



Microeconomic Modeling

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4. Quantile Regresion



Quantile Regression

- $Q(y|\mathbf{x}, \alpha) = \beta' \mathbf{x}$, α = quantile
- Estimated by linear programming
- $Q(y|\mathbf{x}, .50) = \beta' \mathbf{x}$, $.50 \rightarrow$ median regression
- Median regression estimated by LAD (estimates same parameters as mean regression if symmetric conditional distribution)
- Why use quantile (median) regression?
 - Semiparametric
 - Robust to some extensions (heteroscedasticity?)
 - Complete characterization of conditional distribution



Estimated Variance for Quantile Regression

- Asymptotic Theory
- Bootstrap – an ideal application



Asymptotic Theory Based Estimator of Variance of Q - REG

Model: $y_i = \beta_i + u_i$, $Q(y_i | \mathbf{x}_i, \alpha) = \beta_i$, $Q[u_i | \mathbf{x}_i, \alpha] = 0$

Residuals: $\hat{u}_i = y_i - \hat{\beta}_i$

Asymptotic Variance: $\frac{1}{N} (\mathbf{A}^{-1} \mathbf{C} \mathbf{A}^{-1})$

$\mathbf{A} = E[f_u(0)\mathbf{xx}']$ Estimated by $\frac{1}{N} \sum_{i=1}^N \frac{1}{B} \frac{1}{2} 1[|\hat{u}_i| < B] \mathbf{x}_i \mathbf{x}_i'$

Bandwidth B can be Silverman's Rule of Thumb:

$$\frac{1.06}{N^{.2}} \text{Min} \left(s_u, \frac{Q(\hat{u}_i | .75) - Q(\hat{u}_i | .25)}{1.349} \right)$$

$\mathbf{C} = \alpha(1-\alpha)E[\mathbf{xx}']$ Estimated by $\frac{\alpha(1-\alpha)}{N} \mathbf{X}'\mathbf{X}$

For $\alpha=.5$ and normally distributed u , this all simplifies to $\frac{\pi}{2} s_u^2 (\mathbf{X}'\mathbf{X})^{-1}$.

But, this is an ideal application for bootstrapping.



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Quantile Regression Model. Quantile = .250000
Linear Programming estimation method
LHS=HHNINC  Mean = .44583
            Standard deviation = .21650
            Number of observs. = 3377
            Minimum = .04000
            t= .25000 quantile = .30000
            Maximum = 3.00000
Model size  Parameters = 5
            Degrees of freedom = 3372
Residuals   Sum of squares = 193.75951
            Standard error of e = .20226
Fit          R-squared = .12721
            PseudoR2=1-F(0)/F(b) = .11046
Not using OLS or no constant. Rsquared may be <= 0
Functions F= Sum r(t)[y(i)-x(i)b] = 164.31749
          F0=Sum r(t)[y(i)-Qy(t)] = 184.72281
          r(t)[u]=t*u-u*[u<0].t= .250000
  
```

HHNINC	Coefficient	Standard Error	z	Prob. z >Z*	95% Confidence Interval	
Constant	-.07580***	.01839	-4.12	.0000	-.11185	-.03975
AGE	-.00036**	.00016	-2.25	.0244	-.00068	-.00005
EDUC	.02393***	.00137	17.51	.0000	.02125	.02661
MARRIED	.11459***	.00547	20.96	.0000	.10388	.12531
HSAT	.00773***	.00122	6.31	.0000	.00533	.01013
Constant	-.01504	.03479	-.43	.6656	-.08323	.05315
AGE	-.00035	.00039	-.90	.3669	-.00112	.00041
EDUC	.02707***	.00167	16.19	.0000	.02379	.03035
MARRIED	.11361***	.01115	10.19	.0000	.09175	.13547
HSAT	.00777***	.00195	3.99	.0001	.00396	.01158
Constant	.03738	.03246	1.15	.2495	-.02624	.10099
AGE	.00020	.00039	.51	.6100	-.00057	.00097
EDUC	.03240***	.00237	13.68	.0000	.02776	.03704
MARRIED	.08042***	.01112	7.23	.0000	.05863	.10222
HSAT	.00693***	.00231	3.00	.0027	.00240	.01145

Note: ***, **, * ==> Significance at 1%, 5%, 10% level.

$\alpha = .25$

$\alpha = .50$

$\alpha = .75$



OLS vs. Least Absolute Deviations

Least absolute deviations estimator.....					
Residuals	Sum of squares	=	1537.58603		
	Standard error of e	=	6.82594		
Fit	R-squared	=	.98284		
	Adjusted R-squared	=	.98180		
Sum of absolute deviations		=	189.3973484		
-----+-----					
Variable	Coefficient	Standard Error	b/St.Er.	P[Z >z]	Mean of X
-----+-----					
	Covariance matrix based on 50 replications.				
Constant	-84.0258***	16.08614	-5.223	.0000	
Y	.03784***	.00271	13.952	.0000	9232.86
PG	-17.0990***	4.37160	-3.911	.0001	2.31661
-----+-----					
Ordinary least squares regression					
Residuals	Sum of squares	=	1472.79834		
	Standard error of e	=	6.68059	Standard errors are based on	
Fit	R-squared	=	.98356	50 bootstrap replications	
	Adjusted R-squared	=	.98256		
-----+-----					
Variable	Coefficient	Standard Error	t-ratio	P[T >t]	Mean of X
-----+-----					
Constant	-79.7535***	8.67255	-9.196	.0000	
Y	.03692***	.00132	28.022	.0000	9232.86
PG	-15.1224***	1.88034	-8.042	.0000	2.31661
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QUANTILE REGRESSION ANALYSIS OF THE RATIONAL ADDICTION MODEL: INVESTIGATING HETEROGENEITY IN FORWARD-LOOKING BEHAVIOR

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SUMMARY

The time path of consumption from a rational addiction (RA) model contains information about an individual's tendency to be forward looking. In this paper, we use quantile regression (QR) techniques to investigate whether the tendency to be forward looking varies systematically with **the level of consumption of cigarettes**. Using panel data,

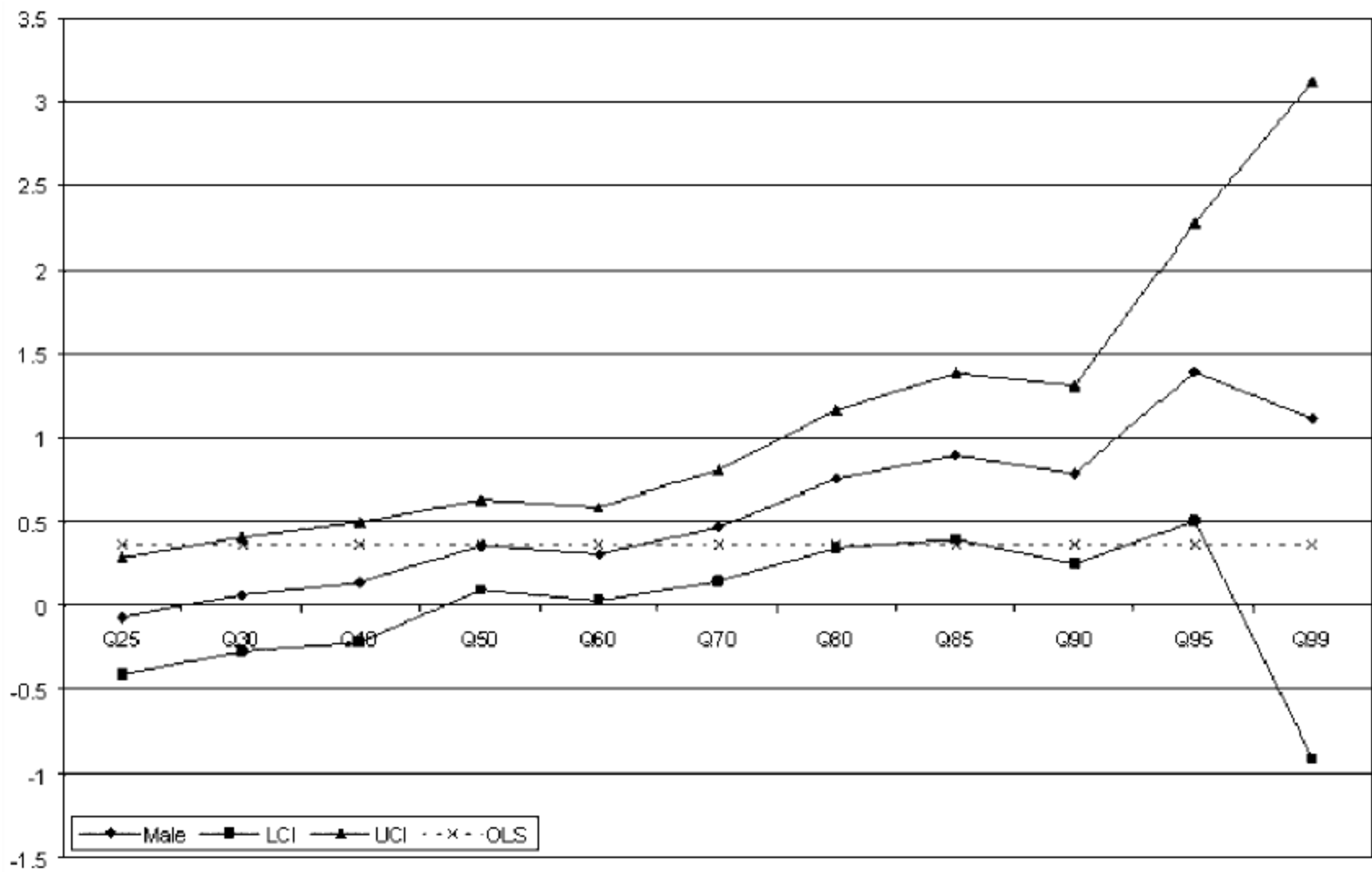


Figure 4. Male