On Quasi-Experimental Shift-Share IV with Heterogeneous Treatment Effects

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In a new working paper, de Chaisemartin and Lei (2023, dCL) suggest panel shift-share (or "Bartik") regressions identify non-convex averages of heterogeneous treatment effects and argue that a new econometric framework is needed for studies of "China shock" effects (e.g. Autor et al. 2013; ADH). This note first reviews existing results on the causal interpretation of shift-share instrumental variable (IV) regressions with as-good-as-randomly assigned shocks from Borusyak et al. (2022a, BHJ). We then explain how these positive results relate to dCL's negative results, and why the former may be more useful in common shift-share applications. We conclude with a discussion of the appropriateness of the BHJ framework for China shock studies specifically.

1. Shift-share IV identifies a convex average of heterogeneous treatment effects when the shocks are as-good-as-randomly assigned

Consider a simple causal model of

$$y_{it} = \beta_{it} x_{it} + \varepsilon_{it} \tag{1}$$

for some outcome y_{it} and treatment x_{it}. Here β_{it} is the potentially heterogeneous effect of the treatment for unit i in period t, and ε_{it} captures the corresponding untreated potential outcome. Of particular interest are models where the outcome and treatment are in first differences: i.e. where $y_{it} = Y_{it} - Y_{i,t-1}$ and $x_{it} = X_{it} - X_{i,t-1}$ for some outcome and treatment levels Y_{it} and X_{it}.

BHJ consider a shift-share IV regression of y_{it} on x_{it} which instruments with

$$z_{it} = \sum_j s_{ijt}. \tag{2}$$

The shift-share instrument z_{it} is a weighted sum of shocks g_{jt} with pre-period weights $s_{ijt} \geq 0$ capturing heterogeneous shock exposure.

BHJ's Appendix A.1 shows that the IV coefficient estimates a convex average of the β_{it} effects when the shocks are (*i*) as-good-as-randomly assigned, (*ii*) excludable from potential outcomes, and (*iii*) satisfy a first-stage monotonicity condition. This result extends the LATE theorem of Imbens and Angrist (1994) to shift-share IV; we sketch a proof at the end of this note. BHJ further extend this result to a general class of causal models (e.g. with non-linear effect heterogeneity).[2]

2. dCL find non-convex *ex-post* weights, but this is not a problem when the shocks are as-good-as-randomly assigned

The first negative result of dCL (Theorem 1) concern the weights underlying the IV estimator. To summarize this result simply, let $\tilde{z}_{it}$ denote the residuals from an OLS regression of the instrument on a constant and included controls. The shift-share IV estimator can then be written:

$$\hat{\beta} = \frac{\sum_{it} \tilde{z}_{it} y_{it}}{\sum_{it} \tilde{z}_{it} x_{it}}. \tag{3}$$

dCL impose a high-level identification condition under which $\tilde{z}_{it}$ and the potential outcomes ε_{it} are uncorrelated in large samples: $\frac{1}{N}\sum_{it} \tilde{z}_{it}\varepsilon_{it} \approx 0$. When y_{it} is in first differences, this can be seen

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[2] See also Appendix C.1 of Borusyak and Hull (2021), who study a more general class of "formula" instruments under rich treatment effect heterogeneity.

as a "parallel trends" assumption. Under this condition, we have by plugging the model (1) into the estimator (3):

$$\hat{\beta} = \frac{\sum_{it} \tilde{z}_{it}(\beta_{it}x_{it} + \varepsilon_{it})}{\sum_{it} \tilde{z}_{it}x_{it}} \approx \sum_{it} w_{it}\beta_{it} \tag{4}$$

where the w_{it} are weights proportional to $\tilde{z}_{it}x_{it}$ and sum to one.[3] We refer to these weights as *ex-post,* in that they are functions of the realized shocks and treatment.

The essence of dCL's critique is that the weights w_{it} are likely to be negative for many treated observations. It would thus appear that $\hat{\beta}$ estimates a non-convex average of causal effects. This concern echos those from a recent literature on negative weights in two-way fixed effect regressions (de Chaisemartin and D'Haultfœuille (2020), Borusyak et al. (2022c), Callaway et al. (2021)).

The presence of ex-post negative weights is unsurprising, however. Even in randomized controlled trials (RCTs) with multiple treatment dosages, OLS regressions of the outcome on the dosage necessarily puts negative weight on groups with low (but non-zero) dosage, and thus on their treatment effects. Only very special estimators, which Borusyak et al. (2022c) call *imputation estimators*, avoid ex-post negative weights by using purely untreated observations as the control group. In many settings, including shift-share IV ones, there are no or few purely untreated observations.

Moreover, as in RCTs, negative ex-post weights in shift-share IV designs are not a cause for concern when the shocks are as-good-as-randomly assigned. In an RCT, each observation can get a low positive dosage of treatment and have a negative ex-post weight, but it can also get a high dosage and have a positive ex-post weight. On average, all observations get the same weight—what we term the *ex-ante* weight—such that the OLS estimator identifies average causal effects. The Appendix A.1 result of BHJ shows how this logic also holds in shift-share IV.[4]

3. The non-convex *ex-ante* weights that dCL find stem from an assumption of randomness in shock levels instead of changes

Theorem 3 of dCL shows that negative *ex-ante* weights can still arise with as-good-as-randomly assignment under some conditions. This apparent contradiction with the BHJ results stems from a difference in non-nested identifying assumptions. To see this, we will use the outcome model in levels from dCL:

$$Y_{it} = \alpha_i + \delta_{it}X_{it} + \epsilon_{it}. \tag{5}$$

They consider an IV regression with unit fixed effect controls instrumented by $Z_{it} = \sum_j s_{ij}G_{jt}$, where $G_{jt} = G_{j,t-1} + g_{jt}$ are accumulated shocks. Critically, they assume the G_{jt} levels are as-good-as-randomly assigned rather than the g_{jt} differences, as in BHJ.[5] They show that under this assumption the panel IV regression can, under some conditions, estimate a non-convex average of the δ_{it} effects.

If the g_{jt} changes, instead of the G_{jt} levels, are considered as-good-as-randomly assigned, the non-convex weighting problem goes away. Indeed, note that the levels model (5) implies a first-differenced model of:

$$\begin{aligned} y_{it} =& Y_{it} - Y_{i,t-1} = \delta_{it}X_{it} - \delta_{i,t-1}X_{i,t-1} + \epsilon_{it} - \epsilon_{i,t-1} \\ =& \beta_{it}x_{it} + \varepsilon_{it}, \end{aligned} \tag{6}$$

where $\beta_{it} = \delta_{it}$ and $\varepsilon_{it} = (\delta_{it} - \delta_{i,t-1})X_{i,t-1} + \epsilon_{it} - \epsilon_{i,t-1}$. When g_{jt} is as-good-as-randomly assigned following the realization of $t-1$ shocks, treatments, and outcomes, it is independent of ε_{it} and the

[3] More formally, $\hat{\beta} = \sum_{it} w_{it}\beta_{it} + o_p(1)$ when $\frac{1}{N}\sum_{it}\tilde{z}_{it}\varepsilon_{it} \xrightarrow{p} 0$ and $\frac{1}{N}\sum_{it}\tilde{z}_{it}x_{it} = O_p(1)$, where N is the number of observations.

[4] The distinction between ex-ante and ex-post weights is related to the distinction Goldsmith-Pinkham et al. (2022) draw between "design-based" and "model-based" regressions. They show design-based regressions based on as-good-as-random assignment avoid negative own-treatment effect weighting, even with multiple treatments.

[5] Because of the formulation in levels, dCL have to use time-invariant shares s_{ij}; only in that case does $Z_{it} - Z_{i,t-1} = z_{it}$. This goes against the applied tradition of using "updating" shares in SSIV regressions in differences with panel data, including in the ADH application (see Section 4.3 in BHJ).

BHJ result applies. dCL instead assume the path of G_{jt} are randomly assigned to units j, in which case $g_{jt} = G_{jt} - G_{j,t-1}$ is generally correlated with $X_{i,t-1}$ and thus with ε_{it} unless $\delta_{it} = \delta_{i,t-1}$.[6]

We argue that for many shift-share settings it is more natural to think of a natural experiment in g_{jt} changes. The G_{jt} levels usually correspond to persistent economic variables, such as tariffs or migration rates; while changes in them (due to e.g. unexpected policies) may be considered as-good-as-random in some cases, this is rarely a plausible view on the levels. Understanding as-good-as-random shocks as changes is also more consistent with typical theoretical justifications for shift-share IVs, which are usually based on first-order approximations to economic models after small changes in fundamentals (e.g. Kovak (2013), Adão et al. (2019), Borusyak et al. (2022b)).[7]

4. As-good-as-random shock assignment can be a reasonable assumption in "China shock" studies

BHJ show how their framework for shift-share IV, which considers the shocks g_{jt} as being conditionally as-good-as-random, is *a priori* reasonable for the "China shock" setting of ADH. They also show how a range of empirical checks—including balance tests, sensitivity analyses, and overidentification tests—are broadly consistent with that assumption.

dCL challenge this view by showing that the industry shocks in ADH (which measure the growth of imports from China in several non-US countries per industry employment in the US) fail a new balance test. Namely, while BHJ show that the shocks are not significantly correlated with five industry-level variables that could be plausible confounders, dCL find that the same variables *jointly* predict the shocks—at odds with the simple assumption of as-good-as-random assignment.

We see this new test as both valuable and informative, even though it need not invalidate the empirical evidence on China shock effects. Indeed, BHJ find their shift-share IV estimates are insensitive to allowing shock assignment to depend on the five industry-level variables by adding appropriate controls (specifically, regional shift-share aggregates of the industry-level confounders). Evidently, while these variables jointly predict the shocks they do not meaningfully predict the outcomes BHJ consider.[8]

We draw a more optimistic conclusion from these results than dCL, however, on the potential of shift-share IV for studying China shock effects. Rather than scrapping the assumption of as-good-as-randomly assigned shocks, we see a fruitful path in using economic theory to understand what shocks from this setting are most plausibly as-good-as-randomly assigned. After all, there are *a priori* reasons for why imports per worker systematically vary across industries: even if productivity shocks in China are drawn completely at random, the resulting imports into non-US countries per US worker need not be. However, under the assumption of as-good-as-random productivity shocks, it is straightforward to develop appropriate controls in shift-share IV regressions as well as new instruments which would leverage these shocks directly. As Appendix A.1 of BHJ shows, such regressions are likely to capture convex averages of heterogeneous causal effects.

Appendix: Sketch of the BHJ results

Suppose the g_{jt} are drawn randomly with zero mean conditional on the s_{ijt}, so that $E[z_{it}] = 0$. Suppose also the g_{jt} affect x_{it} through a first-stage model of $x_{it} = \sum_j \pi_{ijt} g_{jt} + \eta_{it}$. As-good-as-random shocks assignment and the exclusion restriction (that g_{jt} only affects y_{it} through x_{it}) makes the vector of g_{jt} independent from the set of $(\varepsilon_{it}, \beta_{it}, s_{ijt}, \pi_{ijt}, \eta_{it})$. The shift-share IV estimand is

[6] The difference in the BHJ and dCL identifying assumptions relates to an earlier difference in how Hudson et al. (2017) and de Chaisemartin and D'Haultfœuille (2017) formalize difference-in-difference IV regressions. Like BHJ, Hudson et al. (2017) consider the difference-in-differences instrument as a shock which only affects post-shock treatment and outcomes, and find no negative *ex-ante* weights.

[7] Even absent formal theory, the shares in shift-share instruments are usually picked from intuition on how the shocks—not their accumulations—may affect the treatment (e.g. Goldsmith-Pinkham et al. (2020)).

[8] dCL further show the shocks are correlated with a measure of average industry exposure, which is also at odds with simple as-good-as-random assignment. We have confirmed the BHJ shift-share IV estimates are also unchanged with controls based on this potential confounder.

then:

$$\beta = \frac{E\left[\sum_{it} z_{it} y_{it}\right]}{E\left[\sum_{it} z_{it} x_{it}\right]} = \frac{E\left[\sum_{it}\sum_j s_{ijt} g_{jt}(\beta_{it}(\sum_j \pi_{ijt} g_{jt} + \eta_{it}) + \varepsilon_{it})\right]}{E\left[\sum_{it}\sum_j s_{ijt} g_{jt}(\sum_j \pi_{ijt} g_{jt} + \eta_{it})\right]} = \frac{E\left[\sum_{it}\beta_{it}\sum_j s_{ijt}\pi_{ijt} g_{jt}^2\right]}{E\left[\sum_{it}\sum_j s_{ijt}\pi_{ijt} g_{jt}^2\right]}.$$

This is the formula for a convex average of the β_{it} so long as $\pi_{ijt} \geq 0$: i.e., provided the shocks only weakly increase the treatment.

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