# Using Weather-Based Forecasts to Estimate Commodity Demand

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August 12, 2024

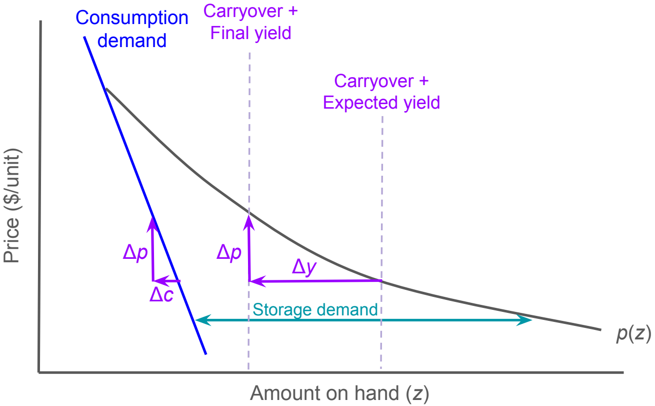
# Outline

# Commodity Pricing Fundamentals

# Commodity Pricing Theory

Commodity prices depend on
**Amount on hand:**

- Stock carried over
- Expectations
- **Current production surprise.** Mainly weather driven



# The Identification Problem

Many shocks besides weather

- Planting adjustments
- Technical change
- Demand changes
- Interest rates, exchange rates, policy
- Input prices (e.g., water, fertilizer)

*Some shocks affect* **demand** *not supply. Some shocks* **anticipated** *by markets.*

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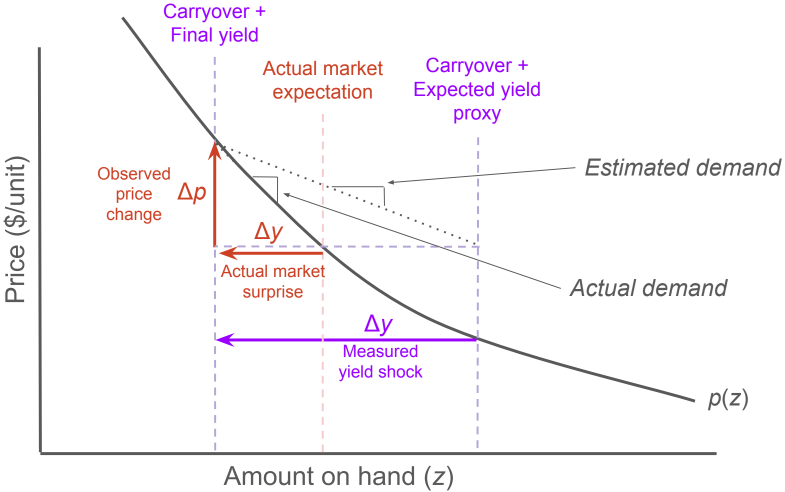

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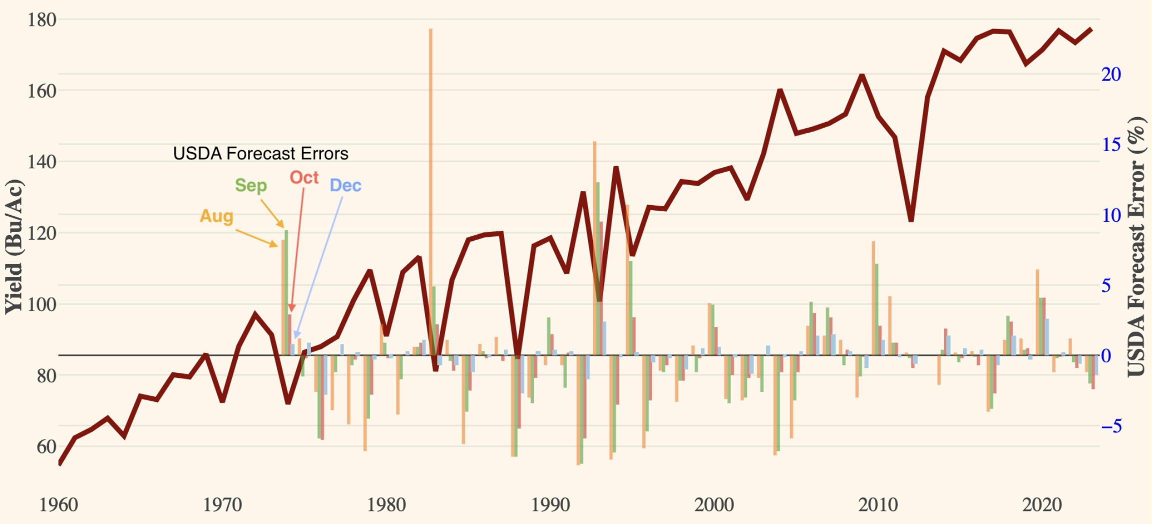
2. USDA yield forecast updates (Adjemian & Smith, AJAE 2012)

# Corn Yields and USDA Forecast Errors



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- **USDA Forecast Errors.**
  Private market forecasts precede USDA forecasts. Remote sensing data. Weather. Some evidence of forecast smoothing (Goyal & Adjemian, 2023).

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- **USDA Forecast Errors.**
  Private market forecasts precede USDA forecasts. Remote sensing data. Weather. Some evidence of forecast smoothing (Goyal & Adjemian, 2023).

- **Weather?**
  Used previously in Roberts & Schlenker, but weak instrument. It is difficult to predict crop yields with weather, outside the U.S.

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# Study Design

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**Two weather-based instruments for the yield surprises**

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   - Link crop yields to weather. Schlenker & Roberts (PNAS 2009) and various extensions and elaborations (proprietary)
   - Forecast season weather from season-to-date weather (proprietary)
   - Find the forecast difference: 6/15 - 8/30

2. **Key weather variable**

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   - Find the forecast difference: 6/15 - 8/30

2. **Key weather variable**
   - Degree days above 29C (replicable)
   - Daily PRISM grids, crop-area weighted (USDA Cropland Data Layer).
   - Sum from 6/15 - 8/30 each year
   - Key ingredient to forecasts.

# Key Variable Definitions

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$$\Delta s_t = \frac{(s_{t+1}^{\text{March 1}} - s_t^{\text{June 1}})}{\text{trend production}} \tag{5}$$

# Main Specifications

$$\Delta p_t = \beta_0 + \beta_1 \Delta y_t + \beta_2 s_t + \beta_3 s_t \Delta y_t + \varepsilon_t \tag{6}$$

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$$\Delta s_t = \gamma_0 + \gamma_1 \Delta y_t + \gamma_2 s_t + \gamma_3 s_t \Delta y_t + \varepsilon_t^s. \tag{7}$$

We consider alternative measures for $\Delta y$ and also IV estimates where $\Delta y$ is instrumented with weather.

# Outline

# Results

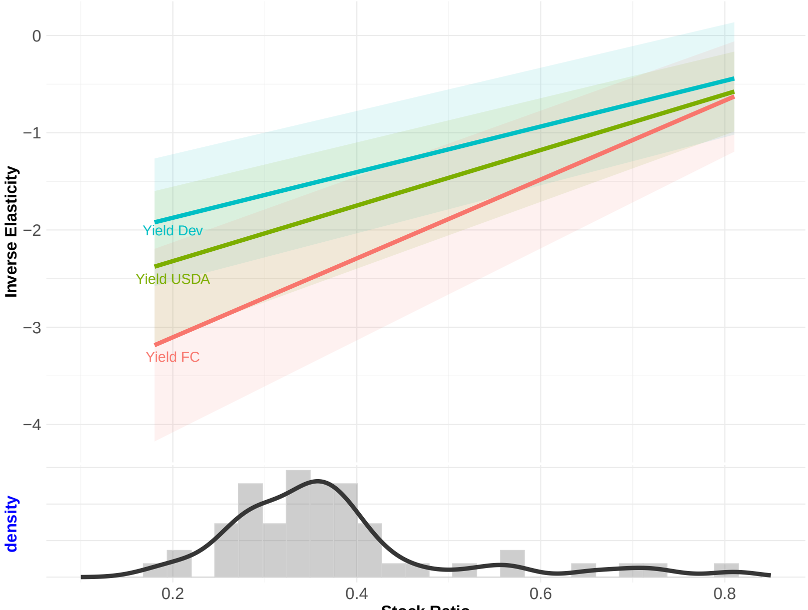
# Main Results: Coefficient Estimates

| | *Dependent variable: $\Delta p_t$* | | | | |
|---|---|---|---|---|---|
| | *OLS* | | | *IV* | |
| | (1) | (2) | (3) | (4) | (5) |
| Yield Dev | $-2.34^{***}$ | | | $-3.24^{***}$ | |
| | (0.44) | | | (0.51) | |
| Yield USDA | | $-2.89^{***}$ | | | $-4.41^{***}$ |
| | | (0.54) | | | (1.15) |
| Yield FC | | | $-3.92^{***}$ | | |
| | | | (0.68) | | |
| Stock Ratio | 0.15 | $0.20^{*}$ | $-0.073$ | 0.17 | $0.30^{**}$ |
| | (0.12) | (0.11) | (0.14) | (0.13) | (0.15) |
| Yield Dev*Stock | $2.35^{***}$ | | | $3.45^{***}$ | |
| | (0.72) | | | (0.87) | |
| Yield USDA*Stock | | $2.86^{***}$ | | | $5.20^{***}$ |
| | | (0.83) | | | (1.81) |
| Yield FC*Stock | | | $4.06^{***}$ | | |
| | | | (1.06) | | |
| Constant | $-0.10^{**}$ | $-0.14^{***}$ | $-0.059$ | $-0.103^{**}$ | $-0.19^{***}$ |
| | (0.047) | (0.051) | (0.055) | (0.047) | (0.061) |
| Observations | 53 | 50 | 53 | 53 | 50 |
| $R^2$ | 0.46 | 0.51 | 0.45 | 0.41 | 0.45 |
| Adjusted $R^2$ | 0.42 | 0.48 | 0.42 | 0.37 | 0.41 |

# Main Results: Inverse Elasticities

| | Implied Inverse Elasticities | | | | |
|---|---|---|---|---|---|
| | *OLS* | | | *IV* | |
| | Yld-Dev | USDA-FC | W-FC | Yld-Dev | USDA-FC |
| | (1) | (2) | (3) | (4) | (5) |
| Mean s.r. (0.375) | -1.46 | -1.82 | -2.39 | -1.95 | -2.46 |
| | (0.25) | (0.25) | (0.33) | (0.24) | (0.49) |
| Stock ratio = 0.2 | -1.88 | -2.32 | -3.10 | -2.55 | -3.37 |
| Stock ratio = 0.5 | -1.17 | -1.46 | -1.89 | -1.52 | -1.81 |
| Stock ratio = 0.7 | -0.70 | -0.89 | -1.08 | -0.83 | -0.77 |

# Inverse Price Elasticity Estimates



# Results: Alternative Weather Instrument

| | Dependent variable: $\Delta p_t$ | | | | |
|---|---|---|---|---|---|
| | *OLS* | *IV* | | | |
| *Instrument*: | | *Yield FC* | | *HDD* | |
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| | (0.68) | | | | |
| Stock Ratio | $-0.073$ | 0.17 | $0.30^{**}$ | 0.17 | $0.33^{**}$ |
| | (0.14) | (0.13) | (0.15) | (0.13) | (0.16) |
| Yield Dev*Stock | | $3.45^{***}$ | | $3.50^{***}$ | |
| | | (0.87) | | (0.90) | |
| Yield USDA*Stock | | | $5.20^{***}$ | | $5.82^{***}$ |
| | | | (1.81) | | (2.16) |
| Yield FC*Stock | $4.06^{***}$ | | | | |
| | (1.06) | | | | |
| Constant | $-0.059$ | $-0.10^{**}$ | $-0.19^{***}$ | $-0.10^{**}$ | $-0.20^{***}$ |
| | (0.055) | (0.047) | (0.061) | (0.05) | (0.06) |
| Observations | 53 | 53 | 50 | 53 | 50 |
| $R^2$ | 0.45 | 0.41 | 0.45 | 0.40 | 0.40 |
| Adjusted $R^2$ | 0.42 | 0.37 | 0.41 | 0.37 | 0.36 |

# All Weather-Based Elasticities

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| Mean s.r. (0.375) | -2.39 | -1.95 | -2.46 | -1.96 | -2.65 |
| | (0.33) | (0.24) | (0.49) | (0.24) | (0.56) |
| Stock ratio = 0.2 | -3.10 | -2.55 | -3.37 | -2.57 | -3.67 |
| Stock ratio = 0.5 | -1.89 | -1.52 | -1.81 | -1.52 | -1.92 |
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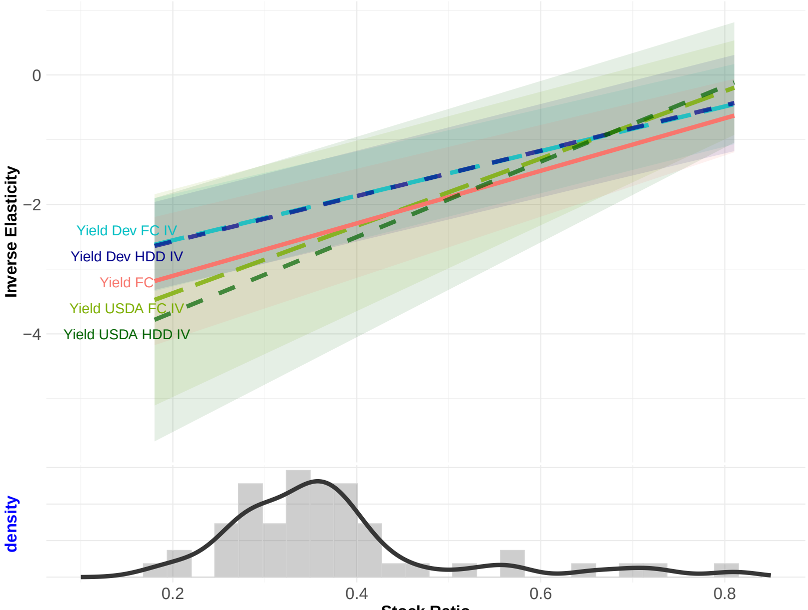

# Storage Response to Yield Surprises

| | Implied responses to yield surprises | | | | |
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| | Yld-Dev | USDA-FC | W-FC | Yld-Dev | USDA-FC |
| | (1) | (2) | (3) | (4) | (5) |
| Mean s.r. (0.375) | 0.82 | 0.79 | 0.98 | 0.82 | 0.98 |
| | (0.11) | (0.15) | (0.24) | (0.15) | (0.29) |
| Stock ratio = 0.2 | 0.60 | 0.60 | 0.87 | 0.68 | 0.97 |
| Stock ratio = 0.5 | 0.98 | 0.93 | 1.05 | 0.93 | 0.99 |
| Stock ratio = 0.7 | 1.24 | 1.15 | 1.17 | 1.09 | 1.00 |

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| | Yld-Dev | USDA-FC | W-FC | Yld-Dev | USDA-FC |
| | (1) | (2) | (3) | (4) | (5) |
| Mean s.r. (0.375) | 0.003 | 0.0001 | 0.01 | 0.01 | 0.01 |
| | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) |
| Stock ratio = 0.2 | 0.01 | 0.01 | 0.03 | 0.03 | 0.03 |
| Stock ratio = 0.5 | -0.003 | -0.005 | 0.0004 | -0.003 | -0.002 |
| Stock ratio = 0.7 | -0.01 | -0.01 | -0.02 | -0.02 | -0.02 |

# Implications

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**inelastic at lower inventory levels**

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# Conclusions

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- Weather can be a useful instrument for identifying commodity pricing fundamentals.
- More compelling instruments indicate more inelastic demand.
- Demand response is mostly comprised of storage adjustments, indicating very inelastic consumption demand.
- Permanent shifts in supply from policy or climate change could have substantial long-run price implications.
- Broader application requires strong links between weather and crop outcomes, which is challenging.
- Potential applications to energy systems, too.