iii)  $\mathbb{K}(rg) = r\mathbb{K}(g)$ ,  $r \geq 0$
- iv)  $\mathbb{K}(g_1) + \mathbb{K}(g_2) \leq \mathbb{K}(g_1 + g_2)$

# Unitary risk aversion

- ▷ consider the **recursive utility** model as in Kreps and Porteus and Epstein and Zin
- ▷ explore **belief distortions** instead of large and/or time-varying risk aversion
- ▷ value assets with the **stochastic discount factor**

$$S_{t+1} = N_{t+1} (Ret_{t+1}^w)^{-1}$$

where  $Ret_{t+1}^w$  denotes the return on wealth.

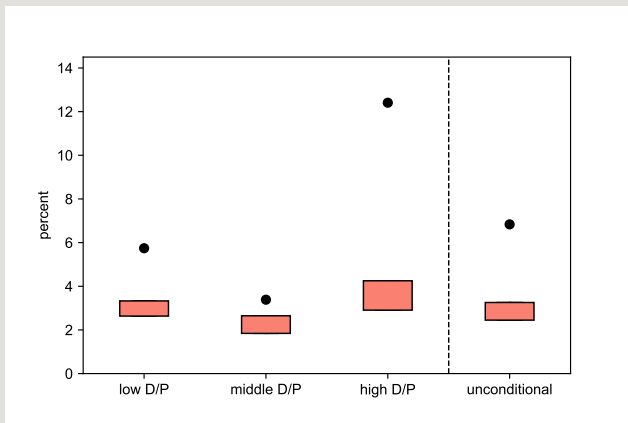
- ▷ Expected logarithm of the wealth portfolio:

$$E \left( N_{t+1} \log Ret_{t+1}^w \mid \mathfrak{A}_t \right) = -\log \beta + \rho E \left[ N_{t+1} \left( \widehat{C}_{t+1} - \widehat{C}_t \right) \mid \mathfrak{A}_t \right].$$

$$\text{since } \widehat{R}_t = \mathbb{E} \left( N_{t+1} \widehat{V}_{t+1} \mid \mathfrak{A}_t \right).$$

**Simple link** between the expected **log return on wealth** and expected **growth rate** in the macro economy.

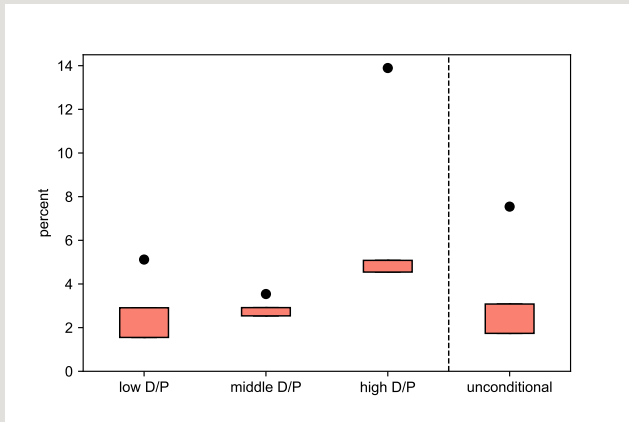
# Risk compensation



The ·'s are empirical averages and the boxes give the imputed bounds when we inflated the minimum relative entropy by 20%. The minimum relative entropy is .028 with a half-life of 24 quarters.

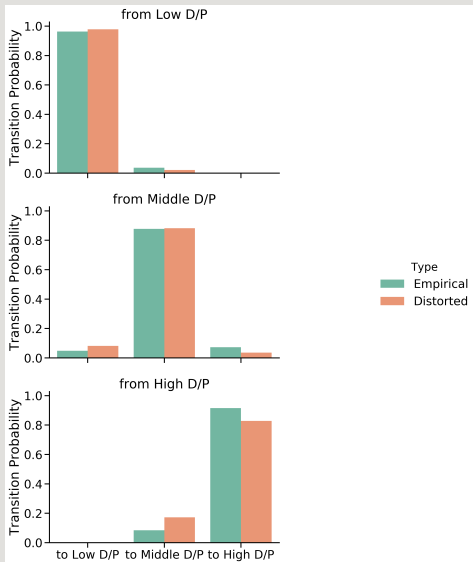


# Expected log market return

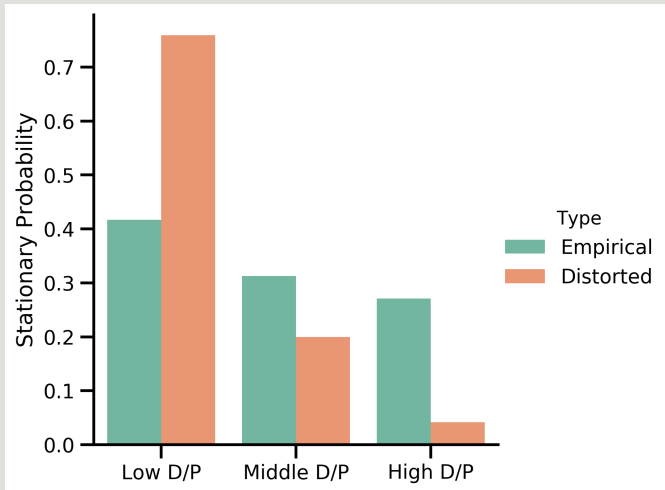


The ·'s are empirical averages and the boxes give the imputed bounds when we inflated the minimum relative entropy by 20%.

# Transition Probability



# Stationary Distribution



# Concluding Remarks

Use intertemporal **statistical divergence** as a form of **bounded rationality** - private sector belief distortions are more prominent when statistical inference challenges are more difficult.

Extensions:

- ▷ incorporate **parameter dependence** in  $f$  and  $g$  by including an additional minimization over the parameter space
- ▷ bound **ratios** (conditional expectations), **log differences** (risk compensations), etc with extra one-dimensional minimizations
- ▷ incorporate into **policy problem** where the policymaker cares about the beliefs of private sector
- ▷ provide **statistical inference** methods for our bound measurements