

Two-sample Instrumental Variable Regressions with Potentially Weak Instruments

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Abstract. We develop a Stata package for two-sample instrumental variables regression models with one endogenous regressor and potentially weak instruments. The package includes the classic two-sample 2SLS estimator whose inference is only valid under the assumption of strong instruments, as well as statistical tests and confidence sets with the correct size and coverage probabilities even when the instruments are weak.

Keywords: st0001, two-sample 2SLS, weak IV, inference

1 Introduction

Conventional instrumental variables (IV) regression requires that the dependent variable, the endogenous regressor, and the instruments come from the same dataset; but in many cases, researchers can only observe the dependent variable and the endogenous regressor in two separate data samples (see Björklund and Jäntti 1997; Miguel 2005; Feldman 2010; Brunner et al. 2012; Siminski 2013; Olivetti and Paserman 2015, among many others). In such situations, a two-sample two-stage least squares (TS2SLS) estimation strategy is frequently adopted. The estimator was proposed by Angrist and Krueger (1992, 1995). Inoue and Solon (2010) developed valid inference under the assumption of strong first stage correlation between the endogenous variable and the instruments. When the first stage is weak, however, the TS2SLS estimation and inference strategy are not valid. Firstly, the estimator is no longer asymptotically normally distributed, invalidating classic Inoue and Solon (2010) inference. Secondly, the TS2SLS estimator may be subject to a large bias under a weak first stage, as the classic attenuation bias of the estimator is inversely proportional to the strength of instruments.

In a recent study, Choi et al. (2018) developed weak-instrument robust tests and confidence sets for the two-sample IV regression model. This article develops a Stata package companion to this newly proposed inference method. Specifically, the new method extends the classic Anderson-Rubin (AR, c.f. Dufour 1997; Staiger and Stock 1997; Dufour and Jasiak 2001), Kleibergen (K, c.f. Kleibergen 2002), and conditional likelihood ratio (CLR, c.f. Moreira 2003; Andrews et al. 2006, 2008; Moreira 2009) tests and confidence sets to the two-sample IV regression model. We also consider cases of homoskedasticity and heteroskedasticity. The proposed package also reports the classic TS2SLS estimator with Inoue and Solon (2010) standard errors for completeness.

2 Model and Theory

Let subscript j , $j = 1, 2$ denote random variables in the first and second dataset with sample size n_j . Assume that $n_1/n_2 \rightarrow \tau$ for some fixed $\tau > 0$. In this article we consider the following two-sample IV regression model with independent and identically distributed data:

$$\begin{aligned} y_1 &= w_1\beta + X_1\gamma + \epsilon_1, \\ w_j &= Z_j\pi + X_j\psi + \epsilon_j, \quad j = 1, 2. \end{aligned} \tag{1}$$

where y_1 , w_1 , ϵ_1 and ϵ_1 are $n_1 \times 1$; w_2 , ϵ_2 are $n_2 \times 1$; Z_j is $n_j \times k$ for $j = 1, 2$; and X_j is $n_j \times p$ for $j = 1, 2$. All variables in the above model are observed except for w_1 , the endogenous regressor in the first dataset. Without loss of generality, assume that $Z_j'X_j = 0$ for $j = 1, 2$. The orthogonality assumption is without loss of generality because one can always define new instruments as residuals from the regression of original

instruments on exogenous regressors. We are interested in the inference problem of the parameter β in the outcome equation.

In the following, we discuss both the benchmark and the robust inference methods discussed in Choi et al. (2018). The benchmark method is developed under the same set of assumptions as in Angrist and Krueger (1992, 1995) and Inoue and Solon (2010), except for allowing for weak instruments. It, therefore, requires both homoskedasticity and equal moment of exogenous regressors in the two-sample IV model. The robust inference method, on the other hand, relaxes these two restrictions. In empirical applications, researchers might want to adopt the robust inference method for its generality and the benchmark method for a direct comparison with the TS2SLS results.

2.1 Benchmark Tests and Confidence Sets

In this section, we assume that the error terms ϵ_1 , ε_1 and ε_2 in model (1) are homoskedastic, and the exogenous covariates X_1 and Z_1 in the first dataset have the same first and second moments as X_2 and Z_2 in the second dataset. We consider the weak IV asymptotic where the first stage parameter π in model (1) satisfies that

$$\pi = C/\sqrt{n_1} \text{ for some non-stochastic } k\text{-vector } C. \quad (2)$$

Let $\hat{\pi}$ and $\hat{\psi}$ be the OLS estimators from first stage regression of w_2 on Z_2 and X_2 , and let $\hat{w}_1 = Z_1\hat{\pi} + X_1\hat{\psi}$ be the predicted endogenous regressor for the first dataset. Let $Y_1 = [y_1 \ \hat{w}_1]$, $a = [\beta \ 1]'$, $\eta = [\gamma \ \psi]$, and $V_1 = [u_1 \ v_1]$, where $\gamma = \gamma_1 + \psi\beta$, $u_1 = \epsilon_1 + \beta\varepsilon_1$, and $v_1 = Z_1(\hat{\pi} - \pi) + X_1(\hat{\psi} - \psi)$. The simultaneous equation model in equation (1) could be rewritten as

$$Y_1 = Z_1\pi a' + X_1\eta + V_1.$$

First, consider the two-sided null hypothesis $H_0 : \beta = \beta_0$ with some pre-determined significance level α . Let $b_0 = [1 \ -\beta_0]'$, $a_0 = [\beta_0 \ 1]'$. For any matrix X , we denote $X(X'X)^{-1}X'$ as P_X and define $M_X = I - P_X$. Define statistics

$$\begin{aligned} \hat{S}_n &= (Z_1'Z_1)^{-1/2}Z_1'Y_1b_0/(b_0'\hat{\Omega}b_0)^{1/2}, \quad \hat{T}_n = (Z_1'Z_1)^{-1/2}Z_1'Y_1\hat{\Omega}^{-1}a_0/(a_0'\hat{\Omega}^{-1}a_0)^{1/2}, \\ \hat{Q}_S &= \hat{S}_n'\hat{S}_n, \quad \hat{Q}_T = \hat{T}_n'\hat{T}_n, \quad \hat{Q}_{ST} = \hat{S}_n'\hat{T}_n, \quad \hat{Q} = \begin{pmatrix} \hat{Q}_S & \hat{Q}_{ST} \\ \hat{Q}_{ST} & \hat{Q}_T \end{pmatrix}, \end{aligned}$$

where $\hat{\Omega} = \begin{pmatrix} \hat{\sigma}_{u_1}^2 & 0 \\ 0 & \hat{\sigma}_{\varepsilon_2}^2 n_1/n_2 \end{pmatrix}$ with $\hat{\sigma}_{u_1}^2 = y_1'M_{[Z_1:X_1]}y_1/(n_1 - k - p)$ and $\hat{\sigma}_{\varepsilon_2}^2 = w_2'M_{[Z_2:X_2]}w_2/(n_2 - k - p)$ are consistent estimators of $\sigma_{u_1}^2$ and $\sigma_{\varepsilon_2}^2$, the variance terms of u_1 and ε_2 , respectively.

Next, define test statistics

$$\begin{aligned} \mathcal{T}_1(\beta_0) &= \hat{Q}_S, \quad \mathcal{T}_2(\beta_0) = \hat{Q}_{ST}^2/\hat{Q}_T, \\ \mathcal{T}_3(\beta_0) &= \frac{1}{2} \left[\hat{Q}_S - \hat{Q}_T + \left[\left(\hat{Q}_S + \hat{Q}_T \right)^2 - 4 \left(\hat{Q}_S\hat{Q}_T - \hat{Q}_{ST}^2 \right) \right]^{1/2} \right]. \end{aligned}$$

Under the weak IV asymptotic in (2), one can show that in the limit $\mathcal{T}_1(\beta_0)$ follows a χ^2 distribution with k degrees of freedom and $\mathcal{T}_2(\beta_0)$ follows a $\chi^2(1)$ distribution when the null condition $\beta = \beta_0$ holds. When $k = 1$, $\mathcal{T}_3(\beta_0)$ reduces to $\mathcal{T}_1(\beta_0)$. When $k \geq 2$, in the limit the probability of $\mathcal{T}_3(\beta_0)$ exceeding m is

$$p(m; q_T) = 1 - 2K \int_0^1 P \left[\chi_k^2 < \frac{q_T + m}{1 + q_T s_2^2/m} \right] (1 - s_2^2)^{(k-3)/2} ds_2$$

under the null, where $K = \Gamma(k/2)/[\pi^{1/2}\Gamma((k-1)/2)]$ and χ_k^2 is a random variable following a χ^2 distribution with k degrees of freedom (Andrews et al. 2007).

Let $q_{1-\alpha}(k)$ be the $(1 - \alpha)$ quantile of the $\chi^2(k)$ distribution. Define the decision rules of the three statistics as “reject the null if $\mathcal{T}_1(\beta_0) > q_{1-\alpha}(k)$ ”, “reject the null if $\mathcal{T}_2(\beta_0) > q_{1-\alpha}(1)$ ”, and “reject the null if $\mathcal{T}_3(\beta_0) > q_{1-\alpha}(1)$ when $k = 1$, and reject the null if $p(\mathcal{T}_3(\beta_0); \hat{Q}_T) < \alpha$ when $k \geq 2$ ”, respectively. All three tests have asymptotic size control under the weak IV asymptotic. When the null hypothesis $H_0 : \beta = \beta_0$ is violated, all three tests have nontrivial power dependent on the value of C . When the instruments are strong, all three tests have power approaching one. We call the test based on $\mathcal{T}_1(\beta_0)$ the TSAR test, the one based on $\mathcal{T}_2(\beta_0)$ the TSK test, and the one based on $\mathcal{T}_3(\beta_0)$ the TSCLR test.

Note that when $k = 1$, all three tests give identical results. When $k \geq 2$, TSCLR generally has better power performances than the other two methods, but there are also some data generating processes where TSAR can outperform. See Choi et al. (2018) for more details.

Given the proposed tests, the $(1 - \alpha) \times 100\%$ confidence sets for β can be obtained by inverting the corresponding tests. Define

$$\begin{aligned} \mathcal{CI}_1(\alpha) &= \{\beta_0 : \mathcal{T}_1(\beta_0) \leq q_{1-\alpha}(k)\}, \quad \mathcal{CI}_2(\alpha) = \{\beta_0 : \mathcal{T}_2(\beta_0) \leq q_{1-\alpha}(1)\}, \\ \mathcal{CI}_3(\alpha) &= \{\beta_0 : p(\mathcal{T}_3(\beta_0); \hat{Q}_T(\beta_0)) \geq \alpha\}. \end{aligned}$$

The confidence sets, since inverted from asymptotic valid tests under the weak IV asymptotics, have correct coverage in the limit. When the instruments are weak, the confidence sets could be unbounded, which is an essential property for confidence sets to have correct coverage with arbitrarily weak instruments (Dufour 1997). The benchmark confidence sets are computed analytically following the fast computation method proposed by Mikusheva and Poi (2006) for the classic one-sample AR, K and CLR confidence sets.

Similar to the classic one-sample case (see Mikusheva and Poi 2006), the TSK method is generally not recommended in practice. This is because, for statistical testing, TSK has irregular non-monotonic power curve when $k \geq 2$, resulting in power loss with some data generating processes. For confidence sets, the TSK confidence set can also take the form of a union of two finite intervals, i.e., $[x_1, x_2] \cup [x_3, x_4]$, while the TSAR and TSCLR confidence sets, conditional on boundedness, only take the usual form of finite interval, or $[x_1, x_2]$ (See Table 1 below).

2.2 Robust Tests and Confidence Sets

This section relaxes the assumption of homoskedastic and equal moment of exogenous covariates, but the data is still assumed to be i.i.d. Specifically, we assume that Σ_{z,u_1} and Σ_{z,ε_2} are probability limits of $V[Z'_1 u_1 / \sqrt{n_1}]$ and $V[Z'_2 \varepsilon_2 / \sqrt{n_2}]$, respectively, and that $\Sigma_{l,ZZ}$ is the probability limit of $Z'_l Z_l / n_l$ for $l = 1, 2$, where it is not necessary for $\Sigma_{1,ZZ}$ and $\Sigma_{2,ZZ}$ to be equal.

Replace the first equation in model (1) by its reduced form

$$y_1 = Z_1 \zeta + X_1 \gamma + u_1.$$

Let $\delta = [\zeta \ \pi]'$, we know that $r(\delta, \beta) = \zeta - \pi\beta = 0$. Let $\hat{\zeta} = (Z'_1 Z_1)^{-1} Z'_1 y_1$, $\hat{\pi} = (Z'_2 Z_2)^{-1} Z'_2 w_2$, and $\hat{\delta} = [\hat{\zeta} \ \hat{\pi}]'$. It is easy to see that, for any β_0 ,

$$\sqrt{n_1} \left(r(\hat{\delta}, \beta_0) - r(\delta, \beta_0) \right) \Rightarrow N(0, \Sigma_{\beta_0}),$$

where $\Sigma_{\beta_0} = \Sigma_{1,ZZ}^{-1} \Sigma_{z,u_1} \Sigma_{1,ZZ}^{-1} + \tau \beta_0^2 \Sigma_{2,ZZ}^{-1} \Sigma_{z,\varepsilon_2} \Sigma_{2,ZZ}^{-1}$ is a $k \times k$ variance-covariance matrix. Let $\hat{\Sigma}_{\zeta, \beta_0} = \frac{n_1^2}{n_1 - k - p} (Z'_1 Z_1)^{-1} \left(\sum_{i=1}^{n_1} \hat{u}_{1i}^2 Z_{1i} Z'_{1i} \right) (Z'_1 Z_1)^{-1}$ and $\hat{\Sigma}_{\pi, \beta_0} = \frac{n_2^2}{n_2 - k - p} (Z'_2 Z_2)^{-1} \left(\sum_{i=1}^{n_2} \hat{\varepsilon}_{2i}^2 Z_{2i} Z'_{2i} \right) (Z'_2 Z_2)^{-1}$, where \hat{u}_{1i} is the i -th entry of $M_{[Z_1 : X_1]} y_1$ and $\hat{\varepsilon}_{2i}$ is the i -th entry of $M_{[Z_2 : X_2]} w_2$. Then Σ_{β_0} could be consistently estimated by $\hat{\Sigma}_{\beta_0} = \hat{\Sigma}_{\zeta, \beta_0} + \frac{n_1}{n_2} \beta_0^2 \hat{\Sigma}_{\pi, \beta_0}$.

Following Magnusson (2010), the robust TSAR, TSK, and TSCLR test statistics for $H_0 : \beta = \beta_0$ can be

written as,

$$\begin{aligned}\mathcal{T}_{1,robust}(\beta_0) &= n_1(\hat{\zeta} - \hat{\pi}\beta_0)' \hat{\Sigma}_{\beta_0}^{-1}(\hat{\zeta} - \hat{\pi}\beta_0), \\ \mathcal{T}_{2,robust}(\beta_0) &= n_1 \left[\hat{\Sigma}_{\beta_0}^{-1/2}(\hat{\zeta} - \hat{\pi}\beta_0) \right]' P_{\hat{\Sigma}_{\beta_0}^{-1/2} \hat{D}_{\beta_0}} \left[\hat{\Sigma}_{\beta_0}^{-1/2}(\hat{\zeta} - \hat{\pi}\beta_0) \right], \\ \mathcal{T}_{3,robust}(\beta_0) &= \frac{1}{2} \left[\mathcal{T}_{1,robust} - \hat{q}_{\beta_0} + \left[(\mathcal{T}_{1,robust} + \hat{q}_{\beta_0})^2 - 4(\mathcal{T}_{1,robust} \hat{q}_{\beta_0} - \mathcal{T}_{2,robust} \hat{q}_{\beta_0}) \right]^{1/2} \right]\end{aligned}$$

where $-\hat{D}_{\beta_0} = \hat{\pi} + \frac{n_1}{n_2} \beta_0 \hat{\Sigma}_{\pi, \beta_0} \hat{\Sigma}_{\beta_0}^{-1}(\hat{\zeta} - \hat{\pi}\beta_0)$, and $\hat{q}_{\beta_0} = n_1 \hat{D}'_{\beta_0} \left(\frac{n_1}{n_2} \hat{\Sigma}_{\pi, \beta_0} - \left(\frac{n_1}{n_2} \right)^2 \beta_0^2 \hat{\Sigma}_{\pi, \beta_0} \hat{\Sigma}_{\beta_0}^{-1} \hat{\Sigma}_{\pi, \beta_0} \right)^{-1} \hat{D}_{\beta_0}$. Under the null hypothesis, $\mathcal{T}_{1,robust}(\beta_0)$ and $\mathcal{T}_{2,robust}(\beta_0)$ have limit distributions $\chi^2(k)$ and $\chi^2(1)$, respectively, and $\mathcal{T}_{3,robust}(\beta_0) \Rightarrow \frac{1}{2} \left[\chi^2(1) + \chi^2(k-1) - q_{\beta_0} + \left[(\chi^2(1) + \chi^2(k-1) + q_{\beta_0})^2 - 4\chi^2(k-1)q_{\beta_0} \right]^{1/2} \right]$, where $\chi^2(1)$ and $\chi^2(k-1)$ are independent chi-squared distributed random variables with 1 and $k-1$ degrees of freedom, respectively, given that $\hat{q}_{\beta_0} = q_{\beta_0}$. Therefore, we reject the null if so we reject the null if $\mathcal{T}_{1,robust}(\beta_0)$ or $\mathcal{T}_{2,robust}(\beta_0)$ is larger than $q_{1-\alpha}(k)$ or $q_{1-\alpha}(1)$, and if $p(\mathcal{T}_{3,robust}(\beta_0); \hat{q}_{\beta_0})$ is smaller than α , where $p(\cdot, \cdot)$ is defined in Section 2.1.

Similar to the benchmark case, robust TSAR, TSK, and TSCLR confidence sets of β can be constructed by inverting the robust TSAR, TSK, and TSCLR tests. The robust TSAR, TSK, and TSCLR confidence sets are computed using grid search. When the robust variance-covariance matrix $\hat{\Sigma}_{\beta_0}$ is replaced with $\bar{\Sigma}_{\beta_0} = \hat{\sigma}_{u_1}^2 \left(\frac{Z_1' Z_1}{n_1} \right)^{-1} + \frac{n_1}{n_2} \beta_0^2 \left(\frac{Z_1' Z_1}{n_1} \right)^{-1} \hat{\sigma}_{\epsilon_2}^2$, the three robust test statistics reduce to the benchmark counterparts.

3 Stata Implementation

By default, the **weaktsiv** command calculates the benchmark TSAR, TSK, and TSCLR tests and confidence regions discussed in Section 2.1. If the **robust** option is specified, **weaktsiv** calculates the robust versions of the tests and confidence regions discussed in Section 2.2. The command also reports the TS2SLS estimator with classic Inoue and Solon (2010) strong IV standard errors.

3.1 Syntax

```
weaktsiv depvar varlist_exog (varlist_endog =varlist_iv) [if] [in] [, noconstant robust level(#)
test(#) point(#) grid(#(##) #)]
```

depvar is the outcome variable.

varlist_exog is the list of exogenous variables.

varlist_endog is the endogenous regressor of the model.

varlist_iv is the list of exogenous variables used together with *varlist_exog* as instruments for *varlist_endog*.

3.2 Options

noconstant suppresses the constant term in the regression model.

robust provides the robust version of the two-sample weak IV tests that allow for heteroskedasticity and unequal moments of exogenous variables across the two samples.

level(#) sets confidence level; default is *level*(95).

test(#) sets the hypothesized value of the endogenous variable's coefficient; default is *test*(0).

grid specifies the grid used for confidence region calculation. *grid* could only be used together with the *robust* option because the benchmark confidence regions are calculated analytically. If not specified, the default uses the TS2SLS estimator plus/minus two times the Inoue and Solon (2010) standard error and 100 grid points.

point specifies the number of points used to create the grid for confidence region calculation. *point* could only be used together with the *robust* option, and could not be used together with the *grid* option. The default uses 100 grid points.

3.3 Saved Results

`weaktsiv` saves the following in `e()`:

Scalars

<code>e(p_TSAR)</code>	TSAR test p-value	<code>e(p_TSK)</code>	TSK test p-value
<code>e(p_TSCLR)</code>	TSCLR test p-value	<code>e(TSAR_xi)</code>	endpoints of benchmark TSAR confidence sets
<code>e(TSK_xi)</code>	endpoints of benchmark TSK confidence sets	<code>e(TSCLR_xi)</code>	endpoints of benchmark TSCLR confidence sets
<code>e(level)</code>	confidence level for weak-iv robust inference	<code>e(H0.b)</code>	value of β under null for weak-iv robust inference
<code>e(n1)</code>	# of obs in the sample 1 (the outcome sample)	<code>e(n2)</code>	# of obs in the sample 2 (the endog. var. sample)
<code>e(chi2)</code>	TS2SLS Wald statistic	<code>e(F_first)</code>	TS2SLS first-stage F
<code>e(numinst)</code>	number of instruments	<code>e(df_m_first)</code>	TS2SLS first-stage residual degrees of freedom
<code>e(df_m)</code>	TS2SLS model degrees of freedom	<code>e(df_r)</code>	TS2SLS residual degrees of freedom
<code>e(r2)</code>	R^2	<code>e(r2a)</code>	adjusted R^2
<code>e(mss)</code>	TS2SLS model sum of squares	<code>e(rss)</code>	TS2SLS residual sum of squares
<code>e(rmse)</code>	TS2SLS root mean squared errors	<code>e(points)</code>	# of grid points for robust confidence sets

Macros

<code>e(cmd)</code>	<code>weaktsiv</code>	<code>e(robust)</code>	whether robust inference methods are used
<code>e(TSAR_type)</code>	type of benchmark TSAR confidence set	<code>e(TSK_type)</code>	type of benchmark TSK confidence set
<code>e(TSCLR_type)</code>	type of benchmark TSCLR confidence set	<code>e(TSAR_cset)</code>	robust TSAR confidence set
<code>e(TSK_cset)</code>	robust TSK confidence set	<code>e(TSCLR_cset)</code>	robust TSK confidence set
<code>e(grid)</code>	grid range for robust confidence set	<code>e(cons)</code>	whether constants are used
<code>e(instd)</code>	instrumented variable	<code>e(inst)</code>	instruments
<code>e(exog)</code>	exogenous variables	<code>e(depvar)</code>	dependent variable

Matrices

<code>e(b)</code>	coefficient vector	<code>e(V)</code>	variance-covariance matrix of the estimators
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Functions

`e(sample)` marks estimation sample

For the benchmark methods, the result types (i.e. `e(TSAR_type)`, `e(TSK_type)`, and `e(TSCLR_type)`) and endpoints (i.e. `e(TSAR_xi)`, `e(TSK_xi)`, and `e(TSCLR_xi)`) information could be used together to retrieve the exact confidence sets using Table 1.

Table 1: Benchmark TSCLR, TSAR, TSK Confidence Sets (Analytical Solution)

Test	Result Type	Interval
TSCLR	1	Empty set
	2	$[x1, x2]$
	3	$(-\infty, +\infty)$
	4	$(-\infty, x1] \cup [x2, \infty)$
TSAR	1	Empty set
	2	$[x1, x2]$
	3	$(-\infty, +\infty)$
	4	$(-\infty, x1] \cup [x2, \infty)$
TSK	1	Not used (not possible)
	2	$[x1, x2]$
	3	$(-\infty, +\infty)$
	4	$(-\infty, x1] \cup [x2, \infty)$
	5	$(-\infty, x1] \cup [x2, x3] \cup [x4, \infty)$
	6	$[x1, x2] \cup [x3, x4]$

4 Example

We use the dataset of Currie and Yelowitz (2000) and illustrate implementing the `weaktsiv` command in the just identified case. We estimate the effects of public housing on monthly rental payments in equations (2) and (3) in their paper. The following command illustrates the just identified case. The first half of the output reports the classic two-sample 2SLS estimation results with Inoue and Solon (2010) standard errors. The inference here is valid only when the instruments are strong. The second half of the output reports results from the weak IV robust tests and confidence regions discussed in Section 2.1. Since the model is just-identified here, only TSCLR is reported because TSAR, TSK, and TSCLR are equivalent under just-identification. The results are also reported in column (1) of Table 3 in Choi et al. (2018).

```
. use sample1.dta
. weaktsiv ry1 h* p* b* (ry2=z)
Two-sample Instrumental variables (TS2SLS) regression
First-stage F Results
-----
F( 1, 10364) = 15.03
Prob > F      = 0.0001
Number of obs = 116901
Wald chi2( 17) = 5611.78
Prob > chi2    = 0.0000
R-squared      = 0.1489
Adj R-squared  = 0.1488
Root MSE      = 0.2205
```

ry1	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
ry2	.3716513	.1123615	3.31	0.001	.1514244	.5918781
hdage	.0192549	.0015888	12.12	0.000	.016141	.0223689
hdage2	-.0198632	.0020119	-9.87	0.000	-.0238065	-.0159198
hdmarr	.0198959	.0062194	3.20	0.001	.007706	.0320859
hdfemale	-.0976462	.0107003	-9.13	0.000	-.1186186	-.0766738
hdblack	-.1211384	.0133036	-9.11	0.000	-.1472133	-.0950634
hdothor	-.0163956	.00506	-3.24	0.001	-.0263131	-.0064781
hdhisp	.0005148	.0040625	0.13	0.899	-.0074478	.0084773
hded0911	.0336821	.0052502	6.42	0.000	.0233919	.0439723
hded1212	.0768111	.0054963	13.97	0.000	.0660384	.0875838
hded1315	.1345398	.0068719	19.58	0.000	.1210711	.1480085
hded16p	.20465	.0078281	26.14	0.000	.1893071	.2199928
pctlihtc	-.7054565	.1697396	-4.16	0.000	-1.038143	-.3727696
pctprj	-.8651579	.1218703	-7.10	0.000	-1.104022	-.6262939
pctrehab	-1.026055	.160297	-6.40	0.000	-1.340235	-.7118757
pctvch	-2.920268	.5245491	-5.57	0.000	-3.948376	-1.89216
boys	-.004395	.0019092	-2.30	0.021	-.008137	-.0006529
_cons	.1192835	.0300903	3.96	0.000	.060307	.17826

```
Instrumented: ry2
Instruments: z
Confidence set and p-value for ry2 are based on normal approximation
```

Weak IV Robust 95% confidence set and p-value
for H0: ${}_b[ry2] = 0$

Test	95% Confidence Set	p-value
Benchmark TSCLR	[.2137159, .7837229]	0.0000

Note: In the just identified case, TSCLR = TSAR = TSK.

Next, we illustrate the `weaktsiv` command in the over identified case using the dataset of Olivetti and Paserman (2015) and its specification in column (1) - row (5) in Table 3. The first half of the output again reports the classic two-sample 2SLS estimation results with Inoue and Solon (2010) standard errors. The second half of the output now reports results from benchmark TSAR, TSK, and TSCLR tests and confidence regions. The results are also reported in column (1) - row (5) in Table 2 of Choi et al. (2018).

```
. use sample2.dta
. weaktsiv ry1 (ry2=z*), level(90)
```

note: z726 omitted because of collinearity

Two-sample Instrumental variables (TS2SLS) regression

First-stage F Results

F(726, 18771) = 1.98
Prob > F = 0.0000

Number of obs = 16650
Wald chi2(1) = 153.60
Prob > chi2 = 0.0000
R-squared = 0.0098
Adj R-squared = 0.0097
Root MSE = 0.4317

ry1	Coef.	Std. Err.	t	P> t	[90% Conf. Interval]	
ry2	.354363	.0285928	12.39	0.000	.3073294	.4013965
_cons	1.92788	.0830654	23.21	0.000	1.791242	2.064518

Instrumented: ry2

Instruments: z1 z2 z3 z4 z5 z6 z7 z8 z9 z10 z11 z12 z13 z14 z15 z16 z17 z18
z19 z20 z21 z22 z23 z24 z25 z26 z27 z28 z29 z30 z31 z32 z33 z34
z35 z36 z37 z38 z39 z40 z41 z42 z43 z44 z45 z46 z47 z48 z49 z50
z51 z52 z53 z54 z55 z56 z57 z58 z59 z60 z61 z62 z63 z64 z65 z66
z67 z68 z69 z70 z71 z72 z73 z74 z75 z76 z77 z78 z79 z80 z81 z82
z83 z84 z85 z86 z87 z88 z89 z90 z91 z92 z93 z94 z95 z96 z97 z98
z99 z100 z101 z102 z103 z104 z105 z106 z107 z108 z109 z110 z111
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z723 z724 z725 z726

Confidence set and p-value for ry2 are based on normal approximation

Weak IV Robust 90% confidence sets and p-values
for H0: $\beta_{ry2} = 0$

Test	90% Confidence Set	p-value
Benchmark TSCLR	[.5706445, .7306929]	0.0000
Benchmark TSAR	empty	0.0000
Benchmark TSK	[-2.803132, -2.362719] U [.5633191, .7388234]	0.0000

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