Ethanol and food prices: price relations and predictability.

Andrea Bastianin[1] Marzio Galeotti[2] Matteo Manera[1]

[1]UNIMIB & FEEM

[2]UNIMI & IEFE-Bocconi

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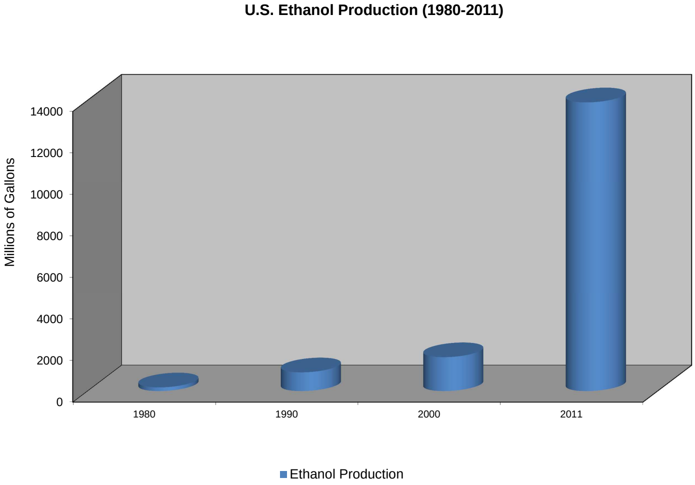
Outline

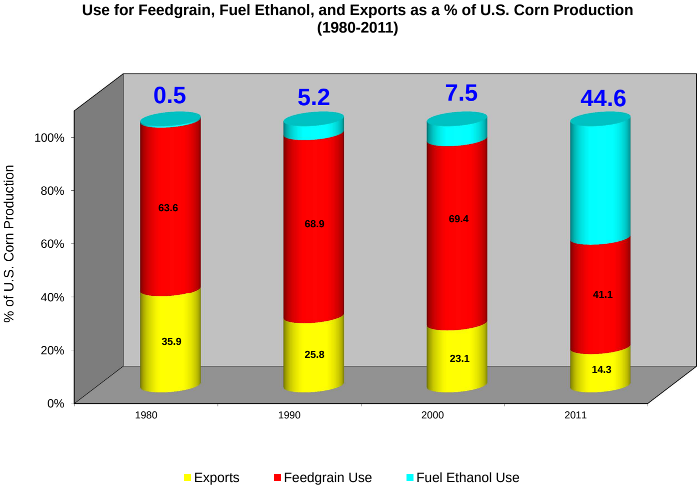
Why do people worry about ethanol?

1. Ethanol production has grown exponentially since the 80's...



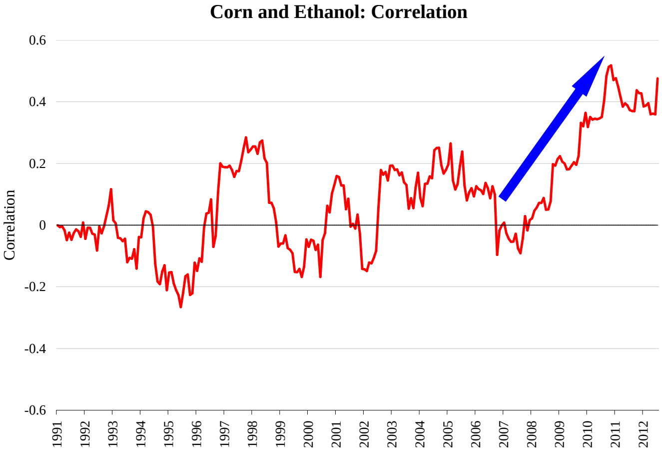
Why do people worry about ethanol?

... and so has the share of corn used for its production.



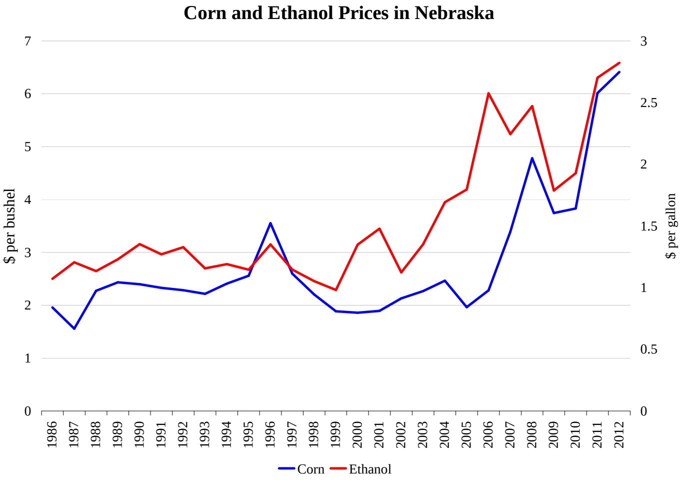
Why do people worry about ethanol?

2. Correlation between corn & ethanol has increased since 2007...



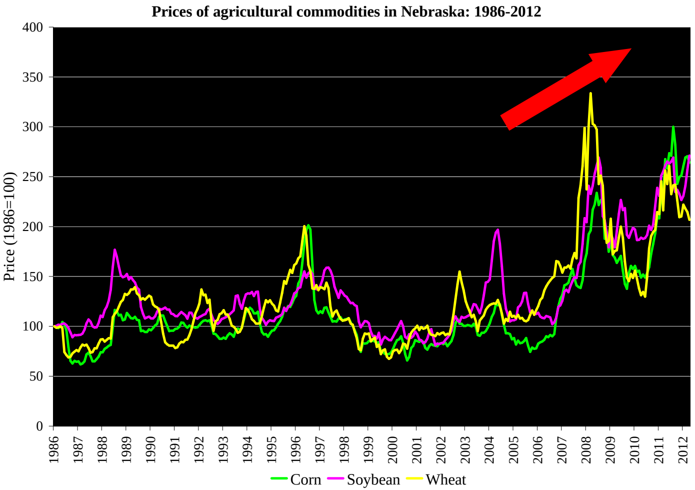
Why do people worry about ethanol?

3. Ethanol and corn prices seem to be moving together...



Why do people worry about ethanol?

Food VS Fuel: has the development of the ethanol industry created a demand-driven boom in agricultural prices?



Aim & Topics

Aim: to study the relationships between the price of ethanol and the prices of field crops (i.e. corn, wheat, soybeans) and cattle

Topics:

1. Price relations.
2. Granger causality and predictability <u>in mean</u>.
3. Granger causality and predictability <u>in distribution</u>.

Research questions & Results

- **Research Questions:**

Q1: are there structural breaks in the price series?

Q2: are there (long-run) price relationships running from ethanol to field crops and cattle? Or vice versa?

Q3: has ethanol in-sample and/or OOS predictive power for field crops and cattle? Or vice versa? Are there instabilities in GC relations?

Q4: can we use ethanol to predict the distribution (or some of parts of it) of returns on field crops? Or vice versa?

- **Results**

A1: there is a structural break in ethanol price in June 2005 (i.e. EPAct 2005);

A2: the price of ethanol is driven by that of field crops in the long-run;

A3: the price of some field crops improve the forecasts for ethanol (i.e. "true" Granger causality). No instabilities in GC relations.

A4: the center and the left-tail of the distribution of returns on ethanol are predictable using returns on field crops.

Outline

The literature

• There are two strands in the literature on biofuels [Zilberman et al. (2012) for a survey]:

1. Time-series econometrics: linkages between ethanol & food prices.

2. Simulations and theory-based methods: impact of introduction biofuels on food prices.

Main conclusions:

1. the price of biofuels is positively correlated with the prices of food, but the reverse correlation is very weak.

2. the introduction of biofuels may affect food prices; this effect varies across regions and crops.

The empirical literature

Price relations:

- Some evidence of linear & non-linear cointegration between ethanol and field crops.
- Most results are potentially affected by pretest biases.

e.g. Structural breaks due to market or policy changes might affect unit-root and hence cointegration tests (i.e. pretest bias).

The empirical literature

Granger Causality & Predictability:

- Some evidence of in-sample Granger causality (GC) from corn to ethanol.
- Out-of-sample (OOS) predictability: no results.
- Predictability beyond the mean/variance: no results, neither IS nor OOS.

⇒ The literature provides only partial answers: GC has to do with improved OOS performance, in-sample GC tests signal only improved goodness-of-fit.

Outline

Data

- Nominal spot prices: ethanol, corn, soybeans, wheat, cattle for Nebraska.

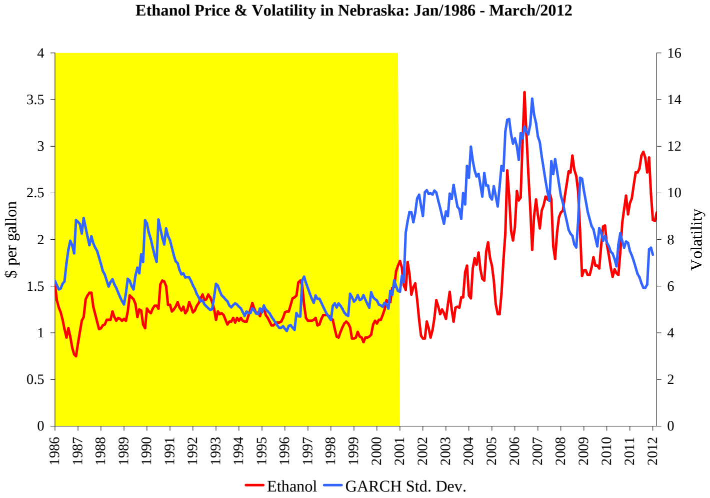
+ 2 Price indices (weights = value of production):
    1. Price index 1: corn, soybeans, wheat;
    2. Price index 2: corn, soybeans, wheat, & cattle.

- Frequency & time span: monthly, 01/1987-03/2012 (12/2010).
- Sources: Nebraska Energy Office & U.S. Dept. of Agriculture.

Outline

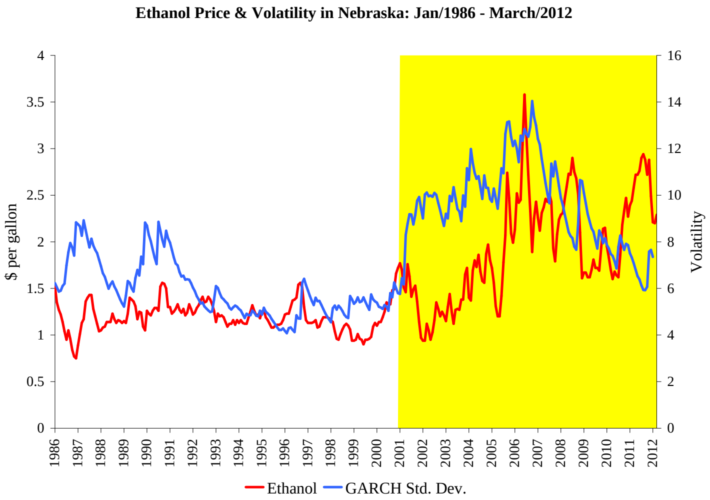
Two epochs of ethanol?

1980's & 1990's: stable price & low volatility



Two epochs of ethanol?

2000's: roller coaster behavior & high volatility



Two epochs of ethanol?

Unit root & Stationarity tests: (ADF, PP, KPSS with asy & simulated p-values)

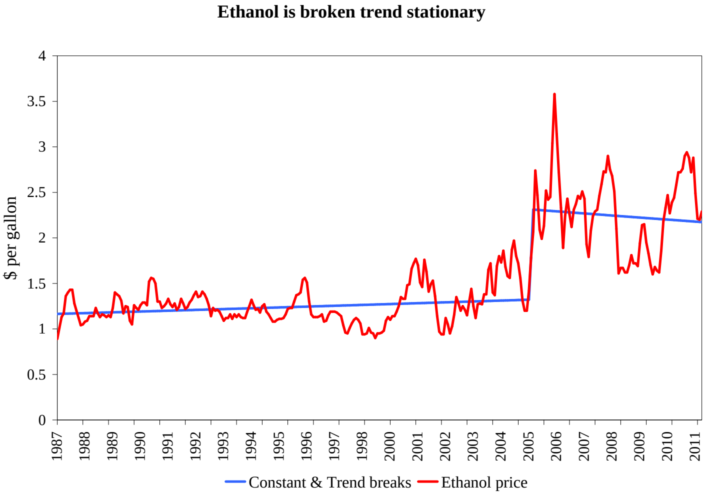
- Price indices, field crops and cattle: I(1)
- Ethanol: mixed results

Unit root VS broken-trend stationarity (Zivot & Andrews, 1992):

- Price indices, field crops and cattle: I(1)
- Ethanol: <u>stationary around a broken trend</u>

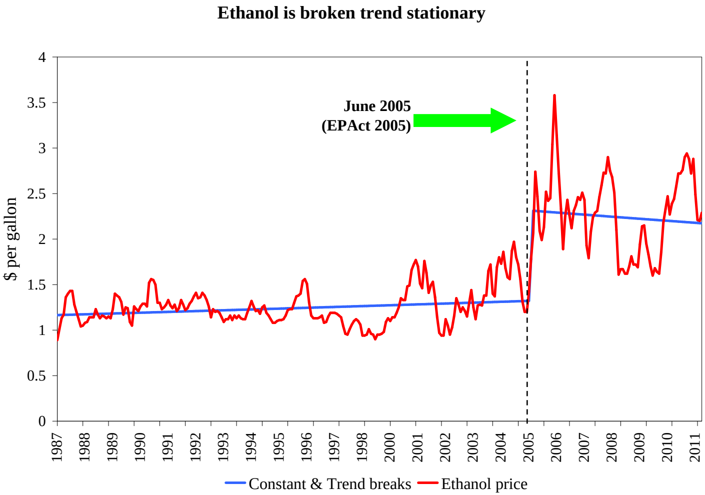
More about broken-trend stationarity

Ethanol is stationary around a broken trend (i.e. shifted intercept & slope)... why?



More about broken-trend stationarity

Possible explanation: EPAct of 2005 increased the share of biofuels to be mixed with gasoline.



Broken-trend stationarity: consequences & remedies

Unit root tests with sample split:

- Price indices, field crops and cattle: I(1);
- Ethanol is I(0) before and after the break date.

Ethanol, field crops and cattle prices have different orders of integration:

- We cannot apply cointegration methods.
- We can rely on the bound testing approach to analyze price relations.

Market changes might also affect ethanol-field crops relations:

- Parameter instability might be an issue;
- GC tests have no power in the presence of instabilities;
- We can use a robust GC test (Rossi, 2005).

Price relations: the bound testing approach

How can we analyze level relations between I(0) and I(1) variables/prices?

- Bound testing approach (Pesaran et al. 2001): a test for the existence of a long-run relationship between (the levels of) a set of variables.
  - Variables can be I(0), I(1) or cointegrated.
  - H_0 : no level (price) relationship
  - The test is based on 2 sets of CVs that represent a lower (all variables are I(0)) and an upper bound (all variables are I(1)).

Price relations: the bound testing approach

- Three possible outcomes:
  1. F-test $<$ Lower bound (LB): do not reject H_0 (i.e. no price relations)
  2. F-test $>$ Upper Bound (UB): reject H_0
  3. LB $<$ F-test $<$ UB: inference is inconclusive.
- Long-run forcing variable: which price drives the other price in the long-run?

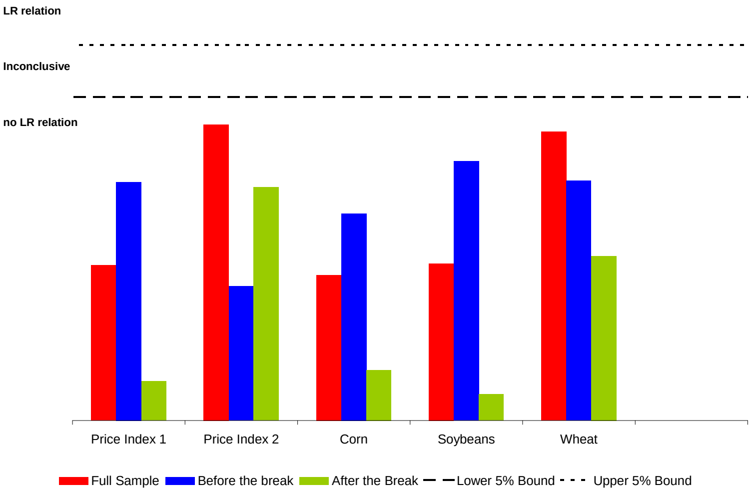
Case 1: ethanol is long-run forcing for price i ($i =$ price indices, corn, soybeans, wheat, cattle);

Case 2: i is long-run forcing for price ethanol.

Case 1: ethanol long-run forcing for i

Bound F-test

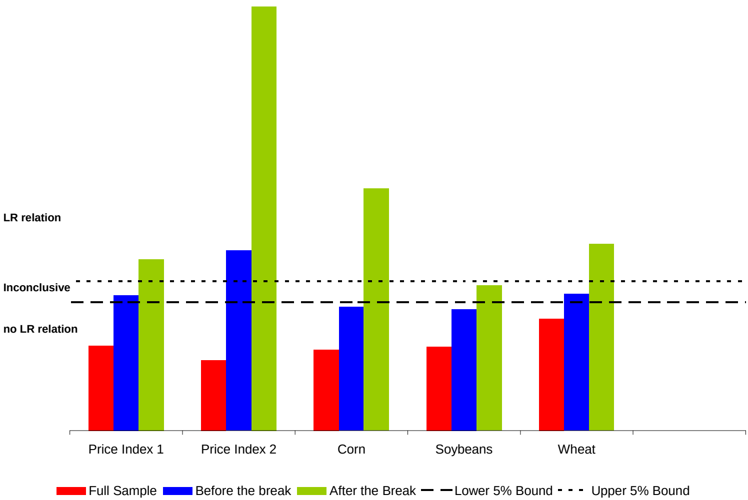
(H_0 : no level/price relation)



Case 2: *i* long-run forcing for ethanol

Bound F-test

(H_0 : no level/price relation)



Predictability in mean

In-sample GC analysis:

- Does Ethanol GC field crops (i.e. $H_0 : \gamma_1 = 0$)?

$$\Delta p^i_{t+1} = \alpha_1 + \beta_1 \Delta p^i_t + \gamma_1 \Delta p^E_t + u_t$$

- Or vice-versa (i.e. $H_0 : \gamma_2 = 0$)?

$$\Delta p^E_{t+1} = \alpha_2 + \beta_2 \Delta p^E_t + \gamma_2 \Delta p^i_t + \epsilon_t$$

- Are there instabilities? (Weak evidence for some series)
- Are GC relations robust to instabilities? (Yes)

Predictability in mean

Out-of-sample GC analysis:

- One-step ahead forecasts.
- Are commodity based forecasts more accurate than benchmarks (i.e. AR and random walk models)?
- MSFE comparisons:

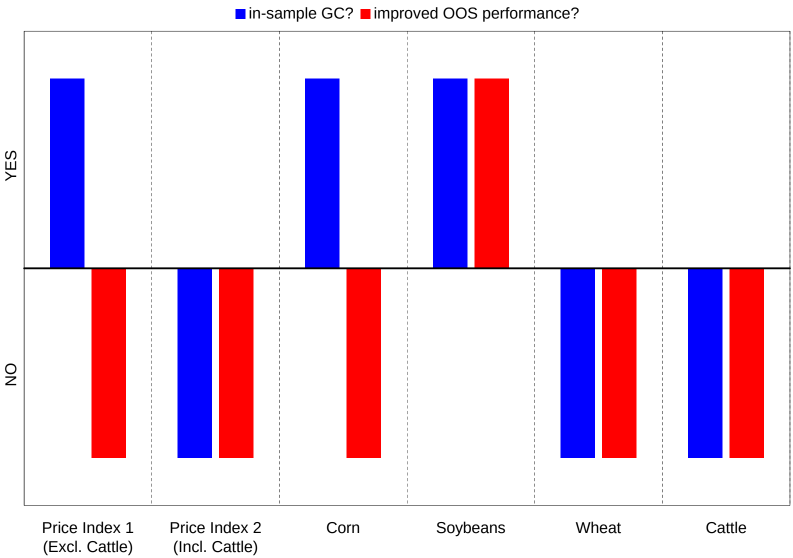
$$\mathcal{M}_i \succ \mathcal{M}_{Benchmark} \text{ if } MSFE(\mathcal{M}_i) < MSFE(\mathcal{M}_{Benchmark})$$

- Encompassing tests:

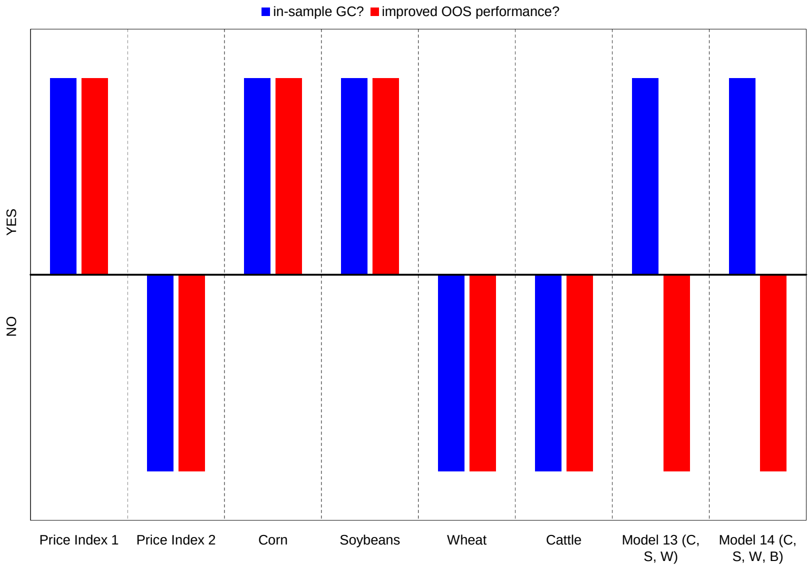
$\mathcal{M}_i \ \mathcal{ENC} \ \mathcal{M}_{Benchmark}$ if in a linear combination, forecasts from $\mathcal{M}_{Benchmark}$ receive zero weight.

$\Rightarrow$ forecasts from $\mathcal{M}_i$ "encapsulate" all the predictive information contained in $\mathcal{M}_{Benchmark}$

Does Ethanol Granger Cause i?



Does i Granger Cause Ethanol?



Some conclusions about predictability in mean

1. Ethanol GC corn & Index 1 in-sample but not OOS (in-sample GC).
2. Corn & Index 1 GC ethanol in-sample and OOS (true GC).
3. Ethanol GC soybeans in-sample & OOS and vice versa (feedbacks).
4. No GC relations between ethanol and wheat and cattle.

Outline

Density forecasting: motivations

Aim: to produce forecasts for the entire distribution of returns.

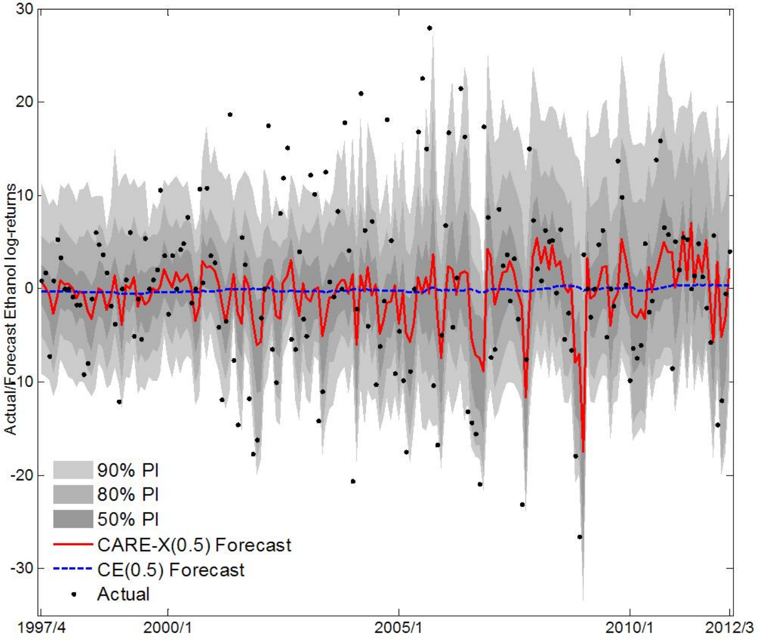
- **Informativeness**: density forecasts measure the uncertainty associated with predictions.
- **Usefulness**: policy makers can observe uncertainty around the mean/consensus forecast (e.g. BoE inflation/GDP fan charts; ECB-SPF).
- **Targeting**: some agents are more interested in some parts of the probability distribution (e.g. tails)

Density forecasting: motivations

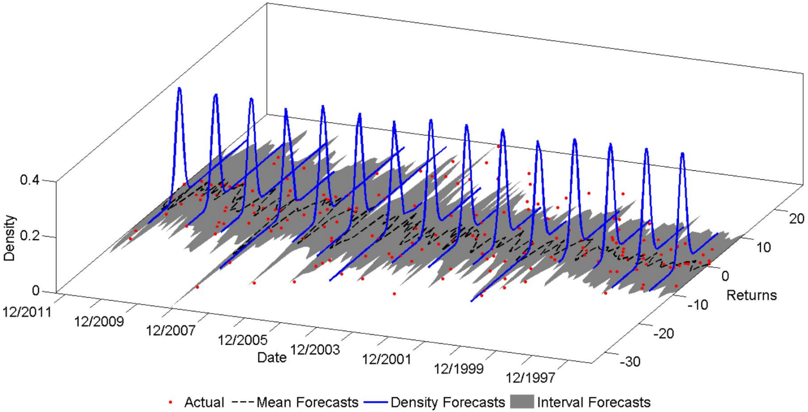
- **Theory:** rational agents need density forecasts to max EU functions (Granger and Pesaran, 2000).
  - Point forecasts sufficient only for LQ problems (i.e. Linear in constraints & Quadratic in the loss function);
  - in non-LQ problems optimal decision rules depend on the whole predictive distribution (Pesaran and Skouras, 2002).

  e.g. in asset allocation mean and variance forecasts are sufficient to solve the investor's problem only if he has quadratic utility function (for arbitrary distributions) or (for arbitrary preferences) if returns are multivariate normal (Huang and Litzenberger, 1998).

Point & Interval forecasts for ethanol



Point, Interval & Density forecasts for ethanol



Density forecasting: methodology

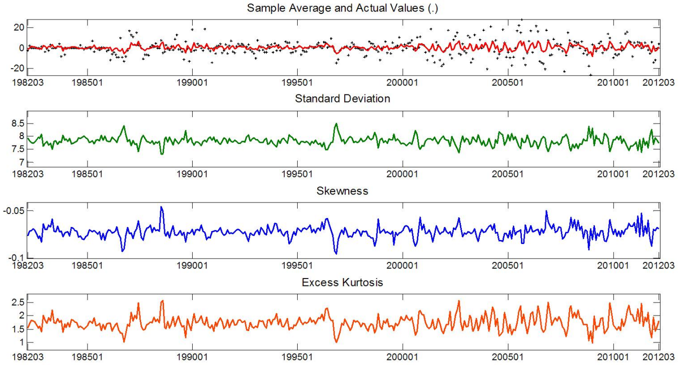
- Density forecasts are produced with ALS (i.e. OLS with squared error loss weighted according to the sign of residuals)
- The solution of the ALS regression is known as <u>expectile</u> (Newey & Powell, 1987)
- Expectiles are similar to quantiles
  - ⋄ strictly monotone increasing functions
  - ⋄ both can be used to characterize the distribution of a r.v.
  - ⋄ some computational advantages (i.e. IWL vs linear programming)

Density forecasting: methodology

- Quantiles can be computed as the proportion of observations lying below the *i*-th expectile (Efron 1991, Granger & Sin, 2000)

- Quantile forecasts can be used to retrieve sample moments, interval and density forecasts (Taylor, 2008; Timmerman & Cenesizoglu, 2008; Kim & White 2004).

Sample moments from quantiles



In-sample GC

- An in-sample test of GC running from ethanol to i involves testing $H_0 : \beta(\omega) = 0$ in:

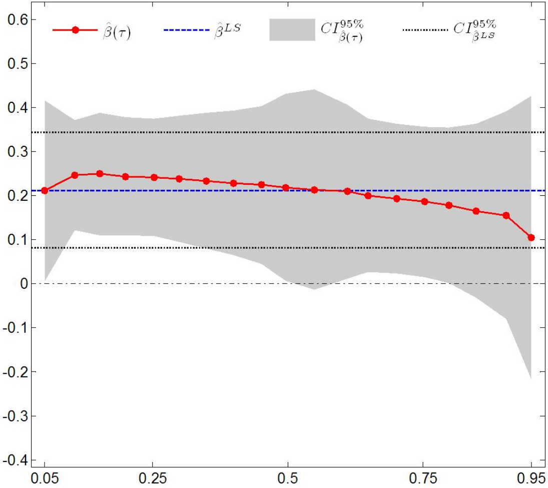
$$\tau^i_{t+1}(\omega) = a(\omega) + \gamma(\omega)\Delta p^i_t + \beta(\omega)\Delta p^E_t + e_t \tag{1}$$

$\Rightarrow$ tests are carried out for each expectile matching the quantile of interest (i.e. $\alpha = .05,...,.95$)

Note: Eq. (1) is known as CARE-X model (Kuan et. al., JoEcnm., 2009)

In-sample GC: an example

Does corn GC ethanol in-sample?



OOS analysis

OOS analysis:

- Produce 1-step ahead quantile & density forecasts from CARE-X models.
- Produce 1-step ahead quantile & density forecasts from benchmark (CE):

$$\tau^{i}_{t+1}(\omega) = a(\omega) + e_t$$

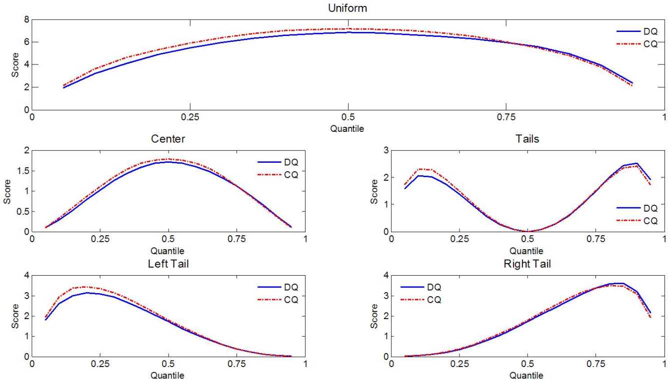
- like a RWD a Constant Expectile model subsumes two hypotheses: no-GC (i.e. exogenous variables have no predictive power) and no-predictability.

Density forecast evaluation

1. Weighted scoring rules (Amisano & Giacomini, JBES, 2007; Gneiting et al., JBES, 2011)
   - a loss function for density forecasts
   - weights allow to emphasize some parts of the distribution (e.g. one or both tails, center)
2. Conditional Predictive Ability test. (Giacomini & White, Ecnm., 2006)
   - Unconditional version: which model has been more accurate (i.e. lowest loss)?
   - Conditional version: which model is more accurate conditionally on the state of the oil market (i.e. a dummy based on Hamilton's, 1996, Net Oil Price Increase)?

Density forecast evaluation

Scoring rules for ethanol density forecasts based corn.



Predictability beyond the mean: results

- Ethanol returns have no predictive power for field crops and cattle. This result holds:
  i. in-sample,
  ii. out-of-sample
  iii. for any part of the returns distribution.
- Field crops have predictive power for ethanol:
  iv. in-sample
  v. out-of-sample.
  vi. for the center and the left-tail of the distribution;
  vii. no evidence of predictability in the right tail of the distribution.

Outline

Conclusions

1. Ethanol does not drive the price of field crops in the long-run.
2. Ethanol does not GC field crops.
3. Corn is long-run forcing for ethanol.
4. Corn has predictive power for ethanol (center & left tail).
5. Ethanol-Cattle linkages are very (very) weak.

Thanks!

(andrea.bastianin@unimib.it)