Simple and Trustworthy Cluster-Robust GMM Inference

Jungbin Hwang

1 Introduction

2 Basic Setting and the First-step GMM Estimator

We want to estimate the ***d*** 1

The F-test version of the Wald test statistic is given by

$$\boldsymbol{F}(\hat{}_1) := (\boldsymbol{R}\hat{}_1 \quad \boldsymbol{r}$$

distributions, respectively. As $\boldsymbol{G}$=($\boldsymbol{G}$ $\boldsymbol{p}$) > 1 *and* $F^{1}_{p;G\ p}$ >

estimators $\hat{}(\hat{}_1)$ and $\hat{}^{c}(\hat{}_1)$ where

$$\hat{}(\ ) = \frac{1}{G} \sum_{g=1}^{G}$$

identi...cation restrictions is

J(^

and so

$$\mathcal{J}(\hat{\lambda}_2) := \frac{G-q}{q}\frac{q\mathcal{J}(\hat{\lambda}_2)}{G-q\mathcal{J}(\hat{\lambda}_2)} \xrightarrow{d} F_{q;G-q}.$$

because we have

$$\boldsymbol{G}\begin{pmatrix}\boldsymbol{B}_p\\ \boldsymbol{B}_q\end{pmatrix}^{\prime}\begin{pmatrix}\mathrm{E}_{\boldsymbol{pp}} & \mathrm{E}_{\boldsymbol{pq}}\\ \mathrm{E}_{\boldsymbol{pq}}^{\prime} & \mathrm{E}_{\boldsymbol{qq}}\end{pmatrix}^{1}\begin{pmatrix}\boldsymbol{B}_p\\ \boldsymbol{B}_q\end{pmatrix} \; 2$$

$$= \boldsymbol{G} \; 4 \begin{pmatrix}\boldsymbol{B}_p\\ \boldsymbol{B}_q\end{pmatrix}^{\prime}$$

1, it is possible to show

p —

Using

Similarly, the limiting distribution T

5 Asymptotic F and t tests

and that $_{\boldsymbol{p}}$ is independent of $\boldsymbol{S}_{\boldsymbol{pp}}^{1}$

t-statistic:

$$\boldsymbol{t}^{\text{adj}}_{\hat{}c(\hat{}_1)}($$

We can obtain the same expression for the CU-GMM estimator $\sqrt{N}(\hat{\beta}_{CU\text{-}GMM} - \beta_0)$.

In view of the representation in (32), the corrected variance estimator for the CU type estimators can be constructed as follows:

$\widehat{var}^{adj}$

dependence in each cluster. When = 0, there is no clustered dependence and our model reduces to that of Windmeijer (2005) which considers a static panel data model with only one regressor.

The individual fixed effects and shocks in group g are generated by:

$$
\begin{aligned}
{}_{(g)} &\quad \text{i.i.d.} N(0; \ ), \ \text{vec}(e_{(g);t}) \quad \text{i.i.d.} N(0; \ _e), \\
u_{(g);t} &= \ _t \ _u^{1=2}(\ _1^g ! _{1t}^g; ; :::; \ _L^g ! _{Lt}^g)^0, \\
{}_i^g &\quad \text{i.i.d.} U[0:5; 1:5], \text{ and } !_{it}^g \quad i:i:d: \ _1^2 \quad 1
\end{aligned}
\qquad (33)
$$

for $i = 1; :::; L_N$ and $t = 1; :::; T$ where $_t = 0:5 + 0:1(t \quad 1)$. The DGP of individual shock $u_{(g);t}$

uses the "plain" F-statistic $\boldsymbol{F}_2 := \boldsymbol{F}_{\hat{}c(\hat{}}$

Figure 1: Emprical size of the …rst-step and two-step tests when $\boldsymbol{G}$ = 50

the empirical size of the …rst-step chi-square test (using (us(s)8311(611(s)8(i)69s)8(ttu)129(f)-110(t)8(hI8 ones in other scenarios, i.e., when the cost of employing CCE weighting matrix outweighs the bene…t

close to each other.

The uncentered two-step GMM estimate of the effect of access to domestic market is $_d$ = 2722.22. The reported standard error 400.5 is about 40% smaller than that of 2SLS. However, the plain two-step standard error estimate might be downward biased because the variation of the

References

[15] Dube, A., Lester, T. W., and Reich, M. (2010). “Minimum wage e¤ects across state borders:

Table 3: Empirical size of …rst-step and two-step tests based on the centered CCE when $L_N = 50$, number of clusters $G = 50$

Figure 4: Size-adjusted power of …rst-step (2SLS) and two-step tests with $\boldsymbol{G} = 50$ and $\boldsymbol{L} = 50$:

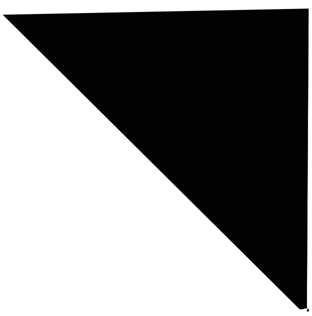

Figure 5: Size-adjusted power of …rst-step (2SLS) and two-step tests with $\boldsymbol{G} = 100$ and $\boldsymbol{L} = 50$:

Figure 6: Empirical size of first-step and two-step tests based on the centered CCE when there is a heterogeneity in cluster size with the nominal size 5% (green line): Design I with $G = 50; q = 8;$ and $p = 3:$

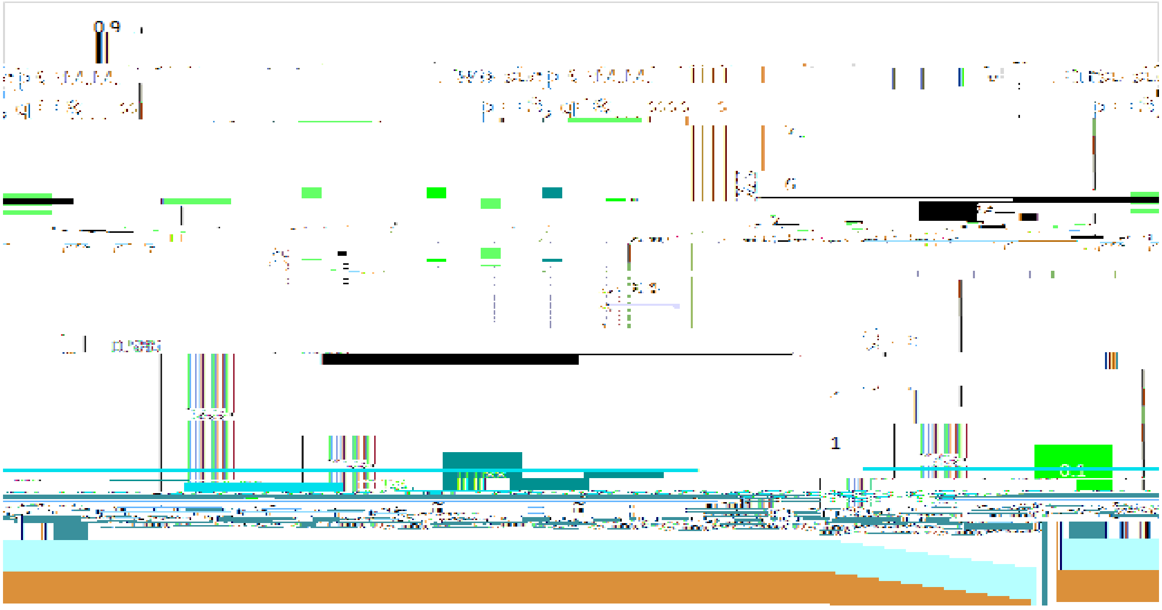

Table 9: Summary of the difference between the conventional large-***G*** asympototics and alternative fixed-***G*** asympotics for the first-step (2SLS) and two-step GMM methods.

2SLS

Table 11: Results for Emran and Hou (2013) data

	2SLS	
Variables	Large-G Asymptotics	Fixed-G Asymptotics
Domestic market (A_i^d)	2713:2 (712:1)	2713:2 (716:8)
	[4109:9; 1316:4]	[4138:0; 1288:0]
International market (		

10 Appendix: Application to Linear Dynamic Panel Model

We discusses how to implement our inference procedures in the context of a linear dynamic panel model:

$$y_{it} = \quad y_{it \quad 1} + x$$

where

$$\widehat{var}(\hat{}_1) = N \quad w'ZW_n^{1}Z' \quad w \quad ^{1} \quad w'ZW_n^{1}\hat{}(\hat{}_1)W_n^{1}Z' \quad w \quad w'ZW_n^{1}Z' \quad w \quad ^{1}:$$

Let Z

and

$$\left.\frac{\partial \hat{\ }^{c}(\ )}{\partial\ _{j}}\right|_{=\hat{\ }_1} = {}_{j}(\hat{\ }_1) + {}'_{j}(\hat{\ }_1),$$

$${}_{j}(\hat{\ }_1$$

Appendix of Proofs

Proof of Proposition 1. Part (a).

Therefore,

$$\boldsymbol{N}\boldsymbol{R}\boldsymbol{var}(\hat{\ }_{1})\boldsymbol{R}^{0}$$

$$=$$

Let $\boldsymbol{U}$ $\boldsymbol{V}^0$

For the estimator ^

with D_{12} and D_{22} given in (42). Therefore*;*

$$\boldsymbol{J}(\hat{}_2) = \boldsymbol{N}\boldsymbol{g}_{\boldsymbol{n}}(\hat{}_2)^{0}$$

of eigenvectors of $(\boldsymbol{RVA}^{-1})'(\boldsymbol{RVA}^{-1})$: Let

$$\mathcal{V} = \begin{pmatrix} \tilde{\boldsymbol{V}}_{d \times d} & \boldsymbol{O} \\ \boldsymbol{O} & \boldsymbol{I}_{q \times q} \end{pmatrix}$$

and define

$$\mathcal{D} = \begin{pmatrix} \mathcal{D}_{11} & \mathcal{D}_{12} \\ \mathcal{D}_{21} & \mathcal{D}_{22} \end{pmatrix} = \begin{pmatrix} \tilde{\boldsymbol{V}}_{d \times d} & \boldsymbol{O} \\ \boldsymbol{O} & \boldsymbol{I}_q \end{pmatrix}' \begin{pmatrix} \mathcal{D}_{11} & \mathcal{D}_{12} \\ \mathcal{D}_{21} & \mathcal{D}_{22} \end{pmatrix} \begin{pmatrix} \tilde{\boldsymbol{V}}_{d \times d} & \boldsymbol{O} \\ \boldsymbol{O} & \boldsymbol{I}_q \end{pmatrix} = \mathcal{V}'\mathcal{D}_1\mathcal{V}.$$

Then

for

$$\boldsymbol{w} = \begin{pmatrix} \tilde{\boldsymbol{w}}^{p} \\ \boldsymbol{I}_q \end{pmatrix} \in \mathbb{R}^{(p+q)\times q}.$$

where the convergence holds jointly for $h = 1, \ldots, G$. As a result,

$$\hat{}^{c}(\hat{}) \xrightarrow{d} \frac{1}{G} \sum_{g}^{G}$$

in (51) as

$$\boldsymbol{Ng}$$

For the CU-GMM estimator, we let $\hat{\ }^{j}(\hat{\ }_{\text{CU-GMM}})$ be the $\boldsymbol{j}$

and so

for each $j = 1; ::::; d:$ For the term, $\frac{@\hat{}c(\ )}{}$

Also, $E_{2n} = o_p(1)$ and we have

$$var\; ;\mathrm{i}$$