Stata Cheat Sheet

Example: Hospital Discharge Data

This cheat sheet uses SPARCS hospital discharge data as the running example:

- Observations: Individual hospital admissions (e.g., 150,000 records)
- Variables: Age, sex, admission type, length of stay, total charges
- Geographic: Multiple counties with socioeconomic data
- Outcome: Total costs (continuous), expensive stay flag (binary)
- Key challenges: Missing values (999/9999), top-coding, strings

PART 1: CONCEPTS & LOGIC

1. Data Types: Pros, Cons, & Use Cases

Cross-sectional Surveys

Examples: BRFSS, NHANES, NHIS

Advantages: Relatively low cost, quick large samples, ideal for prevalence estimates, nationally representative, population-level health estimates

Disadvantages: Cannot track individual changes, difficult causality (associations only), compare different people not same person, declining response rates, cannot control unmeasured time-invariant characteristics

Best for: "What is diabetes prevalence?" "Insurance coverage by income?" "Physical activity guideline adherence?

Longitudinal Surveys

Examples: MEPS, National Longitudinal Survey of Youth

Advantages: Track same individuals (within-person), support fixed effects, stronger causal inference, observe temporal sequences, control time-invariant characteristics Disadvantages: High cost, attrition bias, long collection period, learning effects, complex analysis

Best for: "Does having baby reduce sleep?" "Does retirement improve mental health?" "Job loss effect on health?"

Claims/Hospital Discharge Data

Examples: SPARCS (NY), Medicare Claims

Advantages: Very large samples (population-level), actual costs/utilization, tracks across providers, less missing data, readmission tracking, covers entire populations Disadvantages: No clinical details (labs, vitals), inaccurate diagnoses (billing focus), excludes non-users, limited socioeconomic info, coding errors, cannot capture

Out-of-network care

Best for: "Hospitalization costs by county?" "90-day readmission rate?" "Length of stay patterns?" "High-cost predictors?"

Quality Metrics: Good: Readmission, LOS, utilization, mortality — **Bad:** BP/HbA1c control (need clinical data)

Electronic Health Records (EHR)

Examples: Hospital system EHR, Epic, Cerner

Advantages: Rich clinical info (labs, vitals, meds, imaging), longitudinal visits, real-world data, unstructured notes, clinical decisions

Disadvantages: Single system only (selection bias), variable quality, missing external

visits, hard to standardize, local practice patterns (not generalizable)

Best for: "HbA1c control in our system?" "Real-world drug effectiveness?" "Clinical

reminders impact?"

Quality Metrics: Good: HbA1c/BP control, medication adherence — Bad:

Cross-system readmissions

Text-based Data

Examples: Physician notes, chief complaints, radiology reports

Advantages: Rich unstructured info, details not in structured fields, clinical context Disadvantages: Requires NLP, complex analysis, inconsistent quality, time-intensive 2. Core Regression Concepts

Survey Weights

Why? (1) Design oversampling (minorities for adequate N), (2) Differential response rates by group, (3) Non-representative samples

Understanding: Weight = how many people each respondent represents. Weight=1.5

means represents 1.5 people. Allows generalization to population. Adjusts for unequal selection & non-response.

When: Survey data (BRFSS, NHANES, MEPS) for population-representative results

Stata: svyset [pweight=wt]; svy: reg y x

Categorical vs Continuous

Categorical: Use i. prefix, Stata creates dummies, first = reference (omitted), each coef = difference from reference. Examples: race, admission type, education Continuous: Use c. or direct name, coef = effect of 1-unit increase, assumes linearity. Examples: age, BMI, income, costs
Choose categorical when: Want separate effects, non-linear relationship, meaningful

groups, unequal intervals

Logistic vs Linear Regression

For binary outcomes, both are acceptable but interpret differently!

Feature	Logistic	Linear
Command	logistic or logit	reg
Output	Odds Ratios (OR)	Coefficients
Interpretation	Fold-change in odds	Percentage point diff.

Logistic Interpretation Example:

OR = 1.5: "Each \$1000 increase in county income is associated with 50% increase in

the odds of expensive stay (odds multiply by 1.5)"
Linear Interpretation Example:
Coef = 0.04: "Each \$1000 increase in county income is associated with 4 percentage point increase in probability of expensive stay (e.g., from 10% to 14%)'

Interaction Terms

Purpose: Test whether the relationship between X and Y varies depending on the

Research Question Examples:

- Does the effect of income on health vary by sex?
- $\bullet~$ Does drug effectiveness vary by age group?
- Do hospitalization costs respond differently to county income depending on admission type?

Stata syntax:

```
// ## includes main effects + interaction
reg outcome var1##var2
// Categorical x Continuous (MUST use c.!)
reg outcome i.sex##c.age
// Categorical x Categorical
```

Individual Fixed Effects

When to use:

- Have longitudinal/panel data (same person, multiple time points)
- Want to control for time-invariant individual factors
- · Research question focuses on "within-person changes"
- Concerned about unmeasured confounding from stable traits

Advantages:

- Controls for ALL time-invariant characteristics (observed or unobserved)
- Stronger foundation for causal inference
- Each person serves as their own control
- Eliminates selection bias from stable individual traits

Example: Does having a baby reduce sleep? Compare same person before vs after

```
// Set panel data structure xtset person_id time_var
xtreg outcome predictors, fe
```

Robust Standard Errors

Why use?

- Heteroskedasticity: Error variance differs across observations
- Very common in large samples and cross-sectional data
- Makes standard errors more accurate and reliable
- Improves inference (p-values, confidence intervals)

Stata syntax:

```
reg outcome predictors, robust
// or shorthand:
reg outcome predictors, r
```

Disciplinary differences:

- Economics: Almost always uses robust SE
- Biostatistics: Not always standard practice
- Exam: Won't lose points for not using, but understand why it's useful

3. Statistical vs Practical Significance

Key Distinction:

Statistical Significance	Practical Significance	
p < 0.05	Is difference large enough to	
	matter?	
Affected by sample size	NOT affected by sample size	
Technical judgment	Substantive judgment	
Can detect tiny effects in	Focuses on real-world impor-	
large samples	tance	

Detailed Example:

In BRFSS survey of 500,000 people, we find Gen Z and Millennials differ by 3 minutes in daily exercise (20 min vs 23 min), p=0.007.

Analysis:

- Statistically significant: p: 0.05
 - ? Practically significant: Debatable
 - 3 minutes may be too small for meaningful health benefits
 - But represents ${\downarrow}10\%$ relative difference (15%)
 - In large samples, even tiny differences achieve significance ("overpowered")

Key principle: ALWAYS discuss BOTH statistical and practical significance in your interpretations! Don't just report p-values.

4. Variable Types & Handling

Binary/Dummy Variables (0/1)

Definition: Flag variable coded as 0 or 1

- Common uses: Calculate percentages (e.g., vaccination rate = mean of binary)
 - As outcome variable (logistic or linear regression)
 - As control variable in regression models
 - Create subgroup indicators for analysis

Creation method:

// Standard approach
gen flag = 1 if condition
replace flag = 0 if opposite_condition

// Example: elderly patient flag
gen elderly = 1 if age >= 65 & age != .
replace elderly = 0 if age < 65</pre>

Verification (CRITICAL):

summ flag
// Check: mean 0-1, min=0, maz=1
tab original_var flag
// Verify cross-tabulation is correct

Categorical Variables

Examples: Race, education level, admission type, age groups Handling methods:

// Method 1: encode (string to numeric)
encode string_var, gen(categorical_var)

// Method 2: Manual creation
gen cat = 1 if condition1
replace cat = 2 if condition2
replace cat = 3 if condition3

// Use with i. prefix in regression
reg outcome i.categorical_var

Continuous Variables

Examples: Age, BMI, income, length of stay Common handling:

// Top-coding (cap extreme outliers)
gen var_clean = var
replace var_clean = 1000000 ///
 if var > 1000000 & var != .

// Log transformation (right-skewed data)
gen log_var = log(var + 1)
// +1 to avoid log(0)

String Variables

Common operations:

// Convert to numeric (force = ignore errors)
destring string_var, gen(numeric_var) force
// Check what couldn't be converted
tab string_var if numeric_var == .
// String matching/searching
gen flag = strpos(string_var, "keyword") > 0

Missing Values

CRITICAL PRINCIPLE: Always include & var != . in conditions! Why? Stata treats missing (.) as very large number (infinity). Correct approach:

// CORRECT - protects missing values
replace var_clean = 100 if var > 100 & var != .
// WRONG - will set missing to 100!
replace var_clean = 100 if var > 100

Identifying missing:

// Recode special values to missing
replace var = . if var == 99
replace var = . if var == 999
replace var = . if var < 0</pre>

5. Data Management Operations

Merging Data

Four merge types:

- 1:1 Merge
 - Scenario: Both datasets have 1 row per ID
 Example: Merge NHANES questionnaire to demographics (both 1 row/person)
 - Syntax: merge 1:1 id using "file.dta"

1:M Merge

- Scenario: Master has 1 row per ID, Using has many rows per ID
- Example: Merge visit data to medications per visit
- Syntax: merge 1:m id using "file.dta"

M:1 Merge (MOST COMMON!)

- $\bullet~$ Scenario: Master has many rows per ID, Using has 1 row per ID
- Example: Merge county income to hospital records (many admissions/county)
- Syntax: merge m:1 county using "file.dta"

Post-merge check (CRITICAL):

tab _merge
/*
_merge == 1: master only (no match in using)
_merge == 2: using only (no match in master)
_merge == 3: matched successfully
*/
// Usually keep master records and matched

keep if _merge == 1 | _merge == 3 drop _merge

Reshape/Transpose

Wide to Long:

reshape long var_prefix, i(id) j(time)

Long to Wide:

reshape wide var_name, i(id) j(time)

Append

 ${\bf Scenario:}\ {\bf Combine}\ {\bf datasets}\ {\bf with}\ {\bf same}\ {\bf structure}\ ({\bf stack}\ {\bf rows}\ {\bf vertically})$

append using "second_dataset.dta"

PART 2: STATA CODING

A. Data Management

Setup & Import Standard Setup

// Clear memory and set options
clear all
set more off

// Set working directory
cd "path/to/folder"

// Start logging
capture log close
log using "analysis.log", replace

Import Data

// Example: Load hospital discharge data
use "sparcs_hospital_data.dta", clear

// Load Stata file (general)
use "filename.dta", clear

// Import from SAS XPT (e.g., SPARCS source)
import sasxport5 "sparcs_raw.xpt", clear

// Import from CSV (hospital subset)
import delimited "hospital_subset.csv", ///
clear firstrow

// Save processed data
save "sparcs_processed.dta", replace

A Warning

Always use clear or , clear option to avoid "no; data in memory" error.

Data Exploration View & Describe

// View first 10 hospital admissions
list age los totalcosts county in 1/10

// View high-cost stays (>\$100k)
list if totalcosts > 100000

// Describe all variables
describe

// Explore age and admission type
codebook age admission_type

Summary Statistics

// Summarize hospital costs
summ totalcosts

// Detailed summary with percentiles
summ totalcosts los age, d
// Shows: min, max, mean, median, p25, p75

// Summary by group (admission type)
bysort admission_type: summ totalcosts

Frequency Tables

// Admission type frequencies (show missing)
tab admission_type, m

// Age group distribution
tab age_group

// Cross-tabulation: admission type x sex
tab admission_type sex, row

// Expensive stay by admission type
tab expensive_stay admission_type, col

// Two-way table with both row & col %
tab admission_type admission_source, ///
row col

Check Data Size

// Number of observations
display _N

// Number of variables
describe, short

Variable Creation Basic Generation

// Create empty variable
gen newvar = .
// Create with value
gen age_squared = age^2
// Create constant
gen constant = 1

Replace Values

// Replace all values
replace varname = new_value
// Conditional replace
replace var = value if condition

A Warning

CRITICAL: Use if var != . to protect missing values!

Binary Variables (0/1 Flags)

// Method 1: Standard approach
gen flag = 1 if condition
replace flag = 0 if !condition

// Method 2: One-liner
gen flag = (condition) if var != .

// Example: Elderly patient (age >= 65)
gen elderly = 1 if age >= 65 & age != .
replace elderly = 0 if age < 65

// Example: Expensive stay <= \frac{5}{100,000}
gen expensive_stay = 1 if totalcosts ///
> 100000 & totalcosts != .
replace expensive_stay = 0 if ///
totalcosts <= 100000

// VERIFY binary variable
summ flag
// mean should be 0-1, min=0, max=1

Categorical Variables

Top-coding (Capping Outliers)

Logarithmic Transformation

// Handle right-skewed data
// Step 1: Add small value to avoid log(0)
gen cost_plus1 = cost + 1

// Step 2: Take log
gen log_cost = log(cost_plus1)

// Alternative: only for positive values
gen log_cost = log(cost) if cost > 0

EGEN - Extended Generation

// Row operations

egen total = rowtotal(var1 var2 var3)

egen mean = rowmean(var1 var2 var3)

egen max = rowmax(var1 var2 var3)

egen min = rowmin(var1 var2 var3)

// Grouped statistics

egen mean_by_group = mean(var), ///

by(group_var)

```
// Example: County-level averages
egen avg_income_county = mean(income), ///
   by(county_name)

// Count non-missing
egen count_nonmiss = count(var), ///
   by(group)

// String concatenation
egen fullname = concat(first last), ///
   punct(" ")
```

Missing Values Identify & Recode

// Count missing
count if varname == .

// Summary shows N
summ varname
// Total N vs variable N

// Show missing in table
tab varname, m

Recode Missing Values

// Set specific values to missing
replace var = . if var == 99
replace var = . if var == 999
replace var = . if var < 0

// Example from BRFSS
replace height = . if height == 7777
replace height = . if height == 9999</pre>

▲ Warning

Wrong: replace var = 100 if var > 100 (sets missing to 100!) Right: replace var = 100 if var > 100 & var != .

Create Missing Indicator

// Flag for missing
gen miss_flag = (varname == .)
// Or explicitly
gen miss_flag = 0
replace miss_flag = 1 if varname == .

String Variables Type Conversion

// Basic conversion (force ignores errors)
destring string_var, gen(num_var) force

// Check what couldn't be converted
tab string_var if num_var == .

// Example: Handle "120 +"
destring lengthofstay, gen(los_num) force
replace los_num = 120 //

if lengthofstay == "120 +"

Numeric to String

// Convert number to string
gen str_var = string(numeric_var)

// With formatting
gen str_var = string(num_var, "%9.2f")

String to Categorical (encode)

// Create numeric with labels
encode string_var, gen(categorical_var)

// Example: Admission type
encode typeofadmission, ///
gen(admission_type_num)

// Verify
tab typeofadmission admission_type_num

String Manipulation

// Case conversion
gen upper = strupper(string_var)
gen upper = strlower(string_var)
gen proper = strproper(string_var)

// Extract substring (pos starts at 1!)
gen first5 = substr(string_var, 1, 5)
gen char2to4 = substr(string_var, 2, 3)

// Find substring position
gen pos = strpos(string_var, "keyword")
// Returns 0 if not found

// String length
gen length = strlen(string_var)

// Replace text
gen new = subinstr(string_var, ///
 "old", "new", .)
// Last argument: . = replace all
// Split string_var, gen(part) parse("_")
// Creates: part1, part2, part3, ...

A Warning

substr() starts at 1: substr(str, 1, 2) = first 2 chars

Data Merging Merge Types (1:1, 1:M, M:1)

```
// 1:1 - Both datasets: 1 row per ID
merge 1:1 id_var using "file.dta"

// 1:M - Master: 1 row/ID, Using: many rows/ID
merge 1:m id_var using "file.dta"

// M:1 - Master: many rows/ID, Using: 1 row/ID
merge m:1 id_var using "file.dta"

// M:M - Both: many rows/ID (rare, avoid)

// Use joinby instead if needed
```

M:1 Merge Example (Most Common)

```
// Merge county data to individual records
// Main: Individual hospitalizations
// (many records per county)
// Using: County characteristics
            (one record per county)
use "hospital_data.dta", clear
// Rename if needed to match
rename hospitalcounty County_Name
// Perform M:1 merge
merge m:1 County_Name //
    using "county_data.dta"
// CHECK merge results
tab _merge
_merge values:
 1 = master only (hospital records
  with no county match)
2 = using only (counties with no
hospital records)

3 = matched successfully
*/
// Keep what you want
keep if _merge == 1 | _merge == 3
// Keeps all hospital records
// Clean up
drop _merge
```

Merge Workflow

```
// Step 1: Check merge variable exists
describe merge_var

// Step 2: Check if unique (if "1" side)
duplicates report merge_var

// Should show 0 duplicates

// Step 3: Ensure variable names match

// If not, rename in one dataset
rename old_name new_name

// Step 4: Check variable types match
describe merge_var

// Both should be numeric or string

// Step 5: Perform merge
merge type merge_var using "file.dta"

// Step 6: Always check _merge!
tab_merge

// Step 7: Keep desired records
keep if _merge == 1 | _merge == 3

// Step 8: Drop _merge
drop_merge
```

Ŷ Tip

```
M:1 \to Master(M):Using(1) - 1:M \to Master(1):Using(M) - 1:1 \to Master(1):Using(1)
```

Append (Stack Datasets)

```
// Combine datasets with same structure
use "data2020.dta", clear
append using "data2021.dta"
append using "data2022.dta"

// All rows are kept, stacked vertically
```

$\begin{array}{c} \textbf{Data Reshaping} \\ \textbf{Wide} \leftrightarrow \textbf{Long} \end{array}$

```
// Wide format:
// id bp1 bp2 bp3 hr1 hr2 hr3
// 1 120 118 115 72 70 68

reshape long bp hr, i(id) j(round)

// Long format:
// id round bp hr
// 1 1 120 72
// 1 2 118 70
// 1 3 115 68
```

Long to Wide

```
// Long format:
// id round bp hr
// 1 1 120 72
// 1 2 118 70

reshape wide bp hr, i(id) j(round)

// Wide format:
// id bp1 bp2 hr1 hr2
// 1 120 118 72 70
```

A Warning

Always save before reshape!

Regression Analysis Linear Regression

```
// Simple regression
reg outcome predictor

// Multiple regression
reg y x1 x2 x3

// With robust standard errors
reg y x1 x2, robust
// or
reg y x1 x2, r
```

Categorical Variables in Regression

```
// Use i. prefix for categorical
reg outcome continuous_var i.category

// Example
reg totalcosts lengthofstay ///
    i.agegroup i.admission_type

// Stata automatically:
// - Creates dummy variables
// - Omits first category (reference)
// - Shows each category coefficient
```

Continuous Variables

```
// Default: continuous
reg y x1 x2

// Explicit: c. prefix (optional)
reg y c.x1 c.x2
```

Interaction Terms

```
// Categorical x Categorical
reg y i.var1##i.var2
// ## includes main effects + interaction
// Categorical x Continuous
// IMPORTANT: Use c. for continuous!
reg y i.category##c.continuous
// Example: Do age effects vary by sex?
reg totalcosts i.sex##c.age ///
i.admission_type, robust
// Only interaction (no main effects)
reg y i.var1#i.var2
```

▲ Warning

MUST use c. for continuous: i.sex##c.age (not i.sex##age)

Logistic Regression

```
// Binary outcome (0/1)
logistic binary_y x1 x2 i.category
// Reports Odds Ratios (OR)

// Alternative: logit (reports log-odds)
logit binary_y x1 x2 i.category

// Example
logistic expensive_stay ///
County_Income lengthofstay ///
i.agegroup i.ED_flag
```

Linear vs Logistic Interpretation

```
// LINEAR regression on binary outcome
reg expensive_stay County_Income, r

// Coefficient: Percentage point difference
// Example: coef = 0.04
// Interpretation: "County income increase
// of $1000 associated with 4 percentage
// point increase in probability of
// expensive stay (e.g., 10% to 14%)"

// LOGISTIC regression
logistic expensive_stay County_Income
// Coefficient: Odds Ratio
// Example: OR = 1.02
// Interpretation: "County income increase
// of $1000 associated with 2% increase
// in the odds of expensive stay"
```

Survey Weights

```
// Set survey design
svyset [pweight = weight_var]
```

// Weighted regression
svy: reg y x1 x2 i.category

// Weighted logistic
svy: logistic binary_y x1 x2

// Why use weights?

// - Make results representative
// - Account for survey design
// - Adjust for non-response

Post-Regression Commands

// Test joint significance
reg y x1 x2 x3
test x1 x2
// Tests: x1 = x2 = 0
// Predicted values
predict yhat
// Residuals
predict resid, residuals
// Margins (adjusted predictions)
reg y x1 i.group
margins group
// Shows predicted y for each group

Individual Fixed Effects

// For panel/longitudinal data
// Controls for all time-invariant
// individual characteristics

// Set panel structure
xtset person_id time_var

// Fixed effects regression
xtreg y x1 x2, fe

// Why use FE?
// - Within-person analysis
// - Control for unmeasured confounders
// - Stronger causal inference

Verification & Validation Verify Binary Variables

// Create binary flag
gen flag = 1 if cost > 50000 & cost != .
replace flag = 0 if cost <= 50000

// CHECK 1: Summary statistics
summ flag
// mean: O-1, min: O, max: 1, N correct?

// CHECK 2: Cross-tabulation
tab flag. m
// Should show: O, 1, and . only

// CHECK 3: Verify cutoff
summ cost if flag == 1
// min should be > 50000
summ cost if flag == 0
// max should be <= 50000

Verify Categorical Variables

// After encoding or recoding tab old_var new_var // Check mapping is correct // With percentages tab old var new var. row col

Verify Continuous Variables

// After transformation
summ original_var, d
summ clean_var, d
// Compare: mean, min, max, N
// Grouped summary
bysort group: summ var
// or
summ var if group == 1
summ var if group == 0

Check for Missing

// Count missing
count if var == .
// Identify observations with missing
list id var if var == .
// Missing by group
tab group, m
bysort group: count if var == .

Verify Merge Success

// After merge
tab _merge

// List unmatched from master
list id if _merge == 1

// List unmatched from using
list id if _merge == 2

// Check merged vaniable
summ merged_var if _merge == 3
// Should have valid values

Common Workflows Clean Outcome Variable

// Step 1: Explore
codebook outcome
summ outcome, d
tab outcome, m

// Step 2: Identify issues
// - Missing values?
// - Outliers?
// - Correct range?

// Step 3: Create clean version
gen outcome_clean = outcome

// Step 4: Handle missing
replace outcome_clean = . if outcome == 99
replace outcome_clean = . if outcome < 0

// Step 5: Handle outliers (top-code)
replace outcome_clean = 1000000 ///
if outcome > 1000000 & outcome != .

// Step 6: Verify
summ outcome_clean, d
tab outcome_clean, d

Prepare Covariates

// Continuous variable // - Check range summ age, d replace age = . if age == 99
// - Create squared term if needed
gen age_squared = age^2 // Categorical variable (numeric) Check values tab category, m // - Create labeled version label define cat_lbl 1 "A" 2 "B" 3 "C" label values category cat_lbl // Categorical variable (string) encode string_var, gen(category_num) tab string_var category_num // Binary flag // - Create 0/1 gen flag = 1 if condition & var != . replace flag = 0 if !condition
// - Verify
summ flag tab flag, m

Complete Analysis Example

// Research Q: County income effect on // hospitalization costs? // Step 1: Load and check data use "hospital_data.dta", clear describe summ totalcosts, d // Step 2: Clean outcome gen cost_clean = totalcosts replace cost_clean = 1000000 /// if totalcosts > 1000000 & totalcosts != . // Step 3: Clean covariates encode agegroup, gen(age_num)
gen ED_flag = (ed_indicator == "Y") ///
 if ed_indicator != "" // Step 4: Merge county data rename county County_Name using "county_Name ///
using "county_Income.dta"
keep if _merge == 1 | _merge == 3 drop _merge // Step 5: Check merged data summ County_Income, d // Report min and max // Step 6: Run regression reg cost_clean County_Income /// lengthofstay i.age_num i.ED_flag, r // Step 7: Interpret // Step ': Interpret
// "Controlling for length of stay, age,
// and ED status, each \$1000 increase in
// county income is associated with
// \$XX increase in hospital costs.
// This is statistically significant // (p<0.05)."

Additional Commands Duplicates

// Check for duplicates
duplicates report stay_id

// List duplicate examples
duplicates examples stay_id

```
// Tag duplicates (create flag)
duplicates tag stay_id, gen(dup_flag)

// Drop exact duplicates (keep one)
duplicates drop stay_id, force

// Keep first observation per group
bysort subject_id: keep if _n == 1
```

Bysort Techniques

```
// _n = observation number within group
// _N = total observations in group
// Count admissions per patient
bysort subject_id: gen n_admissions = _N
// Sequence number within group
bysort subject_id: gen admission_seq = _n
// Keep first observation per group
bysort subject_id: keep if _n == 1
// Keep last observation per group
bysort subject_id: keep if _n == _N
// Flag first observation
bysort county_name: gen first = (_n == 1)
```

Date/Time Handling

Test (Hypothesis Testing)

```
// After regression
reg outcome x1 x2 i.category

// Test single coefficient
test x1

// Test multiple coefficients jointly
test x1 x2

// Test categorical variable
test 2.category 3.category

// Test interaction term
reg y i.sex#c.age
test sex#c.age
```

Tabstat

```
// Basic usage
tabstat variable, stat(n mean sd)

// By groups
tabstat bmi, by(age_group) ///
stat(n mean sd min p50 max)

// Multiple variables
tabstat bmi weight height, ///
by(gender) stat(n mean sd)

// Format output
tabstat var, by(group) stat(n mean sd) ///
format(%9.2f)
```

Preserve & Restore

```
// Save current data state
preserve

// Make temporary changes
keep if age >= 65
collapse (mean) var, by(state)

// Restore original data
restore

// Use for temporary exploration
// without losing original dataset
```

Collapse

Key Reminders & Tips

Common Mistakes

▲ Warning

Top Mistakes: Missing values (& var != .) — substr() starts at 1 — Use c. for continuous — Always tab _merge — Binary: check summ shows 0-1

Statistical Significance vs Practical

```
// Example: p=0.007, diff=3 minutes
// Statistical: YES (p<0.05)
// Practical: MAYBE
// - 3 min might be too small
// - But >10% relative difference
// - Large sample = "overpowered"
// (can detect tiny differences)
// Always discuss BOTH in interpretation
```

Regression Interpretation

```
// Linear regression coefficient:
// "Each 1-unit increase in X is
// associated with beta-unit change in Y,
// controlling for other variables."

// Logistic regression OR:
// "Each 1-unit increase in X is
// associated with ORx change in the
// odds of Y, controlling for others."

// Binary outcome + linear regression:
// "Each 1-unit increase in X is
// associated with orders in X is
// associated with beta percentage point
// change in probability of Y."
```

When to Use What

Data Types:

- Cross-sectional survey: Prevalence, associations
- $\bullet\,$ Longitudinal survey: Within-person changes, causality
- Claims data: Utilization, costs, readmission
- EHR data: Clinical details, single system

Merge Types:

- M:1: Individual records + area-level data
- \bullet 1:M: Visits + medications per visit
- 1:1: Same IDs in both datasets

Regression Types:

- Linear: Continuous outcome
- Linear: Binary outcome (percentage points)
- Logistic: Binary outcome (odds ratios)
- Fixed effects: Panel data, within-person

Cheat Sheet Usage Tips

♀ Tip

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During the exam:

- 1. Start with exploration (summ, tab, describe)
- 2. Create clean versions of variables
- 3. Verify each step before moving on
- 4. Check merge with tab _merge
- 5. Verify binary variables with summ
- 6. Write complete interpretations

Quick Reference

Task	Command	
Load data	use "file.dta", clear	
Import CSV	import delimited "file.csv"	
Summary stats	summ var, d	
Frequency	tab var, m	
Create var	gen newvar = expr	
Binary flag	gen flag = (condition)	
Top-code	replace var = cap if var ; cap & var != .	
Encode string	encode str, gen(num)	
String to num	destring str, gen(num) force	
M:1 merge	merge m:1 id using "file.dta"	
Check merge	tab _merge	
Linear reg	reg y x1 x2, r	
With category	reg y x1 i.cat	
Interaction	reg y i.cat1##c.cont	
Logistic	logistic binary_y x1 x2	
Verify binary	summ flag (should be 0-1)	
Cross-check	tab oldvar newvar	

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