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Instrumental Variables Quantile Regression in Stata

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StataCorp

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Motivation: Quantile regression with endogneity

- Beyond the mean: How would the participation in a 401(k) affect the lower-level, median, and upper-level conditional quantile of net wealth?
- Endogeneity: The participation in a 401(k) may depend on the unobservable saving preference that would also affect net wealth growth.
- IV: Conditional on income and other covariates, the eligibility of 401(k) can serve as an instrument (Poterba et al., 1995).

$$\underset{\substack{\Uparrow \\ \text{IV}}}{\text{Endogeneity}} + \text{Quantile regression}$$

When is estimating $E(y|x)$ not adaquate?

Consider $E(y|x) = \beta_0 + \beta_1 x_1$, then

$$\beta_1 = E(y|x = a + 1) - E(y|x = a)$$

Two senarios

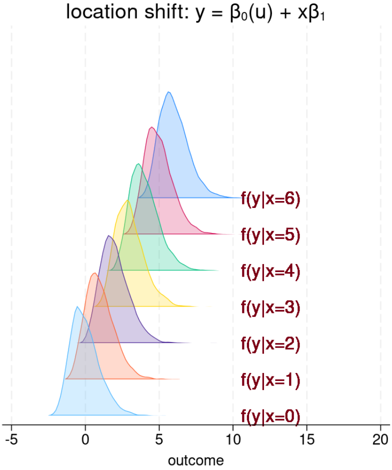
1. The conditional density $f(y|x = a + 1)$ is only location-shifted relative to $f(y|x = a)$. Then

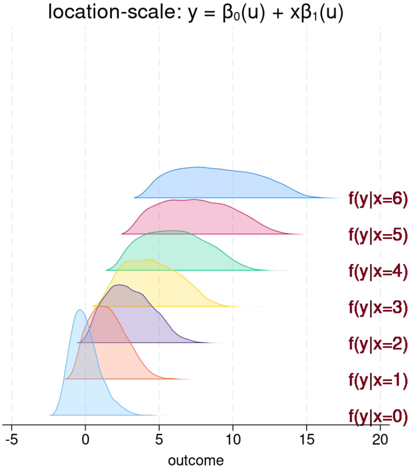
$$\beta_1 = Q(y|x = a + 1, \tau) - Q(y|x = a, \tau)$$

2. The conditional density $f(y|x = a + 1)$ is both location-shifted and scaled relative to $f(y|x = a)$. Then

$$\beta_1 \neq Q(y|x = a + 1, \tau) - Q(y|x = a, \tau)$$

Beyond the mean





Overview of `ivqregress` toolbox (I)

We provide a suite of commands to estimate, visualize, make the inference, and diagnose the linear IV quantile regression models (IVQR).

- Estimation
  - `ivqregress iqr` implements the Inverse Quantile Regression estimator in Chernozhukov and Hansen (2006).
  - `ivqregress smooth` implements the Smoothed Estimating Equation estimator in Kaplan and Sun (2017).

Overview of `ivqregress` toolbox (II)

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- Visualization
  - `estat coefplot` shows how the treatment effects vary at different conditional quantiles of outcome.
- Inference
  - `estat endogeffects` tests the hypothesis regarding the quantile process.
  - `estat dualci` provides the confidence interval robust to weak instruments (only after `ivqregress iqr`).
- Diagnosis
  - `estat waldplot` helps to visually inspect the convergence of the IQR estimator (only after `ivqregress iqr`).
- Standard post-estimation
  - `test`, `testnl`, `predict`, `margins`, ...

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Model

We can write the IV quantile regression model as a random-coefficients model (Chernozhukov and Hansen, 2008).

$$y = \mathbf{d}'\boldsymbol{\alpha}(u) + \mathbf{x}'\boldsymbol{\beta}(u) \qquad u|\mathbf{x}, \mathbf{z} \sim \mathit{Uniform}(0, 1) \tag{1}$$

$$\mathbf{d} = \delta(\mathbf{x}, \mathbf{z}, v) \qquad v \text{ statistically depends on } u \tag{2}$$

$$\tau \to \mathbf{d}'\boldsymbol{\alpha}(\tau) + \mathbf{x}'\boldsymbol{\beta}(\tau) \qquad \text{is strictly increasing} \tag{3}$$

Objective:

- The coefficients ($\boldsymbol{\alpha}(\tau)$ or $\boldsymbol{\beta}(\tau)$) summarize the marginal effects of covariates on the τ-th conditional quantile of outcome.
- Estimate the functions of $\boldsymbol{\alpha}(\tau)$ and $\boldsymbol{\beta}(\tau)$ at different τ's.

Example: 401(k) participation and net wealth

The IVQR model we want to estimate is

$$\texttt{asset} = \texttt{p401k} * \alpha(u) + \textbf{covariates}' * \beta(u)$$

where

- Outcome variable (`asset`) is the net financial assets.
- The participation in a 401(k) (`p401k`) may be endogenous.
- Conditional on income, the 401(k) eligibility can be used as an instrument.
- The ranking variable u is uniformly distributed conditional on `e401k` and covariates.

Objectives of analysis

- **Estimation:**
  - How does the 401(k) participation affect the lower-level, median, and upper-level conditional quantile of net financial assets? $\rightarrow$ Estimate $\alpha(\tau)$ when $\tau = 0.1, 0.2, \ldots, 0.9$.

- **Hypothesis of interest:**
  - No effect: The 401(k) participation does not affect net financial asset for all the estimated quantiles.
  - Constant effect: The 401(k) participation's treatment effect is constant for the different conditional quantiles of asset.
  - Dominance: The 401(k) participation is unambiguously beneficial for all the estimated quantiles of asset.
  - Exogeneity: The 401(k) participation is exogenous.

Define covariates


```
. describe

Contains data from assets2.dta
 Observations:         9,913                  Excerpt from Chernozhukov and
                                                Hanson (2004) Rev. of Economics
                                                and Statistics
    Variables:            12                  18 Jan 2022 08:19
--------------------------------------------------------------------------------
Variable      Storage   Display    Value
    name         type    format    label      Variable label
--------------------------------------------------------------------------------
assets          float   %9.0g                 Net total financial assets
age             byte    %9.0g                 Age
income          float   %9.0g                 Household income
familysize      byte    %9.0g                 Household size
educ            byte    %9.0g                 Years of education
pension         byte    %16.0g     lbpen      Pension benefits
married         byte    %11.0g     lbmar      Marital status
twoearn         byte    %9.0g      lbyes      Two-earner household
e401k           byte    %12.0g     lbe401     401(k) eligibility
p401k           byte    %9.0g                 401(k) participation
ira             byte    %9.0g      lbyes      IRA participation
ownhome         byte    %9.0g      lbyes      Home owner
--------------------------------------------------------------------------------
Sorted by: e401k
. global covariates income age familysize educ i.(married ira pension ownhome)
```

- **IQR estimator**

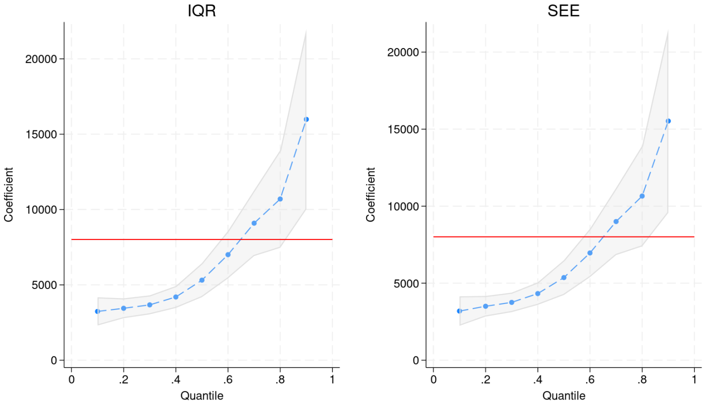
```
ivqregress iqr assets (i.p401k = i.e401k) $covariates   ///
          ,quantile(10(10)90)
```

- **Smooth estimator**

```
ivqregress smooth assets (i.p401k = i.e401k) $covariates ///
          ,quantile(10(10)90)
```

estat coefplot

- Visualize how the treatment effects vary at different conditional quantiles of outcome $\rightarrow$ plot the function $\alpha(\tau)$ or $\beta(\tau)$.



estat endogeffects


```
. estimates restore iqr
(results iqr are active now)

. estat endogeffects

Tests for endogenous effects              Replications = 100
─────────────────────────────────────────────────────────────
Null hypothesis │        KS statistic   95% critical value
────────────────┼────────────────────────────────────────────
No effect       │              11.271                2.481
Constant effect │               5.395                2.524
Dominance       │               0.000                2.569
Exogeneity      │               4.146                2.809
─────────────────────────────────────────────────────────────
Note: If the KS statistic < critical value, there is
      insufficient evidence to reject the null
      hypothesis. (KS = Kolmogorov-Smirnov)

.
. estimates restore smooth
(results smooth are active now)

. estat endogeffects

Tests for endogenous effects              Replications = 100
─────────────────────────────────────────────────────────────
Null hypothesis │        KS statistic   95% critical value
────────────────┼────────────────────────────────────────────
No effect       │              11.507                2.525
Constant effect │               5.351                2.514
Dominance       │               0.000                2.661
Exogeneity      │               4.201                2.573
─────────────────────────────────────────────────────────────
Note: If the KS statistic < critical value, there is
      insufficient evidence to reject the null
      hypothesis. (KS = Kolmogorov-Smirnov)
```

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IVQR model key moment condition

$$Pr(y \leq \mathbf{d}'\alpha(\tau) + \mathbf{x}'\beta(\tau)|\mathbf{x}, \mathbf{z}) = \tau$$

$$\Downarrow$$

$$\mathbf{E}\left[\left(\tau - \mathbb{1}(y - \mathbf{d}'\alpha(\tau) - \mathbf{x}'\beta(\tau) \leq 0)\right)\Psi(\mathbf{x}, \mathbf{z})\right] = 0$$

- The main difficulty is the indicator function $\mathbb{1}()$. The objective function is non-convex and non-smooth.
- In practice, $\Psi(\mathbf{x}, \mathbf{z}) = (\Phi(\mathbf{x}, \mathbf{z})', \mathbf{x}')'$, and $\Phi(\mathbf{x}, \mathbf{z})$ is the linear projection of **d** on the space spanned by **x** and **z**.
- $\Phi(\mathbf{x}, \mathbf{z})$ can be regarded as transformed instruments for **d**, so the over-identification can always be transformed into just-identification.

Nonconvex and non-smooth objective function

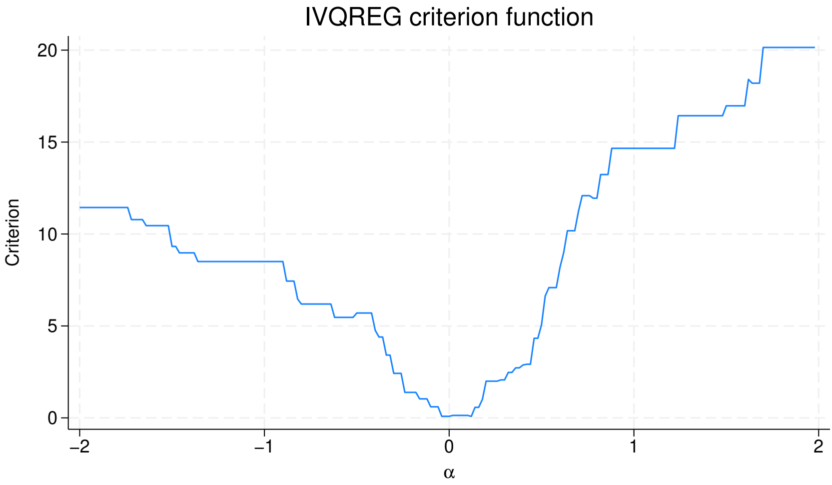


Figure: IVQREG GMM criterion function

Intuition behind IQR and Smooth estimators

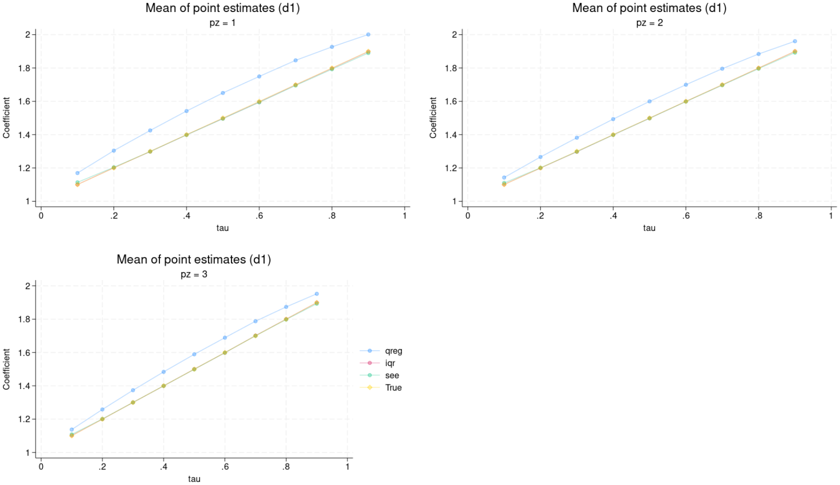
- **IQR** (Chernozhukov and Hansen, 2006 and 2008)
  - Reduce the $p = dim(\alpha) + dim(\beta)$ dimensional non-convex problem into one-dimensional non-convex problem.
  - Do a exhaustive grid search (in one dimension) over high quality of grid points.
  - The bounds for grid points are guarenteed to cover the true value with 95% probability.
  - Good for only one endogenous variable, but can compute the CI that is robust to the weak instrument.
- **Smooth** (Kaplan and Sun, 2017)
  - Smooth the indicator function by kernel method.
  - Solve a system of non-convex equation using `solvenl()`.
  - Good for more than one endogenous variables, but can not provide the CI robust to weak instrument.

Simulation: DGP

$$y = \mathbf{d}'\alpha(u) + \mathbf{x}'\beta(u)$$
$$\alpha(\tau) = \beta(\tau) = 1 + \tau$$

- u is uniformly distributed.
- **d** is a linear function of instrument **z** and it is correlated with u.
- **x** is exogenous.
- When $dim(\mathbf{d}) = 1$, $dim(\mathbf{z}) = 1$, 2 or 3, $N = 1000$. Run `qreg`, IQR, and Smooth.
- When $dim(\mathbf{d}) = 2$, $dim(\mathbf{z}) = 2$, 4, or 6, $N = 5000$. Run `qreg` and Smooth.
- Estimate coefficients when $\tau = 0.1, 0.2, \ldots, 0.9$.
- The number of repetitions is 2030.

Simulation: dim($\mathbf{d}$) = 1 (mean of $\widehat{\beta}$)



Simulation: dim(**d**) = 1 (bias)

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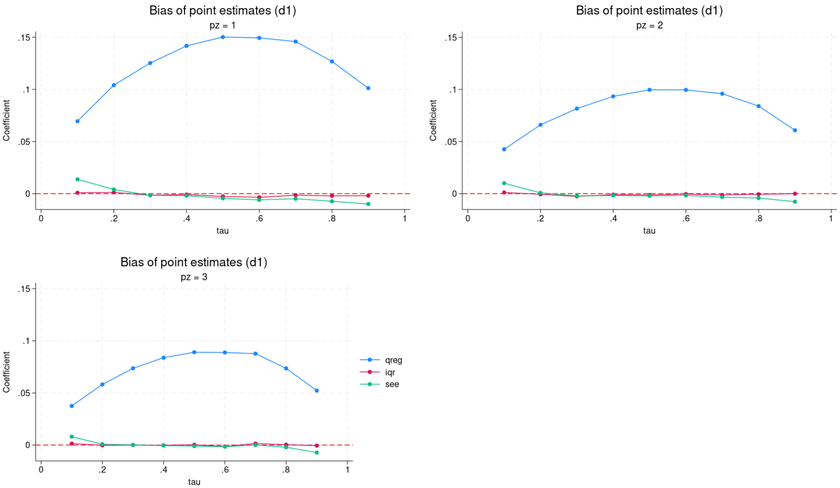
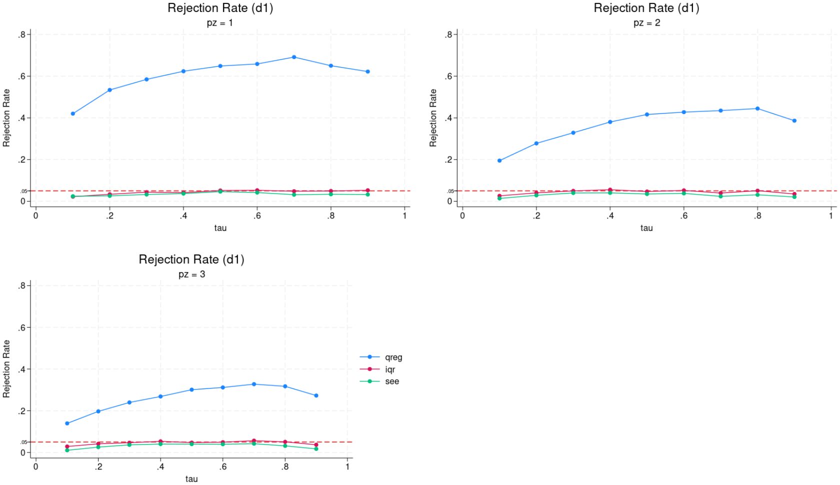
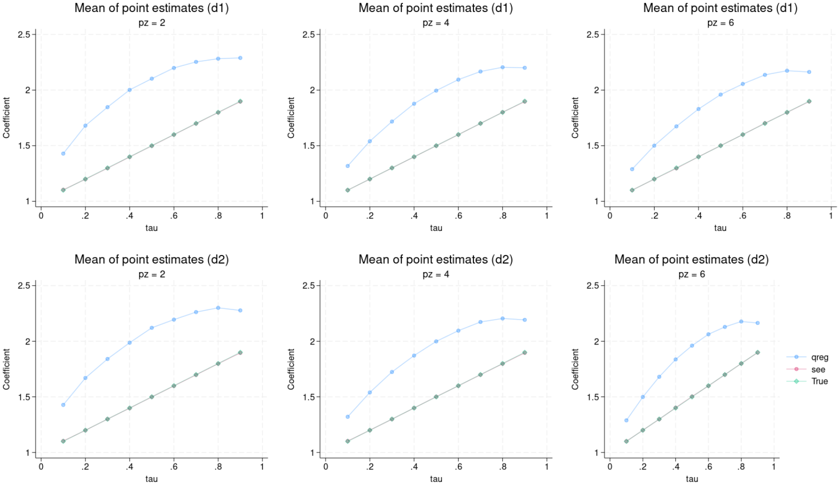


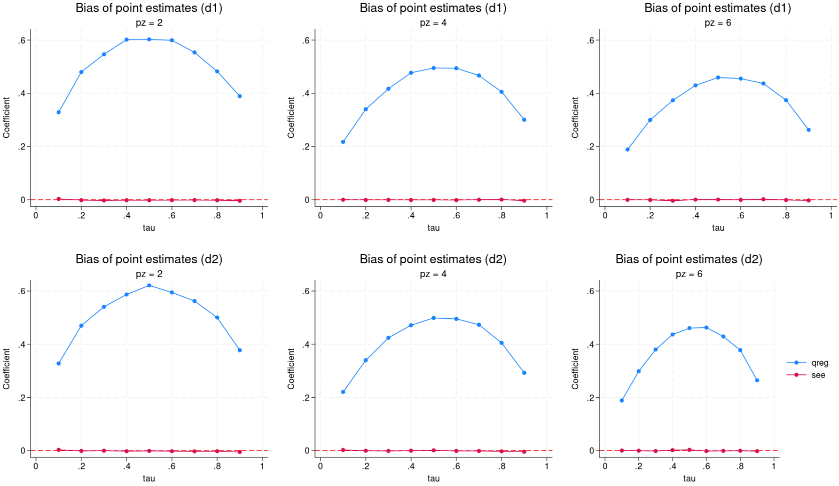
Simulation: dim(**d**) = 1 (rejection rate)



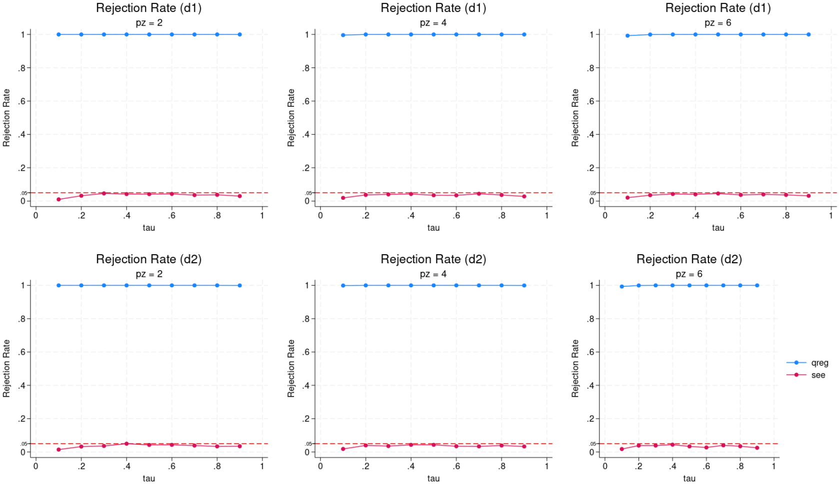
Simulation: dim($\mathbf{d}$) = 2 (mean of $\widehat{\beta}$)



Simulation: dim(**d**) = 2 (bias)



Simulation: dim(**d**) = 2 (rejection rate)



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Inverse quantile regression

QREG

$$\Downarrow$$

$$Pr(y \leq \mathbf{z}'\gamma(\tau) + \mathbf{x}'\beta(\tau) | \mathbf{x}, \mathbf{z}) = \tau$$

$$\Downarrow$$

$$\min \sum_{i=1}^{N} \rho_\tau(y_i - \mathbf{z}_i'\gamma - \mathbf{x}_i'\beta)$$

$$\Downarrow$$

```
qreg y x z
```

IVQREG

$$\Downarrow$$

$$Pr(y \leq \mathbf{d}'\alpha(\tau) + \mathbf{x}'\beta(\tau) | \mathbf{x}, \mathbf{z}) = \tau$$

$$\Updownarrow$$

$$Pr(y - \mathbf{d}'\alpha(\tau) \leq \mathbf{x}'\beta(\tau) + \mathbf{z}' * 0 | \mathbf{x}, \mathbf{z}) = \tau$$

$$\Downarrow$$

qreg y−$\mathbf{d}'\alpha(\tau)$ x z

IQR finds $\alpha(\tau)$ such that the coefficient on **z** is as close to zero as possible.

Constructing grid using dual CI

- Given a grid of $A = \{\alpha_1, \ldots, \alpha_J\}$, **IQR** finds $\alpha(\tau)$ such that the coefficient on **z** is as close to zero as possible, which is measured by the Wald statistic $(W_n(\boldsymbol{\alpha}(\tau)))$.
- The grid points boundary must be more comprehensive than the dual CI, otherwise `ivqregress iqr` will error out.
- Dual CI means it covers the true value of $\alpha(\tau)$ with 95% probability (Chernozhukov and Hansen, 2008).

Dual CI

PROPOSITION

(Proposition 1 in Chernozhukov and Hansen[2008]) When $\alpha = \alpha(\tau)$,

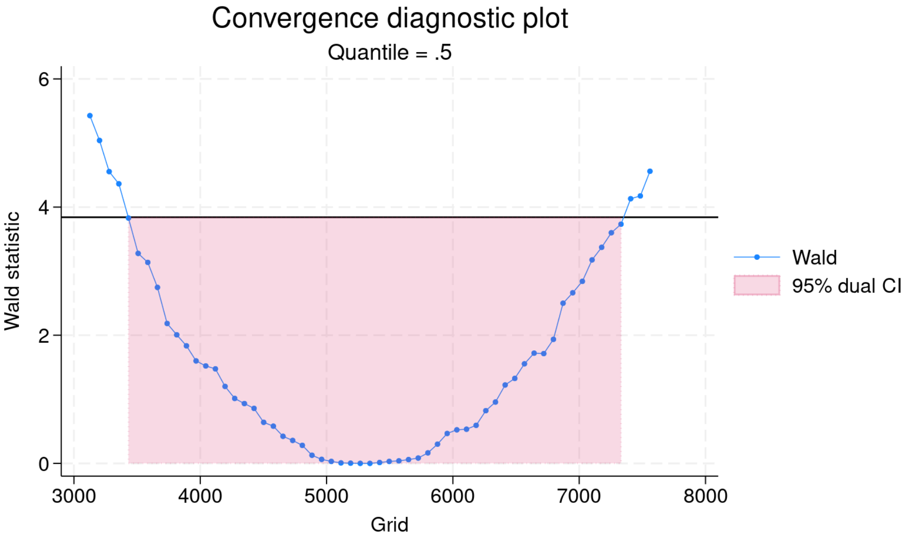
$$W_n[\alpha(\tau)] \to_d \chi^2(dim(\gamma))$$

and for the confidence region $CR_p[\alpha(\tau)] = \{\alpha \in A : W_n(\alpha) < c_p\}$, *where* $P(\chi^2(dim(\gamma)) < c_p) = p$,

$$P\{\alpha(\tau) \in CR_p[\alpha(\tau)]\} = P\{W_n[\alpha(\tau)] < c_p\} = p \tag{4}$$

$CR_p[\alpha(\tau)] = \{\alpha \in A : W_n(\alpha) < c_p\}$ covers the true value of α with probability approaching p.

estat waldplot



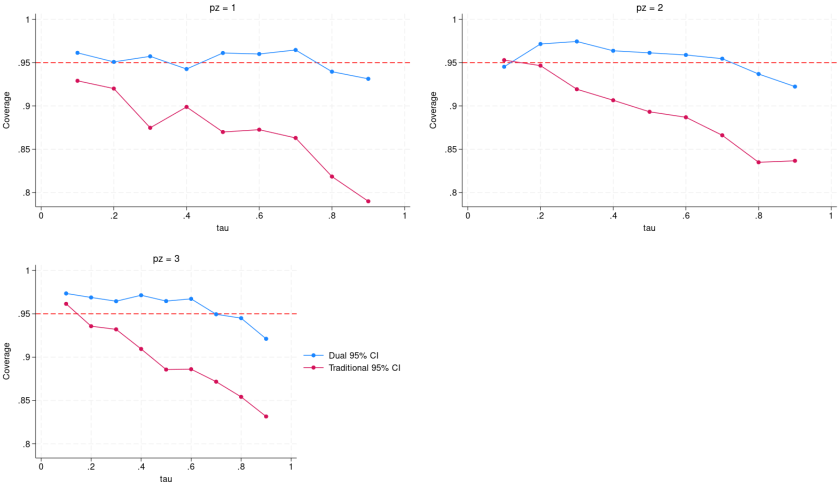
estat dualci


```
. estat dualci

Dual confidence interval                              Number of obs = 9,913

------------------------------------------------------------------------------
             |               Robust                               Dual
      assets | Coefficient  std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
       p401k |
          1  |   5419.717   580.9771     9.33   0.000     3508.301    7407.591
------------------------------------------------------------------------------
```

Simulation: Dual CI coverage with weak instruments



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Smoothed estimating equation estimator

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$$\mathbf{E}\left[\left(\tau - \mathbb{1}\left(y - \mathbf{d}'\alpha(\tau) - \mathbf{x}'\beta(\tau)\right) \leq 0\right)\right)\Psi(\mathbf{x}, \mathbf{z})\right] = 0$$

$$\Big\Downarrow \text{(smooth the indicator function by kernel)}$$

$$\mathbf{E}\left[\left(\tau - \widetilde{\mathbb{1}}\left(\frac{y - \mathbf{d}'\alpha(\tau) - \mathbf{x}'\beta(\tau)}{h}\right) \leq 0)\right)\Psi(\mathbf{x}, \mathbf{z})\right] = 0$$

- Solve this system of non-linear equation by `solvenl()`.
- The Smooth estimator is first-order equivalent to the IQR estimator so that we can use the same variance-covariance estimator (de Castro et al., 2019).

Smoothed indicator function

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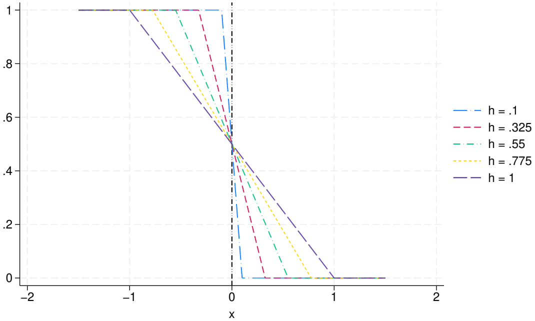
$$\widetilde{\mathbb{1}}(v) = \begin{cases} 1 & \text{if } v \leq -1 \\ 0 & \text{if } v \geq 1 \\ \frac{1-v}{2} & \text{if } -1 < v < 1 \end{cases}$$



- The optimal bandwidth h^* is chosen to minimize the MSE of the estimating equation.
- `ivqregress` also requires that h^* result in a $\alpha(\tau)$ within the dual CI.

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Syntax of `ivqregress`

Inverse Quantile Regression estimator:

`ivqregress iqr` *depvar* $varlist_1$ ($varlist_2$ = $varlist_{iv}$) [`if`] [`in`] [, *options* *IQR_options*]

Smoothed Estimating Equation estimator:

`ivqregress smooth` *depvar* $varlist_1$ ($varlist_2$ = $varlist_{iv}$) [`if`] [`in`] [, *options* *smooth_optior*

where

- $varlist_1$ specifies the exogenous variables.
- $varlist_2$ specifies the endogenous variables. Only one continuous variable or one binary factor variable is allowed for the inverse quantile regression estimator.
- $varlist_{iv}$ specifies the instrumental variables.

Post-estimation

The following postestimation commands are of particular interest after `ivqregress`.

Commands	Description
`estat coefplot`	plot coefficients and their confidence intervals at different quantiles
`estat endogeffects`	process test of no effect, constant effect, stochastic dominance, and endogeneity
*`estat dualci`	provide the dual-confidence interval for the endogenous variables
*`estat waldplot`	plot Wald statistics corresponding to each grid point

Note :

- `estat waldplot` and `estat dualci` are allowed only after `ivqregress iqr`.

Summary

- We provide a suite of commands to estimate, visualize, and make the inference for the linear IVQR model.
- Two estimators: IQR and Smooth. Both are consistent, but the estimates may be different because they approximate the original estimating equation differently.
- IQR is widely used for the one endogenous variable case. It should be used as a benchmark because it provides the dual CI robust to the weak instrument.
- Smooth is suitable for the one or more endogenous variables case.

References

de Castro, L., A. F. Galvao, D. M. Kaplan, and X. Liu. 2019. Smoothed GMM for quantile models. *Journal of Econometrics* 213: 121–144.

Chernozhukov, V., and C. Hansen. 2006. Instrumental quantile regression inference for structural and treatment effect models. *Journal of Econometrics* 132(2): 491–525.

———. 2008. Instrumental variable quantile regression: A robust inference approach. *Journal of Econometrics* 142(1): 379–398.

Kaplan, D. M., and Y. Sun. 2017. Smoothed estimating equations for instrumental variables quantile regression. *Econometric Theory* 33(1): 105–157.

Poterba, J. M., S. F. Venti, and D. A. Wise. 1995. Do 401(k) contributions crowd out other personal saving? *Journal of Public Economics* 58(1): 1–32.

Appendix

Contents

1 ivqregress iqr output

```
. ivqregress iqr assets (i.p401k = i.e401k) $covariates, quantile(10(10)90)

Initial grid:
Quantile = 0.10: .........10.........20.........30 done
Quantile = 0.20: .........10.........20.........30 done
Quantile = 0.30: .........10.........20.........30 done
Quantile = 0.40: .........10.........20.........30 done
Quantile = 0.50: .........10.........20.........30 done
Quantile = 0.60: .........10.........20.........30 done
Quantile = 0.70: .........10.........20.........30 done
Quantile = 0.80: .........10.........20.........30 done
Quantile = 0.90: .........10.........20.........30 done

Adaptive grid:
Quantile = 0.10: .........10.........20.........30 done
Quantile = 0.20: .........10.........20.........30 done
Quantile = 0.30: .........10.........20.........30 done
Quantile = 0.40: .........10.........20.........30 done
Quantile = 0.50: .........10.........20.........30 done
Quantile = 0.60: .........10.........20.........30 done
Quantile = 0.70: .........10.........20.........30 done
Quantile = 0.80: .........10.........20.........30 done
Quantile = 0.90: .........10.........20.........30 done

IV quantile regression                                Number of obs =    9,913
Estimator: Inverse quantile regression                Wald chi2(81) = 5121.46
                                                      Prob > chi2   =  0.0000
```

assets	Coefficient	Robust std. err.	z	P>|z|	[95% conf.	interval]
q10						
1.p401k	3240.08	475.6184	6.81	0.000	2307.885	4172.275
income	.0303072	.0123138	2.46	0.014	.0061725	.0544419
age	131.5908	15.13725	8.69	0.000	101.9223	161.2592
familysize	-329.2838	123.4665	-2.67	0.008	-571.2737	-87.29385
educ	-301.1635	52.02897	-5.79	0.000	-403.1384	-199.1885
married						
Married	-1504.648	380.0373	-3.96	0.000	-2249.508	-759.7886
ira						
Yes	7864.15	344.2198	22.85	0.000	7189.492	8538.809
pension						
Receives ..	63.88643	326.6017	0.20	0.845	-576.2412	704.0141
ownhome						
Yes	969.6861	300.4319	3.23	0.001	380.8503	1558.522
_cons	-7455.806	1192.112	-6.25	0.000	-9792.302	-5119.311
q20						
1.p401k	3446.347	334.4227	10.31	0.000	2790.89	4101.803
income	.0730526	.0083383	8.76	0.000	.0567097	.0893954
age	117.4232	10.09197	11.64	0.000	97.64336	137.2031
familysize	-311.518	77.31495	-4.03	0.000	-463.0525	-159.9835

educ	-198.8986	36.72851	-5.42	0.000	-270.8852	-126.9121
married						
Married	-1023.821	245.1418	-4.18	0.000	-1504.29	-543.3515
ira						
Yes	8728.335	389.1614	22.43	0.000	7965.593	9491.077
pension						
Receives ..	8.450874	211.6773	0.04	0.968	-406.429	423.3307
ownhome						
Yes	247.107	193.7332	1.28	0.202	-132.6031	626.817
_cons	-6064.723	762.7341	-7.95	0.000	-7559.654	-4569.791
q30						
1.p401k	3674.434	318.7578	11.53	0.000	3049.68	4299.188
income	.0900328	.0080609	11.17	0.000	.0742337	.1058319
age	106.4245	8.502461	12.52	0.000	89.76	123.089
familysize	-217.4507	57.05271	-3.81	0.000	-329.272	-105.6295
educ	-122.6666	32.44148	-3.78	0.000	-186.2508	-59.08249
married						
Married	-1021.046	209.9362	-4.86	0.000	-1432.513	-609.5787
ira						
Yes	11974.65	566.1735	21.15	0.000	10864.98	13084.33
pension						
Receives ..	-149.6646	187.9519	-0.80	0.426	-518.0435	218.7144
ownhome						
Yes	118.1594	157.3384	0.75	0.453	-190.2182	426.537
_cons	-5631.287	617.0855	-9.13	0.000	-6840.752	-4421.821
q40						
1.p401k	4196.127	369.6983	11.35	0.000	3471.532	4920.722
income	.1230721	.0104554	11.77	0.000	.1025799	.1435643
age	93.83839	7.963134	11.78	0.000	78.23093	109.4458
familysize	-225.3647	51.96267	-4.34	0.000	-327.2097	-123.5198
educ	-112.4069	30.98445	-3.63	0.000	-173.1353	-51.67845
married						
Married	-1191.624	211.8386	-5.63	0.000	-1606.82	-776.4277
ira						
Yes	16997.44	803.6711	21.15	0.000	15422.28	18572.61
pension						
Receives ..	-511.7032	194.9456	-2.62	0.009	-893.7895	-129.6168
ownhome						
Yes	102.3659	148.1471	0.69	0.490	-187.997	392.7288
_cons	-4787.913	553.4111	-8.65	0.000	-5872.579	-3703.247
q50						
1.p401k	5313.397	573.2818	9.27	0.000	4189.786	6437.009
income	.1577512	.0124889	12.63	0.000	.1332735	.1822289

age	99.96526	8.561923	11.68	0.000	83.1842	116.7463
familysize	-197.8251	54.36773	-3.64	0.000	-304.3838	-91.26627
educ	-96.43983	32.09465	-3.00	0.003	-159.3442	-33.53547
married						
Married	-1359.124	227.3366	-5.98	0.000	-1804.696	-913.5528
ira						
Yes	22629.61	1022.706	22.13	0.000	20625.15	24634.08
pension						
Receives ..	-693.8347	210.6176	-3.29	0.001	-1106.638	-281.0317
ownhome						
Yes	-30.29657	154.7265	-0.20	0.845	-333.555	272.9618
_cons	-4998.673	570.1315	-8.77	0.000	-6116.11	-3881.236
q60						
1.p401k	7006.205	801.4258	8.74	0.000	5435.439	8576.97
income	.2327564	.0174037	13.37	0.000	.1986458	.2668671
age	135.4321	11.38565	11.89	0.000	113.1166	157.7475
familysize	-262.5927	65.82424	-3.99	0.000	-391.6058	-133.5795
educ	-118.7153	40.43096	-2.94	0.003	-197.9585	-39.47208
married						
Married	-1716.762	269.9874	-6.36	0.000	-2245.927	-1187.596
ira						
Yes	30301.55	1241.557	24.41	0.000	27868.15	32734.96
pension						
Receives ..	-988.7325	261.4987	-3.78	0.000	-1501.261	-476.2044
ownhome						
Yes	-122.2135	193.9046	-0.63	0.529	-502.2595	257.8324
_cons	-6290.287	688.2098	-9.14	0.000	-7639.154	-4941.421
q70						
1.p401k	9093.469	1109.745	8.19	0.000	6918.408	11268.53
income	.3459585	.0226207	15.29	0.000	.3016228	.3902942
age	191.2876	16.53737	11.57	0.000	158.875	223.7003
familysize	-242.6605	86.05014	-2.82	0.005	-411.3157	-74.00534
educ	-143.4298	51.12786	-2.81	0.005	-243.6386	-43.22104
married						
Married	-2470.874	352.4949	-7.01	0.000	-3161.751	-1779.996
ira						
Yes	39365.32	1608.07	24.48	0.000	36213.56	42517.08
pension						
Receives ..	-1796.514	344.5429	-5.21	0.000	-2471.806	-1121.222
ownhome						
Yes	-4.058645	262.5795	-0.02	0.988	-518.7051	510.5878
_cons	-8637.647	928.462	-9.30	0.000	-10457.4	-6817.894
q80						

```
     1.p401k |   10699.12   1651.062     6.48   0.000     7463.098    13935.14
      income |   .5103271   .0293056    17.41   0.000     .4528892    .5677649
         age |   280.7892   24.10894    11.65   0.000     233.5366    328.0419
  familysize |  -400.8973   117.2019    -3.42   0.001    -630.6089   -171.1858
        educ |   -130.398   68.51364    -1.90   0.057    -264.6823    3.886266
             |
     married |
    Married  |  -2902.662   480.5005    -6.04   0.000    -3844.426   -1960.899
             |
         ira |
        Yes  |   48875.79   2297.873    21.27   0.000     44372.04    53379.54
             |
     pension |
Receives ..  |  -3072.814   502.6944    -6.11   0.000    -4058.077   -2087.551
             |
     ownhome |
        Yes  |   235.2409   402.9808     0.58   0.559    -554.5869    1025.069
       _cons |  -11871.24   1257.402    -9.44   0.000     -14335.7   -9406.775
-------------+----------------------------------------------------------------
q90          |
     1.p401k |   15983.42   3046.028     5.25   0.000     10013.32    21953.53
      income |   .8247356   .0570029    14.47   0.000      .713012    .9364593
         age |   485.8734   48.99224     9.92   0.000     389.8504    581.8965
  familysize |  -646.4962    185.913    -3.48   0.001    -1010.879   -282.1134
        educ |    48.4205   106.2844     0.46   0.649    -159.8931    256.7341
             |
     married |
    Married  |  -3265.007   753.4701    -4.33   0.000    -4741.782   -1788.233
             |
         ira |
        Yes  |   68543.44   4952.261    13.84   0.000     58837.18    78249.69
             |
     pension |
Receives ..  |  -4656.177   869.4887    -5.36   0.000    -6360.343    -2952.01
             |
     ownhome |
        Yes  |   400.1957   680.2776     0.59   0.556     -933.124    1733.515
       _cons |  -20594.85   2260.983    -9.11   0.000     -25026.3   -16163.41
------------------------------------------------------------------------------
Endogenous: 1.p401k
Exogenous:  income age familysize educ 1.married 1.ira 1.pension 1.ownhome
            1.e401k

. estimates  store iqr
```

2 ivqregress smooth output

```
. ivqregress smooth assets (i.p401k = i.e401k) $covariates, quantile(10(10)90)

Fitting smoothed IV quantile regression:

Quantile = .1:
Step 1: Bandwidth = 1327.0069    GMM criterion Q(b) = 9.224e-11
Step 2: Bandwidth = 1311.3131    GMM criterion Q(b) = 1.997e-10

Quantile = .2:
```

```
Step 1: Bandwidth = 1272.5204    GMM criterion Q(b) = 2.089e-10
Step 2: Bandwidth = 1237.7195    GMM criterion Q(b) = 3.115e-19

Quantile = .3:
Step 1: Bandwidth = 1504.4065    GMM criterion Q(b) = 5.407e-13
Step 2: Bandwidth = 1486.4224    GMM criterion Q(b) = 1.153e-10

Quantile = .4:
Step 1: Bandwidth = 1362.7753    GMM criterion Q(b) = 5.797e-17
Step 2: Bandwidth = 1362.6479    GMM criterion Q(b) = 2.271e-16

Quantile = .5:
Step 1: Bandwidth = 1302.9736    GMM criterion Q(b) = 2.617e-08
Step 2: Bandwidth = 6079.6881    GMM criterion Q(b) = 2.391e-12
Step 3: Bandwidth = 1438.3068    GMM criterion Q(b) = 9.212e-13

Quantile = .6:
Step 1: Bandwidth = 1533.5129    GMM criterion Q(b) = 2.663e-18
Step 2: Bandwidth = 1520.1182    GMM criterion Q(b) = 1.557e-19

Quantile = .7:
Step 1: Bandwidth = 2044.8617    GMM criterion Q(b) = 1.391e-10
Step 2: Bandwidth = 1977.2482    GMM criterion Q(b) = 1.825e-11

Quantile = .8:
Step 1: Bandwidth = 2503.7256    GMM criterion Q(b) = 3.623e-10
Step 2: Bandwidth = 2458.6714    GMM criterion Q(b) = 2.307e-10

Quantile = .9:
Step 1: Bandwidth = 3560.2178    GMM criterion Q(b) = 4.301e-12
Step 2: Bandwidth = 3529.3557    GMM criterion Q(b) = 2.929e-10

IV quantile regression                             Number of obs =    9,913
Estimator: Smoothed estimating equations           Wald chi2(81) = 4932.84
                                                   Prob > chi2   =   0.0000
```

assets	Coefficient	Robust std. err.	z	P>|z|	[95% conf.	interval]
q10						
1.p401k	3191.667	486.2193	6.56	0.000	2238.695	4144.639
income	.0318585	.0123707	2.58	0.010	.0076124	.0561046
age	128.9268	15.42632	8.36	0.000	98.69178	159.1618
familysize	-329.8374	125.4774	-2.63	0.009	-575.7687	-83.90615
educ	-289.8807	53.06713	-5.46	0.000	-393.8904	-185.8711
married						
Married	-1480.013	386.4611	-3.83	0.000	-2237.463	-722.5635
ira						
Yes	7914.049	342.9506	23.08	0.000	7241.878	8586.22
pension						
Receives ..	-5.356704	334.9869	-0.02	0.987	-661.919	651.2056
ownhome						
Yes	1043.279	308.722	3.38	0.001	438.1945	1648.363
_cons	-7631.313	1214.725	-6.28	0.000	-10012.13	-5250.496
q20						
1.p401k	3503.744	338.8383	10.34	0.000	2839.633	4167.854
income	.0737261	.0084716	8.70	0.000	.057122	.0903302

age	114.9688	10.38239	11.07	0.000	94.61965	135.3179
familysize	-277.8925	78.67289	-3.53	0.000	-432.0885	-123.6964
educ	-194.0516	37.98876	-5.11	0.000	-268.5082	-119.595
married						
Married	-1160.725	253.6528	-4.58	0.000	-1657.876	-663.5752
ira						
Yes	8799.905	388.3753	22.66	0.000	8038.703	9561.106
pension						
Receives ..	-33.33779	218.144	-0.15	0.879	-460.8921	394.2165
ownhome						
Yes	386.2308	201.4194	1.92	0.055	-8.543996	781.0057
_cons	-6264.968	792.0489	-7.91	0.000	-7817.356	-4712.581
q30						
1.p401k	3754.908	320.9631	11.70	0.000	3125.832	4383.984
income	.0939826	.0083408	11.27	0.000	.0776348	.1103303
age	103.8314	8.712147	11.92	0.000	86.75593	120.9069
familysize	-250.4947	59.95479	-4.18	0.000	-368.0039	-132.9855
educ	-134.7013	33.4085	-4.03	0.000	-200.1808	-69.22189
married						
Married	-1028.643	217.4311	-4.73	0.000	-1454.8	-602.4861
ira						
Yes	12008.63	563.5555	21.31	0.000	10904.08	13113.18
pension						
Receives ..	-179.5281	192.0513	-0.93	0.350	-555.9418	196.8855
ownhome						
Yes	195.7323	162.634	1.20	0.229	-123.0246	514.4891
_cons	-5536.814	637.1917	-8.69	0.000	-6785.686	-4287.941
q40						
1.p401k	4326.754	371.7419	11.64	0.000	3598.153	5055.354
income	.1288469	.0105877	12.17	0.000	.1080955	.1495983
age	99.89601	8.289602	12.05	0.000	83.64869	116.1433
familysize	-231.3411	53.94265	-4.29	0.000	-337.0668	-125.6155
educ	-114.4753	32.09266	-3.57	0.000	-177.3758	-51.57484
married						
Married	-1212.951	216.8328	-5.59	0.000	-1637.935	-787.966
ira						
Yes	16874.38	801.2841	21.06	0.000	15303.89	18444.86
pension						
Receives ..	-493.1742	198.6221	-2.48	0.013	-882.4663	-103.8821
ownhome						
Yes	105.4536	152.7777	0.69	0.490	-193.9852	404.8925
_cons	-5216.625	581.4362	-8.97	0.000	-6356.219	-4077.031
q50						

1.p401k	5364.468	573.3728	9.36	0.000	4240.678	6488.258
income	.1679934	.013419	12.52	0.000	.1416925	.1942942
age	113.6318	9.352867	12.15	0.000	95.30052	131.9631
familysize	-228.7766	57.61072	-3.97	0.000	-341.6916	-115.8617
educ	-102.2889	34.18527	-2.99	0.003	-169.2908	-35.28701
married						
Married	-1362.56	238.5988	-5.71	0.000	-1830.205	-894.9153
ira						
Yes	22402.04	1043.504	21.47	0.000	20356.81	24447.27
pension						
Receives ..	-713.996	220.476	-3.24	0.001	-1146.121	-281.8709
ownhome						
Yes	-12.71396	161.3703	-0.08	0.937	-328.994	303.5661
_cons	-5672.645	619.7049	-9.15	0.000	-6887.244	-4458.045
q60						
1.p401k	6964.18	799.1829	8.71	0.000	5397.811	8530.55
income	.2422267	.0180009	13.46	0.000	.2069457	.2775078
age	145.0532	11.88882	12.20	0.000	121.7515	168.3549
familysize	-271.8402	68.28584	-3.98	0.000	-405.678	-138.0024
educ	-128.4236	41.84504	-3.07	0.002	-210.4384	-46.40883
married						
Married	-1790.19	278.6729	-6.42	0.000	-2336.379	-1244.001
ira						
Yes	30029.76	1251.554	23.99	0.000	27576.76	32482.76
pension						
Receives ..	-1063.919	269.4261	-3.95	0.000	-1591.984	-535.8533
ownhome						
Yes	-79.57029	198.2018	-0.40	0.688	-468.0387	308.8981
_cons	-6708.442	714.0485	-9.39	0.000	-8107.951	-5308.932
q70						
1.p401k	9002.846	1108.915	8.12	0.000	6829.412	11176.28
income	.3555392	.0229067	15.52	0.000	.310643	.4004354
age	203.3279	17.59732	11.55	0.000	168.8378	237.818
familysize	-314.0023	89.13006	-3.52	0.000	-488.694	-139.3106
educ	-163.099	52.90533	-3.08	0.002	-266.7916	-59.40646
married						
Married	-2396.634	359.7017	-6.66	0.000	-3101.636	-1691.631
ira						
Yes	38962.04	1621.653	24.03	0.000	35783.66	42140.42
pension						
Receives ..	-1882.868	352.3168	-5.34	0.000	-2573.396	-1192.34
ownhome						
Yes	-19.74677	271.0796	-0.07	0.942	-551.053	511.5595
_cons	-8753.875	954.0692	-9.18	0.000	-10623.82	-6883.934

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q80          |
      1.p401k |   10658.02   1665.467     6.40   0.000     7393.765    13922.27
      income |   .5172628   .0298155    17.35   0.000     .4588255       .5757
         age |   293.9692   24.78395    11.86   0.000     245.3935    342.5448
  familysize |  -407.2737   119.8248    -3.40   0.001    -642.1259   -172.4214
        educ |  -131.0776   69.87187    -1.88   0.061    -268.0239    5.868784
             |
     married |
    Married  |   -3077.77   491.0029    -6.27   0.000    -4040.118   -2115.422
             |
         ira |
        Yes  |   48410.11   2296.042    21.08   0.000     43909.95    52910.27
             |
     pension |
Receives ..  |  -3049.023   515.0161    -5.92   0.000    -4058.436    -2039.61
             |
     ownhome |
        Yes  |   272.4814   412.1642     0.66   0.509    -535.3457    1080.308
       _cons |  -12294.73   1284.692    -9.57   0.000    -14812.68   -9776.781
-------------+----------------------------------------------------------------
q90          |
     1.p401k |   15525.23   3035.965     5.11   0.000     9574.848    21475.61
      income |   .8311508   .0574108    14.48   0.000     .7186277    .9436738
         age |   486.9876   51.61654     9.43   0.000      385.821    588.1541
  familysize |  -586.2617   193.5936    -3.03   0.002    -965.6983   -206.8252
        educ |    14.5293   110.8781     0.13   0.896    -202.7878    231.8464
             |
     married |
    Married  |  -3877.165   781.2296    -4.96   0.000    -5408.347   -2345.983
             |
         ira |
        Yes  |   67888.86   4902.106    13.85   0.000     58280.91    77496.81
             |
     pension |
Receives ..  |  -4829.506   898.9147    -5.37   0.000    -6591.346   -3067.665
             |
     ownhome |
        Yes  |   715.6272   722.8727     0.99   0.322    -701.1773    2132.432
       _cons |  -19953.21   2326.698    -8.58   0.000    -24513.45   -15392.96
------------------------------------------------------------------------------
Endogenous: 1.p401k
Exogenous:  income age familysize educ 1.married 1.ira 1.pension 1.ownhome
            1.e401k

. estimates  store smooth
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