

logistic — Logistic regression, reporting odds ratios

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Description

`logistic` fits a logistic regression model of *depvar* on *indepvars*, where *depvar* is a 0/1 variable (or, more precisely, a 0/non-0 variable). Without arguments, `logistic` redisplay the last `logistic` estimates. `logistic` displays estimates as odds ratios; to view coefficients, type `logit` after running `logistic`. To obtain odds ratios for any covariate pattern relative to another, see [R] [lincom](#).

Quick start

Report odds ratios from logistic regression of *y* on *x1* and *x2*

```
logistic y x1 x2
```

Add indicators for values of categorical variable *a*

```
logistic y x1 x2 i.a
```

Same as above, and apply frequency weights defined by *wvar*

```
logistic y x1 x2 i.a [fweight=wvar]
```

Show base level of *a*

```
logistic y x1 x2 i.a, baselevels
```

Menu

Statistics > Binary outcomes > Logistic regression

Syntax

```
logistic depvar indepvars [if] [in] [weight] [, options]
```

<i>options</i>	Description
Model	
<code>noconstant</code>	suppress constant term
<code>offset(<i>varname</i>)</code>	include <i>varname</i> in model with coefficient constrained to 1
<code>asis</code>	retain perfect predictor variables
<code>constraints(<i>constraints</i>)</code>	apply specified linear constraints
SE/Robust	
<code>vce(<i>vcetype</i>)</code>	<i>vcetype</i> may be <code>oim</code> , <code>opg</code> , <code>robust</code> , <code>cluster <i>clustvar</i></code> , <code>bootstrap</code> , or <code>jackknife</code>
Reporting	
<code>level(#)</code>	set confidence level; default is <code>level(95)</code>
<code>coef</code>	report estimated coefficients
<code>nocnsreport</code>	do not display constraints
<code>display_options</code>	control columns and column formats, row spacing, line width, display of omitted variables and base and empty cells, and factor-variable labeling
Maximization	
<code>maximize_options</code>	control the maximization process; seldom used
<code>collinear</code>	keep collinear variables
<code>coeflegend</code>	display legend instead of statistics

indepvars may contain factor variables; see [U] 11.4.3 **Factor variables**.

depvar and *indepvars* may contain time-series operators; see [U] 11.4.4 **Time-series varlists**.

`bayes`, `bootstrap`, `by`, `collect`, `fp`, `jackknife`, `mfp`, `mi estimate`, `nestreg`, `rolling`, `statsby`, `stepwise`, and `svy` are allowed; see [U] 11.1.10 **Prefix commands**. For more details, see [BAYES] **bayes: logistic**.

`vce(bootstrap)` and `vce(jackknife)` are not allowed with the `mi estimate` prefix; see [MI] **mi estimate**.

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`, `iweights`, and `pweights` are allowed; see [U] 11.1.6 **weight**.

`collinear` and `coeflegend` do not appear in the dialog box.

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

Options

Model

`noconstant`, `offset(varname)`, `constraints(constraints)`; see [R] **Estimation options**.

`asis` forces retention of perfect predictor variables and their associated perfectly predicted observations and may produce instabilities in maximization; see [R] **probit**.

SE/Robust

`vce(vctype)` specifies the type of standard error reported, which includes types that are derived from asymptotic theory (`oim`, `opg`), 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(#)`; see [R] [Estimation options](#).

`coef` causes `logistic` to report the estimated coefficients rather than the odds ratios (exponentiated coefficients). `coef` may be specified when the model is fit or may be used later to redisplay results. `coef` affects only how results are displayed and not how they are estimated.

`nocnsreport`; see [R] [Estimation options](#).

`display_options`: `noci`, `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 options are available with `logistic` but are not shown in the dialog box:

`collinear`, `coeflegend`; see [R] [Estimation options](#).

Remarks and examples

[stata.com](http://www.stata.com)

Remarks are presented under the following headings:

[logistic and logit](#)
[Robust estimate of variance](#)
[Video examples](#)

logistic and logit

`logistic` provides an alternative and preferred way to fit maximum-likelihood logit models, the other choice being `logit` ([R] [logit](#)).

First, let's dispose of some confusing terminology. We use the words `logit` and `logistic` to mean the same thing: maximum likelihood estimation. To some, one or the other of these words connotes transforming the dependent variable and using weighted least squares to fit the model, but that is not how we use either word here. Thus, the `logit` and `logistic` commands produce the same results.

The `logistic` command is generally preferred to the `logit` command because `logistic` presents the estimates in terms of odds ratios rather than coefficients. To some people, this may seem disadvantageous, but you can type `logit` without arguments after `logistic` to see the underlying coefficients. You should be cautious when interpreting the odds ratio of the constant term. Usually, this odds ratio represents the baseline odds of the model when all predictor variables are set to zero. However, you must verify that a zero value for all predictor variables in the model actually makes sense before continuing with this interpretation.

Nevertheless, [R] **logit** is still worth reading because `logistic` shares the same features as `logit`, including omitting variables due to collinearity or one-way causation.

For an introduction to logistic regression, see [Lemeshow and Hosmer \(2005\)](#), [Pagano and Gauvreau \(2022, 455–478\)](#), or [Pampel \(2021\)](#); for a complete but nonmathematical treatment, see [Kleinbaum and Klein \(2010\)](#); and for a thorough discussion, see [Hosmer, Lemeshow, and Sturdivant \(2013\)](#). See [Gould \(2000\)](#) for a discussion of the interpretation of logistic regression. See [Dupont \(2009\)](#) or [Hilbe \(2009\)](#) for a discussion of logistic regression with examples using Stata. For a discussion using Stata with an emphasis on model specification, see [Vittinghoff et al. \(2012\)](#).

Stata has a variety of commands for performing estimation when the dependent variable is dichotomous or polytomous. See [Long and Freese \(2014\)](#) for a book devoted to fitting these models with Stata. See `help estimation commands` for a complete list of all of Stata’s estimation commands.

▷ Example 1

Consider the following dataset from a study of risk factors associated with low birthweight described in [Hosmer, Lemeshow, and Sturdivant \(2013, 24\)](#).

```
. use https://www.stata-press.com/data/r18/lbw
(Hosmer & Lemeshow data)
```

```
. describe
```

```
Contains data from https://www.stata-press.com/data/r18/lbw.dta
Observations:      189      Hosmer & Lemeshow data
Variables:         11      15 Jan 2022 05:01
```

Variable name	Storage type	Display format	Value label	Variable label
<code>id</code>	<code>int</code>	<code>%8.0g</code>		Identification code
<code>low</code>	<code>byte</code>	<code>%8.0g</code>		Birthweight<2500g
<code>age</code>	<code>byte</code>	<code>%8.0g</code>		Age of mother
<code>lwt</code>	<code>int</code>	<code>%8.0g</code>		Weight at last menstrual period
<code>race</code>	<code>byte</code>	<code>%8.0g</code>	<code>race</code>	Race
<code>smoke</code>	<code>byte</code>	<code>%9.0g</code>	<code>smoke</code>	Smoked during pregnancy
<code>ptl</code>	<code>byte</code>	<code>%8.0g</code>		Premature labor history (count)
<code>ht</code>	<code>byte</code>	<code>%8.0g</code>		Has history of hypertension
<code>ui</code>	<code>byte</code>	<code>%8.0g</code>		Presence, uterine irritability
<code>ftv</code>	<code>byte</code>	<code>%8.0g</code>		Number of visits to physician during 1st trimester
<code>bwt</code>	<code>int</code>	<code>%8.0g</code>		Birthweight (grams)

Sorted by:

We want to investigate the causes of low birthweight. Here `race` is a categorical variable indicating whether a person is white (`race = 1`), black (`race = 2`), or some other race (`race = 3`). We want indicator (dummy) variables for `race` included in the regression, so we will use factor variables.

```
. logistic low age lwt i.race smoke ptl ht ui
Logistic regression
Log likelihood = -100.724
Number of obs = 189
LR chi2(8) = 33.22
Prob > chi2 = 0.0001
Pseudo R2 = 0.1416
```

low	Odds ratio	Std. err.	z	P> z	[95% conf. interval]	
age	.9732636	.0354759	-0.74	0.457	.9061578	1.045339
lwt	.9849634	.0068217	-2.19	0.029	.9716834	.9984249
race						
Black	3.534767	1.860737	2.40	0.016	1.259736	9.918406
Other	2.368079	1.039949	1.96	0.050	1.001356	5.600207
smoke	2.517698	1.00916	2.30	0.021	1.147676	5.523162
ptl	1.719161	.5952579	1.56	0.118	.8721455	3.388787
ht	6.249602	4.322408	2.65	0.008	1.611152	24.24199
ui	2.1351	.9808153	1.65	0.099	.8677528	5.2534
_cons	1.586014	1.910496	0.38	0.702	.1496092	16.8134

Note: `_cons` estimates baseline odds.

The odds ratios are for a one-unit change in the variable. If we wanted the odds ratio for `age` to be in terms of 4-year intervals, we would type

```
. generate age4 = age/4
. logistic low age4 lwt i.race smoke ptl ht ui
(output omitted)
```

After `logistic`, we can type `logit` to see the model in terms of coefficients and standard errors:

```
. logit
Logistic regression
Log likelihood = -100.724
Number of obs = 189
LR chi2(8) = 33.22
Prob > chi2 = 0.0001
Pseudo R2 = 0.1416
```

low	Coefficient	Std. err.	z	P> z	[95% conf. interval]	
age4	-.1084012	.1458017	-0.74	0.457	-.3941673	.1773649
lwt	-.0151508	.0069259	-2.19	0.029	-.0287253	-.0015763
race						
Black	1.262647	.5264101	2.40	0.016	.2309024	2.294392
Other	.8620792	.4391532	1.96	0.050	.0013548	1.722804
smoke	.9233448	.4008266	2.30	0.021	.137739	1.708951
ptl	.5418366	.346249	1.56	0.118	-.136799	1.220472
ht	1.832518	.6916292	2.65	0.008	.4769494	3.188086
ui	.7585135	.4593768	1.65	0.099	-.1418484	1.658875
_cons	.4612239	1.20459	0.38	0.702	-1.899729	2.822176

If we wanted to see the `logistic` output again, we would type `logistic` without arguments.

▷ Example 2

We can specify the confidence interval for the odds ratios with the `level()` option, and we can do this either at estimation time or when replaying the model. For instance, to see our first model in [example 1](#) with narrower, 90% confidence intervals, we might type

```
. logistic, level(90)
Logistic regression                               Number of obs =   189
                                                    LR chi2(8)      =   33.22
                                                    Prob > chi2     = 0.0001
Log likelihood = -100.724                          Pseudo R2      = 0.1416
```

low	Odds ratio	Std. err.	z	P> z	[90% conf. interval]	
age4	.8972675	.1308231	-0.74	0.457	.7059409	1.140448
lwt	.9849634	.0068217	-2.19	0.029	.9738063	.9962483
race						
Black	3.534767	1.860737	2.40	0.016	1.487028	8.402379
Other	2.368079	1.039949	1.96	0.050	1.149971	4.876471
smoke	2.517698	1.00916	2.30	0.021	1.302185	4.867819
ptl	1.719161	.5952579	1.56	0.118	.9726876	3.038505
ht	6.249602	4.322408	2.65	0.008	2.003487	19.49478
ui	2.1351	.9808153	1.65	0.099	1.00291	4.545424
_cons	1.586014	1.910496	0.38	0.702	.2186791	11.50288

Note: `_cons` estimates baseline odds.

◀

Robust estimate of variance

If you specify `vce(robust)`, Stata reports the robust estimate of variance described in [\[U\] 20.22 Obtaining robust variance estimates](#). Here is the model previously fit with the robust estimate of variance:

```
. logistic low age lwt i.race smoke ptl ht ui, vce(robust)
Logistic regression                               Number of obs =   189
                                                    Wald chi2(8)     = 29.02
                                                    Prob > chi2     = 0.0003
Log pseudolikelihood = -100.724                  Pseudo R2      = 0.1416
```

low	Odds ratio	Robust std. err.	z	P> z	[95% conf. interval]	
age	.9732636	.0329376	-0.80	0.423	.9108015	1.040009
lwt	.9849634	.0070209	-2.13	0.034	.9712984	.9988206
race						
Black	3.534767	1.793616	2.49	0.013	1.307504	9.556051
Other	2.368079	1.026563	1.99	0.047	1.012512	5.538501
smoke	2.517698	.9736417	2.39	0.017	1.179852	5.372537
ptl	1.719161	.7072902	1.32	0.188	.7675715	3.850476
ht	6.249602	4.102026	2.79	0.005	1.726445	22.6231
ui	2.1351	1.042775	1.55	0.120	.8197749	5.560858
_cons	1.586014	1.939482	0.38	0.706	.144345	17.42658

Note: `_cons` estimates baseline odds.

Also, you can specify `vce(cluster clustvar)` and then, within cluster, relax the assumption of independence. To illustrate this, we have made some fictional additions to the low-birthweight data.

Say that these data are not a random sample of mothers but instead are a random sample of mothers from a random sample of hospitals. In fact, that may be true—we do not know the history of these data.

Hospitals specialize, and it would not be too incorrect to say that some hospitals specialize in more difficult cases. We are going to show two extremes. In one, all hospitals are alike, but we are going to estimate under the possibility that they might differ. In the other, hospitals are strikingly different. In both cases, we assume that patients are drawn from 20 hospitals.

In both examples, we will fit the same model, and we will type the same command to fit it. Below are the same data we have been using but with a new variable, `hospid`, that identifies from which of the 20 hospitals each patient was drawn (and which we have made up):

```
. use https://www.stata-press.com/data/r18/hospid1, clear
. logistic low age lwt i.race smoke ptl ht ui, vce(cluster hospid)
Logistic regression                                Number of obs =   189
                                                    Wald chi2(8) =  49.67
                                                    Prob > chi2   =  0.0000
Log pseudolikelihood = -100.724                    Pseudo R2     =  0.1416
                                                    (Std. err. adjusted for 20 clusters in hospid)
```

low	Odds ratio	Robust std. err.	z	P> z	[95% conf. interval]	
age	.9732636	.0397476	-0.66	0.507	.898396	1.05437
lwt	.9849634	.0057101	-2.61	0.009	.9738352	.9962187
race						
Black	3.534767	2.013285	2.22	0.027	1.157563	10.79386
Other	2.368079	.8451325	2.42	0.016	1.176562	4.766257
smoke	2.517698	.8284259	2.81	0.005	1.321062	4.79826
ptl	1.719161	.6676221	1.40	0.163	.8030814	3.680219
ht	6.249602	4.066275	2.82	0.005	1.74591	22.37086
ui	2.1351	1.093144	1.48	0.138	.7827337	5.824014
_cons	1.586014	1.661913	0.44	0.660	.2034094	12.36639

Note: `_cons` estimates baseline odds.

The standard errors are similar to the standard errors we have previously obtained, whether we used the robust or conventional estimators. In this example, we invented the hospital IDs randomly.

Here are the results of the estimation with the same data but with a different set of hospital IDs:

```
. use https://www.stata-press.com/data/r18/hospid2
. logistic low age lwt i.race smoke ptl ht ui, vce(cluster hospid)
Logistic regression                                Number of obs =   189
                                                    Wald chi2(8)    =    7.19
                                                    Prob > chi2     = 0.5167
Log pseudolikelihood = -100.724                    Pseudo R2      = 0.1416
                                                    (Std. err. adjusted for 20 clusters in hospid)
```

low	Odds ratio	Robust std. err.	z	P> z	[95% conf. interval]	
age	.9732636	.0293064	-0.90	0.368	.9174862	1.032432
lwt	.9849634	.0106123	-1.41	0.160	.9643817	1.005984
race						
Black	3.534767	3.120338	1.43	0.153	.6265521	19.9418
Other	2.368079	1.297738	1.57	0.116	.8089594	6.932114
smoke	2.517698	1.570287	1.48	0.139	.7414969	8.548655
ptl	1.719161	.6799153	1.37	0.171	.7919045	3.732161
ht	6.249602	7.165454	1.60	0.110	.660558	59.12808
ui	2.1351	1.411977	1.15	0.251	.5841231	7.804266
_cons	1.586014	1.946253	0.38	0.707	.1431423	17.573

Note: **_cons** estimates baseline odds.

Note the strikingly larger standard errors. What happened? In these data, women most likely to have low-birthweight babies are sent to certain hospitals, and the decision on likeliness is based not just on age, smoking history, etc., but on other things that doctors can see but that are not recorded in our data. Thus, merely because a woman is at one of the centers identifies her to be more likely to have a low-birthweight baby.

Video examples

[Logistic regression, part 1: Binary predictors](#)

[Logistic regression, part 2: Continuous predictors](#)

[Logistic regression, part 3: Factor variables](#)

Stored results

logistic stores the following in `e()`:

Scalars

<code>e(N)</code>	number of observations
<code>e(N_cds)</code>	number of completely determined successes
<code>e(N_cdf)</code>	number of completely determined failures
<code>e(k)</code>	number of parameters
<code>e(k_eq)</code>	number of equations in <code>e(b)</code>
<code>e(k_eq_model)</code>	number of equations in overall model test
<code>e(k_dv)</code>	number of dependent variables
<code>e(df_m)</code>	model degrees of freedom
<code>e(r2_p)</code>	pseudo- R^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(chi2)</code>	χ^2
<code>e(p)</code>	p -value for model test
<code>e(rank)</code>	rank of <code>e(V)</code>
<code>e(ic)</code>	number of iterations
<code>e(rc)</code>	return code
<code>e(converged)</code>	1 if converged, 0 otherwise

Macros

<code>e(cmd)</code>	logistic
<code>e(cmdline)</code>	command as typed
<code>e(depvar)</code>	name of dependent variable
<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(offset)</code>	linear offset variable
<code>e(chi2type)</code>	Wald or LR; type of model χ^2 test
<code>e(vce)</code>	<i>vce</i> type specified in <code>vce()</code>
<code>e(vctype)</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(ml_method)</code>	type of ml method
<code>e(user)</code>	name of likelihood-evaluator program
<code>e(technique)</code>	maximization technique
<code>e(properties)</code>	b V
<code>e(estat_cmd)</code>	program used to implement <code>estat</code>
<code>e(predict)</code>	program used to implement <code>predict</code>
<code>e(marginsok)</code>	predictions allowed by <code>margins</code>
<code>e(marginsnotok)</code>	predictions disallowed by <code>margins</code>
<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 (up to 20 iterations)
<code>e(gradient)</code>	gradient vector
<code>e(mns)</code>	vector of means of the independent variables
<code>e(rules)</code>	information about perfect predictors
<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
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In addition to the above, the following is stored in `r()`:

Matrices	
<code>r(table)</code>	matrix containing the coefficients with their standard errors, test statistics, p -values, and confidence intervals

Note that results stored in `r()` are updated when the command is replayed and will be replaced when any `r`-class command is run after the estimation command.

Methods and formulas

Define \mathbf{x}_j as the (row) vector of independent variables, augmented by 1, and \mathbf{b} as the corresponding estimated parameter (column) vector. The logistic regression model is fit by `logit`; see [R] [logit](#) for details of estimation.

The odds ratio corresponding to the i th coefficient is $\psi_i = \exp(b_i)$. The standard error of the odds ratio is $s_i^\psi = \psi_i s_i$, where s_i is the standard error of b_i estimated by `logit`.

Define $I_j = \mathbf{x}_j \mathbf{b}$ as the predicted index of the j th observation. The predicted probability of a positive outcome is

$$p_j = \frac{\exp(I_j)}{1 + \exp(I_j)}$$

This command supports the Huber/White/sandwich estimator of the variance and its clustered version using `vce(robust)` and `vce(cluster clustvar)`, respectively. See [P] [_robust](#), particularly [Maximum likelihood estimators](#) and [Methods and formulas](#).

`logistic` also supports estimation with survey data. For details on VCEs with survey data, see [SVY] [Variance estimation](#).

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Also see

- [R] **logistic postestimation** — Postestimation tools for logistic
- [R] **brier** — Brier score decomposition
- [R] **cloglog** — Complementary log–log regression
- [R] **exlogistic** — Exact logistic regression
- [R] **logit** — Logistic regression, reporting coefficients
- [R] **npregress kernel** — Nonparametric kernel regression
- [R] **npregress series** — Nonparametric series regression
- [R] **roc** — Receiver operating characteristic (ROC) analysis
- [BAYES] **bayes: logistic** — Bayesian logistic regression, reporting odds ratios
- [FMM] **fmm: logit** — Finite mixtures of logistic regression models
- [LASSO] **Lasso intro** — Introduction to lasso
- [MI] **Estimation** — Estimation commands for use with mi estimate
- [SVY] **svy estimation** — Estimation commands for survey data
- [XT] **xtlogit** — Fixed-effects, random-effects, and population-averaged logit models
- [U] **20 Estimation and postestimation commands**

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