第九届Stata中国用户大会

移动份额工具变量及Stata应用

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移动份额工具变量(shift-share IV)

- 移动份额工具变量(shift-share IV，简记SSIV)，最早由Bartik (1991)提出，故也称为 Bartik IV

- 常用于劳动经济学、区域经济学、国际贸易等领域

- *Today, around one-eighth of all instruments featured in NBER working papers are explicitly described as shift-share, while many others implicitly have a shift-share structure.* --- Borusyak et al. (2025), *p*.182

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A Practical Guide to Shift-Share Instruments

Kirill Borusyak, Peter Hull, and Xavier Jaravel

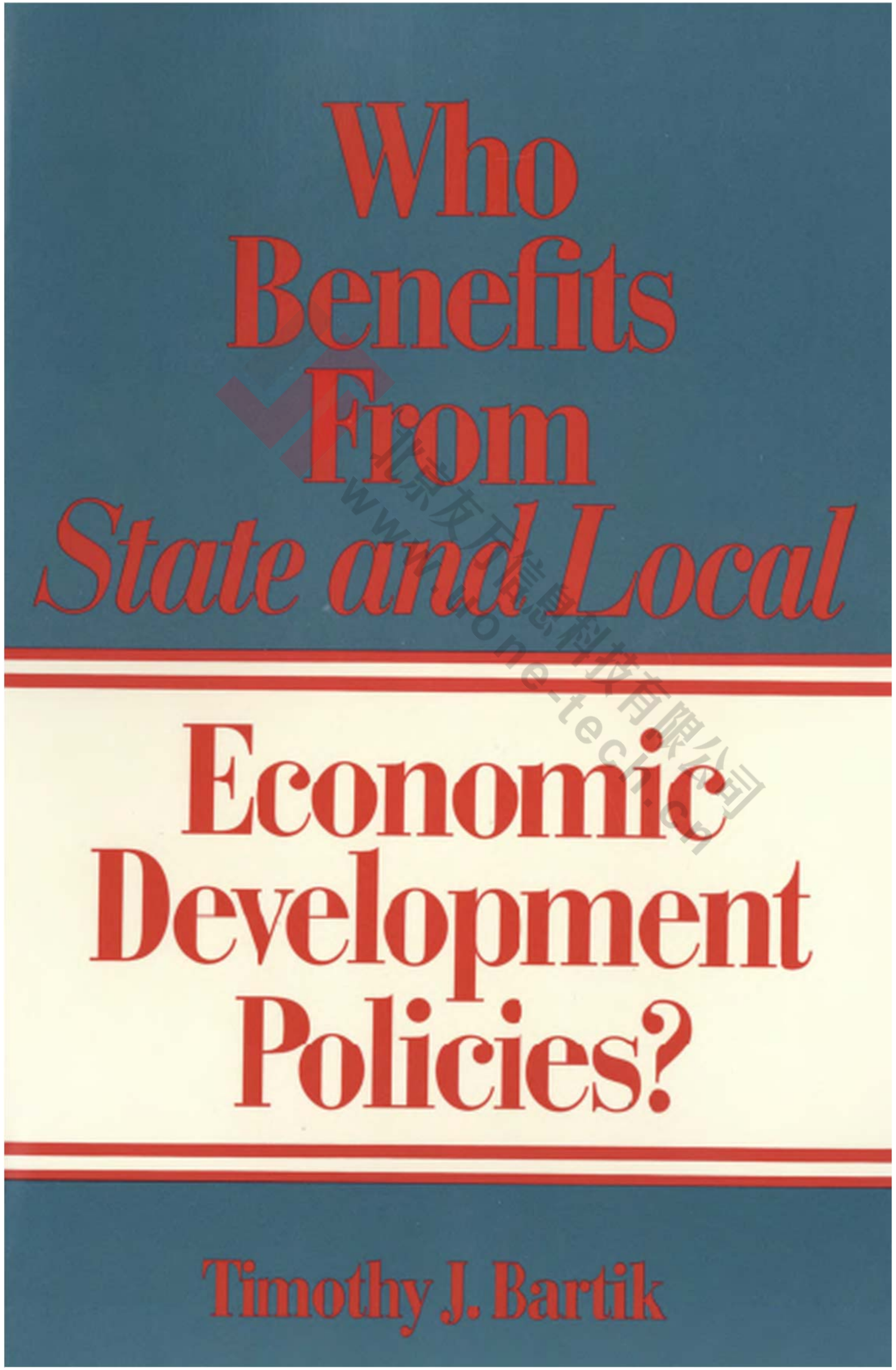
Many economic studies consider units that are exposed differently to a common set of shocks. Consider, for example, the influential Autor, Dorn, and Hanson (2013) study of how the surge in Chinese imports in the 1990s and 2000s affected US local labor markets. They measure regional exposure to this "China shock" by the extent to which workers were employed in industries that saw growing competition with China. This idea is captured by a *shift-share* explanatory vari-

经典的Bartik IV

$$y_i = \beta x_i + \boldsymbol{\gamma}'\mathbf{q}_i + \varepsilon_i \quad (i = 1, \cdots, m)$$

- y_i：地区i的工资增长率（从期初到期末）
- x_i：地区i的就业增长率（从期初到期末）
- β：逆劳动供给弹性（inverse elasticity of labor supply）
- $\mathbf{q}_i$：控制变量（与扰动项不相关，已含常数项）

- 内生性：供给与需求之间存在双向因果，以及遗漏变量偏差


Who Benefits From State and Local
Economic Development Policies?
Timothy J. Bartik

两个会计恒等式（之一）

- 记地区i的期末就业人数为 L_i，分布于n个行业(industry)或部门(sector)，即 $L_i = \sum_{j=1}^{n} L_{ij}$，其中 L_{ij} 为地区i行业j的期末就业人数

$$\Delta L_i = \sum_{j=1}^{n} \Delta L_{ij} = \sum_{j=1}^{n} L_{ij0} g_{ij} \Rightarrow x_i \equiv \frac{\Delta L_i}{L_{i0}} = \sum_{j=1}^{n} \frac{L_{ij0}}{L_{i0}} g_{ij} \equiv \sum_{j=1}^{n} s_{ij} g_{ij}$$

- 其中，L_{ij0}为地区i行业j的期初就业人数，g_{ij} 为地区i行业j的就业增长率，L_{i0} 为地区i的期初就业人数，而 s_{ij}为地区i行业j的期初就业份额(share)。核心变量 x_i具有移动份额的结构，可称为 Bartik (shift-share) regressor

期初(或滞后)就业份额的矩阵

$$\begin{pmatrix} s_{11} & \cdots & s_{1n} \\ \vdots & \vdots & \vdots \\ s_{m1} & \cdots & s_{mn} \end{pmatrix}_{m\times n}$$

- 其中，一般假设 $\sum_{i=1}^{n} s_{ij} = 1$（每行之和为1）
- 若 $0 < \sum_{i=1}^{n} s_{ij} < 1$，可加上一个“缺失行业”(missing industry)，使得 $\sum_{i=1}^{n} s_{ij} = 1$

两个会计恒等式（之二）

- 记 g_j 为全国行业j的就业增长率（national industry growth rate），并将 g_{ij} 分解为

$$g_{ij} \equiv g_j + \tilde{g}_{ij}$$

- 其中，$\tilde{g}_{ij} \equiv g_{ij} - g_j$ 为“idiosyncratic location-industry growth rate”。

- Bartik IV (地区i的预测就业增长率):

$$z_i \equiv \sum_{j=1}^{n} \underbrace{s_{ij}}_{share} \underbrace{g_j}_{shift} \qquad (\,shift = shock\,)$$

Bartik IV的定义

- *We define a Bartik-like instrument as one that uses the inner product structure of the endogenous variable to construct an instrument.*

  -- Goldsmith-Pinkham et al. (2020, AER), *p*. 2590

Bartik IV $z_i \equiv \sum_{j=1}^{n} s_{ij} g_j$ 的直觉

- 全国层面的行业冲击 g_j 外生于地区 i，称 g_j 为shock或shifter。在计算 g_j 时，也可将本地区的行业 j 就业人数排除在全国行业 j 就业人数之外，称为“留一估计”(leave-one-out estimate)

- 行业冲击 g_j 对于地区 i 的影响取决于地区 i 行业 j 的期初就业份额(share) s_{ij}，它度量了地区 i 对于行业冲击 g_j 的暴露程度(exposure)。

- 故名“移动份额IV”(shift-share IV, 简记SSIV)

Bartik IV的有效性

- 相关性：内生变量 $x_i = \sum_{j=1}^{n} s_{ij} g_{ij}$ ，而工具变量 $z_i = \sum_{j=1}^{n} s_{ij} g_j$ ，二者通常相关性较强

- 外生性：对于地区i的扰动项 ε_i 而言，(或许)可以认为行业冲击 g_j 为外生

- 在此条件下，即使地区i的份额 s_{ij} 内生，Bartik IV $z_i \equiv \sum_{j=1}^{n} s_{ij} g_j$ 依然外生

Bartik IV的外生性

- Shift-based identification stems from a simple observation: *a share-weighted average of random shifts is itself as-good-as random. This is true even if the shares are econometrically endogenous*, in the sense that units with different shares may have systematically different unobservables. --- Borusyak et al. (2025), *p*.186

迭代期望定律

$$\operatorname{Cov}(z_i,\varepsilon_i)=\operatorname{Cov}\left(\sum_{j=1}^{n}s_{ij}g_j,\varepsilon_i\right)=\mathrm{E}\left[\left(\sum_{j=1}^{n}s_{ij}g_j\right)\varepsilon_i\right]$$

$$=\mathrm{E}_{s_{i1},\cdots,s_{in}}\left[\mathrm{E}\left(\sum_{j=1}^{n}s_{ij}g_j\varepsilon_i\middle|s_{i1},\cdots,s_{in}\right)\right]$$

$$=\mathrm{E}_{s_{i1},\cdots,s_{in}}\left[\sum_{j=1}^{n}s_{ij}\underbrace{\mathrm{E}\left(g_j\varepsilon_i\middle|s_{i1},\cdots,s_{in}\right)}_{=0}\right]=0$$

Bartik IV的外生性 (续)

- 类似地，如果份额(shares)外生，即使冲击(shifts)内生，Bartik IV依然外生

$$\mathrm{Cov}(z_i,\varepsilon_i)=\mathrm{Cov}\left(\sum_{j=1}^{n}s_{ij}g_j,\varepsilon_i\right)=\mathrm{E}\left[\left(\sum_{j=1}^{n}s_{ij}g_j\right)\varepsilon_i\right]$$

$$=\mathrm{E}_{g_1,\cdots,g_n}\left[\mathrm{E}\left(\sum_{j=1}^{n}s_{ij}g_j\varepsilon_i\,\middle|\,g_1,\cdots,g_n\right)\right]$$

$$=\mathrm{E}_{g_1,\cdots,g_n}\left[\sum_{j=1}^{n}g_j\underbrace{\mathrm{E}\left(s_{ij}\varepsilon_i\,\middle|\,g_1,\cdots,g_n\right)}_{=0}\right]=0$$

Bartik IV的外生性 (小结)

- 为了保证Bartik IV的外生性，要么冲击(shifts)外生，要么份额(shares)外生，但并不要求二者都外生
- 在实践中，看哪个假定更合理，则使用哪个识别策略

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1992
Brookings Papers
on Economic
Activity

Regional Evolutions

In 1987, the unemployment rate in Massachusetts averaged 3.2 percent, three percentage points below the national rate. Only four years later, in 1991, it stood at 9.0 percent, more than two points above the national rate. For firms taking investment decisions and for unemployed workers thinking about relocating, the obvious question is whether and when things will return to normal in Massachusetts. This is the issue that we take up in our paper.

However, instead of looking only at Massachusetts, we examine the general features of regional booms and slumps, studying the behavior of U.S. states over the last 40 years. We attempt to answer four questions. When a typical U.S. state over the postwar period has been affected by an adverse shock to employment, how has it adjusted? Did wages decline relative to the rest of the nation? Were other jobs created to replace those jobs destroyed by the shock? Or did workers move out of the state?

details of construction).[52] It exhibits substantial movements across states and time. On average, from 1951 to 1988 (the period for which we can construct the series) it accounts for more than 6 percent of state income for four states—California, Connecticut, Massachusetts, and Missouri—and the District of Columbia. For those states and the District, the standard deviation of forecast errors from a simple univariate process is on average equal to 14 percent; some forecast errors exceed 30 percent.

The second variable is a mix variable that gives the employment growth in a state predicted by the growth of its industries nationally; it has been constructed and used by Bartik in a similar context.[53] The series is generated for each state and each year, from 1970 to 1989, as a weighted average of the growth rates of national industry employment (aggregated to two-digit SIC categories) with the weights calculated as the previous year share of state employment in each industry. This variable will be a valid instrument in a given state if industry national growth rates are uncorrelated with labor supply shocks in the state. This in turn will be true if sectoral employment at the two-digit level is not too concentrated in any state, a condition that appears satisfied in the data. Because we shall use the deviation of this variable from the national growth rate of employment, this deviation will be a good instrument if states differ sufficiently in their sectoral employment composition. This condition also appears to be satisfied.

Immigrant Inflows, Native Outflows, and the Local Labor Market Impacts of Higher Immigration

David Card, *University of California, Berkeley*

This article uses 1990 census data to study the effects of immigrant inflows on occupation-specific labor market outcomes. I find that intercity mobility rates of natives and earlier immigrants are insensitive to immigrant inflows. However, occupation-specific wages and employment rates are systematically lower in cities with higher relative supplies of workers in a given occupation. The results imply that immigrant inflows over the 1980s reduced wages and employment rates of low-skilled natives in traditional gateway cities like Miami and Los Angeles by 1–3 percentage points.

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0734-306X/2001/1901-0002$02.50

source countries, an estimate of the supply-push component of recent immigrant inflows in occupation group j and city c is

Bartik IV

$$SP_{jc} = \Sigma_g \tau_{gj} \lambda_{gc} M_g. \tag{10}$$

To construct this measure, I used a set of 17 source country groups, identified in table 5.[24] The first column of the table gives the fraction of all 1985–90 immigrants from each source (i.e., M_g/M, where M is the total inflow of new immigrants), while the second column shows the mean education of recent immigrants from each source country group. Mexico is the largest single source country, accounting for 26% of the approximately 3.4 million adult immigrants who entered the United States between 1985 and 1990. The Philippines is the second largest individual source country, accounting for about 5% of all recent immigrants. Other source-country groups account for 1%–8% of recent immigrants.

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The China Syndrome: Local Labor Market Effects of Import Competition in the United States†

By David H. Autor, David Dorn, and Gordon H. Hanson*

We analyze the effect of rising Chinese import competition between 1990 and 2007 on US local labor markets, exploiting cross-market variation in import exposure stemming from initial differences in industry specialization and instrumenting for US imports using changes in Chinese imports by other high-income countries. Rising imports cause higher unemployment, lower labor force participation, and reduced wages in local labor markets that house import-competing manufacturing industries. In our main specification, import competition explains one-quarter of the contemporaneous aggregate decline in US manufacturing employment. Transfer benefits payments for unemployment, disability, retirement, and healthcare also rise sharply in more trade-exposed labor markets. (*JEL* E24, F14, F16, J23, J31, L60, O47, R12, R23)

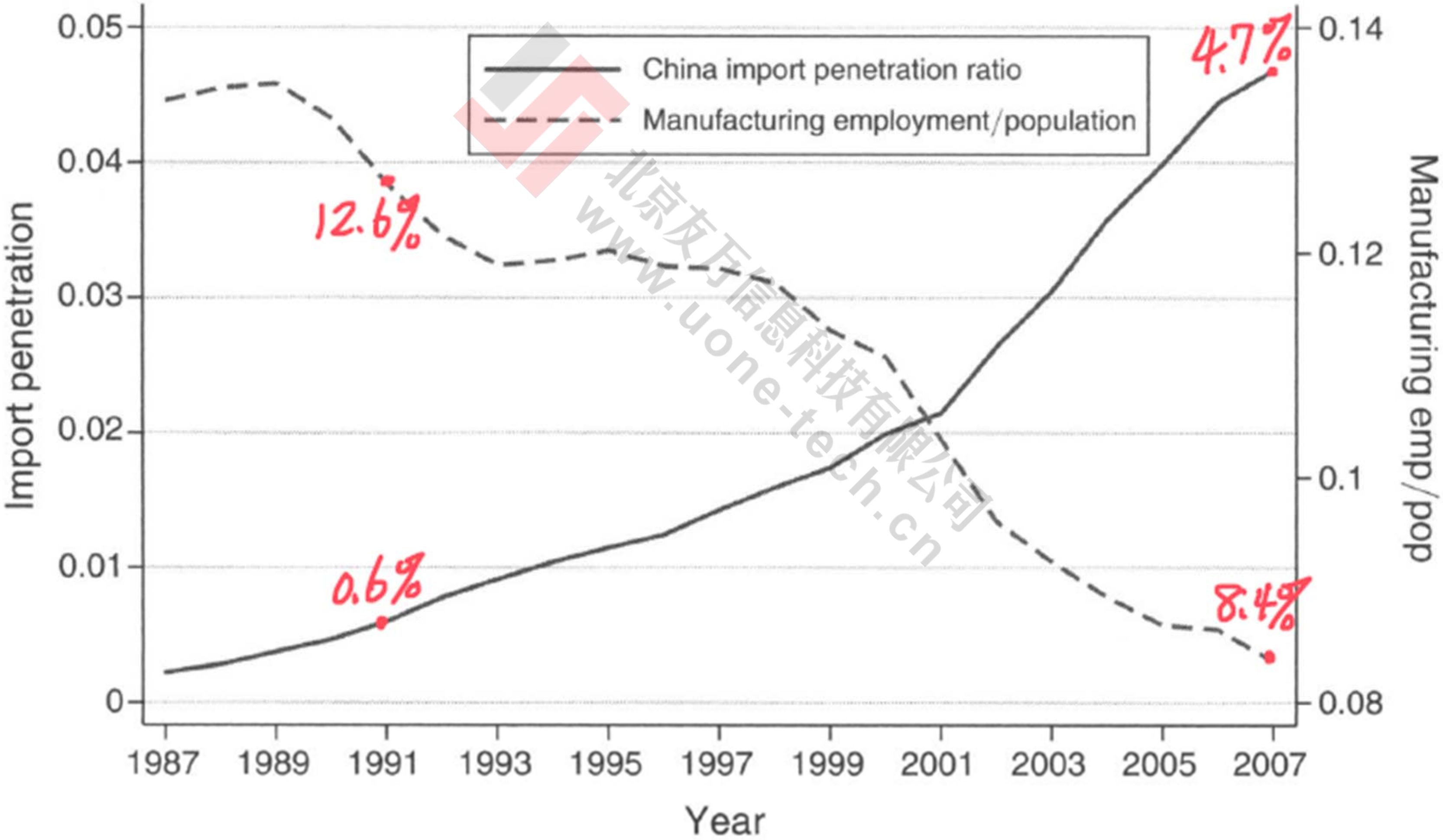

FIGURE 1. IMPORT PENETRATION RATIO FOR US IMPORTS FROM CHINA (*left scale*), AND SHARE OF US WORKING-AGE POPULATION EMPLOYED IN MANUFACTURING (*right scale*)

considerably over time, the expansion was much less dramatic than in the case of Chinese imports. Panel B summarizes trade flows from the same exporters to a group of eight high-income countries located in Europe, Asia, and the Pacific (Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland). Like the United States, these countries experienced a dramatic increase in imports from China between 1991 and 2007, and a more modest growth of imports from Mexico and Central America, and from other low-income countries. We focus on these high-income countries as they are the rich nations for which disaggregated HS trade data are available back to 1991.

To assess the effect of imports of Chinese goods on local labor markets, we need to define regional economies in the United States. Our concept for local labor markets is
通勤区
Commuting Zones (CZs) developed by Tolbert and Sizer (1996), who used county-level commuting data from the 1990 Census data to create 741 clusters of counties that are characterized by strong commuting ties within CZs, and weak commuting ties across CZs. Our analysis includes the 722 CZs that cover the entire
722个地区
mainland United States (both metropolitan and rural areas).

It is plausible that the effects of Chinese imports will vary across local labor markets in the United States because there is substantial geographic variation in industry specialization. Local economies that are specialized in industries whose outputs compete with Chinese imports should react more strongly to the growth of these imports. Our measure for the exposure of local labor markets to Chinese imports in equation (3) combines trade data with data on local industry employment. Information on industry employment structure by CZs, including employment in 397 manufacturing industries, is derived from the County Business Patterns data (see the online Data Appendix).
397个行业

Following (2), our main measure of local labor market exposure to import competition is the change in Chinese import exposure per worker in a region, where imports are apportioned to the region according to its share of national industry employment:

核心解释变量
本身也是:
Bartik-like measure

每个制造业的冲击与每个
制造业份额的内积

$$\Delta IPW_{uit} = \sum_j \frac{L_{ijt}}{L_{ujt}} \frac{\Delta M_{ucjt}}{L_{it}}. \tag{3}$$

per worker

In this expression, L_{it} is the start of period employment (year t) in region i and ΔM_{ucjt} is the observed change in US imports from China in industry j between the start and end of the period.[18]

美国制造业j
从中国进口
额的变化,
M: import
u: USA
c: China
j: industry
t: period

Equation (3) makes clear that the difference in ΔIPW_{uit} across local labor markets stems entirely from variation in local industry employment structure at the start of period t. This variation arises from two sources: differential concentration of employment in manufacturing versus nonmanufacturing activities and specialization in import-intensive industries within local manufacturing. Differences in manufacturing employment shares are not the primary source of variation, however; in a bivariate regression, the start-of-period manufacturing employment share explains less than 25 percent of the variation in ΔIPW_{uit}. In our main specifications, we will control for the start-of-period manufacturing share within CZs so as to focus on variation in exposure to Chinese imports stemming from differences in industry mix within local manufacturing sectors.

A concern for our subsequent estimation is that realized US imports from China in (3) may be correlated with industry import demand shocks, in which case the OLS estimate of how increased imports from China affect US manufacturing employment may understate the true impact, as both US employment and imports

遗漏变量
偏差

To identify the supply-driven component of Chinese imports, we instrument for growth in Chinese imports to the United States using the contemporaneous composition and growth of Chinese imports in eight other developed countries.[19] Specifically, we instrument the measured import exposure variable ΔIPW_{uit} with a *non*-US exposure variable ΔIPW_{oit} that is constructed using data on contemporaneous industry-level growth of Chinese exports to other high-income markets:

$$(4) \qquad \Delta IPW_{oit} = \sum_j \frac{L_{ijt-1}}{L_{ujt-1}} \frac{\Delta M_{ocjt}}{L_{it-1}}.$$

Bartik IV

This expression for non-US exposure to Chinese imports differs from the expression in equation (3) in two respects. First, in place of realized US imports by industry (ΔM_{ucjt}), it uses realized imports from China to other high-income markets (ΔM_{ocjt}). Second, in place of start-of-period employment levels by industry and region, this expression uses employment levels from the *prior* decade. We use ten-year-lagged employment levels because, to the degree that contemporaneous employment by region is affected by anticipated China trade, the use of lagged employment to apportion predicted Chinese imports to regions will mitigate this simultaneity bias.

使用滞后份额使得IV更满足外生性

Our IV strategy will identify the Chinese productivity and trade-shock compo-

Table 3—Imports from China and Change of Manufacturing Employment in CZs, 1990–2007: 2SLS Estimates

Dependent variable: 10 × annual change in manufacturing emp/working-age pop (*in % pts*)

	I. 1990–2007 stacked first differences					
	(1)	(2)	(3)	(4)	(5)	(6)
(Δ imports from China to US)/ worker	−0.746*** (0.068)	−0.610*** (0.094)	−0.538*** (0.091)	−0.508*** (0.081)	−0.562*** (0.096)	−0.596*** (0.099)
Percentage of employment in manufacturing$_{-1}$		−0.035 (0.022)	−0.052*** (0.020)	−0.061*** (0.017)	−0.056*** (0.016)	−0.040*** (0.013)
Percentage of college-educated population$_{-1}$				−0.008 (0.016)		0.013 (0.012)
Percentage of foreign-born population$_{-1}$				−0.007 (0.008)		0.030*** (0.011)
Percentage of employment among women$_{-1}$				−0.054** (0.025)		−0.006 (0.024)
Percentage of employment in routine occupations$_{-1}$					−0.230*** (0.063)	−0.245*** (0.064)
Average offshorability index of occupations$_{-1}$					0.244 (0.252)	−0.059 (0.237)
Census division dummies	No	No	Yes	Yes	Yes	Yes
	II. 2SLS first stage estimates					
(Δ imports from China to OTH)/ worker	0.792*** (0.079)	0.664*** (0.086)	0.652*** (0.090)	0.635*** (0.090)	0.638*** (0.087)	0.631*** (0.087)
R^2	0.54	0.57	0.58	0.58	0.58	0.58

Notes: N = 1,444 (722 commuting zones × 2 time periods). All regressions include a constant and a dummy for the 2000–2007 period. First stage estimates in panel II also include the control variables that are indicated in the corresponding columns of panel I. Routine occupations are defined such that they account for 1/3 of US employment in 1980. The offshorability index variable is standardized to mean of 0 and standard deviation of 10 in 1980. Robust standard errors in parentheses are clustered on state. Models are weighted by start of period CZ share of national population.

Import Competition and the Great US Employment Sag of the 2000s

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A. Industry Trade Shocks

Our baseline measure of trade exposure is the change in the import penetration ratio for a US manufacturing industry over the period 1991–2011, defined as

$$\Delta IP_{j\tau} = \frac{\Delta M^{UC}_{j,\tau}}{Y_{j,91} + M_{j,91} - E_{j,91}}, \tag{1}$$

where for US industry j, $\Delta M^{UC}_{j,\tau}$ is the change in imports from China over the period 1991–2011 (which in most of our analysis we divide into two subperiods, 1991–99 and 1999–2011) and $Y_{j,91} + M_{j,91} - E_{j,91}$ is initial absorption (measured as industry shipments, $Y_{j,91}$, plus industry imports, $M_{j,91}$, minus industry exports, $E_{j,91}$). We choose 1991 as the initial year as it is the earliest period for which we have the requisite disaggregated bilateral trade data for a large number of country pairs that we can match to US manufacturing industries.[16] The quantity in (1) can be motivated by tracing export supply shocks in China—due, for example, to productivity growth—through to demand for US output in the markets in which the United States and China compete. Supply-driven changes in China's exports will tend to reduce demand for and employment in US industries.

One concern about (1) as a measure of trade exposure is that observed changes in the import penetration ratio may in part reflect domestic shocks to US industries that affect US import demand. Even if the dominant factors driving China's export growth are internal supply shocks, US industry import demand shocks may still contaminate bilateral trade flows. To capture this supply-driven component in US imports from China, we instrument for trade exposure in (1) with the variable

$$\Delta IPO_{j\tau} = \frac{\Delta M_{j,\tau}^{OC}}{Y_{j,88} + M_{j,88} - X_{j,88}}, \tag{2}$$

where $\Delta M_{j,\tau}^{OC}$ is the growth in imports from China in industry j during the period τ (in this case 1991–2011 or some subperiod thereof) in eight other high-income countries excluding the United States.[17] The denominator in (2) is initial absorption in the industry in 1988. The motivation for the instrument in (2) is that high-income economies are similarly exposed to growth in imports from China that is driven by supply shocks in the country. The identifying assumption is that industry import demand shocks are uncorrelated across high-income economies and that there are no strong increasing returns to scale in Chinese manufacturing (which might imply that US demand shocks will increase efficiency in the affected Chinese industries and induce them to export more to other high-income countries).[18]

Robots and Jobs: Evidence from US Labor Markets

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We study the effects of industrial robots on US labor markets. We show theoretically that robots may reduce employment and wages and that their local impacts can be estimated using variation in exposure to robots—defined from industry-level advances in robotics and local industry employment. We estimate robust negative effects of robots on employment and wages across commuting zones. We also show that areas most exposed to robots after 1990 do not exhibit any differential trends before then, and robots' impact is distinct from other capital and technologies. One more robot per thousand workers reduces the employment-to-population ratio by 0.2 percentage points and wages by 0.42%.

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i: industry
j: country
t: time

Accounts (see Jägger 2016),[12] which allows us to measure the adjusted penetration of robots, APR_i and $\overline{APR}_i$, for different time periods. Following equation (12), our baseline measure of the adjusted penetration of robots between two dates, t_0 and t_1, is given by

$$\overline{APR}_{i,(t_0,t_1)} = \frac{1}{5} \sum_{j \in EURO5} \left[\frac{M^j_{i,t_1} - M^j_{i,t_0}}{L^j_{i,1990}} - g^j_{i,(t_0,t_1)} \frac{M_{i,t_0}}{L^j_{i,1990}} \right], \tag{15}$$

where $M^j_{i,t}$ represents the number of robots in industry i in country j at time t (from the IFR data), $g^j_{i,(t_0,t_1)}$ is the growth rate of output of industry i in country j between t_0 and t_1 (from the EU KLEMS), and $L^j_{i,1990}$ represents the baseline employment level in industry i and country j (also from the EU KLEMS).[13] In our long-differences models, we take $t_0 = 1993$ and $t_1 = 2007$, though we also present models where we focus on other periods.

For our baseline measure, we use the average penetration in *EURO*5, comprising Denmark, Finland, France, Italy, and Sweden—that is, countries ahead of the United States in robotics, excluding Germany. Focusing on countries that are ahead of the United States helps us isolate the source of variation coming from global technological advances (rather than idiosyncratic US factors). We exclude Germany from our baseline measure because, as figure 1 shows, it is so far ahead of the other countries that its adoption trends may be less relevant for US patterns than the trends in *EURO*5. The appendix presents versions of our main results for different constructions of the $\overline{APR}_i$ measure, including a specification where we use all European countries, one where we use both Germany and the *EURO*5, one where we use the observed increase in robot density without the $g^j_{i,(t_0,t_1)} M_{i,t_0}/L^j_{i,1990}$ term, and a complementary measure where we include an adjustment for variation in the average price of a robot across industries.

We also measure the US adjusted penetration of robots as

$$APR^{US}_{i,(t_0,t_1)} = \frac{M^{US}_{i,t_1} - M^{US}_{i,t_0}}{L^{US}_{i,1990}} - g^{US}_{i,(t_0,t_1)} \frac{M_{i,t_0}}{L^{US}_{i,1990}}. \tag{16}$$

Given the coverage of the IFR data for US industries, this variable goes back only to $t_0 = 2004$.

C. *Commuting Zone Data and Exposure to Robots*

In our main analysis, we focus on the 722 commuting zones covering the US continental territory (Tolbert and Sizer 1996). Following equations (11) and (14), we measure US exposure to robots in a commuting zone as

$$\text{US exposure to robots}_{c,(t_0,t_1)} = \sum_{i \in \mathcal{I}} \ell^{1990}_{ci} \cdot APR_{i,(t_0,t_1)}, \tag{17}$$

where ℓ^{1990}_{ci} represents industry i's share in the total employment of commuting zone c and APR_i is as defined in (16). Exposure to robots is defined analogously, exploiting variation in industry-level adoption of robots in the *EURO*5 countries,

$$\text{Exposure to robots}_{c,(t_0,t_1)} = \sum_{i \in \mathcal{I}} \ell^{1970}_{ci} \cdot \overline{APR}_{i,(t_0,t_1)}, \tag{18}$$

where $\overline{APR}_{i,(t_0,t_1)}$ is given in (15). We now use the 1970 employment shares, ℓ^{1970}_{ci}, as the baseline to focus on historical, persistent differences in the

Shift-Share Instrument Examples

Study	Unit (i)	Outcome (y_i)	Treatment (x_i)	Level of shift variation (k)	Instrument (z_i)	
					Share (s_{ik})	Shift (g_k)
Bartik (1991)	Region	Δ Local wage	Δ Local employment	Industry	$\text{Employment}_{ik}/\text{Employment}_i$	National growth of industry employment
Miguel and Kremer (2004)	Individual	Measures of health or education	Number of neighbors selected for deworming*	Individual	$\mathbf{1}\{k \text{ is friend of } i\}$	Dummy of deworming treatment
Card (2009)	Region	Relative wage of migrants vs. natives	Relative employment of migrants vs. natives	Origin country	$\text{Migrant stock}_{ik}/\text{Population}_i$	$\text{New migrants}_k/\text{Migrant stock}_k$
Autor, Dorn, and Hanson (2013)	Region	Δ Local manufacturing employment	Δ Local exposure to Chinese imports	Industry	$\text{Employment}_{ik}/\text{Employment}_i$	Δ Imports from China in other countries
Hummels et al. (2014)	Worker	Wage	Imports of intermediate goods by employer	Product-by-country	$\text{Imports}_{ik}/\text{Imports}_i$	Imports from k to other countries
Nunn and Qian (2014)	Country-by-year	Conflict	Quantity of food aid (wheat) from the US	Year	Fraction of years with non-zero food aid	US wheat production in previous year
Cai, Janvry, and Sadoulet (2015)	Individual	Takeup of insurance	% of friends selected for an information session*	Individual	$\mathbf{1}\{k \text{ is friend of } i\}/\#$ of friends i has	Dummy of information session
Jaravel (2019)	Product category	Inflation and innovation	Δ Quantity demanded	Sociodemographic group	Sales of i to group k/Total sales of i	Population change
Greenstone, Mas, and Nguyen (2020)	Region	Δ Employment	Δ Credit	Bank	Credit market share of k	Estimated credit supply shock
Aghion et al. (2022)	Firm	Δ Firm employment	Δ Firm stock of automation technologies	Technology-by-country	$\text{Imports}_{ik}/\text{Imports}_i$	Δ Imports from k to other countries
Xu (2022)	Region	Δ Exports	Exposure to banking crisis*	Bank	Credit market share of k	Bankruptcy during banking crisis
Franklin et al. (2024)	Local labor market	Wage	Shift-share exposure to the intervention*	Residential neighborhood	$\text{Commuters}_{ik}/\text{Employment}_i$	Dummy of public works intervention
Mohnen (2025)	Region	Δ Young labor market outcome	Retirement rate	Age group (within 45+)	$\text{Population}_{ik}/\text{Population } 45+_i$	National retirement rate at age k

Note: We simplify many of the settings, suppressing the time dimension (except where it is central to the design), controls and fixed effects, interaction terms, log and other transformations of the outcome and treatment, and so forth. Asterisks (*) indicate ordinary least squares regressions, in which the treatment itself is the shift-share with shares s_{ik} and shifts g_k.

SSIV的Stata实例：ADH(2013)

- Stacked first difference (1990-2000, 2000-2007)：结果变量与核心变量为增长率(已差分)，共 722 x 2 = 1,444观测值。数据集来自Github: https://github.com/borusyak/shift-share

- `use location_level.dta, clear`
- `global cov l_shind_manuf_cbp l_sh_popedu_c l_sh_popfborn l_sh_empl_f l_sh_routine33 l_task_outsource`

- `describe y x z t2 $cov reg* wei clus`
- `sum y x z t2 $cov reg* wei clus`

Variable name	Storage type	Display format	Value label	Variable label
y	float	%9.0g		Growth of manufacturing employment
x	double	%9.0g		Growth of US China import exposure
z	double	%9.0g		ADH shift-share instrument
t2	byte	%9.0g		Decade==2000s
l_shind_manuf~p	float	%9.0g		Beginning-of-period mfg employment
l_sh_popedu_c	float	%9.0g		% college-educated
l_sh_popfborn	float	%9.0g		% foreign-born
l_sh_empl_f	float	%9.0g		% employment among women
l_sh_routine33	float	%9.0g		% of routine employment
l_task_outsou~e	float	%9.0g		Avg offshorability index
reg_midatl	byte	%9.0g		Census region indicators
reg_encen	byte	%9.0g		Census region indicators
reg_wncen	byte	%9.0g		Census region indicators
reg_satl	byte	%9.0g		Census region indicators
reg_escen	byte	%9.0g		Census region indicators
reg_wscen	byte	%9.0g		Census region indicators
reg_mount	byte	%9.0g		Census region indicators
reg_pacif	byte	%9.0g		Census region indicators
wei	float	%9.0g		Beginning-of-period total employment weight
clus	byte	%10.0g		State identified for location clustering

Variable	Obs	Mean	Std. dev.	Min	Max
y	1,444	-1.623098	2.506206	-19.16707	6.350542
x	1,444	1.905606	2.583024	-.6289579	43.0846
z	1,444	1.75464	2.084503	-.7233337	28.65516
t2	1,444	.5	.5001732	0	1
l_shind_ma~p	1,444	.2057526	.1208567	.0010827	.6181967
l_sh_poped~c	1,444	45.25593	9.090543	19.94398	70.55532
l_sh_popfb~n	1,444	4.963635	5.860676	.3845269	48.90823
l_sh_empl_f	1,444	62.73593	7.055914	33.24326	79.60631
l_sh_rout~33	1,444	28.56663	3.137474	19.99184	37.74758
l_task_out~e	1,444	-.5118329	.4269132	-1.635918	1.239722
reg_midatl	1,444	.0360111	.1863822	0	1
reg_encen	1,444	.1163435	.3207475	0	1
reg_wncen	1,444	.232687	.4226908	0	1
reg_satl	1,444	.1495845	.3567872	0	1
reg_escen	1,444	.101108	.3015762	0	1
reg_wscen	1,444	.1509695	.3581432	0	1
reg_mount	1,444	.1301939	.3366332	0	1
reg_pacif	1,444	.0609418	.2393065	0	1
wei	1,444	.001385	.0038045	4.32e-06	.0588728
clus	1,444	30.85873	14.98161	1	56

加权2SLS

- `ivreg2 y (x=z) t2 $cov reg* [aw=wei], cluster(clus)`
- 权重(wei)：各地的期初就业人口占全国就业人口的权重。
- 如果是解决异方差的WLS，则[aw=1/Var]

(sum of wgt is 2.0000e+00)

IV (2SLS) estimation

Estimates efficient for homoskedasticity only
Statistics robust to heteroskedasticity and clustering on clus

Number of clusters (clus) =	48	Number of obs =	1444
		F(16, 47) =	42.53
		Prob > F =	0.0000
Total (centered) SS =	4396.587068	Centered R2 =	0.3429
Total (uncentered) SS =	12720.4953	Uncentered R2 =	0.7729
Residual SS =	2889.068933	Root MSE =	1.414

y	Coefficient	Robust std. err.	z	P>|z|	[95% conf.	interval]
x	-.5963601	.0987739	-6.04	0.000	-.7899533	-.4027668
t2	-.2424246	.4005703	-0.61	0.545	-1.027528	.5426788
l_shind_manuf_cbp	-4.021932	1.314192	-3.06	0.002	-6.597701	-1.446163
l_sh_popedu_c	.01314	.0121955	1.08	0.281	-.0107627	.0370428
l_sh_popfborn	.0303784	.0108416	2.80	0.005	.0091292	.0516275
l_sh_empl_f	-.0058603	.0244685	-0.24	0.811	-.0538176	.042097
l_sh_routine33	-.2448902	.0637471	-3.84	0.000	-.3698322	-.1199483
l_task_outsource	-.0590306	.2369742	-0.25	0.803	-.5234916	.4054303
reg_midatl	.3129508	.281184	1.11	0.266	-.2381598	.8640614
reg_encen	1.260668	.3370428	3.74	0.000	.6000762	1.92126
reg_wncen	1.623558	.372155	4.36	0.000	.8941478	2.352969
reg_satl	-.2882165	.2336566	-1.23	0.217	-.7461751	.1697421
reg_escen	1.076234	.3346871	3.22	0.001	.4202592	1.732208
reg_wscen	.7316363	.23137	3.16	0.002	.2781593	1.185113
reg_mount	.4021016	.2573061	1.56	0.118	-.102209	.9064122
reg_pacif	.026829	.1911116	0.14	0.888	-.3477427	.4014008
_cons	6.278516	1.937265	3.24	0.001	2.481547	10.07548

```
Underidentification test (Kleibergen-Paap rk LM statistic):          16.880
                                                  Chi-sq(1) P-val =    0.0000
------------------------------------------------------------------------------
Weak identification test (Cragg-Donald Wald F statistic):           533.322
                         (Kleibergen-Paap rk Wald F statistic):      47.643
Stock-Yogo weak ID test critical values: 10% maximal IV size          16.38
                                         15% maximal IV size           8.96
                                         20% maximal IV size           6.66
                                         25% maximal IV size           5.53
Source: Stock-Yogo (2005).  Reproduced by permission.
NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.
------------------------------------------------------------------------------
Hansen J statistic (overidentification test of all instruments):      0.000
                                                 (equation exactly identified)
------------------------------------------------------------------------------
Instrumented:         x
Included instruments: t2 l_shind_manuf_cbp l_sh_popedu_c l_sh_popfborn
                      l_sh_empl_f l_sh_routine33 l_task_outsource reg_midatl
                      reg_encen reg_wncen reg_satl reg_escen reg_wscen reg_mount
                      reg_pacif
Excluded instruments: z
------------------------------------------------------------------------------
```

对于SSIV计量理论的研究

- <u>Exogenous shares</u>:

  Goldsmith-Pinkham et al. (2020, AER)

- <u>Exogenous shocks</u>:

  Adao et al. (2019, QJE)

  Borusyak et al. (2022, REStu)

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Bartik Instruments: What, When, Why, and How[†]

By Paul Goldsmith-Pinkham, Isaac Sorkin, and Henry Swift[*]

The Bartik instrument is formed by interacting local industry shares and national industry growth rates. We show that the typical use of a Bartik instrument assumes a pooled exposure research design, where the shares measure differential exposure to common shocks, and identification is based on exogeneity of the shares. Next, we show how the Bartik instrument weights each of the exposure designs. Finally, we discuss how to assess the plausibility of the research design. We illustrate our results through two applications: estimating the elasticity of labor supply, and estimating the elasticity of substitution between immigrants and natives. (*JEL* C51, F14, J15, J22, L60, R23, R32)

Goldsmith-Pinkham et al. (2020)

- 隐含假定行业冲击 g_j 为外生或给定。如果份额 s_{ij} 为外生，则 $\{s_{i1},\cdots,s_{in}\}$ 均可视工具变量，而实际使用的IV为其线性组合：

$$z_i \equiv \sum_{j=1}^{n} s_{ij} g_j$$

- Goldsmith-Pinkham et al. (2020)证明，Bartik IV估计等价于以 $\{s_{i1},\cdots,s_{in}\}$ 为IV，进行GMM估计，且以行业冲击向量的外积为权重矩阵，即

$$\mathbf{gg}' \equiv \begin{pmatrix} g_1 \\ \vdots \\ g_n \end{pmatrix} (g_1 \cdots g_n) = \begin{pmatrix} g_1^2 & \cdots & g_1 g_n \\ \vdots & \ddots & \vdots \\ g_1 g_n & \cdots & g_n^2 \end{pmatrix}$$

A. *Identifying Assumptions*

Two assumptions must hold for consistency. First, the denominator must converge to a nonzero term. Intuitively, for this assumption to hold, there must be an industry and time period when the industry share has predictive power for x_{lt}, conditional on the controls, and the growth rates g_{kt} cannot weight the covariances in such a way that they exactly cancel. This first condition holds under the following low-level assumption.

ASSUMPTION 1 (Relevance): *For all* $k \in \{1, \ldots, K\}$ *and* $s \in \{1, \ldots, T\}$,

$$x_{lt} = D_{lt}\tau + z_{lk0}\mathbf{1}(t = s)C_{k,s} + \eta_{lt},$$

where $E[\eta_{lt}|z_{lk0}, D_{lt}] = 0$, $C_{k,s}$ *is finite for all k and s, and* $\sum_s \sum_k g_{ks} C_{ks} \neq 0$.

The second necessary assumption for consistency is that the numerator must converge to zero. This assumption is the exclusion restriction, and to hold generically, the industry share must be uncorrelated with the structural error term, *after controlling for* D_{lt}, for industries that have nonzero growth rates. The following identifying assumption ensures that the numerator converges to 0.

ASSUMPTION 2 (Strict Exogeneity): $E[\epsilon_{lt} z_{lk0}|D_{lt}] = 0$ *for all k where* $g_k \neq 0$.

This assumption is standard in empirical settings that use exposure designs. For example, this assumption is made in difference-in-differences designs that use location fixed effects.[6]

Rotemberg Weights

A. *Decomposing the Bartik Estimator*

We first present a finite sample decomposition of the linear overidentified GMM estimator due to Rotemberg (1983).[7] For expositional simplicity, we use a single cross section, though it is straightforward to extend results to a panel with T time periods.

PROPOSITION 3: *We can write*

$$\hat{\beta}_{Bartik} = \sum_k \hat{\alpha}_k \hat{\beta}_k,$$

where

$$\hat{\beta}_k = \left(Z_k' X^{\perp}\right)^{-1} Z_k' Y^{\perp} \quad \text{and} \quad \hat{\alpha}_k = \frac{g_k Z_k' X^{\perp}}{\sum_{k'} g_{k'} Z_{k'}' X^{\perp}},$$

so that $\sum_k \hat{\alpha}_k = 1$.

Rotemberg Weights (续)

Proposition 3 has two implications. First, mirroring our results from Section II, the validity of each just-identified $\hat{\beta}_k$ depends on the exogeneity of a given Z_k. Second, for some k, $\hat{\alpha}_k$ can be negative. Under the constant effects assumption we have maintained so far, these negative weights do not pose a conceptual problem. In Section IV, we introduce a restricted form of treatment effect heterogeneity and revisit the implications of the negative Rotemberg weights.

In online Appendix Section E, we discuss how to interpret the Rotemberg weights in terms of sensitivity-to-misspecification following work by Conley, Hansen, and Rossi (2012) and Andrews, Gentzkow, and Shapiro (2017). The basic intuition is that if any particular instrument is misspecified, then α_k tells us how much that misspecification translates into the overall bias of the estimator. For example, if α_k is small, then bias in the kth instrument does not affect the overall bias in the estimator very much. We also show that this measure is different than simply dropping instruments and seeing how estimates change, since dropping an instrument combines sensitivity-to-misspecification (i.e., α_k) as well as the relative misspecification of different instruments (i.e., how far $\hat{\beta}_k$ diverges from $\hat{\beta}$).

SHIFT-SHARE DESIGNS: THEORY AND INFERENCE*

RODRIGO ADÃO
MICHAL KOLESÁR
EDUARDO MORALES

We study inference in shift-share regression designs, such as when a regional outcome is regressed on a weighted average of sectoral shocks, using regional sector shares as weights. We conduct a placebo exercise in which we estimate the effect of a shift-share regressor constructed with randomly generated sectoral shocks on actual labor market outcomes across U.S. commuting zones. Tests based on commonly used standard errors with 5% nominal significance level reject the null of no effect in up to 55% of the placebo samples. We use a stylized economic model to show that this overrejection problem arises because regression residuals are correlated across regions with similar sectoral shares, independent of their geographic location. We derive novel inference methods that are valid under arbitrary cross-regional correlation in the regression residuals. We show using popular applications of shift-share designs that our methods may lead to substantially wider confidence intervals in practice. *JEL* Codes: C12, C21, C26, F16, F22.

Adao et al. (2019)

- 如果存在截面相关，则OLS标准误(异方差稳健或聚类稳健标准误)存在偏差。

- 若截面相关为正，则OLS标准误低估，导致过度拒绝(overrejection)原假设 $H_0: \beta = 0$

- 截面相关可能源于相邻地区的溢出效应，但也可能因为扰动项 ε_i 包含移动份额结构，导致产业结构类似地区的扰动项之间存在正自相关

Adao et al. (2019，续)

- 在一定正则条件下，并假定扰动项的移动份额结构与核心变量相同 (均为 s_{ij})，提出校正的标准误
- 移动份额回归的Stata命令：
`ssc install reg_ss,all replace`
(核心变量有移动份额结构，但无内生性)
- 移动份额IV回归的Stata命令：
`ssc install ivreg_ss,all replace`
(工具变量有移动份额结构)

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Quasi-Experimental Shift-Share Research Designs

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Many studies use shift-share (or "Bartik") instruments, which average a set of shocks with exposure share weights. We provide a new econometric framework for shift-share instrumental variable (SSIV) regressions in which identification follows from the quasi-random assignment of shocks, while exposure shares are allowed to be endogenous. The framework is motivated by an equivalence result: the orthogonality between a shift-share instrument and an unobserved residual can be represented as the orthogonality between the underlying shocks and a shock-level unobservable. SSIV regression coefficients can similarly be obtained from an equivalent shock-level regression, motivating shock-level conditions for their consistency. We discuss and illustrate several practical insights of this framework in the setting of Autor *et al.* (2013), estimating the effect of Chinese import competition on manufacturing employment across U.S. commuting zones.

Borusyak et al. (2022, REStu)

- 假设移动份额s_{ij}内生，而行业冲击g_j外生

- Borusyak et al. (2022, REStu)证明，若$m \to \infty$(很多地区)，$n \to \infty$(很多行业)，每个行业的平均份额均很小(见下)，且行业冲击g_j互不相关(many uncorrelated shocks)，则SSIV为一致估计

- 记$s_j \equiv \frac{1}{m}\sum_{i=1}^{m} s_{ij}$(移动份额矩阵每列的平均)，假定

$$\mathrm{E}\left(\sum_{j=1}^{n} s_j^2\right) \to 0$$

Borusyak et al. (2022, REStu)

- 假设移动份额s_{ij}内生，而行业冲击g_j外生

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$$\mathrm{E}\left(\sum_{j=1}^{n} s_j^2\right) \to 0$$

移动份额的矩阵

$$\begin{pmatrix} S_{11} & \cdots & S_{1n} \\ \vdots & \ddots & \vdots \\ S_{m1} & \cdots & S_{mn} \end{pmatrix}_{m \times n}$$

地区层面的全样本矩条件

- Full-data moment condition: $\mathrm{E}\left(\sum_{i=1}^{m} w_i z_i \varepsilon_i\right) = 0$

- 其中，w_i 为回归权重(比如，期初地区 i 的就业人数占全国就业人数的比重)，满足 $\sum_{i=1}^{n} w_i = 1$

- 对比通常的总体矩条件：$\mathrm{E}(z_i \varepsilon_i) = 0$ (适用于iid数据)

- 全样本矩条件适用于非iid数据。例如，不同地区的 z_i 存在相关性(受到共同行业冲击 g_k 的影响)

冲击层面的正交条件

- 定义 $s_j = \sum_{i=1}^{m} w_i s_{ij}$ (weighted share of industry j)。若权重都相同，则为average share of industry j

- 地区层面的正交条件可等价地写为冲击层面的正交条件

$$\mathrm{E}\left(\sum_{i=1}^{m} w_i z_i \varepsilon_i\right) = \mathrm{E}\left[\sum_{i=1}^{m} w_i \left(\sum_{j=1}^{n} s_{ij} g_j\right)\varepsilon_i\right] = \mathrm{E}\left[\sum_{j=1}^{n} s_j g_j \frac{\sum_{i=1}^{m} w_i s_{ij} \varepsilon_i}{s_j}\right] \equiv \mathrm{E}\left(\sum_{j=1}^{n} s_j g_j \bar{\varepsilon}_j\right) = 0$$

- $\bar{\varepsilon}_j$ 为exposure-weighted average of residuals ε_i

$$\bar{\varepsilon}_j \equiv \frac{\sum_{i=1}^{m} w_i s_{ij} \varepsilon_i}{\sum_{i=1}^{m} w_i s_{ij}}$$

冲击层面的工具变量回归

- 冲击层面的正交条件意味着，也可以进行冲击层面的工具变量回归。
- Borusyak et al. (2022)证明，以 w_i 为权重进行的地区层面的IV回归，等价于以 s_j 为权重进行的冲击层面的IV回归
- 二者所得 $\hat{\beta}$ 在数值上完全相等
- 冲击层面回归的优势：不受地区层面截面相关的影响，可直接使用异方差或聚类稳健的标准误

地区层面的IV回归

$$y_i = \beta x_i + \boldsymbol{\gamma}'\mathbf{q}_i + \varepsilon_i \quad (i = 1, \cdots, m)$$

- 根据偏回归(Frisch-Waugh-Lovell定理)：
  先将 y_i 对 $\mathbf{q}_i$ 进行加权OLS回归，记残差为 $y_i^{\perp}$；类似地，将 x_i 对 $\mathbf{q}_i$ 进行加权OLS回归，记残差为 $x_i^{\perp}$
- 地区层面的加权IV估计量：

$$\hat{\beta} = \frac{\sum_{i=1}^{m} w_i z_i y_i^{\perp}}{\sum_{i=1}^{m} w_i z_i x_i^{\perp}}$$

- 由于 $\sum_{i=1}^{m} w_i y_i^{\perp} = \sum_{i=1}^{m} w_i x_i^{\perp} = 0$，故上式的分子分母均为样本协方差

冲击层面的IV回归

- 记exposure-weighted average $\overline{y}_j^{\perp} \equiv \dfrac{\sum_{i=1}^{m} w_i s_{ij} y_i^{\perp}}{\sum_{i=1}^{m} w_i s_{ij}}$，$\overline{x}_j^{\perp} \equiv \dfrac{\sum_{i=1}^{m} w_i s_{ij} x_i^{\perp}}{\sum_{i=1}^{m} w_i s_{ij}}$，则冲击层面的IV回归，以 s_j 为权重，以 g_j 为IV，对以下方程进行IV估计：

$$\overline{y}_j^{\perp} = \alpha + \beta \overline{x}_j^{\perp} + \overline{\varepsilon}_j^{\perp} \quad (j = 1, \cdots, n)$$

- 可以证明，此冲击层面的IV估计量在数值上等于地区层面的IV估计量 $\hat{\beta}$

冲击层面与地区层面IV回归的等价性

$$\hat{\beta}_{地区} \equiv \frac{\sum_{i=1}^{n} w_i z_i y_i^{\perp}}{\sum_{i=1}^{m} w_i z_i x_i^{\perp}} = \frac{\sum_{i=1}^{m} w_i \left(\sum_{j=1}^{n} s_{ij} g_j\right) y_i^{\perp}}{\sum_{i=1}^{m} w_i \left(\sum_{j=1}^{n} s_{ij} g_j\right) x_i^{\perp}} = \frac{\sum_{j=1}^{n} s_j g_j \left(\frac{\sum_{i=1}^{m} w_i s_{ij} y_i^{\perp}}{\sum_{i=1}^{m} w_i s_{ij}}\right)}{\sum_{j=1}^{n} s_j g_j \left(\frac{\sum_{i=1}^{m} w_i s_{ij} x_i^{\perp}}{\sum_{i=1}^{m} w_i s_{ij}}\right)}$$

$$= \frac{\sum_{j=1}^{n} s_j g_j \bar{y}_j^{\perp}}{\sum_{j=1}^{n} g_j \bar{x}_j^{\perp}} \equiv \hat{\beta}_{冲击}$$

- 由于 $\sum_{j=1}^{n} s_j \bar{y}_j^{\perp} = \sum_{j=1}^{n} s_j \frac{\sum_{i=1}^{m} w_i s_{ij} y_i^{\perp}}{s_j} = \sum_{i=1}^{m} w_i \left(\sum_{j=1}^{n} s_{ij}\right) y_i^{\perp}$ $= \sum_{i=1}^{m} w_i y_i^{\perp} = 0$；类似地，$\sum_{j=1}^{n} s_j \bar{x}_j^{\perp} = 0$，故上式分子分母均为样本协方差

全样本矩条件从何而来

- **Assumption 1** (Quasi-random shock assignment)

$$\mathrm{E}(g_j \mid \bar{\varepsilon}_1, \cdots, \bar{\varepsilon}_n, s_1, \cdots, s_n) = \mu \ \text{(某常数)}, \ j = 1, \cdots, n$$

$$\mathrm{E}\left(\sum_{i=1}^{m} w_i z_i \varepsilon_i\right) = \mathrm{E}\left(\sum_{j=1}^{n} s_j g_j \bar{\varepsilon}_j\right) = \mathrm{E}\sum_{j=1}^{n}\left[\mathrm{E}\left(s_j g_j \bar{\varepsilon}_j \middle| \bar{\varepsilon}_1, \cdots, \bar{\varepsilon}_n, s_1, \cdots, s_n\right)\right]$$

$$= \mu\, \mathrm{E}\left(\sum_{j=1}^{n} s_j \bar{\varepsilon}_j\right) = \mu\, \mathrm{E}\left(\sum_{j=1}^{n} s_j \frac{\sum_{i=1}^{m} w_i s_{ij} \varepsilon_i}{s_j}\right)$$

$$= \mu\, \mathrm{E}\left[\left(\sum_{j=1}^{n} s_{ij}\right)\left(\sum_{i=1}^{m} w_i \varepsilon_i\right)\right] = \mu \sum_{i=1}^{m} w_i\, \mathrm{E}(\varepsilon_i) = 0$$

全样本矩条件从何而来

- **Assumption 2** (Many uncorrelated shocks)

当$n \to \infty$时，$\mathrm{E}\left(\sum_{j=1}^{n} s_j^2\right) \to 0$，且对任意 $j \neq k$

$$\mathrm{Cov}(g_j, g_k \mid \bar{\varepsilon}_1, \cdots, \bar{\varepsilon}_n, s_1, \cdots, s_n) = 0$$

在此条件下，可使用大数定律来证明一致性

冲击层面回归的Stata操作

- 可使用命令ssaggregate完成偏回归，以及从地区层面向冲击层面的变换。数据集来自Github: https://github.com/borusyak/shift-share

- ssc install ssaggregate, replace
- 除了location_level.dta，还将用到3个其他数据集，即Lshares.dta(包含s_{ij}的数据ind_share)，shocks.dta (包含g_j的数据)，以及industries.dta (包含行业分类的数据，例如2位数行业sic2，3位数行业sic3)

变换为冲击层面的数据

- `ssaggregate y x z [aw=wei], n(sic87dd) t(year) sfilename(Lshares) s(ind_share) l(czone) addmissing controls("t2 $cov reg*")`

- 其中，“n(sic87dd)”指定industry identifier，“t(year)”指定时间变量，“sfilename(Lshares)”指定存放份额数据的文件，“s(ind_share)”指定该文件中的变量ind_share为份额变量，“l(czone)”指定location identifier，“addmissing”加上缺失行业(保证份额之和为1)，“controls(”t2 $cov reg*“)”指定控制变量(用于偏回归)

变换为冲击层面的数据(续)

- sum

Variable	Obs	Mean	Std. dev.	Min	Max
year	796	1995	5.003144	1990	2000
sic87dd	794	3061.607	602.3969	2011	3999
s_n	796	.0012563	.0189729	6.39e-06	.3975597
y	796	-.0527453	.4856481	-2.953726	2.636212
x	796	.0536078	.4053164	-1.649984	2.570242
z	796	.0797391	.417438	-1.401897	3.032757

- 其中，变量s_n就是s_j(冲击回归的权重)。变量4位数行业编号sic87dd有两个缺失值(因为使用了addmissing选项)。下面将其缺失值赋值为0：

- replace sic87dd = 0 if missing(sic87dd)

(2 real changes made)

导入行业冲击的数据

- `merge 1:1 sic87dd year using shocks, assert(1 3) nogen`

- 其中，“assert(1 3)”表示保留主数据集(master)中的数据，以及匹配成功的数据；“nogen”表示不生成记录匹配结果的变量_merge(默认生成此变量)

```
Result                      Number of obs
-----------------------------------------
Not matched                             2
    from master                         2
    from using                          0

Matched                               794
-----------------------------------------
```

导入行业分类的数据

- merge m:1 sic87dd using industries, assert(1 3) nogen

```
Result                          Number of obs
---------------------------------------------
Not matched                                 2
    from master                             2
    from using                              0

Matched                                   794
---------------------------------------------
```

将缺失观测值赋值为0

- `foreach v of varlist g year sic3 {`
  `replace `v'= 0 if sic87dd == 0`
- `}`

```
(2 real changes made)
(2 real changes made)
(2 real changes made)
```

- 对于sic87dd取值为0(原本为缺失值)的观测值，将其变量g, year与sic3也赋值为0 (其中，g与sic3本为缺失值)

冲击层面的SSIV回归

- `ivreg2 y (x=g) [aw=s_n], cluster(sic3)`

- 其中，g为工具变量(即 g_j)，回归权重为s_n (即 s_j)，“cluster(sic3)”表示以sic3(3位数行业分类)为聚类变量的聚类稳健标准误

- `list sic87dd sic3 sic2 in 1/3`

	sic87dd	sic3	sic2
1.	2011	201	20
2.	2011	201	20
3.	2015	201	20

```
IV (2SLS) estimation
--------------------

Estimates efficient for homoskedasticity only
Statistics robust to heteroskedasticity and clustering on sic3

Number of clusters (sic3) =        137                Number of obs =        796
                                                      F(  1,   136) =      27.12
                                                      Prob > F      =     0.0000
Total (centered) SS     =  44.66656614                Centered R2   =     0.2111
Total (uncentered) SS   =  44.66656614                Uncentered R2 =     0.2111
Residual SS             =  35.23809809                Root MSE      =      .2104

------------------------------------------------------------------------------
             |               Robust
           y | Coefficient  std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
           x |  -.5963601   .1140326    -5.23   0.000    -.8198598   -.3728603
       _cons |   2.31e-10   .0106666     0.00   1.000    -.0209061    .0209061
------------------------------------------------------------------------------
Underidentification test (Kleibergen-Paap rk LM statistic):              8.285
                                                   Chi-sq(1) P-val =    0.0040
------------------------------------------------------------------------------
Weak identification test (Cragg-Donald Wald F statistic):              122.362
                         (Kleibergen-Paap rk Wald F statistic):         39.649
Stock-Yogo weak ID test critical values: 10% maximal IV size             16.38
                                         15% maximal IV size              8.96
                                         20% maximal IV size              6.66
                                         25% maximal IV size              5.53
Source: Stock-Yogo (2005).  Reproduced by permission.
NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.
------------------------------------------------------------------------------
Hansen J statistic (overidentification test of all instruments):         0.000
                                                 (equation exactly identified)
------------------------------------------------------------------------------
```

Bartik工具变量法在因果识别中的应用与检验

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摘要:Bartik工具变量法在因果识别和政策评估等社会科学研究中的应用日益广泛,受到了越来越多的关注。然而,在大部分国内经济学经验研究中,该方法存在应用不规范甚至是误用的问题。本文结合理论计量的基本原理和前沿成果,尝试在一个统一的标准分析框架下,对Bartik工具变量法在因果识别中的应用进行系统性的归纳总结,以厘清其在实践应用中需要注意的一些问题。本文首先梳理了Bartik工具变量法的发展脉络,明确了Bartik工具变量的经典设定及其推广延伸。其次,阐述了Bartik工具变量法在因果识别中的基本策略,归纳分析了Bartik工具变量在实际构建过程中的一些常见问题,包括如何计算观测样本的份额权重、如何设定政策冲击的维度等。再次,详细分析了Bartik工具变量法在因果识别中的应用条件,并结合具体例子作出了解释说明。最后,在此基础上提出了一个详细的操作清单,并以贸易政策的影响研究为例,全面展示了该方法的应用实践。

关键词:Bartik工具变量 份额权重 政策冲击 应用条件

Thanks ☺