Shift-Share IV

Mixtape Track

MIXTAPE SESSIONS

Roadmap

Who Am I?

The Groos Family Assistant Professor of Economics, Brown University

Who Am I?

The Groos Family Assistant Professor of Economics, Brown University

A big fan of instrumental variable methods:

Who Am I?

The Groos Family Assistant Professor of Economics, Brown University

A big fan of instrumental variable methods:

- Lottery- and non-lottery IVs in studies of educational quality

  (Angrist et al. 2016, 2017, 2021, 2022; Abdulkadiroğlu et al. 2016)

- Quasi-experimental evaluations of healthcare quality

  (Hull 2020; Abaluck et al. 2021, 2022)

- IV-based analyses of discrimination and bias

  (Arnold et al. 2020, 2021, 2022; Hull 2021; Bohren et al. 2022)

- Shift-share instruments (SSIV) and related designs

  (Borusyak et al. 2022; Borusyak and Hull 2021, 2022; Goldsmith-Pinkham et al. 2022)

What is This Course?

A one-day intensive on SSIV, focusing on recent practical advances

- Highlighting key points on identification, estimation, and inference
- Emphasis on *practical*: IV is meant to be used, not just studied!

What is This Course?

A one-day intensive on SSIV, focusing on recent practical advances

- Highlighting key points on identification, estimation, and inference
- Emphasis on *practical*: IV is meant to be used, not just studied!

Two 90-minute lectures

- Please ask questions in the Discord chat!

What is This Course?

A one-day intensive on SSIV, focusing on recent practical advances

- Highlighting key points on identification, estimation, and inference
- Emphasis on *practical*: IV is meant to be used, not just studied!

Two 90-minute lectures

- Please ask questions in the Discord chat!

One 45-minute coding lab

- 25 min: you seeing how far you can get on your own, or with your classmate's help (use Discord rooms!)
- 20 min: me live-coding solutions in Stata (we will also post R code)

Schedule

1:00-2:30pm	Lecture 1: Linear SSIV – Exogenous Shares and Shocks
2:30-2:35pm	*Break*
2:35-3:20pm	Coding Lab: Autor, Dorn, and Hanson (2013)
3:20-3:25pm	*Break*
3:25-4:55pm	Lecture 2: Nonlinear SSIV and Beyond – Instrument Recentering
4:55-5:00pm	Closing Remarks

What is a (Linear) SSIV?

A weighted sum of a common set of shocks, with weights reflecting heterogeneous exposure shares: $z_\ell = \sum_n s_{\ell n} g_n$

What is a (Linear) SSIV?

A weighted sum of a common set of shocks, with weights reflecting heterogeneous exposure shares: $z_\ell = \sum_n s_{\ell n} g_n$

- The shocks vary at a different "level" $n = 1, \ldots, N$ than the shares $\ell = 1, \ldots, L$, where we also observe an outcome y_ℓ & treatment x_ℓ

What is a (Linear) SSIV?

A weighted sum of a common set of shocks, with weights reflecting heterogeneous exposure shares: $z_\ell = \sum_n s_{\ell n} g_n$

- The shocks vary at a different "level" $n = 1, \ldots, N$ than the shares $\ell = 1, \ldots, L$, where we also observe an outcome y_ℓ & treatment x_ℓ

We want to use z_ℓ to estimate parameter β of the model $y_\ell = \beta x_\ell + \varepsilon_\ell$

What is a (Linear) SSIV?

A weighted sum of a common set of shocks, with weights reflecting heterogeneous exposure shares: $z_\ell = \sum_n s_{\ell n} g_n$

- The shocks vary at a different "level" $n = 1, \ldots, N$ than the shares $\ell = 1, \ldots, L$, where we also observe an outcome y_ℓ & treatment x_ℓ

We want to use z_ℓ to estimate parameter β of the model $y_\ell = \beta x_\ell + \varepsilon_\ell$

- Could be a "structural" equation or a potential outcomes model
- Could be misspecified, with heterogeneous treatment effects β_ℓ
- Could be a "reduced form" analysis, with $x_\ell = z_\ell$
- Could have other included controls w_ℓ

What is a (Linear) SSIV?

A weighted sum of a common set of shocks, with weights reflecting heterogeneous exposure shares: $z_\ell = \sum_n s_{\ell n} g_n$

- The shocks vary at a different "level" $n = 1, \ldots, N$ than the shares $\ell = 1, \ldots, L$, where we also observe an outcome y_ℓ & treatment x_ℓ

We want to use z_ℓ to estimate parameter β of the model $y_\ell = \beta x_\ell + \varepsilon_\ell$

- Could be a "structural" equation or a potential outcomes model
- Could be misspecified, with heterogeneous treatment effects β_ℓ
- Could be a "reduced form" analysis, with $x_\ell = z_\ell$
- Could have other included controls w_ℓ

Key question: under what assumptions does this SSIV strategy "work"?

SSIV Examples

$$\text{Instrument } z_\ell = \sum_n \underbrace{\boxed{s_{\ell n}}}^{\text{shares}} \overbrace{\boxed{g_n}}^{\text{shocks}} \quad \text{for model } y_\ell = \beta x_\ell + \gamma' w_\ell + \varepsilon_\ell$$

Bartik (1991); Blanchard and Katz (1992):

- β = inverse local labor supply elasticity
- x_ℓ and y_ℓ = employment and wage growth in region ℓ
- Need a labor demand shifter as an IV

SSIV Examples

$$\text{Instrument } z_\ell = \sum_n \underbrace{\boxed{s_{\ell n}}}_{\text{shares}} \underbrace{\boxed{g_n}}_{\text{shocks}} \quad \text{for model } y_\ell = \beta x_\ell + \gamma' w_\ell + \varepsilon_\ell$$

Bartik (1991); Blanchard and Katz (1992):

- β = inverse local labor supply elasticity
- x_ℓ and y_ℓ = employment and wage growth in region ℓ
- Need a labor demand shifter as an IV
- g_n = national growth of industry n
- $s_{\ell n}$ = lagged employment shares (of industry in a region)
- z_ℓ = predicted employment growth due to national industry trends

SSIV Examples

$$\text{Instrument } z_\ell = \sum_n \underbrace{\boxed{s_{\ell n}}}_{\text{shares}} \quad \underbrace{\boxed{g_n}}_{\text{shocks}} \quad \text{for model } y_\ell = \beta x_\ell + \gamma' w_\ell + \varepsilon_\ell$$

Autor, Dorn, and Hanson (2013, ADH):

- x_ℓ = growth of import competition in region ℓ
- y_ℓ = growth of manuf. employment, unemployment, etc.
- g_n = growth of China exports in manufacturing industry n to 8 other (i.e. non-U.S.) countries
- $s_{\ell n}$ = 10-year lagged employment shares (over total employment)
- z_ℓ = predicted growth of import competition

SSIV Examples

$$\text{Instrument } z_\ell = \sum_n \underbrace{\boxed{s_{\ell n}}}_{\text{shares}} \; \underbrace{\boxed{g_n}}_{\text{shocks}} \quad \text{for model } y_\ell = \beta x_\ell + \gamma' w_\ell + \varepsilon_\ell$$

"Enclave instrument", e.g. Card (2009)

- β = inverse elasticity of substitution between native and immigrant labor of some skill level (need a relative labor supply instrument)
- x_ℓ and y_ℓ = relative employment and wage in region ℓ
- g_n = national immigration growth from origin country n
- $s_{\ell n}$ = lagged shares of migrants from origin n in region ℓ
- z_ℓ = share of migrants predicted from enclaves & recent growth

SSIV Examples

$$\text{Instrument } z_\ell = \sum_n \underbrace{\boxed{s_{\ell n}}}_{\text{shares}} \underbrace{\boxed{g_n}}_{\text{shocks}} \quad \text{for model } y_\ell = \beta x_\ell + \gamma' w_\ell + \varepsilon_\ell$$

Hummels et al. (2014) on offshoring:

- x_ℓ = imports by Danish firm ℓ, y_ℓ = wages
- g_n = changes in transport costs by $n =$ (product, country)
- $s_{\ell n}$ = lagged import shares

What Do We Do With This?

Of course we can always run IV with such z_ℓ ... but what does the corresponding estimand *identify*?

What Do We Do With This?

Of course we can always run IV with such z_ℓ ... but what does the corresponding estimand *identify*?

Recall IV validity condition: $E\left[\frac{1}{L}\sum_\ell z_\ell \varepsilon_\ell\right] = 0$ for model residual ε_ℓ

- Looks a little different than normal because we're not assuming *i.i.d.* sampling, i.e. $E\left[\frac{1}{L}\sum_\ell z_\ell \varepsilon_\ell\right] = E[z_\ell \varepsilon_\ell]$ (you'll see why soon!)

What Do We Do With This?

Of course we can always run IV with such z_ℓ ... but what does the corresponding estimand *identify*?

Recall IV validity condition: $E\left[\frac{1}{L}\sum_\ell z_\ell \varepsilon_\ell\right] = 0$ for model residual ε_ℓ

- Looks a little different than normal because we're not assuming *i.i.d.* sampling, i.e. $E\left[\frac{1}{L}\sum_\ell z_\ell \varepsilon_\ell\right] = E[z_\ell \varepsilon_\ell]$ (you'll see why soon!)

What properties of shocks and shares make this condition hold?

- Is SSIV like a natural experiment? A diff-in-diff? Something new?
- Since z_ℓ combines multiple sources of variation, it can be difficult to think about it being randomly assigned across ℓ...

Roadmap

Exogenous Shocks in Industry-Level Regressions

Acemoglu-Autor-Dorn-Hanson-Price (AADHP, 2016) look at the effects of import competition with China on US manufacturing *industries*:

$$\Delta \log Emp_{nt} = \alpha + \beta \Delta IP_{nt} + \varepsilon_{nt},$$

where ΔIP_{nt} measures growth in import penetration from China in industry n, and ε_{nt} captures industry demand/productivity shocks

Exogenous Shocks in Industry-Level Regressions

Acemoglu-Autor-Dorn-Hanson-Price (AADHP, 2016) look at the effects of import competition with China on US manufacturing *industries*:

$$\Delta \log Emp_{nt} = \alpha + \beta \Delta IP_{nt} + \varepsilon_{nt},$$

where ΔIP_{nt} measures growth in import penetration from China in industry n, and ε_{nt} captures industry demand/productivity shocks

Two Key Problems with OLS estimation:

1. Endogeneity of ΔIP_{nt}: OLS is not consistent for β
2. GE spillovers: β does not capture aggregate effects

Problem 1: Endogeneity of ΔIP_{nt}

$$\Delta \log Emp_{nt} = \alpha + \beta \Delta IP_{nt} + \varepsilon_{nt}$$

ΔIP_{nt} is driven by productivity shocks in China, but also potentially by productivity and demand shocks in the US

- ε_{nt} captures productivity and demand shocks in the US

Problem 1: Endogeneity of ΔIP_{nt}

$$\Delta \log Emp_{nt} = \alpha + \beta \Delta IP_{nt} + \varepsilon_{nt}$$

ΔIP_{nt} is driven by productivity shocks in China, but also potentially by productivity and demand shocks in the US

- ε_{nt} captures productivity and demand shocks in the US

AADHP instrument ΔIP_{nt} with ΔIPO_{nt}, measuring average Chinese import penetration growth in 8 non-US countries

Problem 1: Endogeneity of ΔIP_{nt}

$$\Delta \log Emp_{nt} = \alpha + \beta \Delta IP_{nt} + \varepsilon_{nt}$$

ΔIP_{nt} is driven by productivity shocks in China, but also potentially by productivity and demand shocks in the US

- ε_{nt} captures productivity and demand shocks in the US

AADHP instrument ΔIP_{nt} with ΔIPO_{nt}, measuring average Chinese import penetration growth in 8 non-US countries

- Relevance: both ΔIP_{nt} and ΔIPO_{nt} are driven by the same Chinese productivity shocks
- Validity: local productivity/demand shocks in the US are uncorrelated with those of other countries (entering ΔIPO_{nt})

Identification from a Natural Experiment

Suppose ΔIPO_{nt} is as-good-as-randomly assigned, as in a RCT:

$$E[\Delta IPO_{nt} \mid \mathcal{I}] = \mu \qquad \text{for all } n, t$$

where $\mathcal{I} = \{\varepsilon_{nt}, \text{pre-trends, balance variables}, \ldots\}$

Identification from a Natural Experiment

Suppose ΔIPO_{nt} is as-good-as-randomly assigned, as in a RCT:

$$E[\Delta IPO_{nt} \mid \mathcal{I}] = \mu \qquad \text{for all } n, t$$

where $\mathcal{I} = \{\varepsilon_{nt}, \text{pre-trends, balance variables}, \dots\}$

Consistent IV estimation then follows from many observations of nt, with sufficiently independent variation in ΔIPO_{nt}

Identification from a Natural Experiment

Can relax to add observables capturing systematic variation:

$$E[\Delta IPO_{nt} \mid \mathcal{I}] = q'_{nt}\mu \qquad \text{for all } n, t$$

where q_{nt} may include:

- period FE, isolating within-period variation in the shocks
- FE of 10 broad sectors, isolating within-sector variation, etc.

Identification from a Natural Experiment

Can relax to add observables capturing systematic variation:

$$E[\Delta IPO_{nt} \mid \mathcal{I}] = q'_{nt}\mu \qquad \text{for all } n, t$$

where q_{nt} may include:

- period FE, isolating within-period variation in the shocks
- FE of 10 broad sectors, isolating within-sector variation, etc.

We would then just want to control for q_{nt} in the industry-level IV

Problem 2: GE Spillovers

Spillovers across different industries are likely important:

- When employment shrinks in industry n after a negative shock, aggregate employment may or may not respond

Problem 2: GE Spillovers

Spillovers across different industries are likely important:

- When employment shrinks in industry n after a negative shock, aggregate employment may or may not respond
- In a flexible labor market, comparing wages of similar workers across industries does not make sense

Problem 2: GE Spillovers

Spillovers across different industries are likely important:

- When employment shrinks in industry n after a negative shock, aggregate employment may or may not respond
- In a flexible labor market, comparing wages of similar workers across industries does not make sense

Problem 2: GE Spillovers

ADH Solution: specify the outcome equation for local labor markets

- Works if local economies are isolated "islands"
  (simple model in Adao-Kolesar-Morales 2019; richer structure of spatial spillovers in Adao-Arkolakis-Esposito 2020)

Problem 2: GE Spillovers

ADH Solution: specify the outcome equation for local labor markets

- Works if local economies are isolated "islands"
  (simple model in Adao-Kolesar-Morales 2019; richer structure of spatial spillovers in Adao-Arkolakis-Esposito 2020)

But correct specification is not the same as identification!

- Key point: the same industry-level natural experiment can be used to estimate a regional specification, via SSIV

Borusyak, Hull, and Jaravel (BHJ; 2022)

Consider the SSIV estimator of $y_\ell = \beta x_\ell + \gamma' w_\ell + \varepsilon_\ell$ instrumented by $z_\ell = \sum_n s_{\ell n} g_n$ and, for now, $\sum_n s_{\ell n} = 1$ for all ℓ

- Reduced-form allowed: $x_\ell = z_\ell$
- Only the shift-share structure of z_ℓ matters; x_ℓ can be anything
- Note: view g_n as stochastic, so can't assume z_ℓ is iid

Borusyak, Hull, and Jaravel (BHJ; 2022)

Consider the SSIV estimator of $y_\ell = \beta x_\ell + \gamma' w_\ell + \varepsilon_\ell$ instrumented by $z_\ell = \sum_n s_{\ell n} g_n$ and, for now, $\sum_n s_{\ell n} = 1$ for all ℓ

- Reduced-form allowed: $x_\ell = z_\ell$
- Only the shift-share structure of z_ℓ matters; x_ℓ can be anything
- Note: view g_n as stochastic, so can't assume z_ℓ is iid

E.g. $g_n = \Delta IPO_n$ aggregated w/mfg employment shares $s_{\ell n}$

- Can we leverage a natural experiment in g_n, as before?

Borusyak, Hull, and Jaravel (BHJ; 2022)

Consider the SSIV estimator of $y_\ell = \beta x_\ell + \gamma' w_\ell + \varepsilon_\ell$ instrumented by $z_\ell = \sum_n s_{\ell n} g_n$ and, for now, $\sum_n s_{\ell n} = 1$ for all ℓ

- Reduced-form allowed: $x_\ell = z_\ell$
- Only the shift-share structure of z_ℓ matters; x_ℓ can be anything
- Note: view g_n as stochastic, so can't assume z_ℓ is iid

E.g. $g_n = \Delta IPO_n$ aggregated w/mfg employment shares $s_{\ell n}$

- Can we leverage a natural experiment in g_n, as before?

Leveraging g_n

Shift-Share Estimand

Consider the SSIV estimator of $y_\ell = \beta x_\ell + \gamma' w_\ell + \varepsilon_\ell$ instrumented by $z_\ell = \sum_n s_{\ell n} g_n$ and, for now, $\sum_n s_{\ell n} = 1$ for all ℓ

First step: note that by the FWL thm. the estimator can be written

$$\hat{\beta} = \frac{\sum_\ell z_\ell y_\ell^\perp}{\sum_\ell z_\ell x_\ell^\perp} = \frac{\sum_\ell \sum_n s_{\ell n} g_n y_\ell^\perp}{\sum_\ell \sum_n s_{\ell n} g_n x_\ell^\perp}$$

where $v_\ell^\perp$ denotes sample residuals from regressing v_ℓ on w_ℓ

Leveraging g_n

BHJ Numerical Equivalence

BHJ show $\hat{\beta}$ can be obtained from a shock-level IV procedure that uses g_n to instrument for a shock-level "aggregate" of the treatment:

Leveraging g_n

BHJ Numerical Equivalence

BHJ show $\hat{\beta}$ can be obtained from a shock-level IV procedure that uses g_n to instrument for a shock-level "aggregate" of the treatment:

$$\hat{\beta} = \frac{\frac{1}{L}\sum_\ell \sum_n s_{\ell n} g_n y_\ell^\perp}{\frac{1}{L}\sum_\ell \sum_n s_{\ell n} g_n x_\ell^\perp} =$$

Leveraging g_n

BHJ Numerical Equivalence

BHJ show $\hat{\beta}$ can be obtained from a shock-level IV procedure that uses g_n to instrument for a shock-level "aggregate" of the treatment:

$$\hat{\beta} = \frac{\frac{1}{L}\sum_\ell \sum_n s_{\ell n} g_n y_\ell^\perp}{\frac{1}{L}\sum_\ell \sum_n s_{\ell n} g_n x_\ell^\perp} = \frac{\sum_n g_n \sum_\ell \frac{1}{L} s_{\ell n} y_\ell^\perp}{\sum_n g_n \sum_\ell \frac{1}{L} s_{\ell n} x_\ell^\perp} =$$

Leveraging g_n

BHJ Numerical Equivalence

BHJ show $\hat{\beta}$ can be obtained from a shock-level IV procedure that uses g_n to instrument for a shock-level "aggregate" of the treatment:

$$\hat{\beta} = \frac{\frac{1}{L}\sum_\ell \sum_n s_{\ell n} g_n y_\ell^\perp}{\frac{1}{L}\sum_\ell \sum_n s_{\ell n} g_n x_\ell^\perp} = \frac{\sum_n g_n \sum_\ell \frac{1}{L} s_{\ell n} y_\ell^\perp}{\sum_n g_n \sum_\ell \frac{1}{L} s_{\ell n} x_\ell^\perp} = \frac{\sum_n s_n g_n \bar{y}_n^\perp}{\sum_n s_n g_n \bar{x}_n^\perp},$$

where $s_n = \frac{1}{L}\sum_\ell s_{\ell n}$ are weights capturing the average importance of shock n, and $\bar{v}_n = \frac{\sum_\ell s_{\ell n} v_\ell}{\sum_\ell s_{\ell n}}$ is an exposure-weighted average of v_ℓ

Leveraging g_n

BHJ Numerical Equivalence

BHJ show $\hat{\beta}$ can be obtained from a shock-level IV procedure that uses g_n to instrument for a shock-level "aggregate" of the treatment:

$$\hat{\beta} = \frac{\frac{1}{L}\sum_\ell \sum_n s_{\ell n} g_n y_\ell^\perp}{\frac{1}{L}\sum_\ell \sum_n s_{\ell n} g_n x_\ell^\perp} = \frac{\sum_n g_n \sum_\ell \frac{1}{L} s_{\ell n} y_\ell^\perp}{\sum_n g_n \sum_\ell \frac{1}{L} s_{\ell n} x_\ell^\perp} = \frac{\sum_n s_n g_n \bar{y}_n^\perp}{\sum_n s_n g_n \bar{x}_n^\perp},$$

where $s_n = \frac{1}{L}\sum_\ell s_{\ell n}$ are weights capturing the average importance of shock n, and $\bar{v}_n = \frac{\sum_\ell s_{\ell n} v_\ell}{\sum_\ell s_{\ell n}}$ is an exposure-weighted average of v_ℓ

Leveraging g_n

BHJ Numerical Equivalence

$$\hat{\beta} = \frac{\sum_n s_n g_n \bar{y}_n^{\perp}}{\sum_n s_n g_n \bar{x}_n^{\perp}}$$

The IV estimate from the original shock-level IV procedure is equivalent to a “industry-level” IV regression with model $\bar{y}_n^{\perp} = \alpha + \bar{x}_n^{\perp}\beta + \bar{\epsilon}_n$ instrumented by g_n with weights s_n.

The residual $\bar{\varepsilon}_n$ of this shock-level IV procedure is the average residual of observations with a high share of n

- E.g. in ADH, the average unobserved determinants of regional employment in regions most specialized in industry n

Leveraging g_n

BHJ Numerical Equivalence

$$\hat{\beta} = \frac{\sum_n s_n g_n \bar{y}_n^{\perp}}{\sum_n s_n g_n \bar{x}_n^{\perp}}$$

The IV estimate from the original shock-level IV procedure is equivalent to a "industry-level" IV regression with model $\bar{y}_n^{\perp} = \alpha + \bar{x}_n^{\perp}\beta + \bar{\epsilon}_n$ instrumented by g_n with weights s_n.

The residual $\bar{\varepsilon}_n$ of this shock-level IV procedure is the average residual of observations with a high share of n

- E.g. in ADH, the average unobserved determinants of regional employment in regions most specialized in industry n

It follows that $\hat{\beta}$ is consistent iff this shock-level IV procedure is...

BHJ Baseline Assumptions

A1 (Quasi-random shock assignment): $E[g_n \mid \bar{\varepsilon}, s] = \mu$, for all n

- Each shock has the same expected value, conditional on the shock-level unobservables $\bar{\varepsilon}_n$ and average exposure s_n

BHJ Baseline Assumptions

A1 (Quasi-random shock assignment): $E[g_n \mid \bar{\varepsilon}, s] = \mu$, for all n

- Each shock has the same expected value, conditional on the shock-level unobservables $\bar{\varepsilon}_n$ and average exposure s_n
- Implies SSIV exogeneity, as $z_\ell = \mu + \sum_n s_{\ell n}(g_n - \mu) = \mu +$ "noise"

BHJ Baseline Assumptions

A2 (Many uncorrelated shocks):

- $E\left[\sum_n s_n^2\right] \to 0$: expected Herfindahl index of average shock exposure converges to zero (implies $N \to \infty$)
- $Cov(g_n, g_{n'} \mid \bar{\varepsilon}, s) = 0$ for all $n' \neq n$: shocks are mutually uncorrelated given the unobservables

BHJ Baseline Assumptions

A2 (Many uncorrelated shocks):

- $E\left[\sum_n s_n^2\right] \to 0$: expected Herfindahl index of average shock exposure converges to zero (implies $N \to \infty$)
- $Cov(g_n, g_{n'} \mid \bar{\varepsilon}, s) = 0$ for all $n' \neq n$: shocks are mutually uncorrelated given the unobservables
- Imply a shock-level law of large numbers: $\sum_n s_n g_n \bar{\varepsilon}_n \xrightarrow{p} 0$

BHJ Baseline Assumptions

A2 (Many uncorrelated shocks):

- $E\left[\sum_n s_n^2\right] \to 0$: expected Herfindahl index of average shock exposure converges to zero (implies $N \to \infty$)
- $Cov(g_n, g_{n'} \mid \bar{\varepsilon}, s) = 0$ for all $n' \neq n$: shocks are mutually uncorrelated given the unobservables
- Imply a shock-level law of large numbers: $\sum_n s_n g_n \bar{\varepsilon}_n \xrightarrow{p} 0$

Both assumptions, while novel for SSIV, would be standard for a shock-level IV regression with weights s_n and instrument g_n

BHJ Extensions

Conditional Quasi-Random Assignment: $E[g_n \mid \bar{\varepsilon}, q, s] = q_n'\mu$ for some observed shock-level variables q_n

- Consistency follows when $w_\ell = \sum_n s_{\ell n} q_n$ is controlled for in the IV

BHJ Extensions

Conditional Quasi-Random Assignment: $E[g_n \mid \bar{\varepsilon}, q, s] = q_n'\mu$ for some observed shock-level variables q_n

- Consistency follows when $w_\ell = \sum_n s_{\ell n} q_n$ is controlled for in the IV

Weakly Mutually Correlated Shocks: $g_n \mid (\bar{\varepsilon}, q, s)$ are clustered or otherwise mutually dependent

- Consistency follows when mutual correlation is not too strong

BHJ Extensions

Conditional Quasi-Random Assignment: $E[g_n \mid \bar{\varepsilon}, q, s] = q_n'\mu$ for some observed shock-level variables q_n

- Consistency follows when $w_\ell = \sum_n s_{\ell n} q_n$ is controlled for in the IV

Weakly Mutually Correlated Shocks: $g_n \mid (\bar{\varepsilon}, q, s)$ are clustered or otherwise mutually dependent

- Consistency follows when mutual correlation is not too strong

Estimated Shocks: $g_n = \sum_\ell w_{\ell n} g_{\ell n}$ proxies for an infeasible g_n^*

- Consistency may require a "leave-out" adjustment: $z_\ell = \sum_\ell s_{\ell n} \tilde{g}_{\ell n}$ for $\tilde{g}_{\ell n} = \sum_{\ell' \neq \ell} \omega_{\ell' n} g_{\ell' n}$ (akin to JIVE solution to many-IV bias)

BHJ Extensions (cont.)

Panel Data: Have $(y_{\ell t}, x_{\ell t}, s_{\ell n t}, g_{nt})$ across $\ell = 1, \ldots, L$, $t = 1, \ldots, T$

- Consistency can follow from either $N \to \infty$ or $T \to \infty$
- Unit fixed effects "de-mean" the shocks, if $s_{\ell n t}$ are time-invariant

BHJ Extensions (cont.)

Panel Data: Have $(y_{\ell t}, x_{\ell t}, s_{\ell n t}, g_{nt})$ across $\ell = 1, \ldots, L$, $t = 1, \ldots, T$

- Consistency can follow from either $N \to \infty$ or $T \to \infty$
- Unit fixed effects "de-mean" the shocks, if $s_{\ell n t}$ are time-invariant

Heterogeneous Effects: LATE theorem logic goes through

- Under a first-stage monotonicity condition, SSIV identifies a convex weighted average of heterogeneous treatment effects

Practical Consideration 1: Incomplete Shares

The Problem

So far we have assumed a constant sum-of-shares: $S_\ell \equiv \sum_n s_{\ell n} = 1$

- But in some settings, S_ℓ varies across ℓ
- E.g. in ADH, S_ℓ is region ℓ's share of non-manufacturing emp.

Practical Consideration 1: Incomplete Shares

The Problem

So far we have assumed a constant sum-of-shares: $S_\ell \equiv \sum_n s_{\ell n} = 1$

- But in some settings, S_ℓ varies across ℓ
- E.g. in ADH, S_ℓ is region ℓ's share of non-manufacturing emp.

BHJ show that **A1**/**A2** are not enough for validity of z_ℓ in this case

- Now $z_\ell = \sum_n s_{\ell n} \left(\mu + (g_n - \mu)\right) = \mu S_\ell + \sum_n s_{\ell n}(g_n - \mu)$
- So z_ℓ is mechanically correlated with S_ℓ, which may be endogenous

E.g. in ADH, Comparing locations with larger and smaller z_ℓ could be comparing places with larger manufacturing employment (Midwest vs. South)

Practical Consideration 1: Incomplete Shares

The Solution

$$z_\ell = \sum_n s_{\ell n}\left(\mu + (g_n - \mu)\right) = \mu S_\ell + \underbrace{\sum_n s_{\ell n}(g_n - \mu)}_{\text{Clean Shock Variation}}$$

Controlling for the sum-of-shares S_ℓ isolates clean shock variation

- Further controls are needed when **A1** only holds conditional on q_n; e.g. in panels, S_ℓ should be interacted with time FE

Practical Consideration 2: Exposure Clustering

The Problem

Adão, Kolesar, and Morales (2019) study a novel inference challenge when SSIV identification leverages quasi-random shocks

- Observations with similar shares $s_{\ell 1,}, \dots, s_{\ell N}$ are likely to have correlated z_ℓ, even when observations are not "clustered" in conventional ways (e.g. by distance)
- When ε_ℓ is similarly clustered (e.g. when $\varepsilon_\ell = \sum_n s_{\ell n} \nu_n + \tilde{\varepsilon}_\ell$), large-sample distribution of $\hat{\beta}$ may not be well-approximated by standard central limit theorems (CLTs)

Practical Consideration 2: Exposure Clustering

The Solution

Adão, Kolesar, and Morales then derive a new CLT + SEs to address "exposure clustering"

- "Design-based": leverage *iid*ness of shocks, not observations

Practical Consideration 2: Exposure Clustering

The Solution

Adão, Kolesar, and Morales then derive a new CLT + SEs to address "exposure clustering"

- "Design-based": leverage *iid*ness of shocks, not observations

Practical Consideration 2: Exposure Clustering

The Solution

BHJ use similar logic to show robust/clustered SEs can be valid when $\hat{\beta}$ is given by estimating the 'industry-level' regression

$$\bar{y}_n^{\perp} = \alpha + \beta \bar{x}_n^{\perp} + q_n' \tau + \bar{\varepsilon}_n^{\perp},$$

instrumenting $\bar{x}_n^{\perp}$ by g_n and weighting by s_n

Practical Consideration 2: Exposure Clustering

The Solution

BHJ use similar logic to show robust/clustered SEs can be valid when $\hat{\beta}$ is given by estimating the 'industry-level' regression

$$\bar{y}_n^\perp = \alpha + \beta \bar{x}_n^\perp + q_n' \tau + \bar{\varepsilon}_n^\perp,$$

instrumenting $\bar{x}_n^\perp$ by g_n and weighting by s_n

- Numerically identical IV estimate, when controls include $\sum_n s_{\ell n} q_n$
- Clustering logic: valid SEs are obtained when estimating the IV at the level of identifying variation (here, shocks)

Practical Consideration 2: Exposure Clustering

The Solution

BHJ use similar logic to show robust/clustered SEs can be valid when $\hat{\beta}$ is given by estimating the 'industry-level' regression

$$\bar{y}_n^{\perp} = \alpha + \beta \bar{x}_n^{\perp} + q_n' \tau + \bar{\varepsilon}_n^{\perp},$$

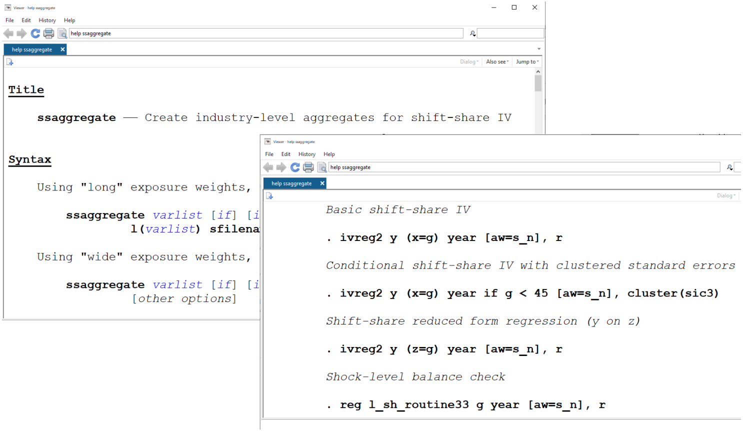
instrumenting $\bar{x}_n^{\perp}$ by g_n and weighting by s_n

- Numerically identical IV estimate, when controls include $\sum_n s_{\ell n} q_n$
- Clustering logic: valid SEs are obtained when estimating the IV at the level of identifying variation (here, shocks)

Same logic applies to performing valid balance/pre-trend tests and evaluating first-stage strength of the instrument

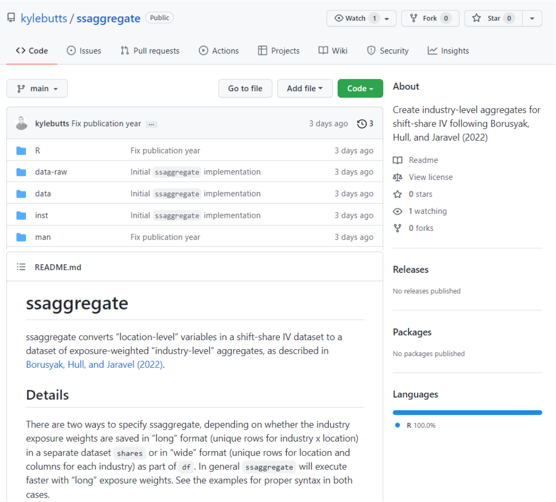
SSIV with *ssaggregate*

Stata package *ssaggregate* leverages the BHJ equivalence result: it translates data to the shock level, after which researchers can proceed with familiar estimation commands (install w/ *ssc install ssaggregate*)



SSIV with *ssaggregate*...in R!

Thanks to our own Kyle Butts, *ssaggregate* is now available in R too!



Download at https://github.com/kylebutts/ssaggregate

Application: "The China Shock"

ADH study the effects of rising Chinese import competition on US commuting zones, 1991-2000 and 2000-2007

- Treatment x_ℓ: local growth of Chinese imports in \$1,000/worker (slightly different from AADHP and ADHS)
- Main outcome y_ℓ: local change in manufacturing emp. share

Application: "The China Shock"

ADH study the effects of rising Chinese import competition on US commuting zones, 1991-2000 and 2000-2007

- Treatment x_ℓ: local growth of Chinese imports in \$1,000/worker (slightly different from AADHP and ADHS)
- Main outcome y_ℓ: local change in manufacturing emp. share

To address endogeneity challenge, use a SSIV $z_{\ell t} = \sum_n s_{\ell nt} g_{nt}$

- n: 397 SIC4 manufacturing industries ($\times$ 2 periods)
- g_{nt}: growth of Chinese imports in non-US economies per US worker
- $s_{\ell nt}$: lagged share of mfg. industry n in *total* emp. of location ℓ

ADH Revisited

BHJ show how ADH can be seen as leveraging quasi-random shocks

- *Ex ante* plausible: imagine random industry productivity shocks in China affecting imports in U.S. & elsewhere

ADH Revisited

*Plausability of **A1/A2***

Evaluate **A1** by regional and industry-level balance tests

- Industry shocks are uncorrelated with observables

ADH Revisited

*Plausability of **A1/A2***

Evaluate **A1** by regional and industry-level balance tests

- Industry shocks are uncorrelated with observables

Check sensitivity to adjusting for potential industry-level confounders:

- Control for $w_{\ell t} = \sum_n s_{\ell n t} q_{nt}$, where q_{nt} include period FE, sector FE, the Acemoglu et al. (2016) observables, ...

ADH Revisited

*Plausability of **A1/A2***

Evaluate **A1** by regional and industry-level balance tests

- Industry shocks are uncorrelated with observables

Check sensitivity to adjusting for potential industry-level confounders:

- Control for $w_{\ell t} = \sum_n s_{\ell nt} q_{nt}$, where q_{nt} include period FE, sector FE, the Acemoglu et al. (2016) observables, ...

Evaluate **A2** by studying variation across industries

- Effective sample size (1/HHI of s_n weights): 58-192
- Shocks appear mutually uncorrelated across SIC3 sectors

BHJ do ADH: Shock-Level Balance

Table 3: Shock Balance Tests in the Autor et al. (2013) Setting

Balance variable	Coef.	SE
Production workers' share of employment, 1991	-0.011	(0.012)
Ratio of capital to value-added, 1991	-0.007	(0.019)
Log real wage (2007 USD), 1991	-0.005	(0.022)
Computer investment as share of total, 1990	0.750	(0.465)
High-tech equipment as share of total investment, 1990	0.532	(0.296)
# of industry-periods	794	

No significant correlations between shocks and industry observables, controlling for year fixed effects

BHJ do ADH: Manufacturing Employment

Table 4: Shift-Share IV Estimates of the Effect of Chinese Imports on Manufacturing Employment

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Coefficient	-0.596	-0.489	-0.267	-0.314	-0.310	-0.290	-0.432
	(0.114)	(0.100)	(0.099)	(0.107)	(0.134)	(0.129)	(0.205)
Regional controls							
Autor et al. (2013) controls	✓	✓	✓		✓	✓	✓
Start-of-period mfg. share	✓						
Lagged mfg. share		✓	✓	✓	✓	✓	✓
Period-specific lagged mfg. share			✓	✓	✓	✓	✓
Lagged 10-sector shares					✓		✓
Local Acemoglu et al. (2016) controls						✓	
Lagged industry shares							✓
SSIV first stage F-stat.	185.6	166.7	123.6	272.4	64.6	63.3	27.6
# of region-periods	1,444	1,444	1,444	1,444	1,444	1,444	1,444
# of industry-periods	796	794	794	794	794	794	794

Roadmap

Introductions

- Me and This Course
- (Linear) SSIV

Shock Exogeneity

- Motivation
- Borusyak et al. (2022)

Share Exogeneity

- Motivation
- Goldsmith-Pinkham et al. (2020)

Choosing an Appropriate Framework

The Mariel Boatlift as a Basic SSIV

Card (1990) leverages a big migration “push” of low-skilled workers from Cuba to Miami, a Cuban-enclave.

The Mariel Boatlift as a Basic SSIV

Card (1990) leverages a big migration "push" of low-skilled workers from Cuba to Miami, a Cuban-enclave. Imagine instrumenting immigrant inflows by the lagged share of Cuban workers $s_{\ell,\text{Cuba}}$ in a diff-in-diff setup

- Need parallel trends: regions with more/fewer Cuban workers on similar employment trends

This can be viewed as a simple shift-share instrument:

$$s_{\ell,\text{Cuba}} \equiv s_{\ell,\text{Cuba}} \cdot 1 + \sum_{n \neq \text{Cuba}} s_{\ell n} \cdot 0$$

The Mariel Boatlift as a Basic SSIV

Card (1990) leverages a big migration "push" of low-skilled workers from Cuba to Miami, a Cuban-enclave. Imagine instrumenting immigrant inflows by the lagged share of Cuban workers $s_{\ell,\text{Cuba}}$ in a diff-in-diff setup

- Need parallel trends: regions with more/fewer Cuban workers on similar employment trends

This can be viewed as a simple shift-share instrument:

$$s_{\ell,\text{Cuba}} \equiv s_{\ell,\text{Cuba}} \cdot 1 + \sum_{n \neq \text{Cuba}} s_{\ell n} \cdot 0$$

If several migration origins had a push shock, we can pool them together with a more traditional SSIV...

Goldsmith-Pinkham, Sorkin, and Swift (GPSS; 2020)

GPSS view the set of n and values of g_n as fixed, so $z_\ell = \sum_n s_{\ell n} g_n$ is a linear combination of shares

Goldsmith-Pinkham, Sorkin, and Swift (GPSS; 2020)

GPSS view the set of n and values of g_n as fixed, so $z_\ell = \sum_n s_{\ell n} g_n$ is a linear combination of shares

They then also establish a numerical equivalence: $\hat{\beta}$ can be obtained from an overidentified IV procedure that uses N share instruments $s_{\ell n}$ and a weight matrix based on the shocks g_n

Goldsmith-Pinkham, Sorkin, and Swift (GPSS; 2020)

Sufficient identifying assumption: shares $s_{\ell n}$ are exogenous for each n (like parallel trends when ε_ℓ are unobserved trends)

$$E[\varepsilon_\ell \mid s_{\ell n}] = 0, \ \forall n$$

Goldsmith-Pinkham, Sorkin, and Swift (GPSS; 2020)

Sufficient identifying assumption: shares $s_{\ell n}$ are exogenous for each n (like parallel trends when ε_ℓ are unobserved trends)

$$E[\varepsilon_\ell \mid s_{\ell n}] = 0,\ \forall n \implies E[\textstyle\sum_\ell z_\ell \varepsilon_\ell] = \displaystyle\sum_\ell \sum_n g_n E[s_{\ell n}] E[\varepsilon_\ell \mid s_{\ell n}] = 0$$

This is N moment conditions at the level of observations, e.g. 38 for Card and 397 for ADH (vs. just 1 in BHJ, at the level of industries)

Rotemberg Weights

How does SSIV pool different diff-in-diffs?

- GPSS propose "opening the black box" of overidentified IV by deriving the weights SSIV implicitly puts on each share instrument
- Builds on Rotemberg (1983), so they call these "Rotemberg weights"

$$\hat{\beta} = \sum_n \hat{\alpha}_n \hat{\beta}_n, \text{ where } \underbrace{\hat{\beta}_n = \frac{\sum_\ell s_{\ell n} y_\ell^\perp}{\sum_\ell s_{\ell n} x_\ell^\perp}}_{n\text{-specific IV estimate}} \text{ and } \underbrace{\hat{\alpha}_n = \frac{g_n \sum_\ell s_{\ell n} x_\ell^\perp}{\sum_{n'} g_{n'} \sum_\ell s_{\ell n'} x_\ell^\perp}}_{\text{Rotemberg weight}}$$

Rotemberg Weights

How does SSIV pool different diff-in-diffs?

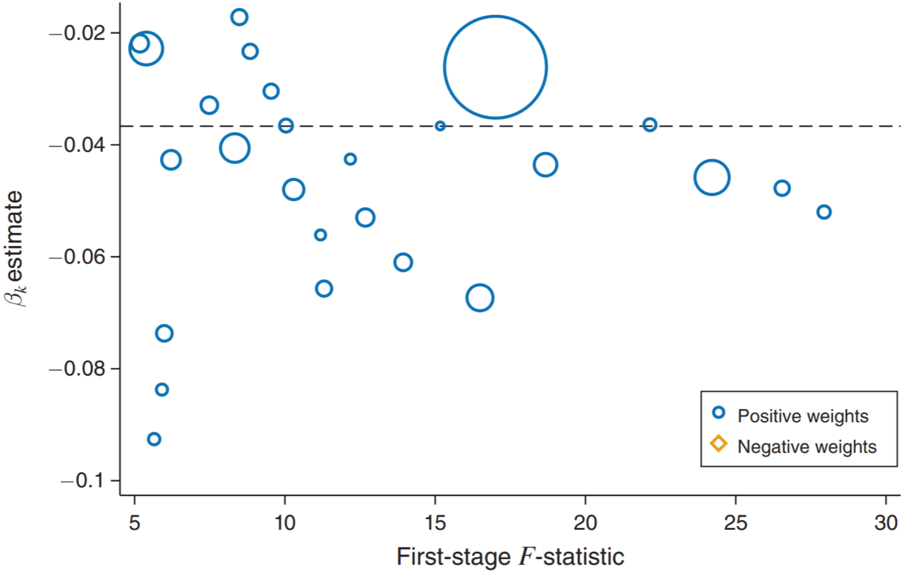
- GPSS propose "opening the black box" of overidentified IV by deriving the weights SSIV implicitly puts on each share instrument
- Builds on Rotemberg (1983), so they call these "Rotemberg weights"

$$\hat{\beta} = \sum_n \hat{\alpha}_n \hat{\beta}_n, \text{ where } \underbrace{\hat{\beta}_n = \frac{\sum_\ell s_{\ell n} y_\ell^\perp}{\sum_\ell s_{\ell n} x_\ell^\perp}}_{n\text{-specific IV estimate}} \text{ and } \underbrace{\hat{\alpha}_n = \frac{g_n \sum_\ell s_{\ell n} x_\ell^\perp}{\sum_{n'} g_{n'} \sum_\ell s_{\ell n'} x_\ell^\perp}}_{\text{Rotemberg weight}}$$

Intuitively, more weight is given to share instruments with more extreme shocks g_n and larger first stages $\sum_\ell s_{\ell n} x_\ell^\perp$

- Weights can be negative (potential issue w/heterogeneous effects)

Rotemberg Weights in Card (2009)



Is Share Exogeneity Plausible?

Share exogeneity assumption is **not** that "shares don't causally respond to the residual" (they can't: shares are pre-determined)

- It's: "all unobservables are uncorrelated with anything about the local share distribution"

Is Share Exogeneity Plausible?

This sufficient condition is typically violated when there are *any* unobserved shocks ν_n that affect ε_ℓ via the same or correlated shares

- I.e. if $\varepsilon_\ell = \sum_n s_{\ell n}\nu_n + \tilde{\varepsilon}_\ell$, then $s_{\ell n}$ and ε_ℓ cannot be uncorrelated in large samples—even if ν_n are uncorelated with g_n
- E.g. in ADH, unobserved technology shocks across industries affect labor markets via lagged emp. shares, along with observed g_n
- Problem arises when shares are “generic” – predicting many things

Card and ADH Revisited

When share exogeneity is *ex ante* plauible, can test its assumptions *ex post* (focusing on high Rotemberg weight n):

- Balance/pre-trend tests
- Overidentification tests (under constant effects)
- Straightforward to implement; no different than any other IV

Card and ADH Revisited

When share exogeneity is *ex ante* plauible, can test its assumptions *ex post* (focusing on high Rotemberg weight n):

- Balance/pre-trend tests
- Overidentification tests (under constant effects)
- Straightforward to implement; no different than any other IV

GPSS find that balance/overidentification tests broadly pass for Card ... but fail badly for ADH, consistent with *ex ante* implausibility

Roadmap

A Taxonomy of SSIV Settings

Case 1 the IV is based on a set of shocks which can be thought of as an instrument (i.e. many, plausibly quasi-randomly assigned)

- BHJ shows how this identifying variation can be mapped to estimate effects at a different “level” (i.e. industries $\rightarrow$ local labor markets)

A Taxonomy of SSIV Settings

Case 1 the IV is based on a set of shocks which can be thought of as an instrument (i.e. many, plausibly quasi-randomly assigned)

- BHJ shows how this identifying variation can be mapped to estimate effects at a different "level" (i.e. industries $\to$ local labor markets)

Case 2 the researcher does not directly observe many quasi-random shocks, but can estimate them in-sample

- Canonical setting of Bartik (1991), where g_n are average industry growth rates (thought to proxy for latent demand shocks)
- See also Card (2009), where national immiration rates are estimated

A Taxonomy of SSIV Settings

Case 1 the IV is based on a set of shocks which can be thought of as an instrument (i.e. many, plausibly quasi-randomly assigned)

- BHJ shows how this identifying variation can be mapped to estimate effects at a different “level” (i.e. industries $\rightarrow$ local labor markets)

Case 2 the researcher does not directly observe many quasi-random shocks, but can estimate them in-sample

- Canonical setting of Bartik (1991), where g_n are average industry growth rates (thought to proxy for latent demand shocks)
- See also Card (2009), where national immiration rates are estimated

Case 3 the g_n cannot be naturally viewed as an instrument

- Either too few or implausibly exogenous, even given some q_n.
- Identification may (or may not) instead follow from share exogeneity

Ex Ante vs. Ex Post Validity

BHJ emphasize that the decision to pursue a “shocks” vs. “shares” identification strategy must be made *ex ante*

- Undesirable to base identifying assumptions on *ex post* tests, though balance/pre-trend tests can be used to falsify assumptions
- The two identification strategies have different economic content

Ex Ante vs. Ex Post Validity

BHJ emphasize that the decision to pursue a “shocks” vs. “shares” identification strategy must be made *ex ante*

- Undesirable to base identifying assumptions on *ex post* tests, though balance/pre-trend tests can be used to falsify assumptions
- The two identification strategies have different economic content

They suggest thinking about whether shares are “tailored” to the economic question/treatment, or are “generic”

- Generic shares (e.g. ADH): unobserved ν_n are likely to enter ε_ℓ via the same or similar shares, violating share exogeneity
- Tailored shares have a diff-in-diff feel; don’t even need the shocks, except to possibly improve power or avoid many-IV bias