The Perils of Panel IV Estimation: Revisiting the Causes of Conflict

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Causes of conflict

- Zurcher 2017 systematic review finds that much/most evidence about aid and conflict comes from:
  - Country cases studies
  - Cross country panel regressions
- Nunn and Qian 2017 instrument for food aid deliveries by US wheat production interacted with regularity of aid receipt
  - Find that increasing food aid 1,000 MT increases conflict by 0.3 percentage points
- Hull and Imai 2018 instrument for economic growth using interest rates
  - Find that 4% negative growth shock increases conflict risk by 30%

NQ Estimation Strategy

$$C_{irt} = \beta F_{irt} + \mathbf{X}_{irt}\Gamma + \varphi_{rt} + \psi_{ir} + \nu_{irt},$$

$$F_{irt} = \alpha(P_{t-1} \times \overline{D}_{ir}) + \mathbf{X}_{irt}\Gamma + \varphi_{rt} + \psi_{ir} + \varepsilon_{irt}$$

Estimate conflict as function of (endogenous) food aid receipts, given controls, incl. region-year and country fixed effects.

Policy generates random variation: *"USDA accumulates wheat in high production years as part of its price stabilization policies. The accumulated wheat is stored and then shipped as food aid to poor countries."*

→Exogenous shocks to wheat production change availability of food aid at margin.

→Primarily among regular food aid recipients?

Identification:

"US wheat production is associated with more conflict among regular US food aid recipients but not among irregular recipients."

Talk Outline

Outline for rest of talk:

1. Panel IV w/o interacted instruments
   - Correlations ignoring the time series
   - Trends in sequenced observations
   - Monte Carlo demonstration of inference problems with co-trending variables
   - Cointegration and reverse causation
   - First differencing to address nonstationarity

2. Do interacted instruments fix the problem?

3. Practical diagnostic steps for panel IV efforts

Estimation w/o shift-share instrument

Start by ignoring the interacted instruments so as to focus on the time series concern of spurious regressions.

The OLS regression:

$$Conflict_{it} = \beta X_{it} + \epsilon_{it}$$

Almost surely suffers endogeneity bias.

So estimate 2SLS, here shown in reduced and 1st stage form:

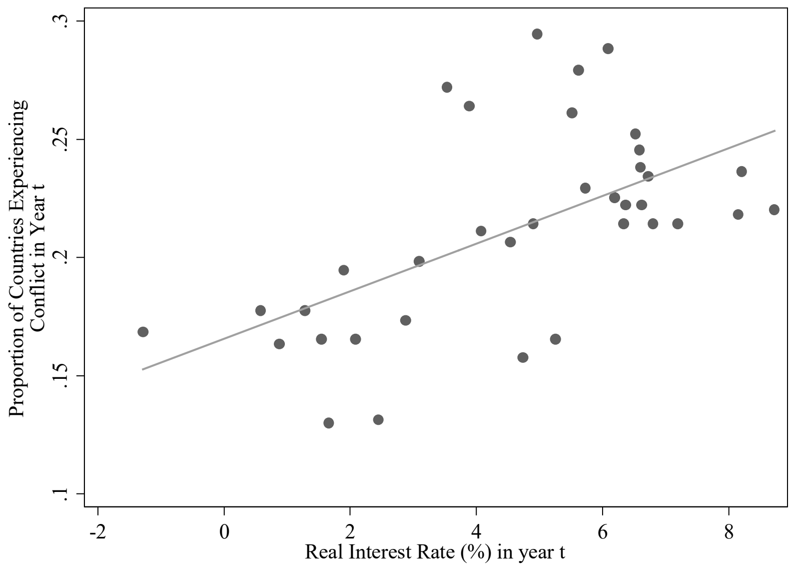
$$Conflict_{ijt} = \gamma Z_t + \theta_i + \rho_j t + \mu_{it}$$
$$X_{ijt} = \pi Z_t + \Theta_i + \mathrm{P}_j t + \eta_{it}$$

IV estimate is the ratio of the reduced form coefficient estimate over the first stage coefficient, $\hat{\gamma}/\hat{\pi}$

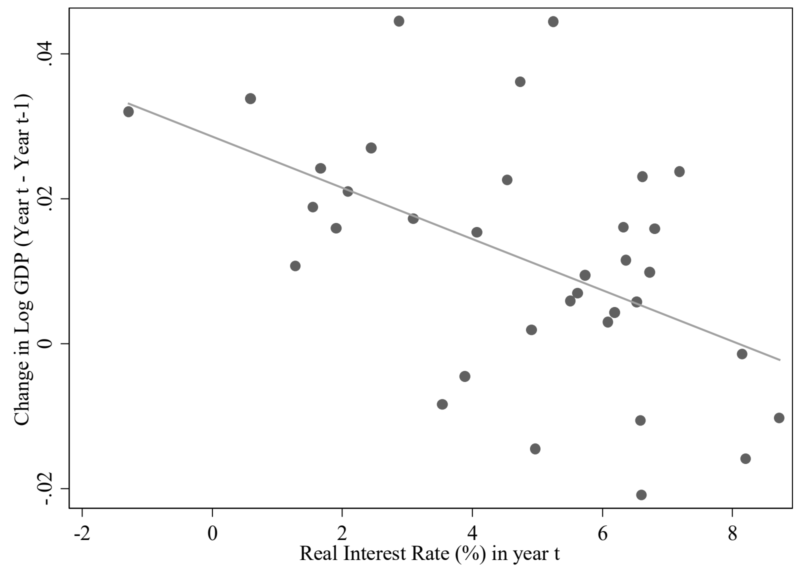
Scatter Plots

If we ignore sequencing of observations, this works for growth and interest rates:

Conflict and real interest rates



GDP growth and real interest rates

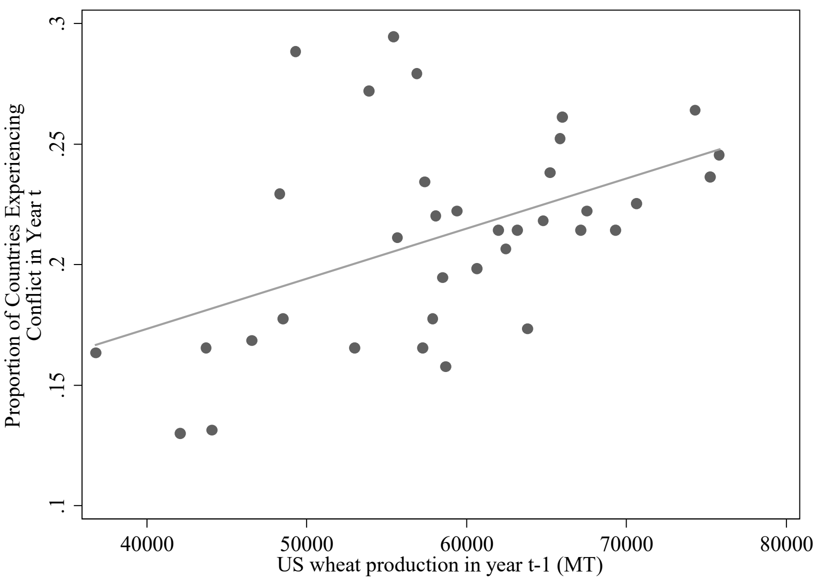


Positive reduced form/Negative 1st stage → negative IV

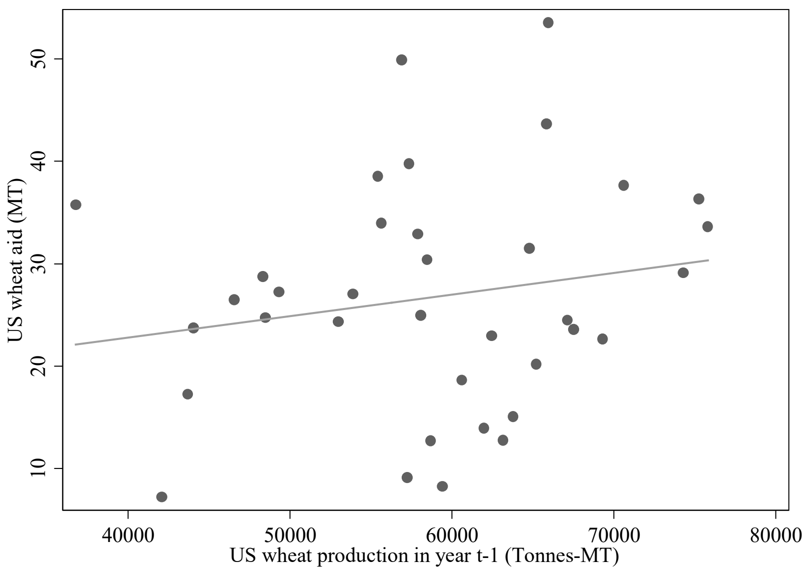
Scatter Plots

If we ignore sequencing of observations, this works for aid and conflict too:

Conflict and lagged US wheat output



Food aid shipments and lagged US wheat output



Positive reduced form/Positive 1st stage → positive IV

Does IV establish causality?

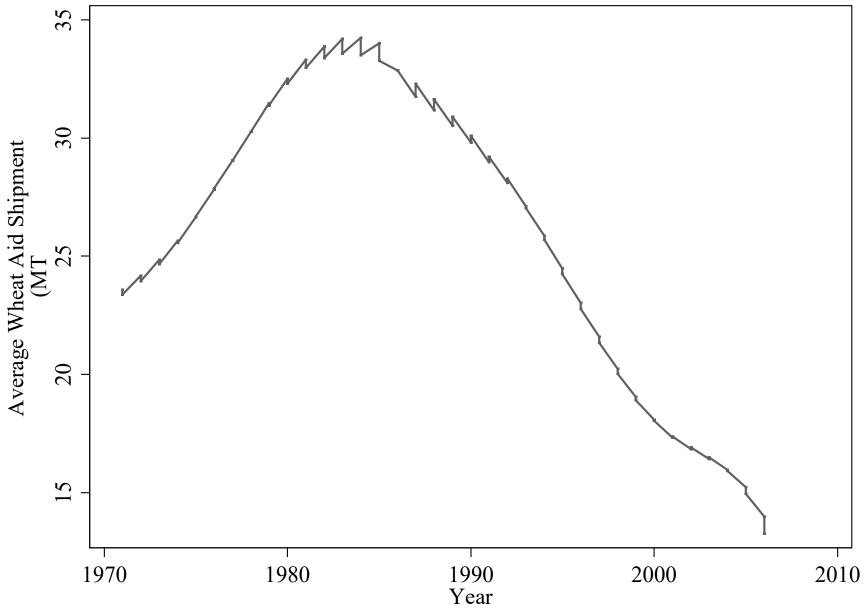
- Argument is usually that it is “hard to think of” a reason (after partialing out included controls) why civil wars would be affected by interest rates or US wheat yields except through endogenous variable (exclusion restriction)
- As long as first stage regression significant and passes weak IV tests, this is taken as evidence of the policy channel establishing the IV (valid first stage)
- BUT, we show (using old insights and methods) that ignoring time series properties means that reduced form coefficient estimates are large and significant more often than conventional tests indicate
- When this happens, the first stage is also significant, because the endogeneity we were worried about in the first place spuriously correlates the outcome and endogenous X variables

  → lots of bad instruments can look like good instruments

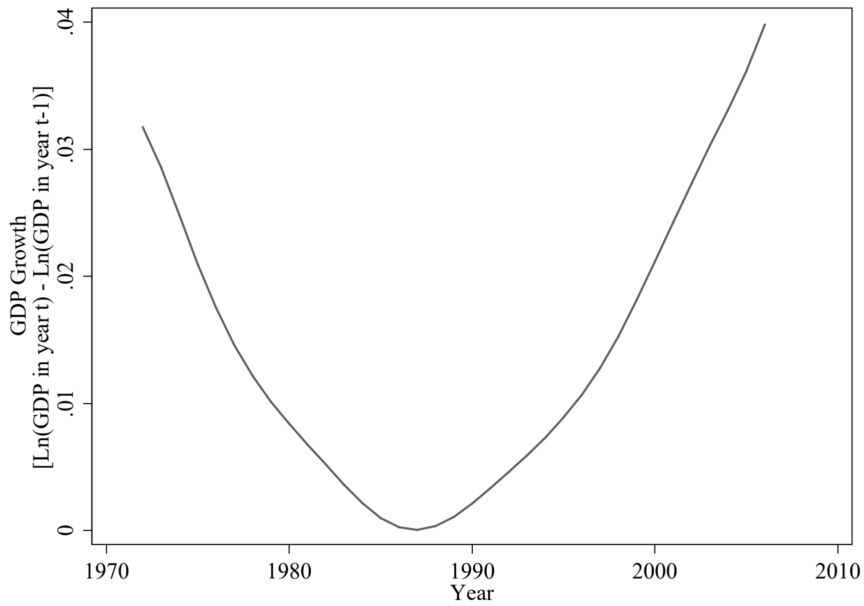
Trends

And the endogenous regressors of interest likewise exhibit similar (or opposite) strong trends:

US wheat food aid shipments



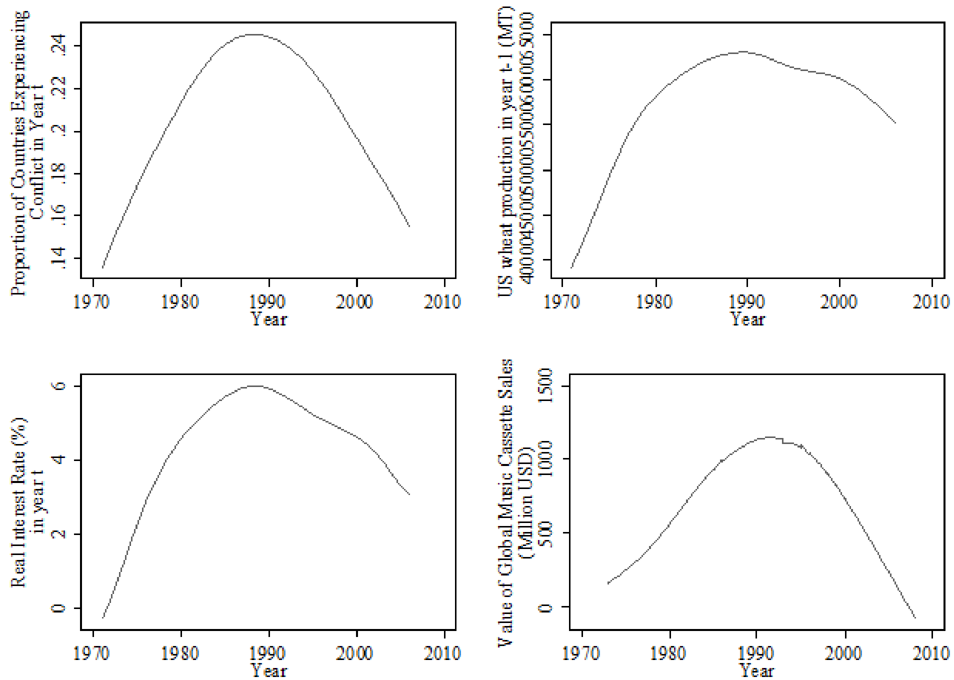
real GDP growth rates



The NQ (HI) endogenous regressor exhibits the same inverted-U (or its opposite, U) shape over the sample period.

Trends

But when we sequence the observations and estimate trends nonparametrically, a common pattern emerges:



The dependent variable, HI and NQ instruments, and an obviously spurious variable (global audio cassette tape sales) exhibit the same inverted-U shape over the sample period.

Trends in IV

Co-trending variables indeed serve as good substitutes for one another. No matter which variable we use as the IV, we get statistically indistinguishable 2SLS estimates.

Co-trending instruments as substitutes for one another

IV =	Dependent variable = incidence of war (of any type)					
Endogenous regressor	(1): R	(2): W	(3): C	(4): R	(5): W	(6): C
GDP growth	-2.97560	-3.12900	-3.49071			
	(1.07478)	(1.27973)	(1.10815)			
US food aid (tons)				0.00844	0.00506	0.00848
				(0.00834)	(0.00332)	(0.00309)
Observations	4,015	4,015	3,917	4,161	4,161	3,964

Note: R= real interest rates, W = lagged US wheat production, C = cassette tape sales

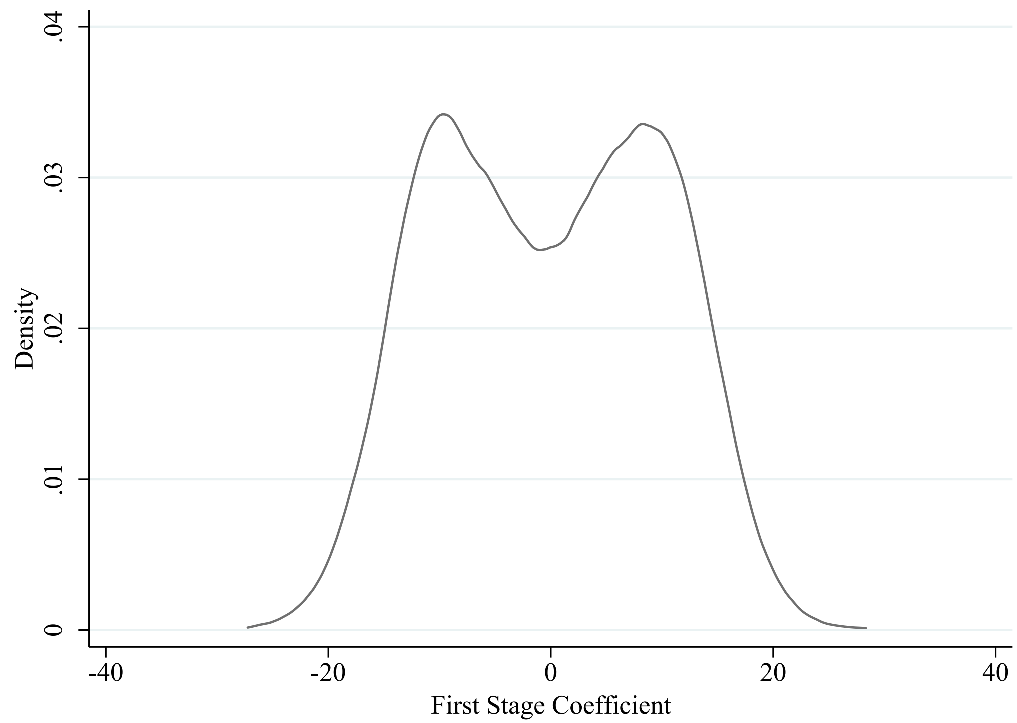
How do we know which are spurious vs. truly causal?

First stage with placebo random walk instrument

When we estimate the 1st stage relationship,

$$Aid_{it} = \pi^{sim} Z_{it} + \eta_{it}^{sim}$$

- By construction, Z_t is uncorrelated with Aid_{it}, i.e., E(π)= 0. But as established by Yule (1926), π exhibits a multi-modal dist'n.
- As predicted by Ernest et al, odd moments are 0, but even moments are large.
- 1st stage is unbiased, but will over-reject the irrelevant IV null. p<.10 in 39.4% of iterations.

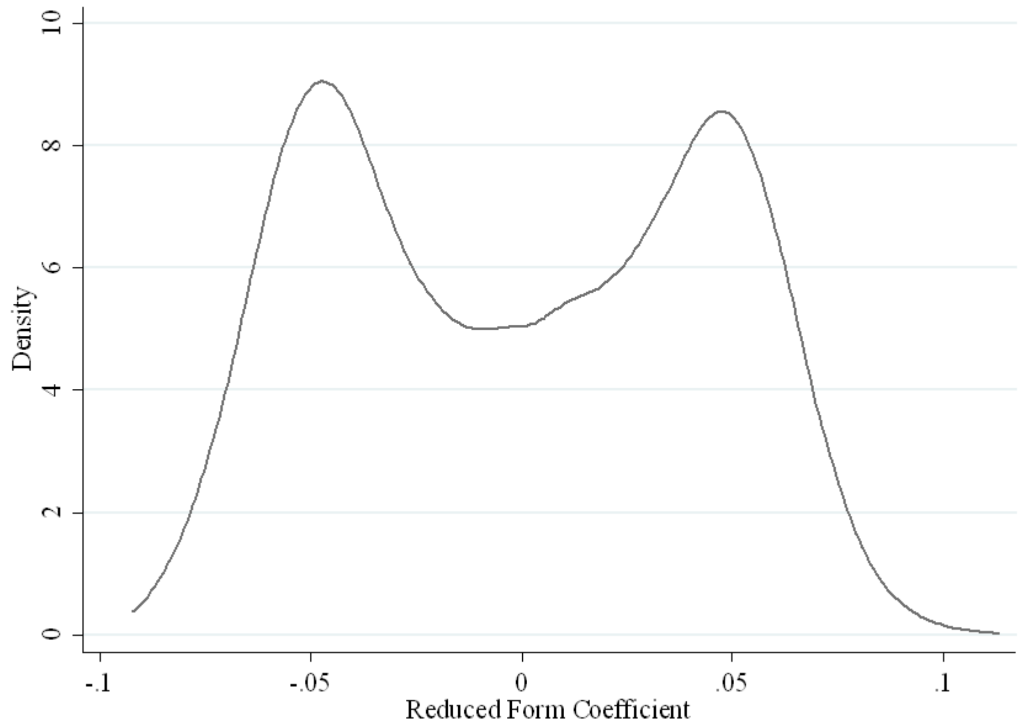


Reduced form with placebo random walk instrument

- The same occurs in the reduced form regression:

$$-Conflict_{\mathrm{it}} = \gamma^{sim} Z_{it} + \mu_{it}^{sim}$$

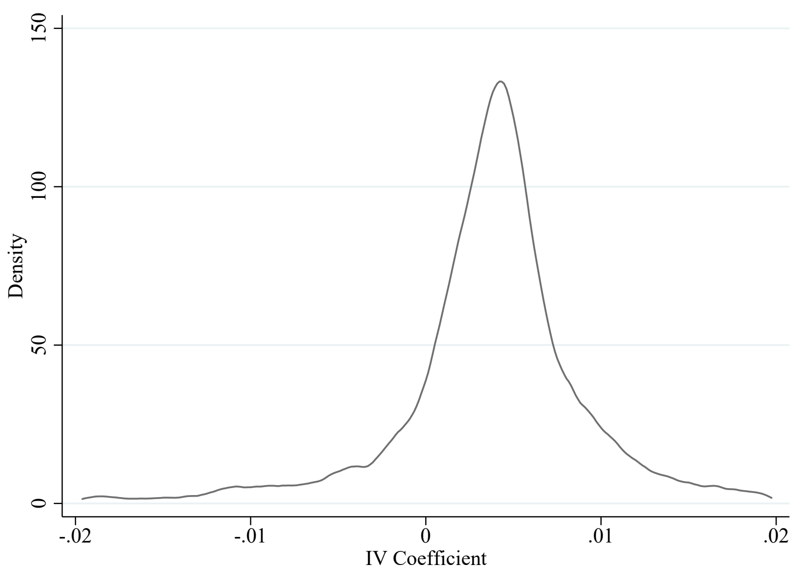
- By construction Z_t is uncorrelated with *Conflict*$_{it}$, i.e., E(γ)= 0.
- But γ also exhibits an unbiased, multi-modal dist'n.
- p<.10 in 67.5% of iterations



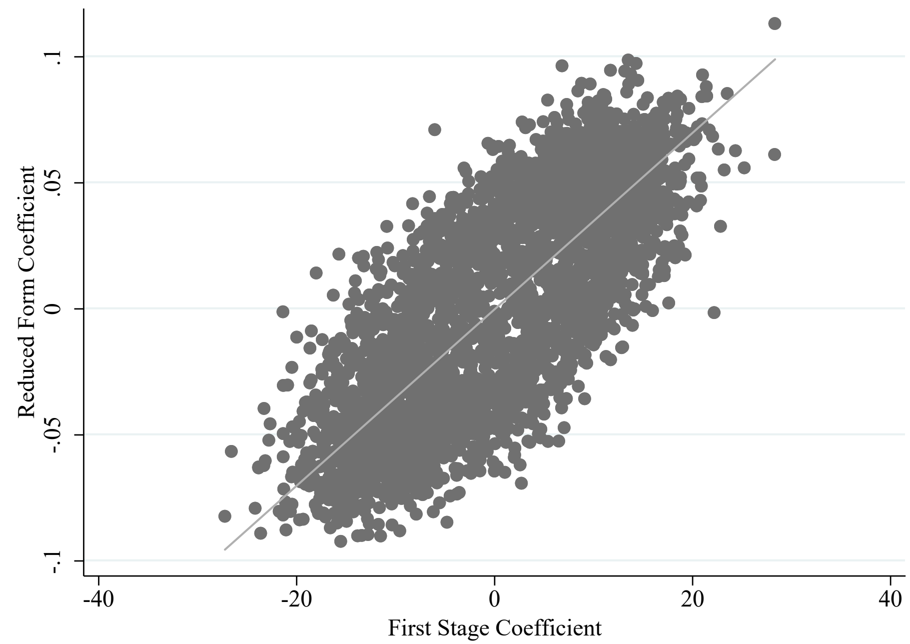
IV Coefficient

The unbiasedness of the single regressions does not carry over to the IV estimate because the common cycling leads to positive correlation in the 1st stage and reduced form parameter estimates.

2SLS coefficient estimate distribution



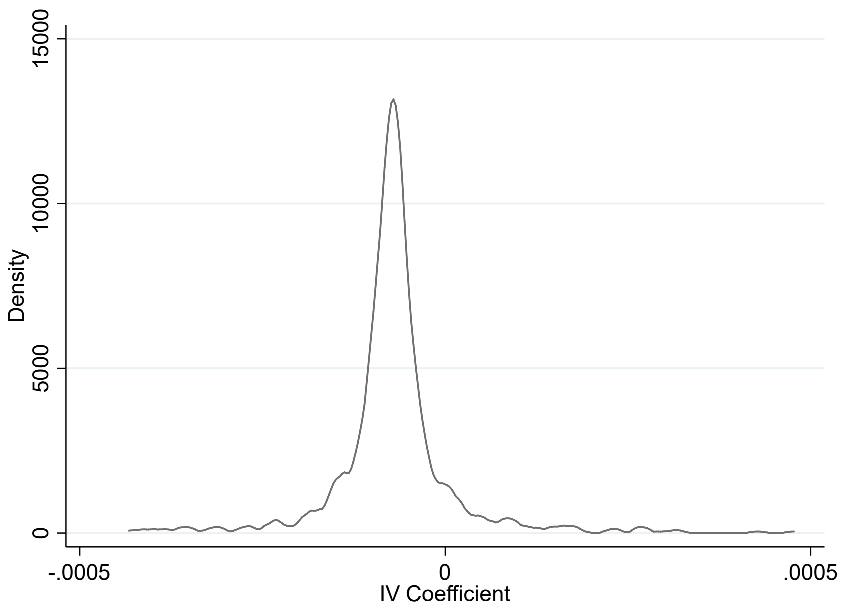
Reduced form vs. 1st stage estimates



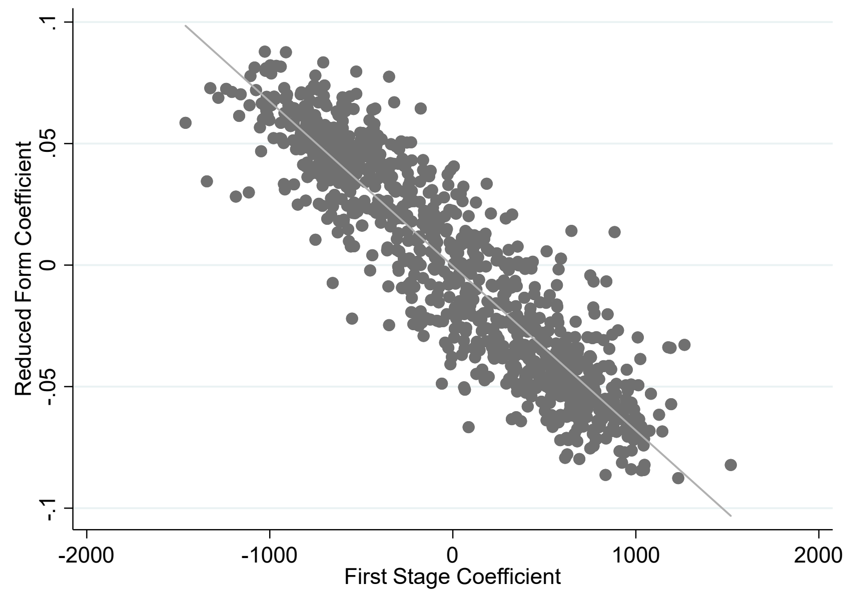
IV Coeff for GDP Growth

We get the exact same result for the MC simulation of the HI estimates, with the important difference that the countercyclical pattern in real GDP growth rates leads to a negative correlation of the 1st stage and reduced form estimates.

2SLS coefficient estimate distribution



Reduced form vs. 1st stage estimates

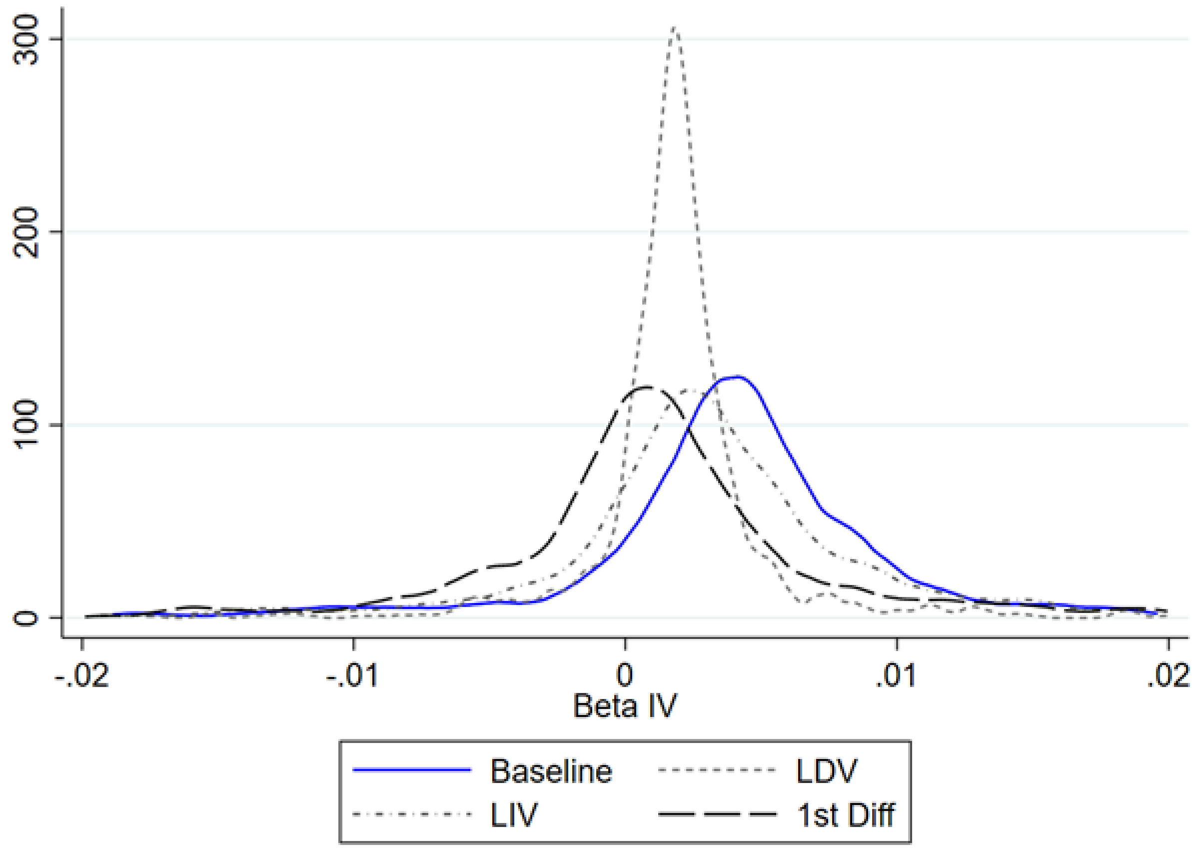


Why are over-rejections one-directional?

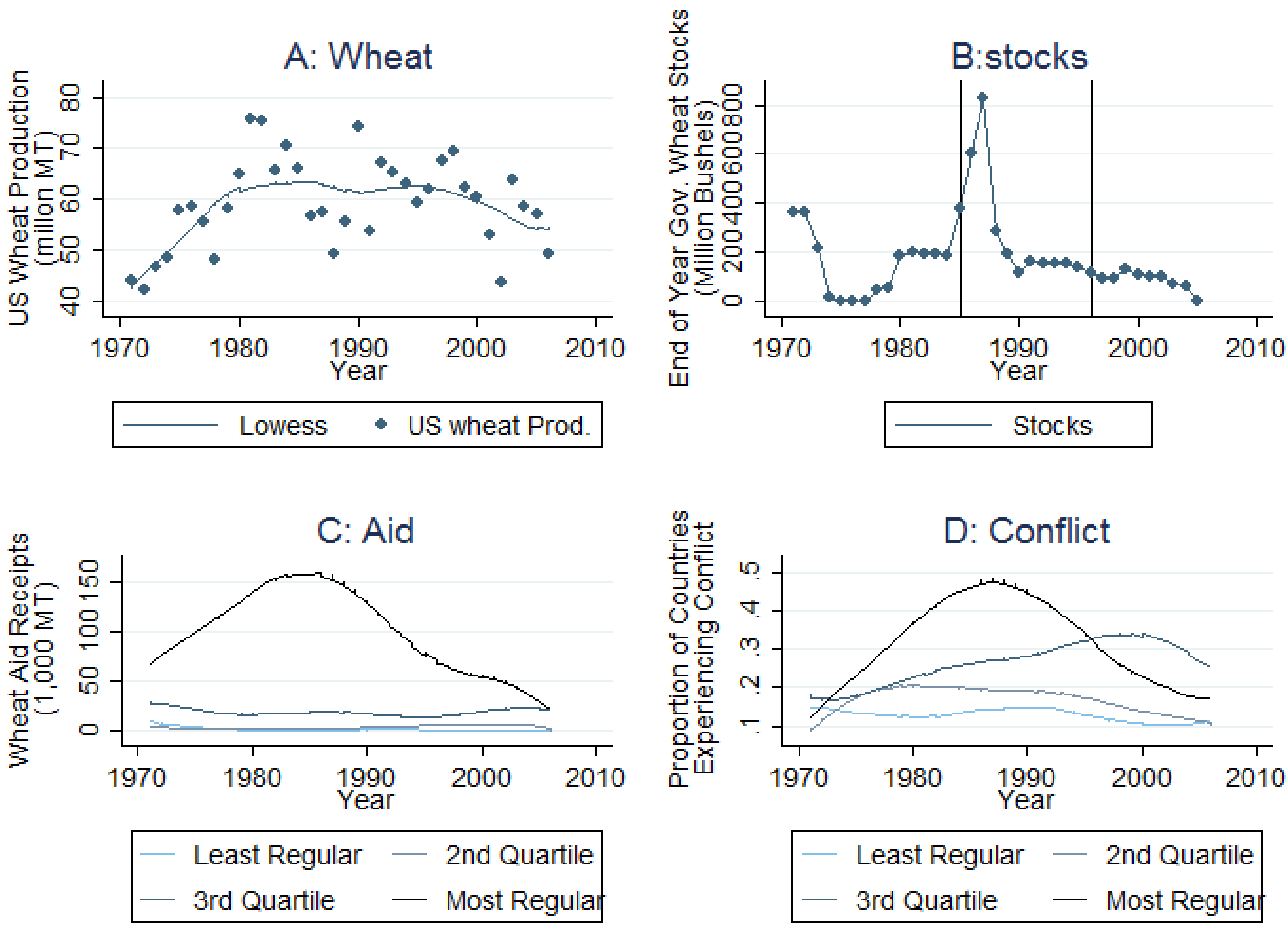
- Random Walk Model:
  - $c_{it} = c_{it-1} + v_{it}$
  - $a_{it} = \phi c_{it-1}$
- Estimation:
  - $c_{it} = \gamma^{rw} Z_t + \mu_{it}^{rw}$
  - $a_{it} = \pi^{rw} Z_t + \eta_{it}^{rw}$
  - $\frac{\widehat{\gamma^{rw}}}{\widehat{\pi^{rw}}} = \frac{\widehat{cov}(c_{t-1}, z_t)}{\phi \widehat{cov}(c_{t-1}, z_t)} + \frac{\widehat{cov}(v_{it}, z_t)}{\phi \widehat{cov}(c_{t-1}, z_t)}$
- Implication: If c_{t-1}, z_t are spuriously correlated, IV will estimate $1/\phi$ -> bias is in same direction as endogeneity
- This model does not use time fixed effects or trends. Do these solve the problem?

Does controlling for lags solve the problem?

Now expand the Monte Carlo 2SLS simulation to test 3 more variants: (i) LDV, (ii) LIV, (iii) first differences. LDV/LIV only work if they match the true ARIMA process. Only 1st diff works in the I(1) case we simulate.



Decomposing Trends in NQ



Solutions

- If we model heterogeneous trends as:

$$conflict_{it} = \beta X_{it} + \psi_i \tau_t$$

$$X_{it} = \alpha conflict_{it} + \chi w_i Z_t$$

- $\hat{\beta}_{IV} = \frac{\hat{\gamma}}{\hat{\pi}} = \frac{\beta\left[\left(\frac{\alpha}{1-\alpha\beta}\right)\bar{\psi}\frac{\widehat{cov}(\tau_t, z_t)}{\widehat{var}(z_t)} + \frac{\chi}{1-\alpha\beta}\right] + \bar{\psi}\frac{\widehat{cov}(\tau_t, z_t)}{\widehat{var}(z_t)}}{\left(\frac{\alpha}{1-\alpha\beta}\right)\bar{\psi}\frac{\widehat{cov}(\tau_t, z_t)}{\widehat{var}(z_t)} + \frac{\chi}{1-\alpha\beta}}$

If $\frac{\widehat{cov}(\tau_t, z_t)}{\widehat{var}(z_t)} = 0$, then $\hat{\beta}_{IV} = \beta$

Solutions

- If $\beta = 0$ and $\frac{\widehat{cov}(\tau_t, z_t)}{\widehat{var}(z_t)} \neq 0$
- Then $\hat{\beta}_{IV} = 1/[\alpha + \frac{\chi}{\bar{\psi}\frac{\widehat{cov}(\tau_t, z_t)}{\widehat{var}(z_t)}}]$
- If conflict trend is a random walk:

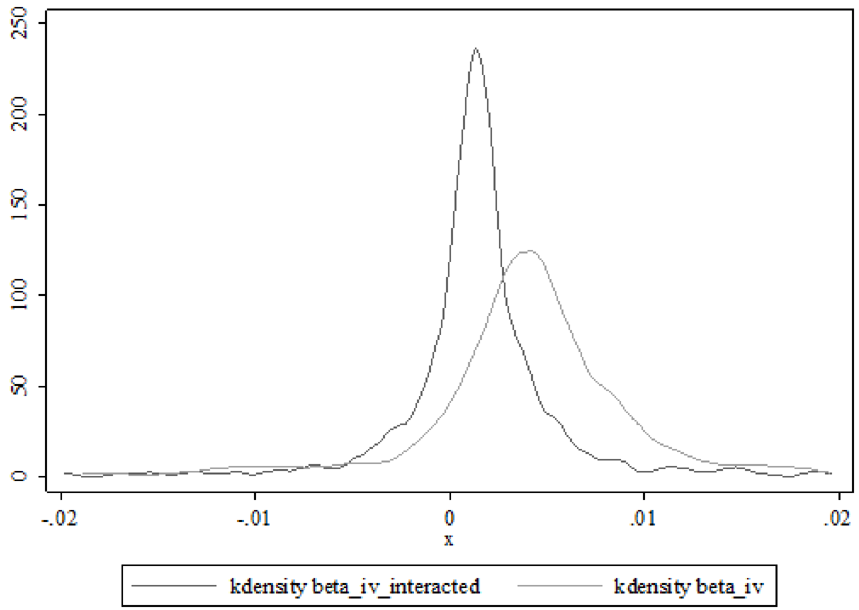
$$\widehat{cov}(\tau_t, z_t) = (\sum_{\ell=0}^{t} \tau_t, z_t)$$

- First differences ID assumption: $\widehat{cov}(\tau_t, z_t) = 0$
- Fixed effects ID assumption:

$$\frac{\widehat{cov}\Big((\psi_i - \bar{\psi}), (w_i - \bar{w})\Big)\, cov\big((\sum_{\ell=j}^{t} \rho^{(t-\ell)} \tau_\ell - \sum_{r=j}^{k} [k-r+1]/T - \sum_{s=j}^{r} \rho^{(r-s)} \tau_r\ ), (z_t - \bar{Z})\big)}{\widehat{var}((w_i - \bar{w})(z_t - \bar{Z}))} = 0$$

Shift-shares in Monte Carlo

When we repeat the Monte Carlo exercise, now using the actual interaction variables but still with a random walk time series instrument independent of both food aid flows and conflict, we find the same pattern. Interaction term merely rescales the bias from the uninteracted case. Because $D_i \in [0,1]$, this rescaling boosts power.



VARIABLES	Dummy for war in year t - dummy for war in year (t-1)	Dummy for war in year t - dummy for war in year (t-1)	Dummy for war in year t - dummy for war in year (t-1)	Dummy for war in year t - dummy for war in year (t-1)	Dummy for war in year t - dummy for war in year (t-1)	Dummy for intrastate war in year t - dummy for war in year (t-1)	Dummy for interstate war in year · - dummy for war in year (t-1)
ΔAid	-0.00802	-0.01155	-0.00832	-0.00726	-0.06586	-0.07786	-0.01625
	(0.01317)	(0.02421)	(0.01467)	(0.00938)	(0.49312)	(0.58185	(0.11351
Controls (for all panels):							
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region-year linear trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes
US real per capita GDP × avg. prob. of any US food aid	No	Yes	Yes	Yes	Yes	Yes	Yes
US democratic president × avg. prob. of any US food aid	No	Yes	Yes	Yes	Yes	Yes	Yes
Oil price × avg. prob. of any US food aid	No	Yes	Yes	Yes	Yes	Yes	Yes
Monthly recipient temperature and precipitation	No	No	Yes	Yes	Yes	Yes	Yes
Monthly weather × avg. prob. of any US food aid	No	No	Yes	Yes	Yes	Yes	Yes
Avg. US military aid × year FE	No	No	No	Yes	Yes	Yes	Yes
Avg. US economic aid (net of food aid) × year FE	No	No	No	Yes	Yes	Yes	Yes
Avg. recipient cereal imports × year FE	No	No	No	No	Yes	Yes	Yes
Avg. recipient cereal production × year FE	No	No	No	No	Yes	Yes	Yes

Notes: This table replicates the 2SLS estimates from Table 2 in NQ, using the same set of controls as NQ and clustering at the country level as in NQ. The change from NQ involves replacing the level values of food aid, conflict and wheat production with first differenced values. For example, ΔAid_t is the quantity of wheat food aid delivered (in metric tons, MT) in year t minus the quantity delivered in year t-1. The instrument for the 2SLS estimate of the effect of ΔAid_t is $\Delta wheat_{t-1}$, where $\Delta wheat_{t-1}$ is the quantity of wheat produced in

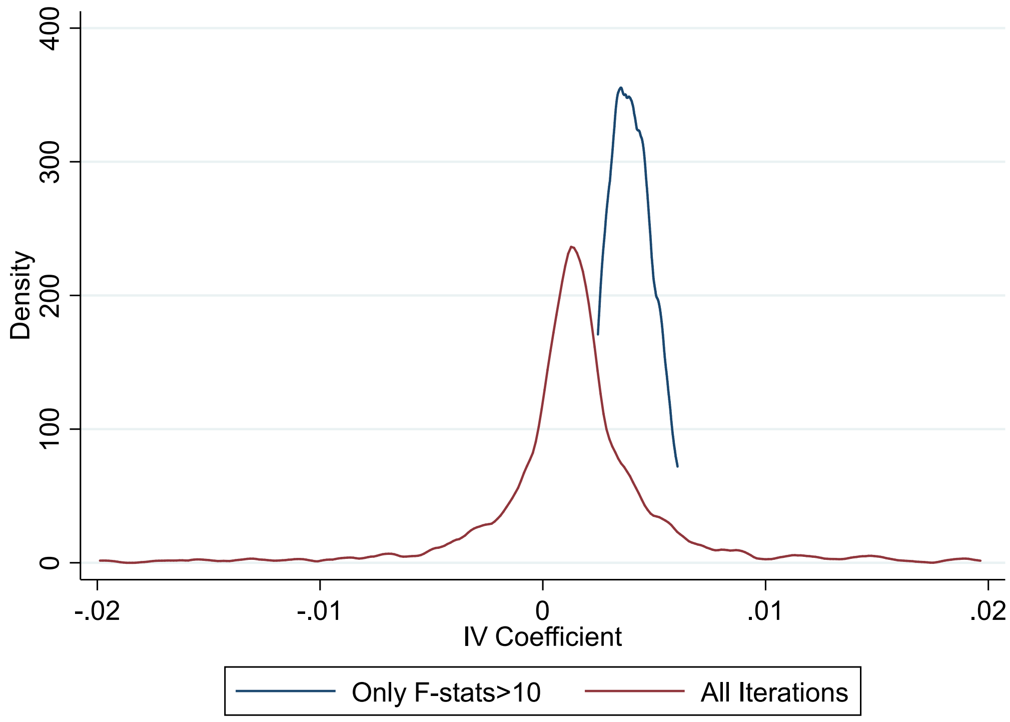
Estimating in first differences, (year to year changes only), NQ estimate flips signs (was positive) and not significant

VARIABLES	Dummy for war in year t - dummy for war in year (t-1)	Dummy for war in year t - dummy for war in year (t-1)	Dummy for war in year t - dummy for war in year (t-1)	Dummy for war in year t - dummy for war in year (t-1)	Dummy for war in year t - dummy for war in year (t-1)	Dummy for intrastate war in year t - dummy for war in year (t-1)	Dummy for interstate war in year t - dummy for war in year (t-1)
ΔLn(GDP)$_t$	-13.02698	27.29817	-663.5553	-5.493698	5.035685	-4.358483	5.630787
	52.06428	179.9781	-.0014869	8.914968	5.492107	5.085462	5.105335
Controls (for all panels):							
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region-year linear trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes
US real per capita GDP × avg. prob. of any US food aid	No	Yes	Yes	Yes	Yes	Yes	Yes
US democratic president × avg. prob. of any US food aid	No	Yes	Yes	Yes	Yes	Yes	Yes
Oil price × avg. prob. of any US food aid	No	Yes	Yes	Yes	Yes	Yes	Yes
Monthly recipient temperature and precipitation	No	No	Yes	Yes	Yes	Yes	Yes
Monthly weather × avg. prob. of any US food aid	No	No	Yes	Yes	Yes	Yes	Yes
Avg. US military aid × year FE	No	No	No	Yes	Yes	Yes	Yes
Avg. US economic aid (net of food aid) × year FE	No	No	No	Yes	Yes	Yes	Yes
Avg. recipient cereal imports × year FE	No	No	No	No	Yes	Yes	Yes
Avg. recipient cereal production × year FE	No	No	No	No	Yes	Yes	Yes

Notes: This table replicates 2SLS estimates of the effect of GDP growth on conflict using the HI approach of instrumenting for GDP growth with real interest rates, but with both conflict and real interest rates first

Estimating in first differences, (year to year changes only), HI estimate mostly keeps its sign, but now never significant

Weak IV tests



- Publication bias is important here
- The distribution of coefficients estimated by the placebo instruments that have F>10 is shifted upward from the overall distribution.
- If we see only the results where the interacted instrument is >10, we get bias
- If finite sample bias is uncorrelated across interaction variables, authors can pick the one that "works"

Recommendations

- **Plot variation as trends, i.e., don't ignore sequencing**
- Use policy changes to find placebo tests (pre-period tests)
- Compare OLS and IV: does direction of change make sense?
- Report auto-correlation and nonstationarity tests (ADF, Fisher)
- **Report alternative trend specifications**
- **Use first differences IV**
- Young (2018) bootstrap test for leverage
- Monte Carlo of DGP under presumed endogeneity
- Randomization tests (Borusyak et al, 2020)

Thank you for your interest and comments!

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TRANSFORM DEVELOPMENT