

churdle — Cragg hurdle regression

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Description

`churdle` fits a linear or exponential hurdle model for a bounded dependent variable. The hurdle model combines a selection model that determines the boundary points of the dependent variable with an outcome model that determines its nonbounded values. Separate independent covariates are permitted for each model.

Quick start

Linear hurdle model of `y1` on `x1` and `x2`, specifying that `y1` is truncated at 0 with `x1` and `x3` predicting selection

```
churdle linear y1 x1 x2, select(x1 x3) ll(0)
```

Add an upper truncation limit of 40

```
churdle linear y1 x1 x2, select(x1 x3) ll(0) ul(40)
```

As above, with the upper truncation limit specified in `trunc`

```
churdle linear y1 x1 x2, select(x1 x3) ll(0) ul(trunc)
```

As above, and use `x3` to model the variance of the selection model

```
churdle linear y1 x1 x2, select(x1 x3, het(x3)) ll(0) ul(trunc)
```

As above, and use `x4` to model the variance of the outcome model

```
churdle linear y1 x1 x2, select(x1 x3, het(x3)) ll(0) ///
    ul(trunc) het(x4)
```

Exponential hurdle model of `y2` on `x1` and `x2`, specifying that `y2` is truncated at 4 with `x1` and `x3` predicting selection

```
churdle exponential y2 x1 x2, select(x1 x3) ll(4)
```

Menu

Statistics > Linear models and related > Hurdle regression

Syntax

Basic syntax

```
churdle linear depvar, select(varlists) {ll(...) | ul(...) }
```

```
churdle exponential depvar, select(varlists) ll(...)
```

Full syntax for churdle linear

```
churdle linear depvar [indepvars] [if] [in] [weight],
select(varlists [, noconstant het(varlisto) ])
{ ll(# | varname) | ul(# | varname) } [options]
```

Full syntax for churdle exponential

```
churdle exponential depvar [indepvars] [if] [in] [weight],
select(varlists [, noconstant het(varlisto) ]) ll(# | varname) [options]
```

options

Description

Model

* <u>select</u> ()	specify independent variables and options for selection model
‡ ll(# <i>varname</i>)	lower truncation limit
‡ ul(# <i>varname</i>)	upper truncation limit
<u>noconstant</u>	suppress constant term
<u>constraints</u> (<i>constraints</i>)	apply specified linear constraints
het(<i>varlist</i>)	specify variables to model the variance

SE/Robust

vce(*vcetype*) *vcetype* may be oim, robust, cluster *clustvar*, bootstrap, or jackknife

Reporting

level(#) set confidence level; default is level(95)
nocnsreport do not display constraints
display_options control columns and column formats, row spacing, line width, display of omitted variables and base and empty cells, and factor-variable labeling

Maximization

maximize_options control the maximization process; seldom used

coeflegend display legend instead of statistics

*`select()` is required.

The full specification is `select(varlists [, noconstant het(varlisto)])`.

`noconstant` specifies that the constant be excluded from the selection model.

`het(varlisto)` specifies the variables in the error-variance function of the selection model.

‡ You must specify at least one of `ul(#|varname)` or `ll(#|varname)` for the linear model and must specify `ll(#|varname)` for the exponential model.

`indepvars`, `varlists`, and `varlisto` may contain factor variables; see [U] 11.4.3 Factor variables.

`bootstrap`, `by`, `fp`, `jackknife`, `rolling`, `statsby`, and `svy` are allowed; see [U] 11.1.10 Prefix commands.

Weights are not allowed with the `bootstrap` prefix; see [R] bootstrap.

`vce()` and weights are not allowed with the `svy` prefix; see [SVY] svy.

`fweights`, `iwweights`, and `pweights` are allowed; see [U] 11.1.6 weight.

`coeflegend` does not appear in the dialog box.

See [U] 20 Estimation and postestimation commands for more capabilities of estimation commands.

Options

Model

`select(varlists [, noconstant het(varlisto)])` specifies the variables and options for the selection model. `select()` is required.

`ll(#|varname)` and `ul(#|varname)` indicate the lower and upper limits, respectively, for the dependent variable. You must specify one or both for the linear model and must specify a lower limit for the exponential model. Observations with `depvar ≤ ll()` have a lower bound; observations with `depvar ≥ ul()` have an upper bound; and the remaining observations are in the continuous region.

`noconstant`, `constraints(constraints)`; see [R] estimation options.

`het(varlist)` specifies the variables in the error-variance function of the outcome model.

SE/Robust

`vce(vctype)` specifies the type of standard error reported, which includes types that are derived from asymptotic theory (`oim`), that are robust to some kinds of misspecification (`robust`), that allow for intragroup correlation (`cluster`, `clustvar`), and that use bootstrap or jackknife methods (`bootstrap`, `jackknife`); see [R] vce_option.

Reporting

`level(#)`, `nocnsreport`; see [R] estimation options.

`display_options`: `nocl`, `nopvalues`, `noomitted`, `vsquish`, `noemptycells`, `baselevels`, `allbaselevels`, `nofvlabel`, `fvwrap(#)`, `fvwrapon(style)`, `cformat(%fmt)`, `pformat(%fmt)`, `sformat(%fmt)`, and `nolstretch`; see [R] estimation options.

Maximization

`maximize_options`: `difficult`, `technique(algorithm_spec)`, `iterate(#)`, `[no]log`, `trace`, `gradient`, `showstep`, `hessian`, `showtolerance`, `tolerance(#)`, `ltolerance(#)`, `nrtolerance(#)`, `nonrtolerance`, and `from(init_specs)`; see [R] maximize. These options are seldom used.

The following option is available with `churdle` but is not shown in the dialog box: `coeflegend`; see [R] [estimation options](#).

Remarks and examples

stata.com

`churdle` fits a linear or an exponential hurdle model. It combines a selection model that determines the boundary points of the dependent variable with an outcome model that determines its nonbounded values. Hurdle models treat these boundary values as observed instead of censored. That is to say, observations where the dependent variable is equal to one of the boundary values are not the result of our inability to observe the distribution above or below a certain point; see [Wooldridge \(2010\)](#) chapter 17 for a thorough discussion of this point.

These models were proposed by [Cragg \(1971\)](#) to explain the demand for durable goods. In the Cragg model, individuals purchase zero or a positive amount of the durable good, with different factors determining each of these choices. This may be generalized to other individual decisions, such as money donated to charity, cigarette consumption, and time spent volunteering.

Hurdle models are characterized by the relationship $y_i = s_i h_i^*$, where y_i is the observed value of the dependent variable.

The selection variable, s_i , is 1 if the dependent variable is not bounded and 0 otherwise. In the Cragg model, the lower limit that binds the dependent variable is 0 so the selection model is

$$s_i = \begin{cases} 1 & \text{if } \mathbf{z}_i \boldsymbol{\gamma} + \epsilon_i > 0 \\ 0 & \text{otherwise} \end{cases}$$

where \mathbf{z}_i is a vector of explanatory variables, $\boldsymbol{\gamma}$ is a vector of coefficients, and ϵ_i is a standard normal error term. `churdle` allows a different lower limit to be specified in `ll()` and, for the linear model, an upper limit in `ul()`. Conditional heteroskedasticity of the random error ϵ_i is allowed if suboption `het()` is specified in `select()`.

The continuous latent variable h_i^* is observed only if $s_i = 1$. The outcome model can be either the linear model or the exponential model, as proposed in [Cragg \(1971\)](#):

$$\begin{aligned} h_i^* &= \mathbf{x}_i \boldsymbol{\beta} + \nu_i && \text{(linear)} \\ h_i^* &= \exp(\mathbf{x}_i \boldsymbol{\beta} + \nu_i) && \text{(exponential)} \end{aligned}$$

where \mathbf{x}_i is a vector of explanatory variables, $\boldsymbol{\beta}$ is a vector of coefficients, and ν_i is an error term.

For the linear model, ν_i has a truncated normal distribution with lower truncation point $-\mathbf{x}_i \boldsymbol{\beta}$. For the exponential model, ν_i has a normal distribution. `churdle` extends the Cragg hurdle models to allow for conditional heteroskedasticity of the random error ν_i if the user specifies the `het()` option.

The parameters and regressors in the models for h_i^* and for s_i may differ.

▷ Example 1: Linear hurdle model

Consider a dataset that contains the number of hours an individual exercises per day (`hours`), their age (`age`), whether they are single (`single`), hours they work per day (`whours`), whether they smoke (`smoke`), their weight in kilograms (`weight`), their distance from the nearest gym (`distance`), and their average commute from work (`commute`).

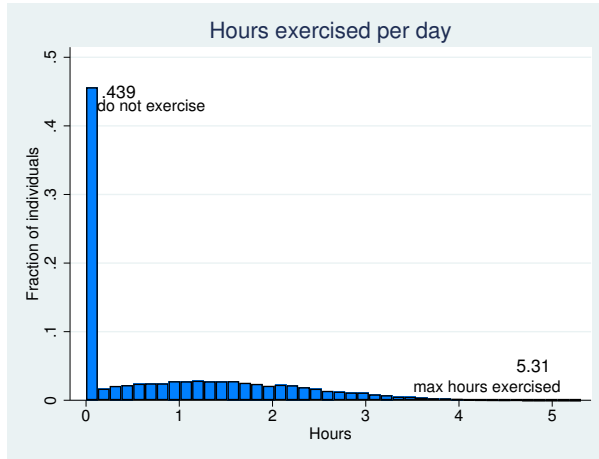


Figure 1

Figure 1 shows that 43.9% of the individuals in the sample do not exercise and that the hours exercised varies among individuals that decide to exercise.

We model the decision to exercise or not as a function of `commute`, `whours`, and `age`. These variables are written in `select()`. Once a decision to exercise is made, the time an individual exercises is modeled as a linear function of `age`, `smoke`, `distance`, and `single`.

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```

. use http://www.stata-press.com/data/r15/fitness
. churdle linear hours age i.smoke distance i.single,
> select(commute whours age) ll(0)
Iteration 0:  log likelihood = -23657.236
Iteration 1:  log likelihood = -23344.182
Iteration 2:  log likelihood = -23340.051
Iteration 3:  log likelihood = -23340.044
Iteration 4:  log likelihood = -23340.044

Cragg hurdle regression                Number of obs   =    19,831
                                       LR chi2(4)      =    9059.26
                                       Prob > chi2     =     0.0000
                                       Pseudo R2      =     0.1625

Log likelihood = -23340.044

```

	hours	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
hours							
	age	.0015116	.000763	1.98	0.048	.0000162	.003007
	smoke						
	smoking	-1.06646	.0460578	-23.15	0.000	-1.156731	-.9761879
	distance	-.1333868	.0126344	-10.56	0.000	-.1581497	-.1086238
	single						
	single	.9940893	.0258775	38.42	0.000	.9433703	1.044808
	_cons	.9138855	.0396227	23.06	0.000	.8362264	.9915447
selection_ll							
	commute	-.2953345	.0624665	-4.73	0.000	-.4177666	-.1729024
	whours	.0022974	.0069306	0.33	0.740	-.0112864	.0158811
	age	-.0485347	.0006501	-74.65	0.000	-.049809	-.0472604
	_cons	2.649945	.0499795	53.02	0.000	2.551987	2.747903
lnsigma							
	_cons	.0083199	.0099648	0.83	0.404	-.0112107	.0278506
	/sigma	1.008355	.010048			.9888519	1.028242

The coefficients in the outcome model for the latent variable appear under `hours`. Because we only specified a lower limit to bind the dependent variable, the output shows parameter estimates for a single selection model under `selection_ll`. Information about the estimated standard deviation of the error term in the outcome model appears under `lnsigma` and `/sigma`.

The coefficient estimates are not directly interpretable. To obtain the effect of a covariate on the model, we need to use the `margins` command; see [R] [churdle postestimation](#). Consider the effect of `age`:

```
. margins, dydx(age)
```

```
Average marginal effects      Number of obs    =    19,831
Model VCE      : OIM
Expression    : Conditional mean estimates of dependent variable, predict()
dy/dx w.r.t.  : age
```

	Delta-method				[95% Conf. Interval]	
	dy/dx	Std. Err.	z	P> z		
age	-.0216855	.000289	-75.03	0.000	-.022252	-.021119

Each additional year of age is associated with about -0.02 fewer hours, or 1.2 minutes, of exercise.

◀

▶ Example 2: Linear hurdle with models for the outcome and selection variances

In this example, we illustrate the possibility of fitting a heteroskedastic probit for the selection and latent model. In both cases, this is done by specifying `age` and `single` as the variables that affect the conditional variance. As in [example 1](#), we have separate parameters for the outcome model and lower-limit selection model.

```
. churdle linear hours age i.smoke distance i.single,
> select(commute whours age, het(age single)) ll(0) het(age single) nolog
Cragg hurdle regression      Number of obs    =    19,831
                             LR chi2(4)           =    9060.63
                             Prob > chi2          =    0.0000
                             Pseudo R2            =    0.1626
Log likelihood = -23339.355
```

	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
hours						
age	.0012559	.0008198	1.53	0.126	-.0003508	.0028626
smoke						
smoking	-1.065564	.0457657	-23.28	0.000	-1.155263	-.9758649
distance	-.1332939	.0126102	-10.57	0.000	-.1580094	-.1085783
single						
single	1.002511	.032535	30.81	0.000	.9387436	1.066278
_cons	.9166356	.0388318	23.61	0.000	.8405268	.9927445
selection_ll						
commute	-.2959986	.0641594	-4.61	0.000	-.4217488	-.1702484
whours	.0024514	.0069769	0.35	0.725	-.0112231	.0161259
age	-.048886	.0021405	-22.84	0.000	-.0530814	-.0446906
_cons	2.669613	.1139478	23.43	0.000	2.44628	2.892947
lnsigma						
age	.0003537	.0004026	0.88	0.380	-.0004354	.0011427
single	-.0080667	.019253	-0.42	0.675	-.0458019	.0296685
lnsigma_ll						
age	-.0002035	.0008424	-0.24	0.809	-.0018546	.0014475
single	.0268271	.0270133	0.99	0.321	-.0261179	.0797721

The coefficients on `age` and `single` have no effect on the conditional variance of the outcome model or on the conditional variance of the selection model. Thus, there is no evidence that the variance depends on age and marital status.



▷ Example 3: Exponential hurdle model

Returning to [example 1](#), if we believe that the conditional mean of the latent variable has an exponential form instead of a linear form, we use `churdle exponential`.

```
. churdle exponential hours age i.smoke distance i.single,
> select(commute whours age) ll(0) nolog
Cragg hurdle regression                               Number of obs   =   19,831
                                                       LR chi2(4)      =   8663.21
                                                       Prob > chi2     =   0.0000
                                                       Pseudo R2      =   0.2166
Log likelihood = -15666.195
```

	hours	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
hours							
	age	.0008368	.0005341	1.57	0.117	-.00021	.0018836
	smoke						
	smoking	-.6431348	.0258509	-24.88	0.000	-.6938016	-.592468
	distance	-.0772879	.0079132	-9.77	0.000	-.0927976	-.0617783
	single						
	single	.5975111	.016108	37.09	0.000	.5659401	.6290821
	_cons	-.0770619	.0254833	-3.02	0.002	-.1270082	-.0271157
selection_ll							
	commute	-.2953345	.0624665	-4.73	0.000	-.4177666	-.1729024
	whours	.0022974	.0069306	0.33	0.740	-.0112864	.0158811
	age	-.0485347	.0006501	-74.65	0.000	-.049809	-.0472604
	_cons	2.649945	.0499795	53.02	0.000	2.551987	2.747903
lnsigma							
	_cons	-.186917	.0067067	-27.87	0.000	-.200062	-.1737721
	/sigma	.8295126	.0055633			.81868	.8404884

What was said previously regarding the interpretation of the effects of the different regressors also holds true for `churdle exponential`. We again use `margins` to estimate the effect of age on time spent exercising.

```
. margins, dydx(age)
Average marginal effects                               Number of obs   =   19,831
Model VCE      : OIM
Expression    : Conditional mean estimates of dependent variable, predict()
dy/dx w.r.t.  : age
```

		Delta-method		z	P> z	[95% Conf. Interval]	
	dy/dx	Std. Err.					
age	-.0353558	.000475	-74.43	0.000	-.0362868	-.0344248	

With the exponential outcome model of the latent variable, our estimate is that each additional year of age decreases exercise time by about 0.04 hours, or 2.4 minutes.



Stored results

churdle stores the following in `e()`:

Scalars

<code>e(N)</code>	number of observations
<code>e(k_eq_model)</code>	number of equations in overall model test
<code>e(df_m)</code>	model degrees of freedom
<code>e(r2_p)</code>	pseudo- <i>R</i> -squared
<code>e(chi2)</code>	χ^2
<code>e(ll)</code>	log likelihood
<code>e(ll_0)</code>	log likelihood, constant-only model
<code>e(N_clust)</code>	number of clusters
<code>e(p)</code>	significance
<code>e(rank)</code>	rank of <code>e(v)</code>
<code>e(converged)</code>	1 if converged, 0 otherwise

Macros

<code>e(cmd)</code>	churdle
<code>e(cmdline)</code>	command as typed
<code>e(depvar)</code>	name of dependent variable
<code>e(estimator)</code>	linear or exponential
<code>e(model)</code>	Linear or Exponential
<code>e(wtype)</code>	weight type
<code>e(wexp)</code>	weight expression
<code>e(title)</code>	title in estimation output
<code>e(clustvar)</code>	name of cluster variable
<code>e(chi2type)</code>	Wald or LR; type of model χ^2 test
<code>e(vce)</code>	<i>vcetype</i> specified in <code>vce()</code>
<code>e(vcetype)</code>	title used to label Std. Err.
<code>e(opt)</code>	type of optimization
<code>e(which)</code>	max or min; whether optimizer is to perform maximization or minimization
<code>e(technique)</code>	maximization technique
<code>e(properties)</code>	b V
<code>e(predict)</code>	program used to implement predict
<code>e(marginsnotok)</code>	predictions disallowed by margins
<code>e(asbalanced)</code>	factor variables <code>fvset</code> as <code>asbalanced</code>
<code>e(asobserved)</code>	factor variables <code>fvset</code> as <code>asobserved</code>

Matrices

<code>e(b)</code>	coefficient vector
<code>e(Cns)</code>	constraints matrix
<code>e(ilog)</code>	iteration log
<code>e(V)</code>	variance-covariance matrix of the estimators
<code>e(V_modelbased)</code>	model-based variance

Functions

<code>e(sample)</code>	marks estimation sample
------------------------	-------------------------

Methods and formulas

Let $\ell\ell$ refer to the lower limit and ul to the upper limit. Also let the probabilities of being at these limits be given by

$$\Pr(y_i = \ell\ell | \mathbf{z}_i) = \Phi(\ell\ell - \mathbf{z}'_i \boldsymbol{\gamma}_{\ell\ell})$$

$$\Pr(y_i = ul | \mathbf{z}_i) = \Phi(\mathbf{z}'_i \boldsymbol{\gamma}_{ul} - ul)$$

where \mathbf{z}_i are the covariates of the selection model for individual i , which may be distinct from the covariates \mathbf{x}_i for the latent model; Φ corresponds to the standard normal cumulative distribution function; $\gamma_{\ell\ell}$ is the parameter vector for the lower-limit selection model; and γ_{ul} is the parameter vector for the upper-limit selection model.

Under the assumptions that ν_i has a truncated normal distribution with lower truncation point $\ell\ell - \mathbf{x}'_i\beta$ and upper truncation point $ul - \mathbf{x}'_i\beta$ and has a homoskedastic variance, the log-likelihood function is given by

$$\begin{aligned} \ln\mathbf{L} = & \sum_{i=1}^n (y_i \leq \ell\ell) \log\Phi(\ell\ell - \mathbf{z}'_i\gamma_{\ell\ell}) + (y_i \geq ul) \log\{1 - \Phi(ul - \mathbf{z}'_i\gamma_{ul})\} \\ & + (ul > y_i > \ell\ell) [\log\{\Phi(ul - \mathbf{z}'_i\gamma_{ul}) - \Phi(\ell\ell - \mathbf{z}'_i\gamma_{\ell\ell})\}] \\ & - (ul > y_i > \ell\ell) \left[\log\left\{ \Phi\left(\frac{ul - \mathbf{x}'_i\beta}{\sigma}\right) - \Phi\left(\frac{\ell\ell - \mathbf{x}'_i\beta}{\sigma}\right) \right\} \right] \\ & + (ul > y_i > \ell\ell) \left[\log\left\{ \phi\left(\frac{y_i - \mathbf{x}'_i\beta}{\sigma}\right) \right\} - \log(\sigma) \right] \end{aligned}$$

Without the homoskedasticity assumption, the heteroskedasticity can be modeled using the form $\sigma^2(\mathbf{w}_i) = \exp(2\mathbf{w}'_i\theta)$, where \mathbf{w}_i are the variables that affect the conditional variance of ν_i . The log-likelihood function is obtained by replacing σ with $\exp(\mathbf{w}'_i\theta)$.

The log-likelihood function for the exponential model is given by

$$\begin{aligned} \ln\mathbf{L} = & \sum_{i=1}^n (y_i \leq \ell\ell) \log\Phi(\ell\ell - \mathbf{z}'_i\gamma) + (y_i > \ell\ell) [\log\{1 - \Phi(\ell\ell - \mathbf{z}'_i\gamma)\}] \\ & + (y_i > \ell\ell) \{ \log\{ \phi[\log(y_i - \ell\ell) - \mathbf{x}'_i\beta]/\sigma \} - \log(\sigma) - \log(y_i - \ell\ell) \} \end{aligned}$$

Analogous to the linear case, we can model heteroskedasticity by $\sigma^2(\mathbf{w}_i) = \exp(2\mathbf{w}'_i\theta)$.

Estimation of both of the aforementioned likelihood functions is done by maximum likelihood.

References

- Belotti, F., P. Deb, W. G. Manning, and E. C. Norton. 2015. [twopm: Two-part models](#). *Stata Journal* 15: 3–20.
- Cragg, J. G. 1971. Some statistical models for limited dependent variables with application to the demand for durable goods. *Econometrica* 39: 829–844.
- Engel, C., and P. G. Moffatt. 2014. [dhrefg, xthrefg, and bootdhrefg: Commands to implement double-hurdle regression](#). *Stata Journal* 14: 778–797.
- Farbmacher, H. 2011. Estimation of hurdle models for overdispersed count data. *Stata Journal* 11: 82–94.
- García, B. 2013. [Implementation of a double-hurdle model](#). *Stata Journal* 13: 776–794.
- Marchenko, Y. V. 2015. Bayesian modeling: Beyond Stata's built-in models. *The Stata Blog: Not Elsewhere Classified*. <http://blog.stata.com/2015/05/26/bayesian-modeling-beyond-statas-built-in-models/>.
- Wooldridge, J. M. 2010. *Econometric Analysis of Cross Section and Panel Data*. 2nd ed. Cambridge, MA: MIT Press.

Also see

[R] [churdle postestimation](#) — Postestimation tools for churdle

[R] [intreg](#) — Interval regression

[R] [tobit](#) — Tobit regression

[SVY] [svy estimation](#) — Estimation commands for survey data

[U] [20 Estimation and postestimation commands](#)