Statistics with Stata

Student guide

Version 0.9.8.4, by François Briatte

Draft version, check for updates!

Contents

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Introduction

This guide was written for a set of five quasi-identical postgraduate courses run at Sciences Po in Paris from Fall 2010 to Spring 2012. The full course material appears online at this address: http://f.briatte.org/teaching/quanti/.

The course is organised around three learning objectives:

First, it introduces some essential aspects of statistics, ranging from describing variables to running a multiple regression. The course requires **reading statistical theory** applied to social surveys as a preliminary to all course sessions.

Second, it introduces how to operate those procedures with Stata, a statistical software that we will practice during class. The course also requires that you **practice using Stata** outside class in order to become sufficiently familiar with it.

Third, the course will lead you to develop a small research project, on which your grade for the course will be based. The course therefore requires regular **attendance and homework**, which will lead to writing up that research project.

This guide covers the following topics:

- The course basics, Stata fundamentals and essential computer skills
- Basic operations in data preparation and management (Part 1)
- Introductory quantitative methods and statistical analysis (Part 2)
- Instructions for the assignments and the final paper (Part 3)

1. Basics

Quantitative methods designate a specific branch of social science methodology, within which statistical procedures are applied to quantitative data in order to produce interpretations of complex, recurrent phenomena.

Just as in other domains of scientific inquiry, the complexity and precision of statistical procedures are necessary requirements to the study of some large-scale phenomena by social scientists. Recent examples of such topics include the evaluation of a program aimed at developing fertilizer use in Kenya (Duflo, Kremer and Robinson, NBER Working Paper, 2009), an explanation of attitudes towards highly skilled and low-skilled immigration in the United States (Hainmueller and Hiscox, *American Political Science Review*, 2010), and a retrospective electoral analysis of the vote that put Adolf Hitler into power in interwar Germany (King *et al.*, *Journal of Economic History*, 2008).

Quantitative methods courses come with a particular set of principles, which might be arbitrarily summarized as such:

- **Researchers learn and share their knowledge** of quantitative methods to the largest possible audience, and to the best of their abilities.
- **Quantitative data are shared publicly**, along with all necessary resources to replicate their analysis (such as do-files when using Stata).

On the learning side, some very simple principles apply:

- **Quantitative methods are accessible to everyone** interested in learning how to use them. Curiosity comes first.
- **There is no learning substitute to reading**, practicing and looking for help, from all kinds of sources. Reading comes first.
- **Making mistakes**, correcting one's own errors and hitting one's own limits are intrinsic to learning. Trial-and-error comes first.

Statistical reasoning and quantitative methods are intellectually challenging for teachers and students alike, and a collective effort is required for the course to work out:

- **You will have to attend all course sessions:** your instructors expect systematic attendance; catch up with the sessions that you have missed.
- **When attending classes, attend classes:** your instructors will feel completely useless if you do anything else, like reading your email or browsing whatever.
- **Assignments will be graded in order to monitor your progress:** no assignments, no progress towards your final research project, no grades.
- **Read all course material:** read everything you are told to if you want to understand what you are learning in this course.

These, of course, are similar to the course requirements for your other classes.

1.1. Homework

Apart from attending the weekly two-hour course sessions, you are required to:

- **Complete readings from the handbook and other material**, as indicated in the course syllabus. This will take you approximately one hour per week, perhaps two if statistics are completely new to you.
- **Replicate course sessions outside class**, using the do-files provided on the course website. This will take you between half an hour and one hour per week, depending on your learning curve.
- **Work on your research project and assignments**, using the instructions provided during class and in the course documentation. Your project will require between one hour and a half to three hours of work per week, depending on your learning curve and on the project itself.

In total, the time of study for this course amounts to two hours of class and between three to six hours of homework spent on your research project. The time of study for this course is variable, but a fair estimate is that you will spend between five and eight hours per week studying for this course.

It is important to state right from the start that it is not possible to follow the course irregularly, either by skipping weeks and trying to catch up later, and/or by allocating long periods of last-minute work before deadlines. Experience shows that these strategies systematically lead to low achievement and grades.

1.2. Assignments

The course was conceived with a hands-on focus. This means that you are not expected to take lecture notes and then revise for a final graded examination. Instead, you will develop a research project throughout the course.

Your work will be corrected, commented and assessed twice during the course, through assignments that will help monitor your progress. The final version of your project will make up for the largest part of your grade.

In practice, your assignments are 'open assignments' that you can complete with all the resources you need at hand (notes, guides, online help). This cancels out a strategic skill often observed among students: memorising large amounts of information for just one occasional exam. Memorizing will not work at all for this course. Instead, you will have to learn and practice regularly throughout the semester. If you are not used to that method of study, then the course will be one critical opportunity to learn it.

The assignments are also cumulative: Assignment No. 1 will be revised and included in Assignment No. 2, just as your final paper will draw extensively on the revised versions of both assignments. To learn more on how to complete assignments, read the instructions provided in Part 3 of this guide.

1.3. Communication

Let's immediately clarify two things about student-instructor communication for this particular course:

- **Email will be used for feedback and all correspondence**. To simplify this process, we will use normalized email subjects.

  A normalized email subject looks like "**SRQM: Assignment No. 1, Briatte and Petev**", where "SRQM" is an acronym for the course, and "Briatte and Petev" are the family names for you and your study partner.

  Normalized email subjects apply to all correspondence, not just when sending assignments. To ask a question on recoding, you should hence use "SRQM: Question on recoding".

  When working in pairs, always copy your partner when sending emails and assignments. Identically, send all your emails to both course instructors if you want a reply (and especially a quick one).

- **You should ask questions in class and email additional ones**, after having made sure that the answer is not already included in the course material. That implies that you **take ownership of that material**, rather than passively absorb it as lecture notes.

  You should not feel uncomfortable asking questions in class. Neither should you expect others to ask questions for you. Unfortunately, you might have survived several courses doing precisely that until now, and might survive more in the future doing the same. This course, however, runs on personalised projects that do not allow exit or free riding.

  The extra effort that is required from you on that side is the counterpart to offering a course where you are learning through practice rather than by rehashing a handbook into a standardized examination or abstract problem sets with no empirical counterpart.

Your instructors receive multiple emails from several classes; normalization really helps in sorting out large volumes of email. There are no direct sanctions for not following this principle, but there are indirect costs, especially if your assignment emails get lost in the instructors' grading pile or if you end up waiting three weeks to send a question that will get you late on your project.

1.4. Research project

The course is built around your elaboration of a small-scale research project. Because the course is introductory by nature, several limits apply:

- **You are required to use pre-existing data**, instead of assembling your own data and building your own dataset, which is a much longer process that require additional skills in data manipulation.
- **You are required to use cross-sectional data**, because time series, panel and longitudinal data require more complex analytical procedures that are not covered in introductory courses.
- **You are required to use continuous data**, because discrete variables also use different techniques not covered at length in the course. This applies principally to your choice of dependent variable.

These requirements and their terminology are covered in Section 5. For now, just remember this basic principle: your research will be based on **one dependent variable**, sometimes called the 'response' variable, and you will try to explain this variable by predicting the different values that it takes in your sample (dataset) by using **several independent variables**, sometimes called the 'explanatory' variables, or 'predictors', or 'regressors' in technical papers.

Because your research is a personal project, you might bend the above rules to some extent if you quickly show the instructors that you can handle additional work with data management. The following advice might then apply:

- **If you are assembling your data** by merging data from several datasets, you will be using the **merge** command in Stata (Section 5.2). You might also choose to use Microsoft Excel for quicker data manipulation. Do not assemble data if you do not already have some experience in that domain.
- **If you are converting your data**, refer to the course and online documentation on how to import CSV data into Stata using the **insheet** command, or how to convert file formats like SAV files for SPSS. Always perform extensive checks to make sure that your data were properly converted into a readable, valid file.
- **If you are interested in temporal comparison**, such as economic performance before and after EU accession, you can compute a variable that will capture, for example, the change in average disposable income over ten years. Stick with a single variable, and ask for advice in class before proceeding.
- **If you have selected nominal data as your dependent variable**, such as religious denomination, then something went wrong in your research design—unless you know about multinomial logit, in which case you should skip this class. Please identify a different variable that is either continuous or 'pseudo-continuous'—i.e. a categorical variable with an ordinal (or better, interval) scale, such as educational attainment.

1.5. Guidance

This guide works only if you use it. Its writing actually started with students questions: several sections were first written as short tutorials concerning specific issues with data management. One thing led to another, and we ended up with the current document. The aim is to cover 99% of the course by version 1.0. A handful of students also provided valuable feedback on the text—thanks!

The Stata Guide is a take on the course requirements: it offers a narrative for the commands used, by tying them up together with core elements of statistical reasoning and quantitative methods. The guide aims at covering the most useful introductory concepts of statistics for the social sciences, and to offer a detailed exploration of these concepts with Stata.

The 'introductory' term is important: the course focuses on selected commands and options to work through selected operations of 'frequentist' statistics. To fully support these learning steps, it also introduces basic computer and research skills that are often missing to the training of students, and offers a way to assess all aspects of the course through a small-scale research project.

Several sections of the guide are still in draft form, so watch for updates and read it along other documentation. As explained in Section 2.5, there is a wealth of documentation out there, and you should be able to locate help files to complement the Stata Guide on how to use Stata to analyse your data.

2. Computers

A course on quantitative methods is bound to make intensive use of computer software. You all use computers routinely for many different activities, but your level of familiarity with some of the fundamental aspects of computers can vary dramatically. Being reasonably familiar with computers is required for this class.

Please read this section in full and assess whether you are familiar enough with the notions covered, otherwise you should start practicing as soon as possible. A reasonable level of familiarity with computers will help you with using Stata and completing assignments, and will also generally come in handy.

2.1. Basics

The course requires minimal computer skills. In order to open and save files in Stata, you should be able to:

- **Locate files using their file path.** In recent, common operating systems, a file path looks like **/Users/fr/Courses/SRQM/Datasets/qog2011.dta** in Mac OS X, or like **C:\Users\Ivo\Desktop\SRQM\Replication\week2.log** in Windows. Get used to these if you have never used them before.

- **Locate online resources using their URL.** The URL for the course website is http://f.briatte.org/teaching/quanti/. We will use URLs extensively when guiding you through coursework and course material.

- **Understand file and memory size**, which is often displayed in megabytes (MB). Using Stata 11 or below correctly requires setting memory to load large files: for instance, **set mem 500m** sets memory to 500MB.

2.2. Filenames

Filenames are another essential aspect of computer use, especially when you are handling a large number of files and/or using multiple copies of the same file. Some general recommendations apply:

- **In all cases, filenames should be short and informative.** Regularly accessed files, like datasets, have short filenames for faster manipulation, and contain the time period covered by the data.

- **In some cases, filenames require normalization.** This implies using sensible filenames and standard version numbers for files that are chronologically ordered. This point is important because you will be required to normalize the filenames for your work files in this class (Part 3).

2.3. Equipment

Regarding computer equipment, you will need:

- **Access to a computer**, both at university and at home. You should bring your personal laptop to class if you own one. Make sure that you know how to work with your computer and that it is fast enough.
- **A university email account** subscribed to the course, and possibly a personal email account to share larger files and to **backup your work**. The standard solution for an efficient work mailbox is Gmail.
- **Access to the ENTG**, as provided by Sciences Po. The course will use the "Documents" pane to share the course emails and readings. Other files will be available from the course website.
- **A word processor** to type in your final paper. Despite being a worldwide standard, Microsoft Word is unstable: **always backup your work**. Any solution is good as long as it can be printed to a PDF file.
- **A working copy of Stata** (our software of choice, introduced in Section 3) on the computer(s) used during the course and at home. This point will be discussed during class. Stata includes a plain text programming editor.
- **A USB stick**, to build a course 'Teaching Pack' by saving and organizing all course material, as well as the files from your research project. **Always make regular backups of your data** in at least two different locations.

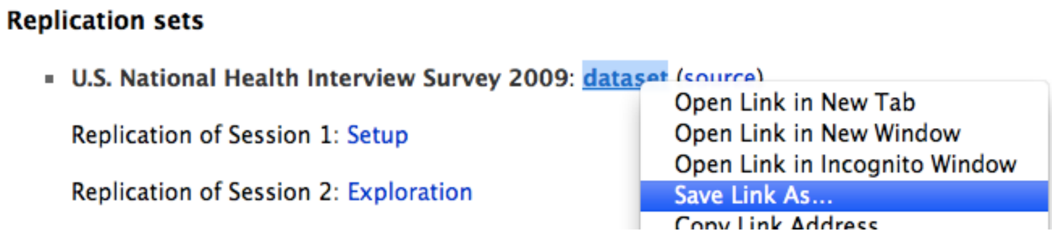
Some of these items will be provided to you through Sciences Po. Please make sure that you have equipped yourself as early as possible in the semester, and as indicated several times in the list above, **always backup your work!**

2.4. Downloads

The course will regularly require that you locate and download resources online, from datasets to do-files, as well as other course material, mostly in PDF format or as ZIP archives. Make sure that you know how to handle these formats.

When downloading files, do not use counter-productive browser settings that download files into temporary folders, or that automatically open files, or even worse, that add file extensions to your downloads. For instance, if your browser automatically adds a "**.txt**" extension to your do-files, you will need to rename the file by turning its file extension back to just "**.do**" to open it in Stata.

Google Chrome, Mozilla Firefox and Apple Safari are common Internet browsers with appropriate "Save As" options available from their contextual menus. The example below shows the contextual menu for Google Chrome on Mac OS X.



Replication sets

- U.S. National Health Interview Survey 2009: dataset (source)

  Replication of Session 1: Setup

  Replication of Session 2: Exploration

All course material should be archived into a structured folder hierarchy, which will depend on your own preferences and operating system. A simple hierarchy, such as **~/Documents/SRQM/** on Mac OS X, will let you access all files quickly.

2.5. Help

Quantitative methods cannot be learnt once and for all: the course will require that you frequently search for help, often from online sources. Always consult the course material for each session before seeking additional help: the answer is very often just before your eyes or a few clicks away.

If you are looking for help on a Stata command, use the **help** command to access the very large internal documentation included in Stata. Even experienced users use help pages on a daily basis. Learning to use Stata help pages is a course objective in itself.

Stata **help** command: http://www.stata.com/help.cgi?help

If you are looking for help on statistics, please first refer to the course readings listed in the course syllabus. Feinstein and Thomas' *Making History Count* (Cambridge University Press, 2002) is the main handbook for this course; help on graphics and other topics can also be found in the additional readings.

If you are looking for help on statistical procedures in Stata, please first refer to the course website for a selection of Stata tutorials. Two American universities, Princeton and UCLA, have produced excellent Stata tutorials that cover similar material than the course sessions. More tutorials are available online.

Course website: http://f.briatte.org/teaching/quanti/

If you are stuck, do not panic! Please first make sure that you have explored the software and course resources listed above. It is safe to assert that 99% of Stata questions for this course can be answered from the course material. If still stuck, try a Google search on your question: thousands of online sources hold answers to identical questions asked by Stata users around the world. Researchers often check the Statalist and the statistics section of the StackOverflow website for answers to their own questions.

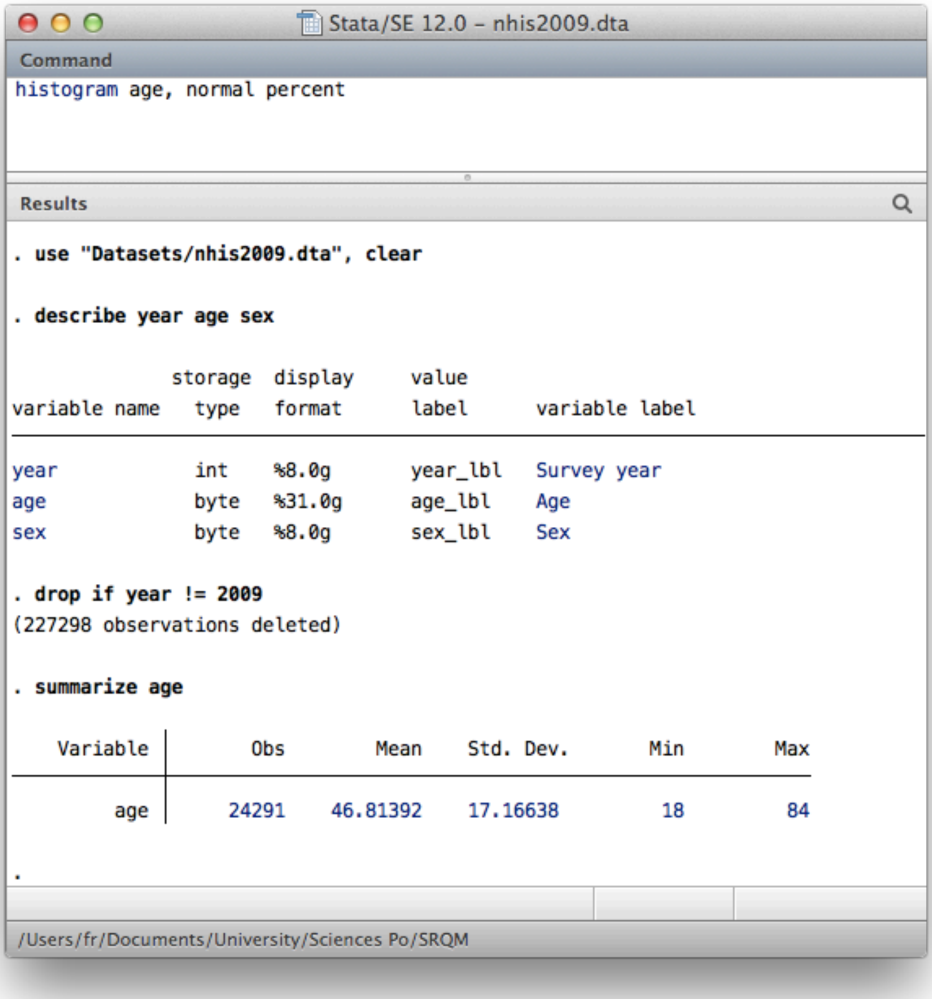
Finally, if still stuck, and in this case only, **email us** to ask your questions directly. It would be preferable if email correspondence could be limited to questions on your research design, rather than questions that could be answered by simply reading the course material mentioned above.

2.6. Commands

Stata can be used either through its Graphical User Interface (GUI), like most software, or through a 'command line' terminal, which is a very common aspect of programming environments. As explained just below, learning how to use the command line and writing do-files are compulsory for replication purposes.

The 'command line' terminal works by entering lines of instructions that are reproduced, along with their results, in another window. The next sections of this guide explain further how Stata works and document the usual commands used in this course for data management, description, analysis and graphing. A 'cheat sheet' for these commands is offered in Section 12.

The screenshot below shows an example of such commands, typed manually in the Command window (top); after running them by pressing Enter, their output showed in the Results window (bottom).



Stata/SE 12.0 – nhis2009.dta
Command

```
histogram age, normal percent
```

```
. use "Datasets/nhis2009.dta", clear

. describe year age sex

              storage  display     value
variable name   type   format      label      variable label
------------------------------------------------------------------

year            int    %8.0g       year_lbl   Survey year
age             byte   %31.0g      age_lbl    Age
sex             byte   %8.0g       sex_lbl    Sex

. drop if year != 2009
(227298 observations deleted)

. summarize age

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
         age |     24291    46.81392    17.16638         18         84

.
```

/Users/fr/Documents/University/Sciences Po/SRQM

Command line terminals work by entering commands, such as **set mem 500m** (which assigns 500MB of computer memory in Stata 11–). When you press Enter, Stata will try to execute, or 'run,' the command, which might occasionally take a little bit of time if your data or command are computationally intensive.

If your command ran successfully, Stata will display its result:

```
. set mem 500m

Current memory allocation

                    current                                 memory usage
    settable          value     description                 (1M = 1024k)
    --------------------------------------------------------------------
    set maxvar         5000     max. variables allowed           2.105M
    set memory          500M    max. data space                500.000M
    set matsize         400     max. RHS vars in models          1.254M
                                                            -----------
                                                               503.359M
```

Note that some commands produce 'blank' outputs in the Results window, i.e. the command was successfully entered and executed, but there is no indication of its actual result(s). In these cases, a simple "**.**" line dot will appear in the Results window, as to show that Stata encountered no problem while executing the command, and that it is ready to process another one.

If the command is not valid, which often happens due to typing errors or for other reasons related to how Stata works, it will display an error or a warning. In that case, you have to fix the issue, often by re-typing the command correctly (as in the '**summarizze**' example below), or by checking the documentation to understand where you made a mistake and how to fix it.

```
. summarizze age
unrecognized command:  summarizze
r(199);

. summarize age

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
         age |     24291    46.81392    17.16638         18         84
```

Stata commands are case-sensitive. Use only lowercase letters when typing commands. Variables can come in both uppercase and lowercase letters, which you will have to type in exactly to avoid errors. As a rule of thumb, when creating variables, use only lowercase letters.

If you need to correct an invalid command or re-run a command that you have already used earlier on, you can use the **PageUp** or **Fn-UpArrow** keys on your keyboard to browse through the previous commands that you typed, which are also displayed in the Review window.

Some commands can be abbreviated for quicker use. If you run the **help summarize** command in Stata, the help window will tell you that the **summarize** command can be shorthanded as **su**:

```
. su age

    Variable |        Obs        Mean    Std. Dev.       Min        Max
-------------+---------------------------------------------------------
         age |      24291    46.81392    17.16638         18         84
```

Abbreviations exist for most commands and come in handy especially with commands such as **tabulate** (shorthand **tab**), **describe** (shorthand **d**) or even **help** (shorthand **h**). They also work for options like the **detail** option for the **summarize** command:

```
. su age, d

                             Age
-------------------------------------------------------------

      Percentiles      Smallest
 1%           18             18
 5%           21             18
10%           24             18       Obs               24291
25%           32             18       Sum of Wgt.       24291

50%           46                      Mean           46.81392
                        Largest       Std. Dev.      17.16638
75%           60             84
90%           71             84       Variance       294.6846
95%           77             84       Skewness        .234832
99%           83             84       Kurtosis        2.09877
```

Some commands have particular attributes. Comments, for example, are lines of explanation that start with * or //. They are not executed, but are necessary to make your do-files and logs understandable by others as well by yourself. The first and third lines in the example below are comments.

```
. * Creating a variable for Body Mass Index (BMI).

. gen bmi = weight*703/height^2

. * Summary statistics for BMI.

. tabstat bmi, s(n mean sd min median max)

    variable |         N      mean        sd       min       p50       max
-------------+------------------------------------------------------------
         bmi |     24291     27.27  5.134197  15.20329  26.57845  50.48837
--------------------------------------------------------------------------
```

You will find many comments in the course do-files: use them to describe what you are doing as thoroughly as necessary. You will be the first beneficiary of these comments when you reopen your own code after some time.

Additional commands can be installed. Stata can 'learn' to 'understand' new commands through packages written by its users, most often academics with programming skills. We will use the **ssc install** command at a few points in this guide to install some of these packages. Installation with **ssc install** requires an Internet connection.

Right away, you should install the **fre** command in Stata by typing **ssc install fre**, as we will use this command a lot to display frequencies. Other handy commands like **catplot**, **spineplot** or **tabout** will be installed throughout the course, as in the example below, which shows possible installation results:

```
. ssc install tabout
checking tabout consistency and verifying not already installed...
installing into /Users/fr/Library/Application Support/Stata/ado/stbplus/...
installation complete.

. ssc install fre
checking fre consistency and verifying not already installed...
all files already exist and are up to date.
```

2.7. Replication

In this guide, terms like commands, logs and do-files collectively designate an essential aspect of quantitative methods: replication, i.e. providing others as well as yourself with the means to replicate your analysis.

Replication requires that you keep your original files intact. The dataset that you will use for your research project should be left unmodified in your course folder, and should be provided along with your other files when handing in assignments.

Replication also requires the list of commands you used to edit your data, for instance to drop observations or to recode variables, as well as the commands that you used to analyse the data, such as **tabstat**, **histogram** and **regress**. The commands can all be stored into a single text file, with one command appearing on each line: this structure is common to computer scripts and programs.

A **do-file** is a text file that contains your commands and comments. A **log file** is a separate text file that contains these commands, along with their results. The production of do-files will be practiced in class, and additional documentation appear in many Stata tutorials listed in the course material.

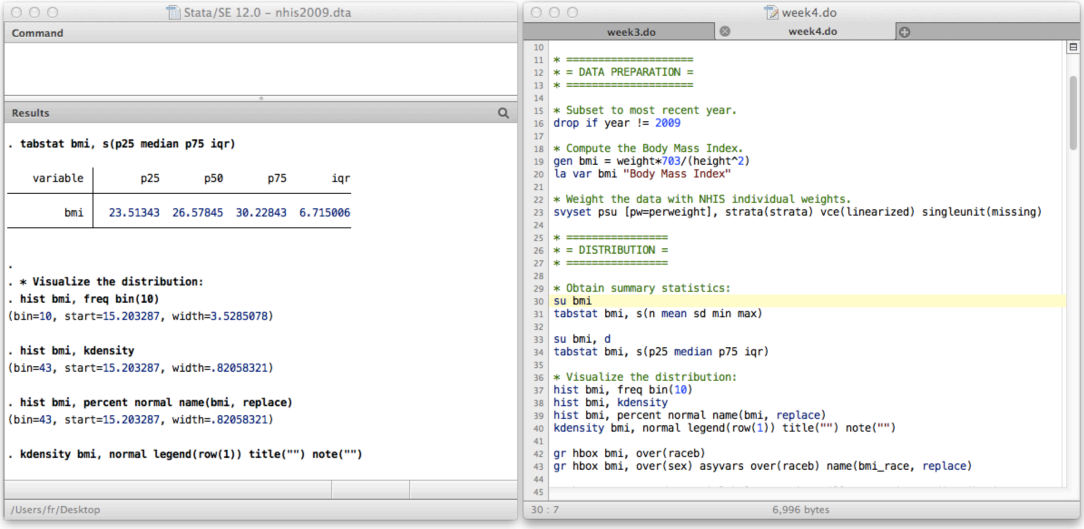
Replication files are a crucial aspect of programming. If you open the do-files for this course in the Stata do-file editor or in any other Stata-capable editor, you will notice that the files feature line numbers and a coloured syntax. These generic features are built in most programming environments.

Learning to understand and write in programming languages takes time, and therefore constitutes a particular skill. Writing do-files in Stata requires learning commands and their syntax, exactly like languages require learning vocabulary and grammar. Just like with languages, the learning curve also decreases once you already know one. Finally, since programming can also reflect high or low writing skills, you should read the coding recommendations in Section 13.3 on coding before submitting your own work.

3. Stata

Our course uses a recent version of Stata, a common software choice in social science disciplines. Using any statistical software requires some basic skills in file management and programming. The following steps apply to virtually any Stata user, and should be practised until you are familiar enough with them.

Once you start exploring the Stata interface, you will realize that most windows can be hidden to concentrate on your commands, do-files and results, as below. We won't use any other element of the interface in this course, but feel free to explore Stata and use other functionalities.



```
. tabstat bmi, s(p25 median p75 iqr)

    variable |       p25       p50       p75       iqr
-------------+----------------------------------------
         bmi |  23.51343  26.57845  30.22843  6.715006
------------------------------------------------------

.
. * Visualize the distribution:
. hist bmi, freq bin(10)
(bin=10, start=15.203287, width=3.5285078)

. hist bmi, kdensity
(bin=43, start=15.203287, width=.82058321)

. hist bmi, percent normal name(bmi, replace)
(bin=43, start=15.203287, width=.82058321)

. kdensity bmi, normal legend(row(1)) title("") note("")
```

```

* ====================
* = DATA PREPARATION =
* ====================

* Subset to most recent year.
drop if year != 2009

* Compute the Body Mass Index.
gen bmi = weight*703/(height^2)
la var bmi "Body Mass Index"

* Weight the data with NHIS individual weights.
svyset psu [pw=perweight], strata(strata) vce(linearized) singleunit(missing)

* ================
* = DISTRIBUTION =
* ================

* Obtain summary statistics:
su bmi
tabstat bmi, s(n mean sd min max)

su bmi, d
tabstat bmi, s(p25 median p75 iqr)

* Visualize the distribution:
hist bmi, freq bin(10)
hist bmi, kdensity
hist bmi, percent normal name(bmi, replace)
kdensity bmi, normal legend(row(1)) title("") note("")

gr hbox bmi, over(raceb)
gr hbox bmi, over(sex) asyvars over(raceb) name(bmi_race, replace)

```

3.1. Command line

Stata has a graphic user interface (GUI) and a command line system. The latter is much more versatile and teaches you the syntax used by Stata. More importantly, the command line forces you to plan your work with data management and analysis.

Because the commands entered through the command line can be recorded, i.e. stored as **logs** (see below), it will enable you to maintain a record of your operations and to store comments along. This step is essential to keep afloat with your own work, as well as to share it with others, usually as **do-files**.

The Stata GUI can be used occasionally for routine operations that need not appear in your do-files. Keyboard shortcuts also save some time, as with 'File > Open…' (**Ctrl-O** in Stata for Windows) or 'File > Change Working Directory…' (**Cmmd-Shift-J** in Stata for Macintosh; this document uses '**Cmmd**' to designate the '⌘', a. k. a. '**Command**', '**Cmd**' or '**Apple**' modifier key).

3.2. Memory

Stata 12 works memory on its own, but older versions of Stata usually open with a very small memory allocation for data. To safely open large files in Stata 11 or below, we recommend you run the **set mem 500m** command to allocate it 500MB.

Very large datasets might require allocating more memory, using a different version of Stata with enhanced capacities, or even switching from Stata to software with higher computational power. This course will not require doing so.

3.3. Working directory

The working directory is the folder from which Stata will open and save files by default. **You will have to set the working directory every time you launch Stata.** The path to your working directory depends on your system (Section 2.1).

To learn what is the current work directory, use the **pwd** command. To set it to a new location, type **cd** followed by the path to the desired folder. To list the contents of the working directory, use the **ls** or **dir** command.

Your working directory should be the main '**SRQM**' folder for this course, which we also call the '**Teaching Pack**' because you will be required to download all course material to it. Download the Teaching Pack from the course website and unzip it to an easily accessible location, such as your Documents folder.

The example below reflects all directory commands for a user called 'fr' using Mac OS X to change the Stata working directory from the user's Desktop to the SRQM folder, which was downloaded and moved to the Documents folder:

```
. pwd
/Users/fr/Documents

. cd ~/Documents/Teaching/SRQM/
/Users/fr/Documents/Teaching/SRQM

. ls, w

Admin/          Datasets/       Software/       readme.pdf*     website.url*
Course/         Replication/    emails.txt      readme.txt*
```

The quotes around the file path are optional in this example, but are compulsory if your file path contains spaces. The **ls** command above was given the **wide** (shorthand **w**) option to make its output simpler to understand.

If you are unsure what the path to your SRQM folder is, do not just ignore this step as if it were optional. Select '**File > Change Working Directory…**' in the Stata menus, and from there, select your SRQM folder.

3.4. Open/Save

Stata can use the usual open/save routine that you are familiar with from using other software. It can also open datasets and save them from the command line if you have correctly set your working directory in the first place.

The example below shows how to download a Stata dataset from an online source and then save it on disk. The **use** command with the **clear** option removes any previously opened dataset from memory, and the **save** command with the **replace** option will overwrite any pre-existing data:

```
. use http://f.briatte.org/teaching/quanti/data/trust.dta, clear

. save datasets/trust.dta, replace
file datasets/trust.dta saved
```

In this course, you will never have to save any data: instead, you should leave all datasets intact and use do-files to transform them appropriately. This will ensure that your work stays entirely replicable.

3.5. Log files

The log is a text file that, once open with **log using**, will save every single command you enter in Stata as well as its results. Systematically logging your work is good practice, even when you are just trying out a few things. Logs can be closed with the **log close** command followed by the name of your log if it has one:

```
. log using example.log, name(example) replace
--------------------------------------------------------------------------------

      name:  example
       log:  /Users/fr/Documents/Teaching/SRQM/example.log
  log type:  text
 opened on:  17 Feb 2012, 00:01:42

. use datasets/qog2011, clear

. * Count countries with 0% malaria risk in 1994.

. count if sa_mr==0
  76

. log close example
      name:  example
       log:  /Users/fr/Documents/Teaching/SRQM/example.log
  log type:  text
 closed on:  17 Feb 2012, 00:02:53
--------------------------------------------------------------------------------
```

Comments will also be saved to the log file, which is particularly useful when you have to read through your work again or share it with someone. In the example above, all comments, commands and results were saved to the log file.

3.6. Do-files

Logs are useful to save every operation and result from a practice session. If you need someone else to replicate your work, however, you just need to share the commands you entered, along with the comments that you wrote to document your analysis. Files that contain commands and comments are called **do-files**.

Writing do-files is a crucial aspect of this course. Absent of a do-file, your work will be mostly incomprehensible, or at least impossible to reproduce, to others. Your do-file should include your comments, and it should run smoothly, without returning any errors. You will discover that these steps require a lot of work, so start to program early. To open a new do-file, use either the **doedit** command or the 'File > New Do-file' menu (keyboard shortcut: **Ctrl-N** on Windows, **Cmmd-N** on Macintosh).

You should take inspiration from the do-files produced for the course to write up your own do-file for your research project. All our do-files are available from the course website. This course requires only basic programming skills, as illustrated by the do-files that we run during our practice sessions. More sophisticated examples can be found online.

To execute (or 'run') a do-file, open it, select any number of lines, and press **Ctrl-D** in Stata for Windows or **Cmmd-Shift-D** in Stata for Macintosh. You can also use either the GUI icons on the top-right of the Do-file Editor window, or use the **do** or **run** commands. Use the **Ctrl-L** (Windows) or **Cmmd-L** (Macintosh) keyboard shortcuts to select the entire current line in order to run it.

Get some practice with do-files as soon as possible, since your coursework will include replicating one do-file a week. Replicating is nothing more than reading through the comments of a do-file, while running all its commands sequentially.

3.7. Shutdown

When you are done with your work, just quit Stata like you would quit any other program. At that stage, any unsaved operation will be lost, so make sure that your do-file contains all the commands that you might want to replicate.

To quit with the command line, use **log close _all** to tell Stata to close all logs, and then type **exit, clear** to erase any data stored in Stata memory and quit. Alternatively, just exit Stata like any other program to close logs and clear data automatically.

Remember *not* to save your data on exit (Section 3.4).

3.8. Alternatives

This course uses **Stata** (by StataCorp) as its statistical software of choice. Stata is commonly used by social scientists working with quantitative data in areas such as economics and political science. It is a powerful solution that provides a good middle ground between spreadsheet editors and **R**, which is the most powerful–and least expensive, since it's free and open source–but also the most difficult statistical choice of software.

Stata is also more advanced than **SPSS** because of its emphasis on programming, which has led to the development of a large set of additional packages. Most statistical procedures know some form of implementation in Stata, and the software is supported by a large user community that meets on the Statalist mailing-list.

Stata has a few limitations. Its graphics engine is not bad, but not excellent either. It is not as capable as **SAS** with large datasets, nor as focused on a particular approach to quantitative analysis as **EViews** for econometrics. Finally, unlike free and open source software, it is a commercial product.

Within these limitations, Stata remains an appropriate solution for the kind of procedures that you will learn to use during this course. Its programming features, operated through the command line, are central to the learning objectives of the course.

The Stata website will tell you more about the different versions of Stata. It also holds an online version of the software documentation: http://www.stata.com/. The website also links to Stata books, journals, and to the Statalist mailing list.

If you are planning to continue using quantitative methods during your degree, you should also start learning more about R as soon as you are familiar with Stata. Alternatives to Stata are documented in the course material.

4. Research

The course is built around small research projects, on which you will write your final paper. Every student (grouped in pairs when applicable) is expected to participate, which requires some basic knowledge of scientific reasoning.

Scientific research aims at **establishing theories** of particular knowledge items, such as elections (political science), continents (geography), international trade (economics), history, proteins, galaxies and so on. All these items are grounded in real events that are partially processed through theoretical models of what they represent: competitions of political elites within the structural constraints of partisan realignments, drifting tectonic plates on top of the lithosphere, markets dominated by agents interested in macroeconomic performance, representations of particular historical events, biological compounds of amino acids, gravitational systems of stars… Our collective knowledge of reality is directly mediated by these abstract conceptions.

Quantitative social science explores some particular phenomena of usually large scale, in order to produce complex **explanatory models** that follow a common set of rules with the ones cited above. Precisely, it looks for the regularities and mechanisms that intervene in the distribution of social events such as military conflict, economic development or democratic transitions, all of which tend to happen under particular conditions at different points of space and time. The aims of quantitative social science consist in building theories that simplify these conditions by pointing at the specific variables that might intervene in causing the events under scrutiny.

The final model used in this course, linear regression, offers one possible way of identifying these variables, by looking at how a set of independent (explanatory) variables can predict a fraction of another dependent (explained) variable. Can we understand, for example, the spread of tuberculosis in a country by looking only at the different levels of sanitation in a sample of the world? Is it the case that the support of violent action decreases with age and education? Are states more likely to be concerned by environmental issues when they possess a high level of national wealth? Or is it rather the case that their attention varies in function of their own exposure to, for instance, natural disasters?

Thousands of researchers spend their whole lives on similar questions. Several millions of theories exist on all aspects of the real (natural, material) world.

4.1. Comparison

A fundamental motive behind theory building lies in comparison. Our units of observations, such as individuals or countries, express different characteristics that can be compared with each other. Nation states, for instance, express various levels of authority over their citizens, to the point where we can (or at least wish to) distinguish some political systems as democracies—structures of authority that are ultimately controlled by citizens through means such as open elections. Identically, some nation states go through periods of acute political disruption that lead to social revolutions. Even more fundamentally, some nation states hardly qualify to that title: the extent to which states and nations coincide also varies from a country to another. These questions are fundamental issues in comparative politics (the selection of issues above come from a course by David Laitin at Stanford University). Similar research questions structure all other fields of social science, from economic history to analytical sociology.

To understand the variety of political configurations in (geographical) space and in (historical) time, social science researchers formulate arguments in which they posit **explanatory factors**, which we will call **independent variables**. Continuing with the examples above, an early explanation of democracy is Montesquieu's theory that climate influences political activity, and an early explanation of social revolution is Marx's theory of class structure. Both authors examined particular cases of democracies and revolutions, and then derived a particular theory from their observations. Modern theories tackle the same issues, but provide different explanations, using factors such as elections, state/society interactions, or the precise timing of industrialization in each country under examination.

Advances in social science consist in providing analytically more precise **concepts** and **typologies** for the phenomena under study. Revolutions, for instance, are now studied under several categories, which distinguish, for instance, "white" (non-violent) revolutions from other ones. By doing so, researchers improve the specification of these phenomena, which we will technically designate as our **dependent variables**. The deep anatomy of these social phenomena nonetheless poses a constant challenge to scientists, since before we can start understanding their causes, we need to define and conceptualize complex phenomena such as "civil war", "counter-insurgency", "morality" or "identity".

The quantitative analysis of social phenomena cannot solve any of these issues, but it can contribute to improving our knowledge of concept formation, theory building and comparison across units of observation.

4.2. Theory

Formally, theory building starts with a certain knowledge of scientific advances in a given field. A certain amount of knowledge already exists, for example, on why young mothers abort, or on how durable peace occurs and then persists between nation states. Everything that you know from your previous courses in the social sciences will be useful in thinking about your data, especially what you have learned in the fields of demography, economics, public health or sociology. Once previous knowledge has been considered, however, the unique method of verification that exists for a particular phenomenon is its observation.

Several methods of observation coexist. All of them, and not just quantitative methods, are based on structured comparisons of different units of observation, would it be protesters in a public demonstration, voters in an election, young mothers in an abortion clinic, national governments in a technological race, or random members of the public. Observations are then produced either through **experimental** or through **observational** studies, both of which provide a number of facts, such as a response rate to a question or the adoption of a particular behaviour. These facts are collected in order to build theories to explain why and how they occur.

When it is impossible to work on all instances of a phenomenon in the material world, such as the development of cancer cells or the occurrence of revolutions, scientists focus their attention on carefully selected **samples** of observations and then **generalise** their findings to a larger number of observations. Scientific theories therefore exist for phenomena as diverse, as common and as important as the democratic election of extreme-right parties, or the effect of radiations on the physiological status of human beings.

These operations of theory building guide scientific inquiry. Additional principles concern the rules under which we construct theoretical models. A crucial rule of science consists in the suppression of all personal judgement over the data (**objectivity**), in order to formulate statements that hold generally true rather than only towards a given end (normativity). Social science is a branch of inquiry where these principles are particularly difficult to follow, but where they apply nonetheless, and where they allow to formulate scientific statements on several aspects of social interaction, from suicide terrorism to divorce, from increases in exports to changes in political leadership.

4.3. Quantitative social science

Quantitative approaches to social science apply the aforementioned scientific rules in order to identify **variations** in events that involve a number of **units** such as people, states, elections or civil wars, and that we describe through a certain number of characteristics that vary from a unit to another—**variables**.

An example of quantitative result relates to presidential approval: social surveys that measure the extent to which people tend to support their presidents have found that economic performance is often very influential in determining that support. Theoretical models, such as David Easton's systemic theory of political inputs and outputs, support that kind of finding. Identically, health expenditure has been measured in Western countries for several decades. Variations in health spending seem easily explained by variations in life expectancy, but also by the increasing costs caused by improvements in medical technology. Current data contribute to explain that phenomenon: health expenditure growth does not directly depend on the age structure of a country and on the longevity of its residents, but rather on the health status and behaviour of its individuals, which themselves happen to vary with age.

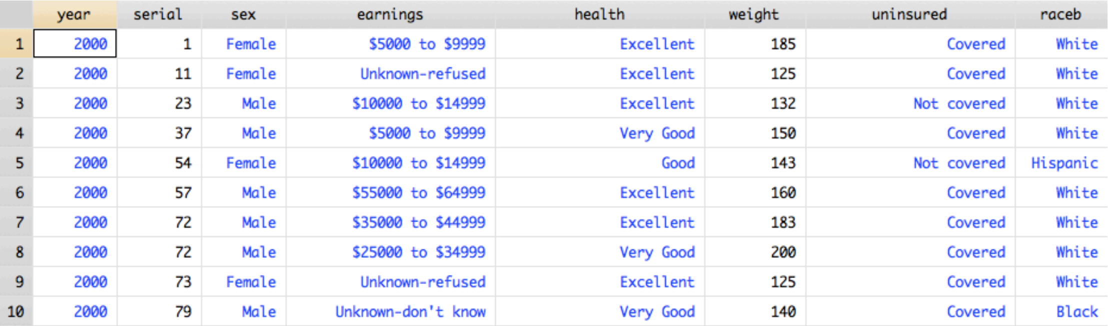
Variables appear in these results and in their explanatory theories. Economic performance, for instance, is a variable often measured through unemployment levels, gross domestic product, public deficits and annual changes in per capita disposable income. Identically, health expenditure and health behaviour are also measured through complex computations of health services supply and demand. The processes and mechanisms that causally connect these variables come from quantitative, qualitative and also from theoretical research, in order to provide **causal efficacy** to the **correlations** that we observe.

There are multiple sources of error in that process. One of the most important comes from the **measurement** of our variables: a survey question can contain unwanted incentives to answer in a particular way, or it can simply be confused and misleading, or the answer to a question can be misinterpreted. The careful creation of **concepts** for complex phenomena such as racism, political identity or illness solves part of that issue.

Valid and reliable data are then used to test particular **hypotheses**, such as the presumption that education and xenophobia are negatively correlated, or that economic growth is proportionate to the openness of national economies to all possible competitors. Quantitative social science verifies, or nullifies, these kinds of hypotheses, based on various sources of data, or statistics.

4.4. Social statistics

Quantitative data come in the form of **datasets**, which themselves are numeric collections of variables for a given set of units of observation. The example below is taken from the U.S. National Health Interview Survey (NHIS):



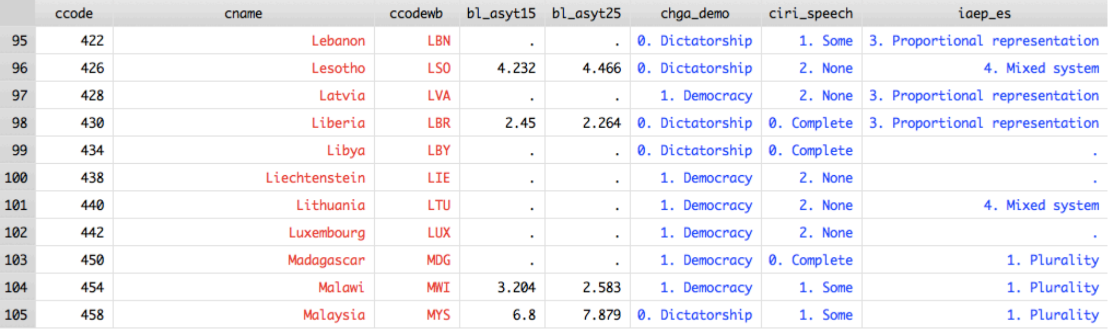
	year	serial	sex	earnings	health	weight	uninsured	raceb
1	2000	1	Female	$5000 to $9999	Excellent	185	Covered	White
2	2000	11	Female	Unknown-refused	Excellent	125	Covered	White
3	2000	23	Male	$10000 to $14999	Excellent	132	Not covered	White
4	2000	37	Male	$5000 to $9999	Very Good	150	Covered	White
5	2000	54	Female	$10000 to $14999	Good	143	Not covered	Hispanic
6	2000	57	Male	$55000 to $64999	Excellent	160	Covered	White
7	2000	72	Male	$35000 to $44999	Excellent	183	Covered	White
8	2000	72	Male	$25000 to $34999	Very Good	200	Covered	White
9	2000	73	Female	Unknown-refused	Excellent	125	Covered	White
10	2000	79	Male	Unknown-don't know	Very Good	140	Covered	Black

- **The rows hold observations:** each row of numeric data designates the answers of one individual respondent (the unit of observation).
- **The columns hold variables:** each column designates designate to a particular question, such as gender, earnings, health status and so on.

In this example, some variables can be ordered: health, for instance, is based on a self-reported measure that ranges from “poor” to “excellent”. Other variables take values that cannot be ordered: **raceb**, for instance, corresponds to the respondent’s racial-ethnic profile, for which there is no ordering. Other variables have only two possible values, such as sex (either male or female) or insurance status (either covered or not).

These are examples of different **types of variables** that come in addition to 'purely numeric' ones like weight, measured in pounds.

Units of observations are not necessarily individuals: they can be anything from organizations to historical events (Section 5.1). Sometimes, not all variables can be measured for all observations: there will be **missing values**. The example below is taken from the Quality of Government (QOG) dataset:



	ccode	cname	ccodewb	bl_asyt15	bl_asyt25	chga_demo	ciri_speech	iaep_es
95	422	Lebanon	LBN	.	.	0. Dictatorship	1. Some	3. Proportional representation
96	426	Lesotho	LSO	4.232	4.466	0. Dictatorship	2. None	4. Mixed system
97	428	Latvia	LVA	.	.	1. Democracy	2. None	3. Proportional representation
98	430	Liberia	LBR	2.45	2.264	0. Dictatorship	0. Complete	3. Proportional representation
99	434	Libya	LBY	.	.	0. Dictatorship	0. Complete	.
100	438	Liechtenstein	LIE	.	.	1. Democracy	2. None	.
101	440	Lithuania	LTU	.	.	1. Democracy	2. None	4. Mixed system
102	442	Luxembourg	LUX	.	.	1. Democracy	2. None	.
103	450	Madagascar	MDG	.	.	1. Democracy	0. Complete	1. Plurality
104	454	Malawi	MWI	3.204	2.583	1. Democracy	1. Some	1. Plurality
105	458	Malaysia	MYS	6.8	7.879	0. Dictatorship	1. Some	1. Plurality

The Quality of Government dataset uses countries as its unit of analysis. Due to several difficulties with data collection and measurement, it shows an important number of **missing observations** for several variables: the "bl_asyt15" and "bl_asyt25" variables, for instance, measure the average number of schooling years among the population, and have a high number of missing values. There are also some missing values in the column for the **iaep_es** variable, which holds the legislative electoral system for each observation.

The combined effect of sampling and missing observations forces us to work on a finite number of observations, which introduces a further risk of **error** when we start analysing the data. Furthermore, we will use more than one model, as the type of variables under examination calls for different statistical procedures. Similarly, the number of variables influences these procedures:

- The **distribution** of one variable, such as the number of democracies observed at a given point in time or the proportions of each religious group in a given population in 2004, is captured by **univariate statistics**. These statistics allow to calculate to what extent our sample might be different with respect to the universe of data that we are sampling from, such as the whole population of a country, all countries or all instances of civil war. This **standard error** will appear in all our statistical procedures.

- The **relationship** between two variables, such as racism and income or national wealth and defence spending, is addressed by **bivariate tests**. These tests provide the probability that a relationship observed within our sample could be caused by mere chance. This crucial statistic is called the **p-value**: only when it stays under a certain **level of significance** will we accept that an observed relationship is **statistically significant**.

- The relationship between two or more variables can also be **modelled** into an equation, such as $\textit{productivity} = \alpha \cdot \textit{technology} + \beta \cdot \textit{education}$. Formally, models include an error term ε in the equation, to account for the sampling error previously mentioned. Identically to bivariate tests, models also come with a **p-value** for us to decide whether they can be confidently followed or not.

These three types of procedures are the essential building blocks of the course, and of **quantitative analysis** in general. Because they require thinking about so many different factors at the same time, they also require to think about data and analysis in a particular manner—**statistical reasoning**, the primary teaching objective of this course.

More details on the statistical operations covered in the course appear in the course syllabus, which you should read before reading the next section on data. You should also read a few pages of quantitative social science before going further, as to make sure that you understand the kind of research that you will be learning to perform, using some introductory procedures.

4.5. Readings

Depending on your experience with quantitative analysis and on your general themes of interest, you should read **at least four** of the texts below, after making your own selection based on personal interests. If you are not familiar with political science, you will want to include Charles Cameron's presentation of quantitative analysis in that discipline.

Some additional recommendations apply:

- **Do not try to understand in full the methods used by the authors: concentrate on the style of writing and reasoning instead**, as well as on the particular form of research question that quantitative researchers examine in different disciplines.
- **If you have little experience with either quantitative analysis or with scientific writing, you will need more and not less from that list.** Actually, you should read the full list if you have no experience with either, and stop only when you feel familiar enough with the material.
- **The reading of these texts is unmonitored, and left entirely up to you to organise.** You might want to read at least two texts in the first two weeks, then one more before writing up each assignment, and finally one last before writing your final paper.

If you are selecting **political science** as your major interest for the readings, start with the reading by Cameron, then read either one of the Gelman *et al.* texts or the Bartels one, and then read either Jordan or Tavits.

- Larry M. Bartels, *Unequal Democracy. The Political Economy of the New Gilded Age*, Princeton University Press, 2008, chapter 5.

In this chapter I explore four important facets of Americans' views about equality. First, I examine public support for broad egalitarian values, and the social bases and political consequences of that support. Second, I examine public attitudes toward salient economic groups, including rich people, poor people, big business, and labor unions, among others. As with more abstract support for egalitarian values, I investigate variation in attitudes toward these groups and the political implications of that variation. Third, I examine public perceptions of inequality and opportunity, including perceptions of growing economic inequality, normative assessments of that trend, and explanations for disparities in economic status. Finally, I examine how public perceptions of inequality, its causes and consequences, and its normative implications are shaped by the interaction of political information and political ideology.

- Charles Cameron, "What is Political Science?" in Andrew Gelman and Jeronimo Cortina, *A Quantitative Tour of the Social Sciences*, Cambridge University Press, 2009, chapter 15.

  Politics is part of virtually any social interaction involving cooperation or conflict, thus including interactions within private organizations ("office politics") along with larger political conflicts. Given the potentially huge domain of politics, it's perfectly possible to talk about "the politics of X," where X can be anything ranging from table manners to animal "societies." But although all of these are studied by political scientists to some extent, in the American academy "political science" generally means the study of a rather circumscribed range of social phenomena falling within four distinct and professionalized fields: American politics, comparative politics, international relations, and political theory (that is, political philosophy).

- Ashley M. Fox, "The Social Determinants of HIV Serostatus in Sub-Saharan Africa: An Inverse Relationship Between Poverty and HIV?" *Public Health Reports* 125(s4), 2010.

  Contrary to theories that poverty acts as an underlying driver of human immunodeficiency virus (HIV) infection in sub-Saharan Africa (SSA), an increasing body of evidence at the national and individual levels indicates that wealthier countries, and wealthier individuals within countries, are at heightened risk for HIV. This article reviews the literature on what has increasingly become known as the positive-wealth gradient in HIV infection in SSA, or the counterintuitive finding that the poor do not have higher rates of HIV. This article also discusses the programmatic and theoretical implications of the positive HIV-wealth gradient for traditional behavioral interventions and the social determinants of health literature, and concludes by proposing that economic and social policies be leveraged as structural interventions to prevent HIV in SSA.

- Andrew Gelman et al., Red State, Blue State, Rich State, Poor State. Why Americans Vote the Way They Do, Princeton University Press, 2008, chapter 2.

This book [chapter] was ultimately motivated by frustration at media images of rich, yuppie Democrats and lower-income, middle-American Republicans—archetypes that ring true, at some level, but are contradicted in the aggregate. Journalists are, we can assume, more informed than typical voters. When the news media repeatedly make a specific mistake, it is worth looking at. The *perception* of polarization is itself a part of polarization, and views about whom the candidates represent can affect how political decisions are reported. And, as we explore exhaustively, the red–blue culture war does seem to appear in voting patterns, but at the high end of income, not the low, with educated professionals moving toward the Democrats and managers and business owners moving toward the Republicans.

- David Karol and Edward Miguel, "The Electoral Cost of War: Iraq Casualties and the 2004 U.S. Presidential Election", *Journal of Politics* 69(3), 2007.

  Many contend that President Bush's reelection and increased vote share in 2004 prove that the Iraq War was either electorally irrelevant or aided him. We present contrary evidence. Focusing on the change in Bush's 2004 showing compared to 2000, we discover that Iraq casualties from a state significantly depressed the President's vote share there. We infer that were it not for the approximately 10,000 U.S. dead and wounded by Election Day, Bush would have won nearly 2% more of the national popular vote, carrying several additional states and winning decisively. Such a result would have been close to forecasts based on models that did not include war impacts. Casualty effects are largest in "blue" states. In contrast, National Guard/Reservist call-ups had no impact beyond the main casualty effect. We discuss implications for both the election modeling enterprise and the debate over the "casualty sensitivity" of the U.S. public.

- Rachel Margolis and Mikko Myrskyla "A Global Perspective on Happiness and Fertility", *Population and Development Review* 37(1), 2011.

  The literature on fertility and happiness has neglected comparative analysis. we investigate the fertility/happiness association using data from the world values Surveys for 86 countries. we find that, globally, happiness decreases with the number of children. this association, however, is strongly modified by individual and contextual factors. most importantly, we find that the association between happiness and fertility evolves from negative to neutral to positive above age 40, and is strongest among those who are likely to benefit most from upward intergenerational transfers. in addition, analyses by welfare regime show that the negative fertility/ happiness association for younger adults is weakest in countries with high public support for families, and the positive association above age 40 is strongest in countries where old-age support depends mostly on the family. overall these results suggest that children are a long-term investment in well-being, and highlight the importance of the life-cycle stage and contextual factors in explaining the happiness/fertility association.

- Patrick Sturgis and Patten Smith, "Fictitious Issues Revisited: Political Interest, Knowledge and the Generation of Nonattitudes", *Political Studies* 58(1), 2010.

  It has long been suspected that, when asked to provide opinions on matters of public policy, significant numbers of those surveyed do so with only the vaguest understanding of the issues in question. In this article, we present the results of a study which demonstrates that a significant minority of the British public are, in fact, willing to provide evaluations of non-existent policy issues. In contrast to previous American research, which has found such responses to be most prevalent among the less educated, we find that the tendency to provide 'pseudo-opinions' is positively correlated with self-reported interest in politics. This effect is itself moderated by the context in which the political interest item is administered; when this question precedes the fictitious issue item, its effect is greater than when this order is reversed. Political knowledge, on the other hand, is associated with a lower probability of providing pseudo-opinions, though this effect is weaker than that observed for political interest. Our results support the view that responses to fictitious issue items are not generated at random, via some 'mental coin flip'. Instead, respondents actively seek out what they consider to be the likely meaning of the question and then respond in their own terms, through the filter of partisan loyalties and current political discourses.

Part 1

Data

Quantitative data is a particular form of data that simplifies information into variables that take different types and values. Some variables, such as gross domestic product or monthly income, hold **continuous** data that are strictly numeric, while others hold **categorical** data, such as social class for individuals or political regime type for nation states.

The collection of data for quantitative analysis systematically creates issues of measurement and reliability that also apply to qualitative research. These issues are usually explored by classes that focus on **social surveys** and **research design**. In this course, we assume that you already know of some of the issues that apply to data collection.

Manipulating a dataset is a complex task that requires some familiarity with the structure of the data, with the software commands available to prepare the data, and with the research design in which your analysis will take place. Using predefined datasets, as we will in this course, will simplify these operations a great deal, but will not entirely suppress them.

This section describes the essential steps that you should follow to prepare your data before starting your analysis. The four sections are better read as just one block of the guide, as they frequently overlap. If you are using a pre-assembled Stata dataset that comes in cross-sectional format, skip Sections 7.1 to 7.3.

5. Structure

In quantitative environments, information is stored in **datasets** that hold **observations** and **variables**. Understanding the structure of your data is an absolute requirement to its analysis, for the following reasons:

- The **studies** that motivate data collection have different goals. This course will cover only **observational** studies using **cross-sectional** data (Section 5.1).
- The **observations** contained in a dataset generally consist in a **sample** taken from a larger population. The representativeness of your data depends on how that sample was initially constructed (Section 5.2).
- The **variables** of a dataset consist of numerical, text or missing **values** assigned to each observation, following a consistent **level of measurement** (Section 5.3).

This section briefly reviews each of these aspects.

5.1. Studies

All quantitative studies use samples, variables and values, but distinctions apply among them given the wider **research strategy** for which the data were collected. The principal issue at stake is the type of randomization employed in the study:

- **Experimental studies** designate research designs where the observer is able to interact with the subjects or patients that compose the sample. Experimental settings are common in psychology and clinical studies, where subjects or patients are often randomly assigned to a 'treatment' and a 'control' group to study the effects of a particular drug or setting on them. These studies generally rely on small samples and on an analysis of variance (ANOVA).
- **Observational studies** designate research designs where the observer is not able to interact with the sample. The randomized component does not have to do with assigning treatments but with randomly sampling observations, which are most often individuals from a given population. Such studies are extremely common in research that focuses on social and political 'treatments' (such as environmentalism or drug addiction) that cannot be assigned to subjects.

This course explores non-experimental data collected in observational studies. A further distinction applies between these studies, depending on the period of observation for which the data were collected:

- **Cross-sectional studies** are collected at one particular point in time and provide 'snapshots' of data in a given period, such as political attitudes in the American population a few days after September 2001, or health expenditure levels in EU member states in 2010–2011.

- **Time series** are collected at repeated points in time. In the case of **cross-sectional time series** (CSTS), a different sample is collected at each point. If the same sample is used throughout, the study provides **longitudinal** information on a given 'panel' or 'cohort', such as U.S. households or OECD countries.

This course will focus on cross-sectional data, which are the most readily available because of the sunk costs of collecting longitudinal data. Many common forms of surveys, such as opinion polls, are cross-sectional, although larger research surveys often have a panel component that involve following a group of individuals over several years.

Cross-sectional data has its own statistical limits. Although it allows comparing across observations, it provides no information on the changes that occur through time within and between the units of analysis. That information appears in longitudinal data, which require additional statistical methods outside of the scope of this course.

5.2. Sampling

An observation is one single instance of the unit of analysis. The unit of analysis is a unique entity for which the data were collected, and can be virtually anything as long as a clear definition exists for it. Voters, countries or companies are common units of analysis, but events like natural disasters and civil wars are also potential candidates.

The definition of the unit of analysis sets the population from which to sample from. For instance, if you are studying voting behaviour in France, your study is likely to apply only to the French adult population that was allowed to vote at the time you conducted your research. Dataset codebooks usually discuss these issues at length.

The sample design then sets how observations were collected. The various techniques that apply to sampling form a crucial component of quantitative methods, that can be broken down to a few essential elements that you will need to understand in order to assess the representativeness of your data:

- The **sample size** designates the number of observations, noted *N*, contained in the dataset. Since variables often have missing values, large segments of your analysis might run on lower number of observations than *N* (Section 6.3).

  Sample size affects statistical significance through **sampling error**, which characterises the difference between a sample parameter, such as the average level of support for Barack Obama in a sample of *N* respondents, and a population parameter, such as the actual average level of support for Barack Obama in the full population of U.S. voters (the size of which we might know, or not).

  The Central Limit Theorem (CLT) shows that repeated sample means are normally distributed around the population mean.

  Sampling error is calculated using the **standard error**, from which are derived confidence intervals for parameters such as the sample mean. The standard error decreases either with the level of confidence of an estimate, or with the square root of the sample size. Consequently, the law of large numbers applies: larger sample sizes will approach population parameters better and are preferable to obtain robust findings.

- The **sampling strategy** designates the method used to collect the units contained within the sample (i.e. the dataset) from a larger **universe** of units, which can be a reference population such as adult residents in the United States or all nation-states worldwide at a given point in time.

  Sampling strategy has an impact on representativeness. Surveys often try to achieve **simple random sampling** to select observations from a population, using a method of data collection designed to assign each member of the population an equal probability of being selected, so that the results of the survey can be generalised to the population.

  Random or systematic sampling from particular strata or clusters of the population are among the methods used by researchers to approximate that type of representativeness. These methods can only approximate the whole universe of cases, as when a study ends up containing a higher proportion of old women than the true population actually does, which is why observations in a sample will be **weighted** in order to better match the sample with its population of reference.

  Other methods of data collection rely on **nonprobability sampling**. When the unit of analysis exists in a small universe, such as states or stock market companies, or when the study is aimed at a particular population, such as Internet users or voters, the sampling strategy targets specific units of analysis, with results that are not necessarily generalizable outside of the sample.

  The sampling strategy can correct for design effects such as clustering, systematic noncoverage and selection bias, all of which negatively affect the representativeness of the sample. Representativeness can be obtained through careful research design and **weighted sampling**. Stata handles complex survey design with several weights options passed to the **svyset** and **svy:** commands, both covered at length in the Stata documentation.

Important: Neither sample size or sampling strategy will remove measurement errors that occur at earlier or later stages of data collection. Representativeness is only one aspect of survey design. On the one hand, it is technically possible to collect representative answers to very poorly written survey questions that will ultimately measure nothing. Ambiguously worded questions, for instance, will trigger unreliable answers that will cloud the results regardless of the statistical power and representativeness carried by the sample size and strategy. There is no statistical solution to the bias induced by question wording and order. On the other hand, coding and measurement errors can reduce the quality of the data in any sample: again, representativeness does not control for such issues. The "**garbage in, garbage out**" principle applies: poorly designed studies will always yield poor results, if any.

Application 5a. Weighting a cross-national survey — Data: ESS 2008

The European Social Survey (ESS) contains a design weight variable (**dweight**) to account for the fact that some categories of the population are over-represented in its sample. The table below was obtained by selecting a few observations from the study, using the **sample** command with the **count** option to draw a random subsample of 10 observations; the **list** command was then used to display the country of residence, gender and age of each respondent in this subsample, along with the design and population weights.

```
. sample 10, count
(51132 observations deleted)

. list cntry gndr agea dweight pweight

     +-------------------------------------------+
     | cntry   gndr   agea   dweight   pweight   |
     |-------------------------------------------|
  1. | UA         M     18    1.3027      2.15   |
  2. | CH         F     51    1.0826      0.35   |
  3. | CH         M     52    1.0826      0.35   |
  4. | NL         M     24    1.0099      0.76   |
  5. | RU         F     25    0.4878      4.82   |
     |-------------------------------------------|
  6. | RU         F     19    2.1556      4.82   |
  7. | CY         F     47    0.7652      0.05   |
  8. | GB         M     54    1.0141      2.14   |
  9. | CH         M     31    1.0835      0.35   |
 10. | RU         M     41    1.1936      4.82   |
     +-------------------------------------------+
```

The ESS documentation describes **dweight** (design weight) as follows:

> Several of the sample designs used by countries participating in the ESS were not able to give all individuals in the population aged 15+ precisely the same chance of selection. Thus, for instance, the unweighted samples in some countries over- or under-represent people in certain types of address or household, such as those in larger households. The design weight corrects for these slightly different probabilities of selection, thereby making the sample more representative of a 'true' sample of individuals aged 15+ in each country.

By looking at the subsample listed above, you can spot two observations for which the **dweight** variable is inferior to 1: both are females who were drawn from households that are over-represented by the sampling strategy used by the ESS, and are therefore assigned design weights under 1. Conversely, the other Russian female, aged 19, was drawn from a very under-represented household, and her assigned design weight is therefore above 2. These weights, when used with the **[weight]** operator or **svyset** command, ensure that these observations are given more or less importance when using frequencies and other aspects of the data, as to compensate for their under- or over-representation in the ESS sample in comparison to the actual population from which they were drawn.

The ESS documentation describes **pweight** (population weight) as follows:

> This weight corrects for the fact that most countries taking part in the ESS have very similar sample sizes, no matter how large or small their population. Without weighting, any figures combining two or more country's data would be incorrect, over-representing smaller countries at the expense of larger ones. So the Population size weight makes an adjustment to ensure that each country is represented in proportion to its population size.

By looking again at the data above, you can indeed observe that the two respondents from Ukraine and Britain, two countries with large populations, have population weights around 2, and that the three respondents from Russia have an even higher population weight, whereas small countries like Cyprus or Switzerland have much smaller values. This makes sure that, when calculating the frequencies of a variable over several countries (such as the percentage of right-wing voters in Europe), the actual population size of each country is taken into account.

In conclusion, to weight the data at the European level, we need to account for both design and population weights. Design weights correct for the over- and under-representation of some socio-demographic groups, and population weights make sure that each national population accounts for its fraction of the overall European population.

This is done with the **svyset** command by creating a multiplication of both weights and using it as a probability weight:

```
. gen wgt=dweight*pweight

. svyset [pw=wgt]

      pweight: wgt
          VCE: linearized
  Single unit: missing
     Strata 1: <one>
         SU 1: <observations>
        FPC 1: <zero>
```

While population and design weights are pretty straightforward in this example, surveys can reach high levels of complexity when researchers try to capture multistage contexts by sampling from several strata and clusters of the target population. For example, large demographic surveys will often sample cities, and then sample neighbourhoods within them, and then sample households within them, and finally sample adults within them.

Application 5b. Weighting a multistage probability sample Data: NHIS 2009

The National Health Interview Survey (NHIS) is a good example of "a complex, multistage probability sample that incorporates stratification, clustering, and oversampling of some subpopulations" for some of its available years of data. It would take too much space to document the study fully, but the most basic weight, **perweight**, provides a good example of how weights are constructed:

> This weight should be used for analyses at the person level, for variables in which information was collected on all persons. [The weight] represents the inverse probability of selection into the sample, adjusted for non-response with post-stratification adjustments for age, race/ethnicity, and sex using the [U.S.] Census Bureau's population control totals. For each year, the sum of these weights is equal to that year's civilian, non-institutionalized U.S. population.

More documentation from the NHIS then introduces **strata**, which "represents the impact of the sample design stratification on the estimates of variance and standard errors," and **psu**, which "represents the impact of the sample design clustering on the estimates of variance and standard errors." Both parameters would require a course on survey design to be fully explained. In the meantime, they can be passed to the svyset along with **perweight**, the sampling weight:

```
. svyset psu [pw=perweight], strata(strata)

      pweight: perweight
          VCE: linearized
  Single unit: missing
     Strata 1: strata
         SU 1: psu
        FPC 1: <zero>
```

5.3. Variables

A variable is any measurement that can be described using more than one numeric value. The value should hence vary across observations to make up for a variable.

Each variable is defined by a range of possible values. At the most basic level, some variables are considered quantitative because their values can be ordered meaningfully into levels, and some variables are considered qualitative because there is no substantively significant ordering of their values. This distinction is rather imprecise and relatively misleading, which is why we will use a more advanced classification of variables below.

The **level of measurement** used by each variable in your dataset is the very first thing that you need to understand about the data before analysing it:

- A **nominal** scale qualifies a variable that was measured using discrete categories that cannot be objectively ordered. Examples of nominal variables are religious beliefs and legal systems: there is no objective ordering of "Jewish" and "Muslim", and "English Common Law" is a discrete category from "French Commercial Code".

  A specific nominal scale uses **dichotomous** categories, which result in **binary** variables that can take only 0 or 1 as values. Examples of binary variables are sex and democracy: an individual person is either female (1) or not (0), and a political regime is either democratic (1) or not (0). The discrete values denote a nominal difference, not an objective order.

- An **ordinal** scale qualifies a variable that was measured using categories that can be ordered regardless of their distance. Examples of ordinal variables are educational attainment and internal conflict: 'primary school', 'secondary school' and 'university degree' can be ordered, just like 'low', 'medium' and 'high' internal conflict.

  Ordinal scales do not reflect meaningful distances between their categories. For example, the difference in educational attainment between 'primary school' and 'secondary school' is not equal to the difference in educational attainment between 'secondary school' and 'university degree'. The **interval** between the categories is variable.

- An **interval** scale qualifies a variable that was measured using categories that can be ordered at **equal distance**. Examples of interval variables are age groups and approximate indexes: the same distance exists between the "15–19", "20–24" and "25–29" age groups, as well as between each category of Transparency International's Corruption Perceptions Index, which ranges from 0 (highly corrupt) to 10 (highly clean).

  Interval variables do not have an **absolute zero**, insofar as the first level of the interval is relative and does not designate a meaningful zero point. For example, being in the lowest age group does not literally signify being 0-year-old, just as being in the highest category of the Corruption Perceptions Index does not indicate that the level of corruption is 0%.

- A **ratio** scale qualifies a variable that was measured against a numeric scale with an absolute zero point. Examples of ratio variables are income and inflation: either of them can take 0 as a substantive value, indicating the absence of income and a 0% inflation rate respectively. Variables of this type might be thought of as 'purely' continuous.

The level of measurement is a determinant aspect in statistical models, as it will determine how to describe, analyse and interpret each variable. The type of the dependent variable is particularly important, and a simpler classification applies:

- **Continuous variables** hold values for which we can calculate counts or ratios. Examples of continuous variables are number of children and economic growth: an individual can have any number of children, and a state can experience any percentage of economic growth. In both cases, we can meaningfully compare the values across observations.

  Some distinctions apply within continuous data: **count data** holds positive integer values, as applies to the number of children, since it is impossible to have '7.5 children' or '–3 children' but only { 1, 2, 3… *n* } children. Continuous variables like economic growth can take virtually any value, from – ∞ to + ∞, even though they empirically exist in a more restricted range.

- **Categorical variables** hold values for which we can only observe discrete categories. In statistical modelling, however, any categorical variable with an ordinal or interval scale can be treated as pseudo-continuous, and the categorical classification will finally apply only to nominal variables. This course will often refer to continuous data in this looser sense to include ordinal and interval variables.

  The dependent variable in your research project should ideally be 'purely' continuous (ratio), but ordinal, interval and count variables are also possible candidates, since linear regression will also function for these types of data. More advanced models exist to better handle categorical data, but they are beyond the scope of this course.

Further instructions apply to variable manipulation, as you will often be required to modify the variables in your dataset. These are described in Section 8, but the "garbage in, garbage out" principle still applies: poorly designed studies cannot be rescued by good data manipulation.

5.4. Values

The "number-crunching" aspect of quantitative research methods is due to the fact that all the information considered by the analyst will come in the form of numbers rather than text (called "strings" in computer environments). Numeric values in a dataset can point to three different kinds of data:

- **Continuous data** are stored in numeric values, using integer and float formats. The unit of measurement for the values, such as years for a variable describing age or percentage points for a variable describing gross domestic product, are not stored with the values but are often indicated in the **variable label**.

  When necessary, as with cross-tabulations (Section 10), continuous data can easily be turned into categorical data using the **recode** command. Variables such as age or income, for example, can be better crosstabulated in the form of age or income groups. When performing linear regression (Section 11), however, continuous data are more appropriate.

- **Categorical data** are also stored in numeric values, to which **labels** are assigned. For example, a possible variable for gender will take the value 1 to for males and 2 for females—although a better encoding would consist in using a binary variable called **female** that would code 0 for males and 1 for females.

  The **recode** command allows creating new variables by assigning new value labels to the data, based on existing ones. For example, if your data contains a variable measured on an ordinal scale of ten categories from 1 'Strongly agree' to 10 'Strongly disagree', this scale can be recoded into a more simple scale of five categories, or even into a binary variable.

- **Missing data** are observations for which the variable takes no value due to an issue that arose at the level of data collection, such as respondents being unable (or refusing) to answer, or insufficient information to measure the value. Stata identifies missing data with the "**.**" character.

  When missing data are not coded by "**.**" but by numeric values, such as "-1" or "999" for variables that cannot take these values, you will have to use the **replace** command in Stata to change this coding to "**.**" coding, as illustrated in Section 8.2.

  Missing values will actually require a lot of attention at all points of your analysis, in order to avoid all sorts of calculation and interpretation errors when looking at frequencies and crosstabulations. Furthermore, missing values will constrain the number of observations available for correlation and regression analysis.

As suggested by this description of values, a very important part of quantitative analysis consists in learning about the exact coding of the data in order to better manipulate variables later on. The practical aspect of that task (modifying values and labels) is covered in more detail in Section 8.

The substantive aspect of that task relies entirely on the analyst. Reading from the dataset codebook is essential to understand how the values of each variable were obtained. For example, issues of measurement and reliability will inevitably exist with aggregate indices, self-reported data and psychometric scales.

Application 5c. Reading frequencies — Data: ESS 2008

The third-party **fre** command displays frequencies for a given variable in a better way than the built-in **tab** command does. After installing the command, we look at attitudes towards immigration from outside Europe in a sample of European respondents:

```
. fre impcntr [aw=dweight*pweight]

impcntr — Allow many/few immigrants from poorer countries outside Europe
─────────────────────────────────────────────────────────────────────────────
                                  │      Freq.    Percent      Valid       Cum.
──────────────────────────────────┼──────────────────────────────────────────
Valid   1  Allow many to come and │   6090.343      11.91      12.68      12.68
           live here              │
        2  Allow some             │   16460.09      32.19      34.26      46.94
        3  Allow a few            │   15799.46      30.89      32.89      79.83
        4  Allow none             │   9688.713      18.94      20.17     100.00
        Total                     │   48038.61      93.93     100.00
Missing .a                        │   140.6597       0.28
        .b                        │   2938.206       5.75
        .c                        │   24.52225       0.05
        Total                     │   3103.388       6.07
Total                             │      51142     100.00
─────────────────────────────────────────────────────────────────────────────
```

- **The observations are weighted**, which explains why the frequencies are not integers but still sum up to $N = 51142$.

  We used the Stata **[aw]** suffix, which allows the use of weights like the design and population weights in the ESS (Application 5a). Since we are looking at the whole sample of European respondents, we used both weights, as recommended in the ESS documentation.

- **The variable under examination is an ordinal one,** with four categories that can be ordered by their degree of tolerance towards immigrants.

  If we wanted to isolate the last categories, 'Allow few/none', in order to focus on respondents who are most resilient to immigration, we could recode the variable as a binary one, using a dichotomous separation between 'Allow some/many' and 'Allow few/none'.

- **There are missing values,** coded as **.a**, **.b** and **.c**. These are variations of the "**.**" Stata format for missing data (examined again in Section 8).

  The difference in letters is used to code for different types of missing data: as the ESS documentation explains, **.a** codes for respondents who refused to answer, **.b** codes for respondents who did not know what to answer (often called 'DK' or 'DNK'), and **.c** codes for respondents who did not answer ('NA').

  Detailed missing values can hint at why there is missing data in the first place: here, most of the 6% missing data come from respondents who declared not having, or not being able to form, an opinion on the topic, rather than from respondents refusing to answer, which is common when the question touches upon a topic affected by desirability bias (i.e. when some answers are more positively or negatively connoted than others).

*

A serious issue in scientific inquiry is overreliance on a limited number of data sources and methods of study. If you are willing to spend some time exploring around, then quantitative analysis will expand your abilities on both counts. Your skills with data and methods are not just part of your academic curriculum: if you care enough to maintain your level of knowledge in that area, they will stay with you all your life. My experience with these skills shows that they have both personal and professional value.

The first step in acquiring those skills consists in training yourself to work with quantitative data. As with most activities, there is no substitute for training: your familiarity with quantitative data and methods primarily reflect the time you spent on them. With a few key terms of interest in mind, you should therefore start exploring data as soon as you can. At its most basic, this implies accessing and downloading a selection of datasets onto your computer.

Prior to opening the datasets, take a look at their documentation files. Do not aim at understanding every single aspect of the documentation: focus on survey design and sampling, which should be fully documented in the data codebook. The next sections will then guide you through data exploration and management: Section 6 explains how to explore a dataset, Section 7 explains how to prepare it for analysis, and Section 8 covers further data management operations with variables.

6. Exploration

Exploring quantitative data requires either assembling your own data (an option not covered in this course) or locating some pre-assembled datasets online. The diffusion of quantitative data has made tremendous progress in the past decade, and an amazing range of – often underused – datasets are available online.

The socio-political and technological determinants of the current 'data deluge', as an article in *The Economist* once put it, are outside of the scope of this guide, but a lot of online commentary and analysis exists on the 'data revolution' in science, journalism and government (check Victoria Stodden's work first).

6.1. Access

The course makes extensive of a few recommended datasets that were selected based on several criteria ranging from topical interest to simplicity and quality. For your own project, you will be first offered to work with recent versions of the European Social Survey (ESS) and Quality of Government (QOG) data.

If you plan to go beyond these recommended sources, turn to the course material to learn more on data repositories and data libraries. High-quality data is still rare, and good sources to look for such data are the ICPSR and CESSDA repositories, listed on the course website.

Important aspects of data retrieval include the following:

- **Always download the documentation for your data.** Professional-quality datasets come with extensive codebooks that help with understanding the data structure, as well as with other notes on the data itself.
- **Never rely on any source to preserve the data for you.** Even if the integrity of data repositories is improving, always keep a pristine (intact) copy of the (original) datasets that you use in your personal archives.
- **Full acknowledgment of the source is an ethical counterpart.** In order to make a legitimate use of datasets for either research or teaching purposes, reference the source in full and follow all related instructions.

6.2. Browsing

The simplest way to quickly explore your data is to open the Data Editor after you loaded your dataset: type in **browse** (or **edit** if you plan to modify the data) in the Command window, and the Data Editor window will open. Alternatively, use the **Ctrl-8** (Windows) or **Cmmd-8** (Macintosh) keyboard shortcut.

The variables contained in Stata datasets can be explored with the **codebook** command. That same command will also return information about the dataset itself, as will the **notes** command if the dataset comes with Stata data notes. It is not, however, very practical to explore data with these tools.

Instead, use the following commands to start exploring your data:

- Always start with the **describe** command, which can be abbreviated to its single-letter shorthand, '**d**'. Simply typing **d** into Stata will return the list of variables, and typing **d** followed by a list of one or many variable names will describe only these. High-quality datasets should always come with intelligent variable names and labels.

- When the list of variables is too long to be inspected in full, use the **lookfor** command to search for keywords in the names and labels of variables. The keywords need not be complete terms: 'immig' will work fine, for instance. You can use any number of keywords with **lookfor**: be aware of synonyms and try different possibilities.

- Finally, learn how to use the **rename** command (shorthand: **ren**) as soon as possible. When you identify a variable of interest, there is a fair probability that its name will be some kind of strange acronym or something even less comprehensible, like 'v241' or 's009'. Renaming the variable will help solving that issue.

In some situations, you might also want to use the **sort** and **order** commands, respectively to sort the observations according to the values of one particular variable, or to reorder the variables in the dataset. Turn to the Stata help pages for the full documentation of these commands.

Application 6a. Locating and renaming variables Data: ESS 2008

'Microdata' is a term that generally refers to data based on individual respondents. At that level of analysis, common demographic and socioeconomic variables include age, gender, income and education.

We used the **lookfor** command to identify variables that refer to **income** and **earnings**, which we did not type in full to allow for all '**earn-**' terms to show up in the results:

```
. lookfor income earn

                storage  display     value
variable name    type    format      label      variable label
----------------------------------------------------------------------------
gincdif          byte    %1.0f       gincdif    Government should reduce
                                                  differences in income levels
hincsrc          byte    %2.0f       hincsrc    Main source of household income
hincsrca         byte    %2.0f       hincsrca   Main source of household income
hinctnta         byte    %2.0f       hinctnta   Household's total net income, all
                                                  sources
hincfel          byte    %1.0f       hincfel    Feeling about household's income
                                                  nowadays
```

Once the variable of interest has been identified, we use the **rename** (shorthand **ren**) command to give it a more explicit name. When successfully run, the command does not send back any output:

```
. ren hinctnta income
```

After doing the same for other variables and writing all **ren** commands to our do-file, we obtain a list of variables that can be described as follows:

```
. d age gender edu income

                storage  display     value
variable name    type    format      label      variable label
----------------------------------------------------------------------------
age              int     %3.0f       agea       Age of respondent, calculated
gender           byte    %1.0f       gndr       Gender
edu              byte    %2.0f       eduyrs     Years of full-time education
                                                  completed
income           byte    %2.0f       hinctnta   Household's total net income, all
                                                  sources
```

6.3. Selections

At several points of your analysis, you will want to apply commands to selected parts of your data, as in the case where you might want to summarize a variable only for a selected category of subjects in a survey. In that case, you will be using the **if** conditional statement.

The **if** statement works by adding a specific condition written with mathematical signs to indicate equality or inequality, summarised below:

==	equal to	>	greater than

!=	not equal to	**<**	less than
mi()	missing	**>=**	greater than or equal to
!mi()	not missing	**<=**	less than or equal to

Conditions can be combined to each other by using two logical operators:

&	and	**|**	or

The use of conditions is pretty intuitive, except for more elaborate patterns that use brackets to create sophisticated conditions that we should not need for this course. It is important to be able to use conditions, since they apply to almost all operations that we will use for analysis.

Application 6b. Counting observations Data: ESS 2008

The **count** command simply counts observations in a dataset, based on a given condition. Without any condition, it just counts all observations:

```
. count
51142
```

If we are interested in knowing how many observations the dataset includes for respondents strictly over 64 years-old, we type the following, which uses the renamed variables from Application 6a:

```
. count if age > 64
10949
```

A slight issue here is that Stata counts missing values encoded as "**.**" as positive infinity, which means that the above command included the missing values of the variable in its count of observations over value 64 for the "age" variable.

The following command recounts respondents strictly over 64 years old without these, by combining two conditions with the conjunctive **&** ("and") operator:

```
. count if age > 64 & !mi(age)
10803
```

The last command literally translates as: count observations for which the **age** variable takes a value strictly over 64 and is non-missing. Missing values often appear in different forms than "**.**", which is another issue that we will learn to solve in Section 8.4.

Application 6c. Selecting observations Data: ESS 2008

Turning to gender and education, we want to look at the average schooling years of young females. We start with the **list** command to show a fraction of the data, and then compute summary statistics with the **su** command to learn the basics about the distribution of the **edu** variable:

```
. list age gender edu in 1/10, clean

       age   gender   edu
  1.    36        M    18
  2.    26        F    15
  3.    69        M    18
  4.    77        F    15
  5.    27        M    13
  6.    32        F    12
  7.    19        F    13
  8.    28        F    17
  9.    49        M    16
 10.    57        M    16

. su edu

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
         edu |     50682    11.96253    4.225673          0         50
```

The **list**... **in**... command is purely exploratory: it allows you to take a glance at a few lines of data in the same way as browse or edit would let you do from the Stata Data Browser/Editor window. The **clean** option is just a cosmetic fix.

If we are interested in the average schooling years for male and female adult respondents below 65 years-old, we form a conjunctive conditional statement for age and use the **bysort** command to separate respondents by gender:

```
. bysort gender: su edu if age >= 18 & age < 65

----------------------------------------------------------------------------------
-> gender = M

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
         edu |     17890    12.73181    3.836265          0         48

----------------------------------------------------------------------------------
-> gender = F

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
         edu |     20461    12.62538    4.011698          0         40

----------------------------------------------------------------------------------
-> gender = .a

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
         edu |         4       12.25         1.5         11         14
```

Note that we did not use the **& !mi(age)** conditional statement, because Stata will not include missing values in the (18-65] interval as it would in the (65; +∞] interval formed in the previous command.

The use of conditionals is very common at all stages of analysis. The 'or' logical statement also becomes useful when selecting observations based on the values taken by a categorical variable, which can be explored with the **fre** command:

```
. fre cntry, rows(9)

cntry — Country
─────────────────────────────────────────────────────────────────
               │      Freq.    Percent      Valid       Cum.
───────────────┼─────────────────────────────────────────────────
Valid   BE     │       1760       3.44       3.44       3.44
        BG     │       2230       4.36       4.36       7.80
        CH     │       1819       3.56       3.56      11.36
        CY     │       1215       2.38       2.38      13.73
        :      │          :          :          :          :
        SI     │       1286       2.51       2.51      88.13
        SK     │       1810       3.54       3.54      91.67
        TR     │       2416       4.72       4.72      96.39
        UA     │       1845       3.61       3.61     100.00
        Total  │      51142     100.00     100.00
─────────────────────────────────────────────────────────────────
```

In the command above, we tabulated the countries (**cntry**) of residence of the respondents to the ESS. The variable **cntry** is a nominal variable encoded as text: no numeric value exists for the labels "BE" (Belgium, for which the dataset holds a total number of observations of *N* = 1760 respondents), "BG" (Bulgaria, *N* = 2230), … "TR" (Turkey, *N* = 2416) and "UA" (Ukraine, *N* = 1845). This means that we will need to use strings (text) in "double quotes" to pass a command to them with Stata, as in this count of Greek respondents:

```
. count if cntry=="GR"
  2072
```

If our analysis were to focus on the average level of male and female education in Greece and Cyprus, we would run a command using a disjunctive **|** ("or") operator to include respondents from both respondents:

```
. bysort gender: su edu if cntry=="GR" | cntry=="CY"

--------------------------------------------------------------------------------------
-> gender = M

    Variable |        Obs        Mean    Std. Dev.       Min        Max
-------------+---------------------------------------------------------
         edu |      1544    11.83679    3.988876          0         24

--------------------------------------------------------------------------------------
-> gender = F

    Variable |        Obs        Mean    Std. Dev.       Min        Max
-------------+---------------------------------------------------------
         edu |      1723    11.37725    3.925022          0         24

--------------------------------------------------------------------------------------
-> gender = .a

    Variable |        Obs        Mean    Std. Dev.       Min        Max
-------------+---------------------------------------------------------
         edu |         0
```

Of course, if the whole analysis is focused on Greece and Cyprus, we would first think of subsetting the data to these countries only. This matter is covered in Section 7, along with other instructions about dataset manipulation. Issues to do with variable coding, such as encoding string variables or manipulating labels, are covered in Section 8. Finally, the **su** and **fre** commands are explained again in detail when covering distributions and frequencies in in Section 9.

7. Datasets

Stata datasets are characterised both by the DTA dataset file format and by the way that the data are arranged within the file:

- **File format.** Your dataset should come as a single file in Stata **.dta** format. If your data come in any other format, you will have to convert it (Section 7.1). If your data come in more than one file, you will need to merge all components into one file (Section 7.2).

  Many issues can appear during dataset conversion, such as text conversion errors with accents or other characters, or mismatches in merged data; these issues will require manual fixing or using advanced editing techniques that are beyond the scope of this course.

- **Data format**. The rows of your dataset should hold your units of observation (most commonly of which, individuals or states) and its columns should hold your variables (such as sex or country name). To quickly check that structure, open the Data Editor by typing **browse**.

  If your data are formatted as time series, with variables in rows and values for each time unit (such as years) in columns, you will need to use the **reshape** command (Section 7.3). This often happens with country-level data measured over several years.

  Finally, for the purposes of this course, you are required to work on cross-sectional data that were collected at only one point in time. If your dataset contains time series or any form of longitudinal study, you will need to subset it to a single time period (Section 7.4).

Important: data management is time-consuming, error-prone and complex. All the operations described in this section, at the exception of subsetting, *will* draw a lot of energy from you. If your dataset for this course is not ready in very short delays (i.e. around two full days of work), do not engage into longer operations that might eventually fail and leave you without usable data.

If you get stuck, start by checking the UCLA Stat Computing advice page for guidance: http://www.ats.ucla.edu/stat/stata/topics/data_management.htm.

7.1. Conversion

Most simply, **some datasets come in compressed archives** like ZIP files, which you will need to decompress while making sure that no error occurred during decompression. Free decompression software exists for all operating systems.

Do not try to use ASCII data for which you need to use the **infix** and dictionary commands, which are too time-consuming for the purpose of this course. Ask us for help if you really need to bypass this recommendation.

If your files come in SPSS or SAS format, or in any other format for use in another statistical package, you will need to use a conversion utility to convert the data. We should be able to use Stat/Transfer to help with that process.

Check the Stata FAQ from UCLA Stat Computing for guidance on dataset conversion: http://www.ats.ucla.edu/stat/stata/faq/default.htm. Again, several encoding issues can occur during dataset conversion, and you will be required to perform a thorough check of the result to clear any possible mistake.

If your data come in a format supported by Microsoft Excel, you should export your data to CSV format and import it into Stata with the **insheet** command; see http://dss.princeton.edu/online_help/stats_packages/stata/excel2stata.htm.

Briefly put, your data should all fit on one single Excel spreadsheet and contain nothing else than the data, except for the header row on the first line of your file. The header must contain the variable names, which should have short names and must not start with an underscore (_) or a number.

Your numeric data must not contain formulae and must be formatted as plain numbers—do not use any other format, as it might cause issues when importing into Stata. Furthermore, the numeric values should not use commas (,) as they can disrupt the CSV format.

Finally, make sure that the missing observations are represented by blank cells in your data. To do this, you must find and replace all characters that are often used to mark missing observations (such as "NA") with either blank space or the standard "**.**" symbol for missing values in Stata.

7.2. Merging

You can merge your data in either Stata or Microsoft Excel. Units of analysis are naturally expected to be identical in both datasets.

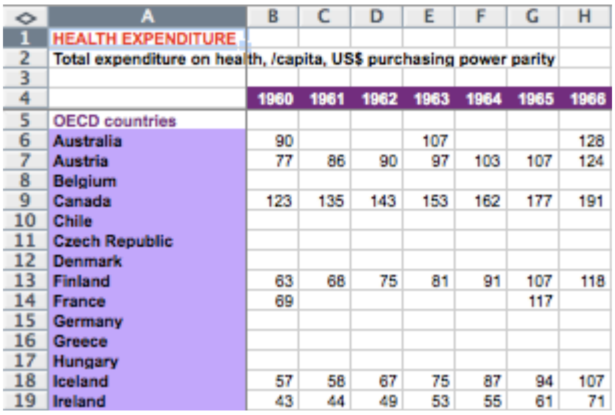
It is essential that your observations match identically when merging files: for instance, when merging two datasets with country-level data, you will have to make sure that the countries are present in both datasets under identical names.

Merging Stata datasets uses the Stata **merge** command, a very powerful tool for merging and matching your data. The command is very well documented in this handy tutorial by Roy Mill:

http://stataproject.blogspot.com/2007/12/combine-multiple-datasets-into-one.html

7.3. Reshaping

Your dataset should hold your units of observation in rows, and your variables in columns. If that format is not respected, you will need to reshape your dataset in order to fit that format.



◇	A	B	C	D	E	F	G	H
1	HEALTH EXPENDITURE							
2	Total expenditure on health, /capita, US$ purchasing power parity							
3								
4		1960	1961	1962	1963	1964	1965	1966
5	OECD countries							
6	Australia	90			107			128
7	Austria	77	86	90	97	103	107	124
8	Belgium							
9	Canada	123	135	143	153	162	177	191
10	Chile							
11	Czech Republic							
12	Denmark							
13	Finland	63	68	75	81	91	107	118
14	France	69					117	
15	Germany							
16	Greece							
17	Hungary							
18	Iceland	57	58	67	75	87	94	107
19	Ireland	43	44	49	53	55	61	71

In this example, the data are formatted with year values in columns, while the units of observation are displayed in rows.

This format often applies to time series for country-level data. For example, this format applies to OECD data, as shown here. The data were provided for Microsoft Excel.

Solving this issue requires to run a series of steps called "reshaping".

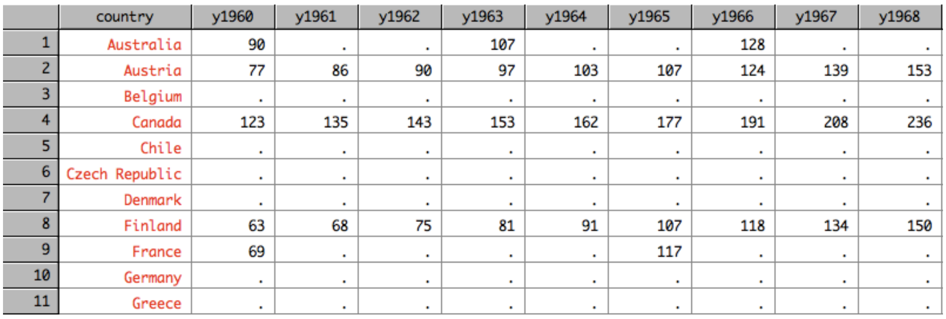
To reshape data for **one** variable, follow the following steps carefully:

- **Start by making sure that your data have been properly prepared**: all variables must be numeric, and missing observations should be encoded as such.

- **Prepare your data as a CSV file**. All variables should be labelled on the first line, and the rest of the file should contain only data (remove any other text or information).

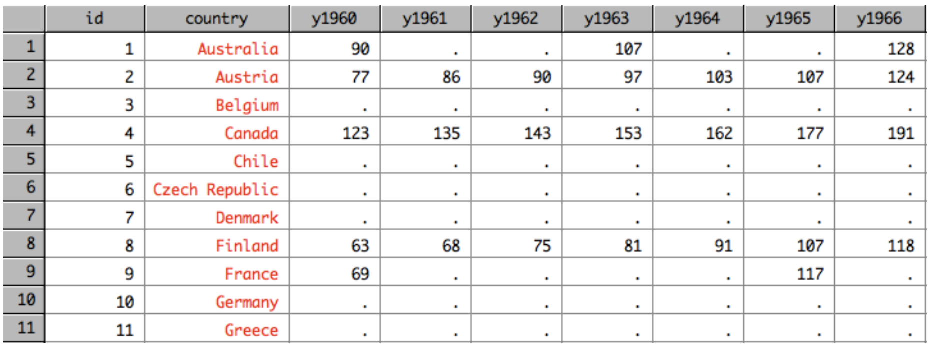
- **Add a letter in front of each year**. Select your first line, which contains the variable names, and then use the 'Edit > Replace…' menu item in Excel to add a 'y' in front of each year. For instance, if your data were collected for years 1960–2010, find '19' and replace by 'y19', and find '20' and replace by 'y20'.

- **Import using the insheet command**, and check your data in the Stata data editor. The example below shows the result with only one variable (health expenditure per capita in some OECD countries).



	country	y1960	y1961	y1962	y1963	y1964	y1965	y1966	y1967	y1968
1	Australia	90	.	.	107	.	.	128	.	.
2	Austria	77	86	90	97	103	107	124	139	153
3	Belgium	.	.	.	.	.	.	.	.	.
4	Canada	123	135	143	153	162	177	191	208	236
5	Chile	.	.	.	.	.	.	.	.	.
6	Czech Republic	.	.	.	.	.	.	.	.	.
7	Denmark	.	.	.	.	.	.	.	.	.
8	Finland	63	68	75	81	91	107	118	134	150
9	France	69	.	.	.	.	117	.	.	.
10	Germany	.	.	.	.	.	.	.	.	.
11	Greece	.	.	.	.	.	.	.	.	.

- Create a unique id value for each unit of observation (in this case, OECD countries) by typing **gen id = _n** and then **order id**. This will add an additional variable to your data.



	id	country	y1960	y1961	y1962	y1963	y1964	y1965	y1966
1	1	Australia	90	.	.	107	.	.	128
2	2	Austria	77	86	90	97	103	107	124
3	3	Belgium	.	.	.	.	.	.	.
4	4	Canada	123	135	143	153	162	177	191
5	5	Chile	.	.	.	.	.	.	.
6	6	Czech Republic	.	.	.	.	.	.	.
7	7	Denmark	.	.	.	.	.	.	.
8	8	Finland	63	68	75	81	91	107	118
9	9	France	69	.	.	.	.	117	.
10	10	Germany	.	.	.	.	.	.	.
11	11	Greece	.	.	.	.	.	.	.

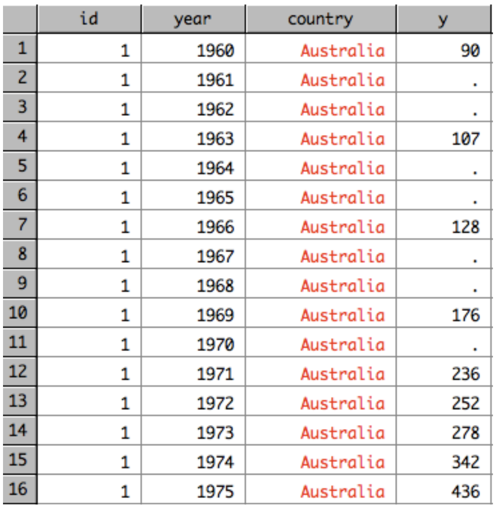
– To reshape your data, type **reshape long, y i(id) j(year)** to reshape your data columns that start with a 'y', for all rows identified by the **id** variable, into a different data format, called "long", where the years will have been fit into a **year** variable.

```
. reshape long y, i(id) j(year)
(note: j = 1960 1961 1962 1963 1964 1965 1966 1967 1968 1969 1970 1971 1972 1973 1974 1975)

Data                               wide   ->   long
-----------------------------------------------------------------------------
Number of obs.                       16   ->     256
Number of variables                  18   ->       4
j variable (16 values)                    ->   year
xij variables:
                  y1960 y1961 ... y1975   ->   y
-----------------------------------------------------------------------------
```

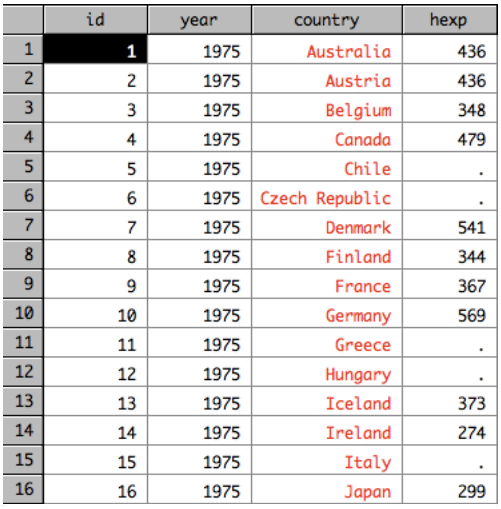
Your dataset will have been converted from its initial "wide" format, with values for each year in columns, to a "long" format where the values for each year appear on separate rows.

Once you are in "long" mode, you can rename the variable that you were working on and drop the observations that you do not need (remember that you are working to obtain cross-sectional data and not time series).

```
ren y hexp

la var hexp "Health expenditure per capita"

drop if year != 1975
```



	id	year	country	y
1	1	1960	Australia	90
2	1	1961	Australia	.
3	1	1962	Australia	.
4	1	1963	Australia	107
5	1	1964	Australia	.
6	1	1965	Australia	.
7	1	1966	Australia	128
8	1	1967	Australia	.
9	1	1968	Australia	.
10	1	1969	Australia	176
11	1	1970	Australia	.
12	1	1971	Australia	236
13	1	1972	Australia	252
14	1	1973	Australia	278
15	1	1974	Australia	342
16	1	1975	Australia	436



	id	year	country	hexp
1	1	1975	Australia	436
2	2	1975	Austria	436
3	3	1975	Belgium	348
4	4	1975	Canada	479
5	5	1975	Chile	.
6	6	1975	Czech Republic	.
7	7	1975	Denmark	541
8	8	1975	Finland	344
9	9	1975	France	367
10	10	1975	Germany	569
11	11	1975	Greece	.
12	12	1975	Hungary	.
13	13	1975	Iceland	373
14	14	1975	Ireland	274
15	15	1975	Italy	.
16	16	1975	Japan	299

The screenshot on the left shows your data in "long" mode; the screenshot on the right shows the same data after executing the commands described above.

If you are trying to reshape a dataset that is formatted in "wide" mode with **more than one variable**, more steps are required to separate the variables, as described in this tutorial: http://dss.princeton.edu/training/DataPrep101.pdf (locate the "Reshape" slides #3–5).

Note that data reshaping will take a lot of time to achieve if you are merging and reshaping data over a large number of files. Do not try to merge more than a handful of datasets, as any other operation would require more time than this course can reasonably require from you.

Additional options in the **reshape** command allow to reshape data where the suffix is not numeric: type **help reshape** (or the shorthand version, **h reshape**) for additional documentation about this step.

7.4. Subsetting

Subsetting your data is a way to analyse only a selected subsample of the data. This can happen principally for two reasons:

- **This course focuses on cross-sectional data** and therefore requires that you subset only one time period if your dataset spans over more than one period of survey data.
- **If you want to analyse only one segment of the data**, such as only one country in a Europe-wide dataset or one age group in a population-wide dataset, you should subset the data to it.

Application 7a. Subsetting to cross-sectional data — Data: NHIS 2009

In order to calculate and analyse the Body Mass Index (BMI) of American respondents, we use recent data from the National Health Interview Series (study: **NHIS**). We examine the structure of the dataset by inspecting the **year** variable with the **fre** command (with trivial formatting options):

```
. fre year, rows(5) nol

year
─────────────────────────────────────────────────────────────
              │      Freq.    Percent      Valid       Cum.
──────────────┼──────────────────────────────────────────────
Valid   2000  │      28712      11.41      11.41      11.41
        2001  │      29459      11.71      11.71      23.12
        :     │          :          :          :          :
        2008  │      18913       7.52       7.52      90.34
        2009  │      24291       9.66       9.66     100.00
        Total │     251589     100.00     100.00
─────────────────────────────────────────────────────────────
```

At that stage, we need to select which year we want to work on. An intuitive choice is the most recent year, if it holds a sufficient number of observations. In this example, survey year 2009 forms a large subsample of observations, though not the largest.

Given that our dependent variable, the Body Mass Index, will require the height and weight of each respondent to be calculated, we verify the total number of observations for the **height** and **weight** variables among respondents who were interviewed during survey year 2009:

```
. su height weight if year==2009

    Variable │       Obs        Mean    Std. Dev.       Min        Max
─────────────┼──────────────────────────────────────────────────────────
      height │     24291    66.61652    3.865753         59         76
      weight │     24291    172.5895    37.12779        100        285
```

The results indicate that survey year 2009 holds a sufficiently large number of observations, and that the variables of interest are not missing for that year. We thus subset the dataset to that year with the **keep** command and the **if** operator set to select observations where the year is equal (“**==**”) to 2009:

```
. keep if year==2009
(227298 observations deleted)
```

We could also have used the **drop** command to suppress all years that are different (“**!=**”)from 2009, although that writing is somehow less intuitive:

```
. drop if year!=2009
(227298 observations deleted)
```

An additional check of the year variable shows that subsetting was successful:

```
. fre year, nol

year
-----------------------------------------------------------
              |      Freq.    Percent      Valid       Cum.
--------------+--------------------------------------------
Valid   2009  |      24291     100.00     100.00     100.00
-----------------------------------------------------------
```

In this example, the total number of observations which we study in our analysis is thus *N* = 24,291, rather than 215,589 for all survey years. The **keep** and **drop** commands also apply to variables, and we could continue here by subsetting the dataset to only a handful of variables which we plan to use in the analysis, but this course will not require you to do so.

8. Variables

The basic anatomy of a variable consists of its name and values, to which we can add labels in order to provide short descriptions of what the variable measures. Data, and categorical data especially, are rarely understandable without labels.

Your primary source of information for variable codes is always the dataset codebook, but for practical reasons, some of that information is also stored in your dataset, as you might have to modify it before running your statistical analysis.

This chapter shows:

- **How to inspect variables** (Section 8.1). Variable inspection is necessary to learn how the variable is coded, in order to select appropriate commands for its manipulation and analysis.
- **How to show and set variable labels** (Section 8.2). Labels are short text descriptions attached to your variables and to their numeric values. They increase the readability of your dataset, especially for categorical data.
- **How to recode variables into different categories** (Section 8.3). Recoding allows you to select the categories in which to manipulate your variables, which is helpful when you want to analyse particular groups of observations.
- **How to solve encoding issues** (Section 8.4). Encoding applies to missing data, which should be coded as "**.**", and to variables that hold text, i.e. "strings", which are better manipulated when they are encoded with numeric values.

8.1. Inspection

The following commands allow inspecting the names, values and labels of variables:

- **codebook** is the most exhaustive command if you need to understand your data structure in depth.

  Stata also offers a **note** function that makes it possible to write an annotated codebook within a Stata dataset, but this function is idiosyncratic to the DTA format and limits interoperability.
- **describe** (shorthand **d**) is generally used to describe several variables at once, as when opening a dataset for the first time. It provides three kinds of information:
  - The **variable name** is how the variable is named in your dataset. It is the name that you pass to Stata through your commands.
  - The **variable label** is a short text description of the variable (gender). It usually includes the unit of measurement used by the variable when relevant.

  - The **value label** is the name of a distinct element of data structure that assigns text labels to the numeric values of the variable. It will often be the case that value labels will have the same name as your variable.
- **label list** (shorthand **la li**) is one of many label commands to show and edit the labels featured in a dataset.

Application 8a. Inspecting a categorical variable Data: NHIS 2009

The example below shows the encoding of a variable that codes for respondents' sex:

```
. d sex

              storage  display     value
variable name   type   format      label      variable label
--------------------------------------------------------------------

sex             byte   %8.0g       sex_lbl    Sex
```

To understand how the male and female respondents are coded by the **sex** variable, use the **label list** command (shorthand **la li**) to display the value label **sex_lbl**:

```
. la li sex_lbl
sex_lbl:
           1 Male
           2 Female
```

The **sex_lbl** value label is a separate entity from the **sex** variable itself: it can be applied to any other variable where it is suitable to have males coded as 1 and females as 2, as with variables that code for the gender of other persons in the respondent's household.

When you need to access all information above in a single command, the **codebook** command provides detailed output on names, values and labels, as well as more details on missing data:

```
. codebook sex

--------------------------------------------------------------------
sex                                                              Sex
--------------------------------------------------------------------


                  type:  numeric (byte)
                 label:  sex_lbl

                 range:  [1,2]                        units:  1
         unique values:  2                        missing .:  0/24291

            tabulation:  Freq.   Numeric  Label
                         10978         1  Male
                         13313         2  Female
```

We later explore a way to code this variable as a dummy, which is actually smarter. On its own, the mean value of the **sex** variable is unreadable, but if we code sex as 0 for males and 1 for females and make that coding explicit by naming the variable **female**, then its mean explicitly shows the percentage of women in the sample.

Application 8b. Inspecting a continuous variable — Data: NHIS 2009

For continuous data, the **d** and **codebook** commands can show the same information as for categorical data. The **codebook** command used with the **compact** (shorthand **c**) option displays the variable name and label along its total number of observations, mean and range. The example below shows its results for age, height, weight and health:

```
. codebook age height weight health, c

Variable      Obs Unique      Mean  Min  Max  Label
---------------------------------------------------------------------------
age         24291     67  46.81392   18   84  Age
height      24291     18  66.61652   59   76  Height in inches without shoes
weight      24291    186  172.5895  100  285  Weight in pounds without clothes...
health      24284      5  2.288709    1    5  Health status
---------------------------------------------------------------------------
```

This table presents descriptive statistics in an efficient way that resembles the table of summary statistics that we will produce at the end of Section 9. Note however that the **health** variable is not a truly continuous variable but an ordinal one that codes the self-reported health of respondents on a subjective scale from 1 (excellent) to 5 (poor).

8.2. Labels

Section 6.2 already introduced the **rename** (shorthand **ren**) command to modify variables names. We now turn to modifying variable and value labels:

- All your variables should be assigned at least one label, the variable label, which is already set in most datasets.

  When creating variables, label them with the **label variable** (shorthand **la var**) command. Include, if applicable, their unit of measurement.

- A second form of label then applies to the values of categorical data, as when 1 codes for "Strongly Agree", 2 codes for "Agree" and so on.

  These labels are modifiable with the **label define** (shorthand **la def**) and **label values** (shorthand **la val**) commands.

Application 8c. Labelling a dummy variable — Data: NHIS 2009

In this example, we create a variable for the respondents' Body Mass Index (BMI) and examine it under three different forms. We first create the variable from the respondents' **weight** and **height** measurements, respectively in pounds and inches:

```
. gen bmi=weight*703/height^2

. su bmi

    Variable │       Obs        Mean    Std. Dev.       Min        Max
─────────────┼────────────────────────────────────────────────────────
         bmi │     24291       27.27    5.134197   15.20329   50.48837
```

Immediately after creating the variable and checking its results, we label the variable with the signification of the 'BMI' acronym to help ourselves and others make sense of the data at later stages of analysis:

```
. la var bmi "Body Mass Index"

. d bmi

              storage  display     value
variable name   type   format      label      variable label
─────────────────────────────────────────────────────────────────────────
bmi             float  %9.0g                  Body Mass Index
```

Given that Body Mass Index is a continuous measurement that comes in its own metric, the **bmi** variable does not require any additional label. Let's assume, however, that we are further interested in identifying respondents with a BMI of 30+, which designates obesity in the WHO classification of BMI. To that end, we create a dummy variable for respondents over that threshold:

```
. * Dummy for obesity.
. gen obese:obese = (bmi >= 30) if !mi(bmi)
```

The **gen** command created the **obese** variable and assigned the **obese** value label to it. The logical test **(bmi >= 30)** returned 1 when that statement was true, 0 if false. Observations for which the **bmi** variable was missing were excluded from the operation and therefore preserved as missing.

The result is a dichotomous variable where 1 codes for obesity and 0 otherwise. When we summarize the **obese** dummy as a continuous variable with the **su** command, its mean provides the percentage of obese respondents in the sample:

```
. su obese

    Variable │       Obs        Mean    Std. Dev.       Min        Max
─────────────┼────────────────────────────────────────────────────────
       obese │     24291    .2626076      .44006          0          1
```

In the next commands, we label the **obese** variable and define the **obese** value label in reference to its two possible values (1 if obese, 0 if not):

```
. la var obese "Obesity (BMI 30+)"

. la def obese 0 "Not obese" 1 "Obese"
```

The variable and value labels show in the categorical display of the dummy through the **fre** command. The variable is fully specified:

```
obese — Obesity (BMI 30+)
-----------------------------------------------------------------
                       |     Freq.    Percent      Valid     Cum.
-----------------------+-----------------------------------------
Valid   0 Not obese    |     17912      73.74      73.74    73.74
        1 Obese        |      6379      26.26      26.26   100.00
        Total          |     24291     100.00     100.00
-----------------------------------------------------------------
```

The **obese** value label can also be assigned to other variables with the **la val** command, if you are interested in coding for obesity in other persons than the respondent.

8.3. Recoding

Recoding is a way of producing a new variable out of an existing one, by collapsing values of the original variable into different categories. Most of the variables in your dataset are probably ready for use in their original metric, but in some cases, you might want to recode your variable using one of the following techniques:

- The **recode** command is very handy to create groups from continuous data or to permute values in categorical data, as shown in Application 8d. It can also create dummies, as shown in Application 8e along with the **tab, gen()** equivalent.
- The **gen** command has three extensions – **recode()**, **irecode()** and **autocode()** – that basically produce the same result as the **recode** command in less code and with a bit more flexibility, as shown in Application 8f.
- The **replace** command can be used to 'hard-recode' variables, but you would be altering your original variables in doing so and therefore running an additional risk of data-related error. We use the **replace** command for missing data only.

When you are creating groups from continuous variables, make sure that your categories do not omit any values from the original variable (exhaustiveness), and that they do not overlap (mutual exclusiveness). For example, if you plan to recode educational attainment, make sure that each diploma appears in only one category, and that all levels of education are represented in your new categories.

The number of categories is a substantive issue that depends on your variable. Aggregation can take the form of birth cohorts, age groups or income bands. The only intangible rules that apply are exhaustiveness and mutual exclusiveness (recode all values of the original variable to a single category of the new variable).

Application 8d. Recoding continuous data to groups — Data: NHIS 2009

The **age** variable, which measures the age of respondents, can be used in its continuous form or can be recoded into age groups for crosstabulations. To recode the **age** variable into four age groups, we use the **recode** command and create the **age4** variable with the **gen** option, keeping all names and labels as concise and explicit as possible:

```
. * Recoding age to 4 groups.
. recode age ///
>         (18/29=1 "18-29") ///
>         (30/44=2 "30-44") ///
>         (45/64=3 "45-64") ///
>         (65/max=4 "65+"), gen(age4)
(24291 differences between age and age4)

. la var age4 "Age (4 groups)"
```

Never operate a transformation like the one above without checking its results. The whole point of programming your analysis into a do-file is that you can include comments and checks throughout your work. Here, the **fre** command serves as a technical verification for the operation:

```
. fre age4

age4 — Age (4 groups)
────────────────────────────────────────────────────────────
                │     Freq.    Percent      Valid       Cum.
────────────────┼───────────────────────────────────────────
Valid   1 18-29 │      4744      19.53      19.53      19.53
        2 30-44 │      6715      27.64      27.64      47.17
        3 45-64 │      8477      34.90      34.90      82.07
        4 65+   │      4355      17.93      17.93     100.00
        Total   │     24291     100.00     100.00
────────────────────────────────────────────────────────────
```

The number of age groups ultimately depends on your research design. A more fine-grained categorisation might apply if your hypotheses predict strong generational or cohort effects, or rely on specific positions in the life cycle—for instance, being part of the generation that was young and politically active around 1968 in Western countries.

Application 8e. Recoding dummies — Data: NHIS 2009

In Application 8a, we saw that the **sex** variable coded 1 for males and 2 for females in our dataset. However, we prefer to manipulate dichotomous measures in the form of dummy variables that use sensible values of 0 and 1 in relation the variable name.

To that end, we recode the **sex** variable to the **female** dummy where 1 naturally codes for being female and 0 for not being female, i.e. male. We could use the **gen** command as we did in Application 8c, but the **recode** command is just as efficient here:

```
. * Recoding sex as a female dummy.
. recode sex (1=0 "Male") (2=1 "Female") (else=.), gen(female)
(24291 differences between sex and female)
```

You should check for exact concordance at that point. Crosstabulating the original and recoded variables will work, but a quicker concordance test exists here:

```
. count if female != sex-1
  0
```

Dummies are very common in statistical modelling, and Stata offers more ways to code information into dummies. The **tab** command, for instance, can create dummies for each of its categories with the **gen** option, as here with marital status:

```
. * Recoding marital status as dummies.
. tab marstat, gen(married)

       Legal marital status |      Freq.     Percent        Cum.
----------------------------+-----------------------------------
                    Married |     11,221       46.19       46.19
                    Widowed |      1,874        7.71       53.91
                   Divorced |      3,696       15.22       69.12
                  Separated |        906        3.73       72.85
              Never married |      6,542       26.93       99.79
     Unknown marital status |         52        0.21      100.00
----------------------------+-----------------------------------
                      Total |     24,291      100.00
```

In this example, the **marstat** variable has been used to create six dummies, all named with the **married** prefix, and each coding for one category of martial status. The dummies are given descriptive variable labels, as shown by the **d** command when used on all **married1**, **married2**, … **married6** dummies at once with the * operator:

```
. codebook married*, c

Variable     Obs Unique      Mean  Min  Max  Label
--------------------------------------------------------------------------------
married1   24291      2  .4619406    0    1  marstat==Married
married2   24291      2  .0771479    0    1  marstat==Widowed
married3   24291      2  .1521551    0    1  marstat==Divorced
married4   24291      2  .0372978    0    1  marstat==Separated
married5   24291      2  .2693179    0    1  marstat==Never married
married6   24291      2  .0021407    0    1  marstat==Unknown marital status
--------------------------------------------------------------------------------
```

The **codebook** command with the **c** option shows the mean value for each dummy, which is also the frequency of its category in the data. The dummy for being divorced, **married2**, hence has a mean of .15 and represents 15% of all observations.

Application 8f. Recoding bands — Data: NHIS 2009

If you need to produce more complex recodes, the **recode()**, **irecode()** and **autocode()** extensions of the **gen** command produces results similar to **recode** in less code and in a more flexible way that is particularly appropriate to recode continuous data into bands, as with age class or income bands.

The following example uses **irecode()** to recode Body Mass Index as the four groups established by its international classification:

```
. * Recoding BMI to 4 groups.
. gen bmi4:bmi4 = irecode(bmi, 0, 18.5, 25, 30, .)
```

This command creates a first category of respondents for which 0 ≤ BMI < 18.5, which is classified as underweight, up to a fourth category for 30 ≤ BMI < ∞, which designates obese respondents. We add variable and value labels to specify the recoded variable, and finally proceed in checking the recoded variable with the **table** command:

```
. la def bmi4 1 "Underweight" 2 "Normal" 3 "Overweight" 4 "Obese"

. la var bmi4 "BMI classes"

. table bmi4, c(freq min bmi max bmi) f(%9.4g)
```

```
------------------------------------------
BMI classes |     Freq.   min(bmi)  max(bmi)
------------+-----------------------------
Underweight |       274       15.2     18.48
     Normal |      8625      18.51        25
 Overweight |      9013      25.01     29.99
      Obese |      6379      30.02     50.49
------------------------------------------
```

The **table** command is used here as a technical check comparing the categories of the **bmi4** variable to the minimum and maximum values of BMI that they respectively hold. The **format** (shorthand **f**) option limits the number of visible floating digits.

8.4. Encoding

Encoding issues have to do with the format of your data. Fundamentally, your dataset is just a text file with a text encoding and delimiters for columns and rows. Within your data, additional encoding applies to your data:

- **Missing data are often encoded as arbitrary numeric values.** These values can be distinctive, such as -1 for strictly positive data or 9 for ordinal data on a five-point scale. In other cases, multiple codes are used, as in 77 for "Refused to answer", 88 for "Do not know" (DNK) and 99 for "No answer" (NA).

  Stata requires missing data to be encoded as a dot (.). It also supports multiple missing data formats: **.a**, **.b**, … , **.z** can be used to encode missing data of different kinds. Stata treats all missing data as +∞ (positive infinity).

  Missing data that are not yet coded in Stata format can be addressed with the **replace** command. When encoding several variables with identical coding schemes, the **mvdecode** command can perform batch encodings.

- **Textual data are often encoded as chains of characters.** These “strings” of text, as they are called in programming environments, are difficult to manipulate from Stata because they do not come with a numeric framework.

  Stata requires strings to be encoded with numeric values. Only in specific circumstances is encoding text neither necessary nor particularly desirable, as when manipulating singular information like country names.

  Text data that are not yet supported by numeric values can be addressed with the **encode** command. In the specific case of numbers encoded as text, the **destring** command is used instead.

Encoding missing data

Data: NHIS 2009

The following example shows a typical encoding issue. If analysed in its current state, the **diayrsago** variable will treat values 96, 97 and 99 as valid measurements, therefore distorting completely any analysis of the variable:

```
. fre diayrsago, row(10)

diayrsago — Years since first diagnosed with diabetes
-----------------------------------------------------------------------------
                              |      Freq.    Percent      Valid       Cum.
------------------------------+----------------------------------------------
Valid   0  Within past year   |         86       0.35       0.35       0.35
        1  1 year             |        151       0.62       0.62       0.98
        2  2 years            |        163       0.67       0.67       1.65
        3  3 years            |        164       0.68       0.68       2.32
        4  4 years            |        117       0.48       0.48       2.80
        :                     |          :          :          :          :
        81 81 years           |          1       0.00       0.00       8.85
        82 82 years           |          1       0.00       0.00       8.85
        96 NIU                |      22111      91.03      91.03      99.88
        97 Unknown-refused    |          2       0.01       0.01      99.88
        99 Unknown-don't know |         28       0.12       0.12     100.00
        Total                 |      24291     100.00     100.00
-----------------------------------------------------------------------------
```

To solve this issue, we need to replace values 96, 97 and 99 with missing data codes that are recognisable by Stata, i.e. either just “.” for all values or **.a**, **.b** and **.c** for each of them if we are interested in keeping them distinct from each other. The precise choice entirely has to do with our research design.

Assuming that we want to fix the issue in the simplest way, two solutions apply. The first solution modifies the **diayrsago** variable directly, using the **replace** command to substitute values over 95 with missing data:

```
. * Simple encoding.
. replace diayrsago=. if diayrsago > 95
(22141 real changes made, 22141 to missing)
```

The alternative code uses the **gen** command with the **cond()** operator to create a new variable through a simple "if… else" statement. The **diabetes** variable will be equal to the original **diayrsago** variable except when it is superior to 95, in which case it will replace it with missing data:

```
. * Alternative.
. gen diabetes = cond(diayrsago < 95, diayrsago, .)
(22141 missing values generated)
```

Both solutions are almost equivalent, and users might generally prefer the first one for its simplicity. The second is actually more secure, since it does not overwrite the original variable; however, it loses creates a new variable and therefore loses labels.

Assuming that we want to preserve a distinction between types of missing data, two other solutions apply. The first one proceeds as before with the **replace** command, but uses the **.a**, **.b** and **.c** missing data markers:

```
. * Detailed encoding.
. replace diayrsago=.a if diayrsago == 96
(22111 real changes made, 22111 to missing)

. replace diayrsago=.b if diayrsago == 97
(2 real changes made, 2 to missing)

. replace diayrsago=.c if diayrsago == 99
(28 real changes made, 28 to missing)
```

The alternative code is, again, more secure and this time also much quicker. It uses the **recode** command to create the **diabetes** variable, recoding values to missing data in the process while leaving untouched all other values by default:

```
. * Alternative.
. recode diayrsago (96=.a) (97=.b) (99=.c), gen(diabetes)
(22141 differences between diayrsago and diabetes)
```

Finally, let's introduce a case where multiple variables are using the same scheme for missing data, as with the **ybarcare** and **uninsured** variables below:

```
. fre ybarcare uninsured

ybarcare — Needed but couldn't afford medical care, past 12 months
-----------------------------------------------------------------------
                             |      Freq.    Percent      Valid      Cum.
-----------------------------+-----------------------------------------
Valid    1 No                |      21811      89.79      89.79     89.79
         2 Yes               |       2477      10.20      10.20     99.99
         9 Unknown-don't know|          3       0.01       0.01    100.00
         Total               |      24291     100.00     100.00
-----------------------------------------------------------------------

uninsured — Health Insurance coverage status
-----------------------------------------------------------------------
                             |      Freq.    Percent      Valid      Cum.
-----------------------------+-----------------------------------------
Valid    1 Not covered       |       4510      18.57      18.57     18.57
         2 Covered           |      19727      81.21      81.21     99.78
         9 Unknown-don't know|         54       0.22       0.22    100.00
         Total               |      24291     100.00     100.00
-----------------------------------------------------------------------
```

In this case, the **mvencode** and **mvdecode** commands are quicker than others. Correctly encoding missing data will actually require to use the **mvdecode** command on both variables while passing the values to be encoded as missing through the **mv** option:

```
. * Batch encoding.
. mvdecode ybarcare uninsured, mv(9)
    ybarcare: 3 missing values generated
   uninsured: 54 missing values generated
```

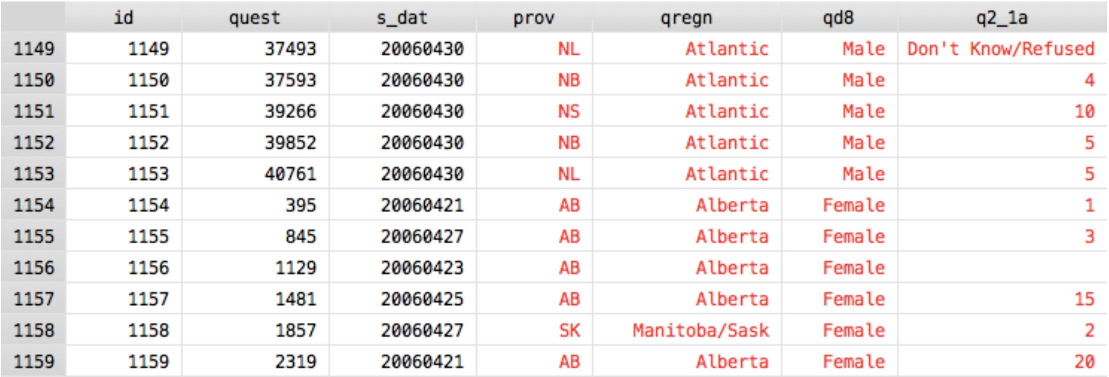
Data structures can differ markedly, and encoding issues will frequently arise as soon as you start opening datasets created in other software than Stata. Different encodings for missing data can be solved quickly, but only if diagnosed: always spend enough time inspecting your data to learn enough about them.

Application 8g. Encoding strings — Data: MFSS 2006

In this example, we look at the Music File Sharing Study, which the Canadian government contracted in 2006 to study how digital content affects consumer behaviour. The survey was documented and analysed in a paper by Birgitte Andersen and Marion Frenz (*Journal of Evolutionary Economics*, 2010), and is available from the Industry Canada website: http://www.ic.gc.ca/eic/site/ic1.nsf/eng/01464.html.

The dataset was imported into Stata using the **insheet** command, but substantial encoding issues plague the data at that stage. These issues can be diagnosed by inspecting the storage type of each variable, but they are more easily evident when browsing data from the Data Editor, which you can open with the **browse** command:

```
. browse id quest s_dat prov qregn qd8 q2_1a in 1149/1159
```



	id	quest	s_dat	prov	qregn	qd8	q2_1a
1149	1149	37493	20060430	NL	Atlantic	Male	Don't Know/Refused
1150	1150	37593	20060430	NB	Atlantic	Male	4
1151	1151	39266	20060430	NS	Atlantic	Male	10
1152	1152	39852	20060430	NB	Atlantic	Male	5
1153	1153	40761	20060430	NL	Atlantic	Male	5
1154	1154	395	20060421	AB	Alberta	Female	1
1155	1155	845	20060427	AB	Alberta	Female	3
1156	1156	1129	20060423	AB	Alberta	Female	
1157	1157	1481	20060425	AB	Alberta	Female	15
1158	1158	1857	20060427	SK	Manitoba/Sask	Female	2
1159	1159	2319	20060421	AB	Alberta	Female	20

In this screenshot, variables with values in red are simply coded as text with no numeric value to designate them—a format also known as 'string', which is impractical for statistical analysis as hinted by the warning colour that Stata assigns to their columns.

Let's start with the **prov** variable codes for the respondent's province of residence. Because of the string format, we have to include double quotes around its values to designate respondents from, for example, Alberta and British Columbia:

```
. count if prov=="AB" | prov=="BC"
  293
```

This quickly becomes impractical, so we use the **encode** command to produce a similar variable with automatically generated numeric values and labels for each of them:

```
. encode prov, gen(province)

. fre province

province — PROV
-----------------------------------------------------------
                |      Freq.    Percent      Valid       Cum.
----------------+------------------------------------------
Valid   1  AB   |        152       7.24       7.24       7.24
        2  BC   |        141       6.71       6.71      13.95
        3  MB   |         57       2.71       2.71      16.67
        4  NB   |         54       2.57       2.57      19.24
        5  NL   |         23       1.10       1.10      20.33
        6  NS   |         48       2.29       2.29      22.62
        7  ON   |        559      26.62      26.62      49.24
        8  PE   |          6       0.29       0.29      49.52
        9  QC   |       1006      47.90      47.90      97.43
        10 SK   |         54       2.57       2.57     100.00
        Total   |       2100     100.00     100.00
-----------------------------------------------------------
```

The numeric encoding makes it possible to select respondents in Alberta or British Columbia with shorter and more flexible commands, using the values assigned by the **encode** command to each category:

```
. count if province < 3
  293
```

Similarly, the **qd8** variable coding for gender cannot be easily manipulated in its current form: Stata needs numeric values attached to each of its categories in order to include it in a regression model, for example.

A simple solution consists in creating a dummy coding for females, as we previously did in Application 8e. The data is in string format, so we need to use double quotes and text instead of numeric values to create the appropriate conditional statement:

```
. * Creating a female dummy from string values.
. gen female = (qd8 == "Female") if !mi(qd8)
```

The **encode** command would produce a similar result, but dummy variables with explicit names and codes need not feature labels, so we will settle for that simple solution.

The last example concerns the **q2_1** variable, which measures the number of music CDs that the respondent bought in 2005 for his or her personal use. The variable is stored as a string because it includes both numbers and text, including empty cells. In that state, the variable is virtually unusable, so we apply several transformations to it:

```
. replace q2_1a=".a" if q2_1a==""
(426 real changes made)

. replace q2_1a=".b" if q2_1a=="None"
(33 real changes made)

. replace q2_1a=".c" if q2_1a=="Don't Know/Refused"
(34 real changes made)

. destring q2_1a, replace
q2_1a has all characters numeric; replaced as byte
(493 missing values generated)
```

The first three commands code for missing data where the **q2_1a** variable featured text or empty cells. Since the **q2_1a** variable is based on text, the arguments of the **replace** commands feature double quotes. Once the variable contained only numeric or missing values, we got rid of the string format with the **destring** command.

Finally, the **numlabel** command is a handy workaround for serious encoding issues: try **numlabel _all, add** to prefix all textual labels with numeric values. This makes the **tab** command more practical (a problem solved in this handbook by using the **fre** command instead), and might or might not help in your situation.

*

Data management, as shown by the topics covered in Sections 5–8, is not only long, it is also complex in its more elaborate stages, and very sensitive to even the smallest mistake. We will circumvent that issue by using readymade datasets for which data management will be reduced to a minimum, but in a real research environment, quantitative data skills will often extend to data management, in addition to the other skills introduced in Section 4.

Part 2

Analysis

Statistical analysis requires learning about the statistical theory that underlies the analysis, as well as about the particular procedures that allow to run the analysis from Stata. **This step is the most knowledge-intensive aspect of the course**, as it requires to operate several commands while knowing what they correspond to in theory, and how to interpret their results.

Statistical analysis is a professional, scientific activity. Making mistakes while analysing quantitative data is common, and several rounds of analysis are usually required to obtain reliable results. In practice, it requires the collective effort of scientists worldwide to work on large projects and to verify that their respective research does not contain errors of interpretation.

This class emulates that professional setting by organising small-scale research projects that are then submitted to the scrutiny of the course instructors. The tools used in the analysis will be restricted to a selection of **statistical tests**, and to the most common form of statistical modelling, **linear regression**.

At that stage, it is **essential** that you are familiar with working in Stata, and that you have read the handbook chapters that document the most basic aspects of data structure, such as sampling. The following section introduces several tests, procedures and models that will connect your data to particular interpretations, all of which you will be learning along performing them.

9. Distributions

Assessing the normality of your dependent variable is essential to your analysis because the regression model assumes that this variable is normally distributed. This assumption, and many others that apply to regression modelling, are systematically violated, because the normal distribution is a theoretical construct.

At that stage, you should make sure that you have understood the Central Limit Theorem by reading from your handbook. Try plotting the normal distribution in Stata by typing **twoway function y=normalden(x), range(-4 4)**, and check that you understand how standard deviations relate to this curve. As a side note, the course will also mention other (Poisson, binomial) distributions, but you will not be working directly with either of them.

Thankfully, linear regression is quite robust to deviations from normality in your dependent variable. This basically means that your analysis retains most of its validity even if your variables express some departure from normality. Still, you should aim at having as normally distributed a dependent variable as possible.

Assessing normality is a two-step process that starts with **visual inspections** of the distribution, and then continues with **formal tests** of normality. Following that step, you might try different **variable transformations** to see whether there exists a mathematical way to make the distribution of your dependent variable approach normality. Finally, you will have to think about outliers (outstanding observations in your data).

These operations are absolutely essential to your analysis, because quantitative analysis does not magically proceed by throwing aggregate data at a statistical software solution. Instead, it relies on careful modelling that aims at **fitting** real-world observations into abstract models. The 'goodness of fit' of your model will determine the quality of your analysis.

9.1. Visualizations

Prior to visualizing a variable, you can learn about it with descriptive statistics. These steps come after reading the dataset documentation, and thus presume that you have an idea of how the variable is coded and how many observations are available for it, even if the commands listed below also inspect these:

- **For continuous data**, the **summarize** command (shorthand **su**) provides the number of observations for a variable, as well as its mean, standard deviation, minimum and maximum values.

  The **summarize** command with the **detail** option will add percentiles and variance, as well skewness and kurtosis, which we will return to when assessing the normality of the distribution (Section 9.3).

For more specific operations, the **tabstat** command is a more flexible tool that will provide any statistics passed with its **s()** option, including any of the above as well as all possible statistics listed in its documentation.

- **For categorical data**, the **fre** command will give you the best approach to the variable by listings its frequencies while paying attention to its coding and missing values. Install it with **ssc install fre**.

  Using the standard Stata commands, you would have to use the **tab** command with the **missing** and **nolabel** options, along with the label list command, to obtain similar results.

Once you have learnt enough about your variable through descriptive statistics, you should turn to visualizations:

- **With continuous variables**, you will be using the **histogram** as your main tool, complemented with the **box plot** in order to spot outliers (Section 9.5). Useful central tendency descriptive statistics will be the mean and median.
- **With categorical variables**, you will be using the **categorical bar plot**, although its value added to a simple frequency table is often open to question. A useful descriptive central tendency statistic will be the mode.

The examples below illustrate these options. We will alternate between several of the course datasets to illustrate how descriptive statistics and visualization work with different types of data.

Important: observations in each example are not systematically weighted, as to keep the code as simple and demonstrative as possible, but you should apply weights when your dataset offers them. Weighting, as shown in Example 5a and Example 5b, modify the statistical importance of observations within the sample in relation to how it was initially designed. Sample size might also affect your description of the data, as shown with confidence intervals in Example 9d.

Example 9a. Visualizing continuous data — Data: NHIS 2009

The dependent variable in this example is the Body Mass Index (BMI) for a large sample of American respondents in 2009, calculated from measures of **weight** in pounds and squared **height** in inches, labelled, and then described, using the following commands:

```
. gen bmi = weight*703/(height^2)

. la var bmi "Body Mass Index"

. su bmi

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
         bmi |     24291       27.27    5.134197   15.20329   50.48837
```

The interpretation of the statistics above will cover different things:

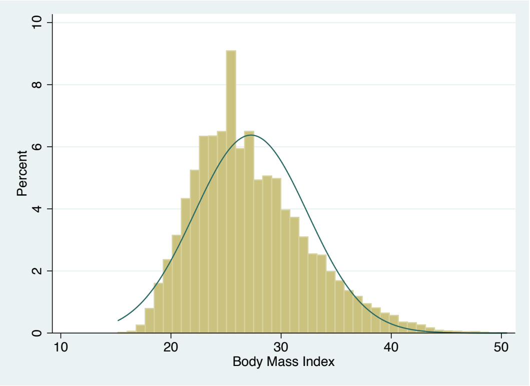
- First, the total number of observations (**Obs**) is satisfying: the **bmi** variable is available in a large fraction of the data—actually, for 100% of observations in the dataset.
- Then, the average Body Mass Index (**Mean**) in our sample is remarkably high—as a BMI of 27 is already considered to be "overweight" in the official categorization of the BMI measure.
- The standard deviation (**Std. Dev.**) further qualifies the distribution by giving its spread: for instance, 95% of all observations fall within two standard deviations from the mean, i.e. between 22 and 32.
- Finally, the range of values (**Min** and **Max**) indicate that the distribution is skewed, since the maximum value of 50 is further away from the mean than the minimum value of 15. A box plot will confirm this.

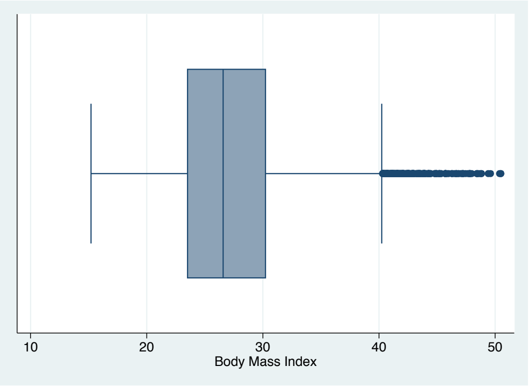
We then turn to visualizations, using appropriate graphs for continuous data:

```
. hist bmi, normal percent
(bin=43, start=15.203287, width=.82058321)

. gr hbox bmi
```

The **histogram** (shorthand **hist**) command was passed with two options: **normal**, which overlays a normal distribution to the histogram bars, and **percent**, to use percentages instead of density on the vertical y-axis. The **graph hbox** command comes in two distinct words because it belongs to the **graph** (shorthand **gr**) class of commands, which can be passed options to modify its axes, titles and so on.

From the graphical results of these commands, we observe that the **bmi** variable is not normally distributed due to its disproportionate amount of right-hand-side values that form a long 'right tail' in the histogram, and outliers in the box plot:





The histogram shows a distribution that is skewed to the right, and the box plot shows that BMI values over 40 are outliers to the distribution, located over 1.5 times the interquartile range (Section 9.5 deals with outliers in more detail).

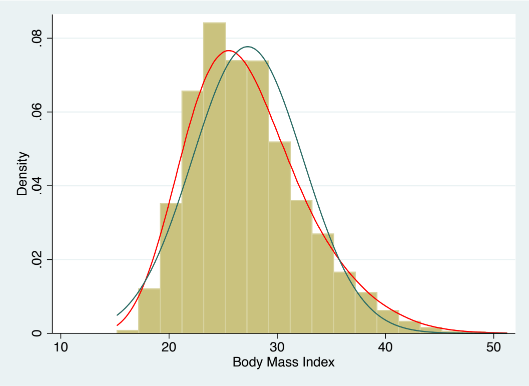
A precise look at the BMI variable would also reveal that its mean and median are quite close, indicating some extent of symmetry in the distribution despite the skewness mentioned before. We will come back to these notions.

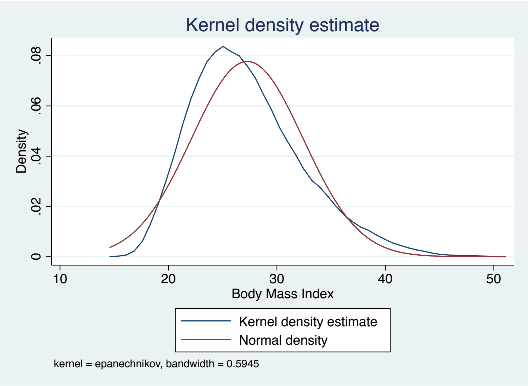
Example 9b. Kernel density plots — Data: NHIS 2009

Histograms use bars (or "bins") to represent a distribution. A different tool to visualize a distribution is the **kernel density plot**, which also displays the density of the distribution, but uses smoothed lines instead of bars.

The left-side example below shows the commands to produce a histogram and a kernel density plot for the distribution of Body Mass Index. The options set the width of the histogram and kernel density along other options (see **help histogram**):

```
. hist bmi, w(2) normal kdens kdenopts(bw(2) lc(red))
(bin=18, start=15.203287, width=2)
```





The graph on the right shows a quicker way to draw a kernel density with the **kdensity** command and the **normal** option. In both graphs, the skewness observed in the kernel density curve also shows in a comparison of the mean and median values:

```
. tabstat bmi, s(n mean median skewness)

    variable |         N      mean       p50  skewness
-------------+----------------------------------------
         bmi |     24291     27.27  26.57845  .7207431
------------------------------------------------------
```

Example 9c. Visualizing categorical data — Data: ESS 2008

If you are inspecting a categorical variable, you will realise that the distribution of the variable makes little sense. Furthermore, the tools described above will turn out to be either inappropriate or of very little help. Instead, you will look at **proportions**, and you will need to install the additional **fre** and **catplot** packages.

The **fre** command is particularly useful to handle missing observations. In the example below, we look at attitudes towards poorer immigration in/to Europe. We can tell from the distribution of that only 4.5% of observations are missing, and can also read the percentages of each response item to the question:

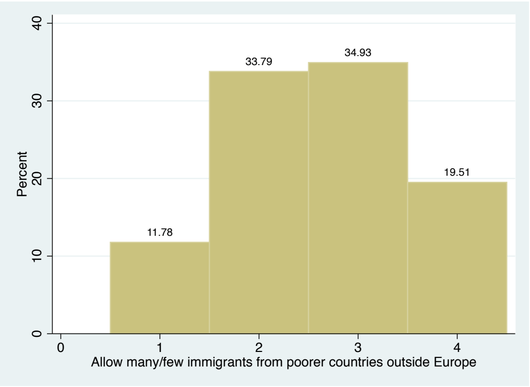
```
. fre impcntr

impcntr — Allow many/few immigrants from poorer countries outside Europe
-----------------------------------------------------------------------------------
                                    |      Freq.    Percent      Valid       Cum.
------------------------------------+----------------------------------------------
Valid   1  Allow many to come and   |       5750      11.24      11.78      11.78
           live here                |
        2  Allow some               |      16496      32.26      33.79      45.56
        3  Allow a few              |      17054      33.35      34.93      80.49
        4  Allow none               |       9523      18.62      19.51     100.00
        Total                       |      48823      95.47     100.00
Missing .a                          |        119       0.23
        .b                          |       2144       4.19
        .c                          |         56       0.11
        Total                       |       2319       4.53
Total                               |      51142     100.00
-----------------------------------------------------------------------------------
```

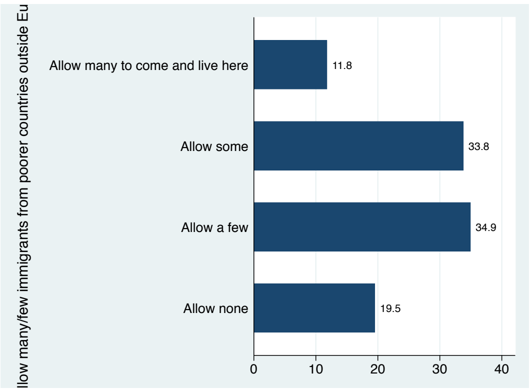
When visualizing categorical data, follow two recommendations:

- **Do not use pie charts**. The human eye is not used to read polar coordinates, which makes the vast majority of pie charts useless at best, deceitful at worst.
- **Produce a horizontal bar plot** of the valid cases with the **catplot** command, but ask yourself whether the graph brings any substantial information to the reader. The answer is most likely negative.

The plots below show the **impcntr** variable as a histogram and as a categorical bar plot, but neither visualization brings little more than a frequency table:

```
. hist impcntr, percent discrete addl
(start=1, width=1)

. catplot impcntr, percent blabel(bar, format(%3.1f)) yti("")
```





Frequency tables like the ones produced by the **fre** command can be formatted to fit into tables with other descriptive statistics (Section 13.4).

Example 9d. Survey weights and confidence intervals Data: ESS 2008

A drawback of plotting distributions without first taking a look at the underlying data structure is that the resulting plots can hide large **confidence intervals**. Differences in proportions that are based on a low number of observations come with large confidence intervals that might minimise – or even cancel – the visual differences that we might observe on a graph.

In the example below, the survey question from Example 9c is analysed for French adult citizens only (study: **ESS**, variable: **impcntr**, with additional variables to select the target group made of French adult citizens). The number of valid observations for this target group is markedly lower than previously, with only 1884 non-missing observations:

```
. fre impcntr if cntry=="FR" & age >= 18 & ctzcntr==1

impcntr — Allow many/few immigrants from poorer countries outside Europe
-----------------------------------------------------------------------------------
                                  |      Freq.    Percent      Valid       Cum.
----------------------------------+------------------------------------------------
Valid   1  Allow many to come and |        151       7.80       8.01       8.01
           live here              |
        2  Allow some             |        771      39.84      40.92      48.94
        3  Allow a few            |        704      36.38      37.37      86.31
        4  Allow none             |        258      13.33      13.69     100.00
        Total                     |       1884      97.36     100.00
Missing .a                        |         13       0.67
        .b                        |         38       1.96
        Total                     |         51       2.64
Total                             |       1935     100.00
-----------------------------------------------------------------------------------
```

From that question, the actual proportion of French respondents who support a harsh anti-immigration policy is hard to determine:

- As shown in the frequency table above, respondents who prefer allowing "some" or "many" immigrants from poorer countries outside Europe form a minority of 48.94%, as calculated from the cumulative distribution of all non-missing observations. Any politician who plans on campaigning on the issue of immigration will be interested in the figure, to side with either the minority or the majority of potential voters.
- An important issue, however, is that the sample uses **survey weights** to make its observations more representative of the actual national population, as explained in Example 5a. Furthermore, the number of observations in the sample only allows us to estimate values for the rest of the population, therefore involving **confidence intervals**.

If we weight the data before producing the frequency table, using the **[aw]** prefix and the **dweight** variable mentioned in Example 5a, respondents who prefer allowing “some” or “many” immigrants actually form a majority:

```
. fre impcntr if cntry=="FR" & age >= 18 & ctzcntr==1 [aw=dweight]

impcntr — Allow many/few immigrants from poorer countries outside Europe
───────────────────────────────────┬──────────────────────────────────────────
                                   │      Freq.    Percent      Valid       Cum.
───────────────────────────────────┼──────────────────────────────────────────
Valid   1  Allow many to come and  │   163.0514       8.43       8.63       8.63
           live here               │
        2  Allow some              │   795.0004      41.09      42.09      50.72
        3  Allow a few             │   692.9715      35.81      36.69      87.40
        4  Allow none              │   237.9166      12.30      12.60     100.00
        Total                      │    1888.94      97.62     100.00
Missing .a                         │   11.82642       0.61
        .b                         │   34.23363       1.77
        Total                      │   46.06004       2.38
Total                              │       1935     100.00
───────────────────────────────────┴──────────────────────────────────────────
```

Survey weights also apply with the **[pw]** suffix to commands like **prop**, which computes the confidence interval of each category based on a normal approximation:

```
. prop impcntr if cntry=="FR" & age >= 18 & ctzcntr==1 [pw=dweight]

Proportion estimation                Number of obs     =     1884

      _prop_1: impcntr = Allow many to come and live here
      _prop_2: impcntr = Allow some
      _prop_3: impcntr = Allow a few
      _prop_4: impcntr = Allow none

─────────────┬────────────────────────────────────────────────
             │ Proportion   Std. Err.     [95% Conf. Interval]
─────────────┼────────────────────────────────────────────────
impcntr      │
     _prop_1 │    .086319    .0073835      .0718383    .1007997
     _prop_2 │   .4208712    .0124809      .3963932    .4453491
     _prop_3 │   .3668574    .0120768       .343172    .3905427
     _prop_4 │   .1259525    .0081542      .1099602    .1419447
─────────────┴────────────────────────────────────────────────
```

The confidence intervals above are large because of the limited number of valid observations. We selected the convenience standard 95% level of significance, and intervals would widen even more at 99% significance.

9.2. Options

You might have noticed that many graphs produced above use **graph options**, often to modify the unit, scale or title of an axis. Full-fledged books have been written on the topic, and the most common options for this course follow:

- Scales that use percentages (**percent**) or frequencies (**frequency**) are often more useful than density or fractions in histograms. Additionally, you will sometimes want to add labels to your **histogram** plots with the **addlabel** option, or to **catplot** bar plots with the **blabel(bar)** option. Learn more from the documentation pages for each type of graph.

- You might also need to use the **ytitle** and **xtitle** options to give shorter titles to the axes in plots produced by **graph** commands, or to remove the titles. The same applies to the title of your graph, which you can set with the **title** option. Additionally, you can add a short note to your graph (often a mention of the data source) with the **note** option.

- Finally, the **xscale** and **yscale** options allow controlling the full range of your axes, along with the **xlabel** and **ylabel** options that control the spacing between labelled ticks. These options also apply to all **graph** commands and are particularly useful to make the values on your axes correspond to the real set of values that your data can possibly take.

Example 9e. Democratic satisfaction Data: ESS 2008

In this example, the main variable of interest is the assessment of democracy in the respondent's country (**stfdem**). The codebook indicates that answers to the question were coded on an interval scale of 0 ("Extremely dissatisfied") to 10 ("Extremely satisfied"), which means that we can read the mean of the variable as an average score of satisfaction with democracy. We applied both design and country weights to compute a European average score of democratic satisfaction, as explained in Example 5b:

```
. su stfdem [aw=dweight*pweight]

    Variable |     Obs      Weight        Mean   Std. Dev.       Min        Max
-------------+-----------------------------------------------------------------
      stfdem |   48711  52569.9013    4.628696   2.615244          0         10
```

We could try collapsing individual answers by country in order to observe, for example, if respondents in Greece are more supportive of democracy than those in Britain. Both countries can claim a long historical experience with democratic institutions, but Greece went through an autocratic period in the recent period, and general levels of economic wealth are lower in Greece than they are in Britain. Grouping observations at the country-level might thus provide some useful heuristics preliminary to our analysis.

Further to grouping by country (**cntr**), we will separate citizens from non-citizens (**ctzcntr**) to observe any gap in appreciation between both groups. At that stage, the most straightforward graph command to plot these insights would be to use the following, which also accounts for design weights:

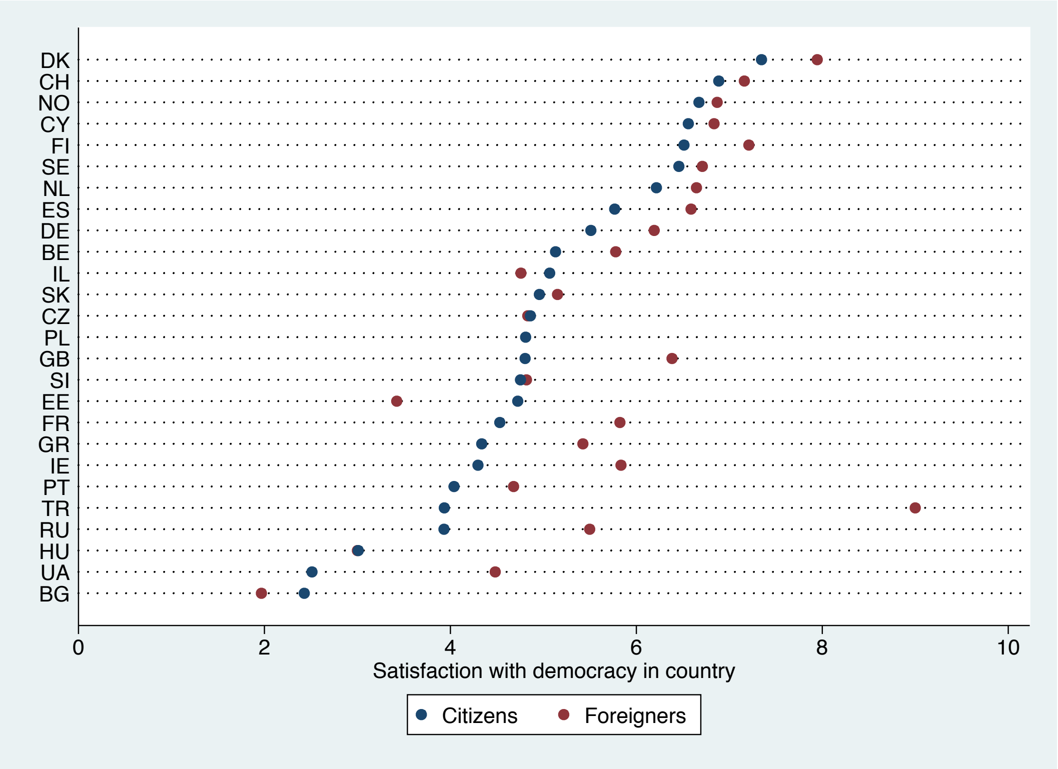
```
. gr dot stfdem [aw=dweight], over(ctzcntr) over(cntr)
```

Unfortunately, the default settings produces a distressfully confused result:

- The vertical y-axis is unreadable because it plots the **stfdem** variable over 26 countries and over two groups of non-/citizens, ending in 52 lines of graph.
- Since the average support scores for democracy are not properly ordered, we will not be able to read the average scores from most to least satisfied.
- Additionally, we will want to add an informative legend to the scale: the default one, "mean of **stfdem**", is not straightforward enough.

The graph above is almost entirely useless. A suitable dot plot will use several additional options and look like the following command, which runs over more than one line, as the "///" breaks indicate:

```
. gr dot stfdem [aw=dweight], over(ctzcntr) asyvars over(cntr, sort(1) des) ///
>         legend(label(1 "Citizens") label(2 "Foreigners")) ///
>         ytitle("Satisfaction with democracy in country") ///
>         scale(.8) name(stfdem, replace)
```



The graph reveals an interesting gradient of opinions, and sometimes large gaps (at least at the intuitive, visual level) between the subpopulations of citizens and foreigners. The list of options used in the graph goes as follows:

- The vertical axis is called with the **over()** options, and the **asyvars** option makes sure that both citizens foreigners, the categories of the **ctzcntr** variable, are plotted on the same lines.
- The **sort(1) des** option orders the categorical (country) axis by using the descending order of first value displayed on the graph, namely satisfaction among citizens.
- The **legend** and **label** options allow to rewrite the legend of the graph to "Citizens" and "Foreigners" instead of using the "Yes/No" labels of the **ctzcntr** variable.
- The **ytitle** option provides a title to the continuous axis; this ids different to the **name** option, which stores the graph in Stata memory under **stfdem**, overwriting (**replace**) any previous graph with that name.
- The **scale(0.8)** option serves to reduce the size of all items in the graph to 80% of their default size, including the labels on both axes and the dots that mark the average score for democratic satisfaction.

Other useful graph options are:

- **yreverse** reverses the continuous y-axis (which is, in fact, horizontal), in order to plot variables where the coding and labels are inversed, as in questions where high approval is coded as "1" and disapproval as "4".
- **yscale(log)** switches the axis to logarithmic scale, in order to obtain a better visual differentiation of high values. It is better, however, to transform the variable if you plan to use a logarithmic scale to measure it.
- **ylabel(1(1)4)** and **exclude0** modify the continuous axis by respectively setting the range to 1–4 with ticks every 1 point, and by excluding 0 from the axis of dot plots, when 0 is not a relevant variable value.

Tweaking the plot to obtain what can be considered a suitable visual result relies on an admittedly long list of options. However, quality is always preferable over quantity when it comes to graphs, and these options are useful in many settings.

You might also object that the final graph is still quite difficult to read, and you would be right: even though recent versions of Stata come with rather powerful graphing capabilities, its poor default settings are sometimes discouraging, and some researchers prefer to use other software at that stage.

9.3. Normality

Normality is the assessment of whether a variable follows the normal distribution. The normal distribution is an abstract concept: it refers to a curve that can be translated into a probabilistic situation, called a probability density function. This function is used to produce estimates of values and their confidence intervals. Cut the music, we need your full attention for a few moments.

Start with a **constant**, $k = 5$. Let's say that k is the amount of money that you are willing to donate right now to a human rights organization. Captured at this unique moment of time and of your own preferences, this number alone does not vary: $k = 5$. If I try to guess it, there is a 100% chance that the answer "5" is correct: $\Pr(k = 5) = 1$. All other predictions of k have a probability of 0: $\Pr(k \neq 5) = 0$.

Release a few assumptions and let k vary in space; call it x to mark that step. We keep our cross-sectional assumption, and will thus leave aside temporal variation in preferences about human rights organizations. Let us assume for now that we want to predict k for the whole population of, say, Russian citizens: how many is each of them willing to donate to human rights organizations? The **variable** k can now take any value.

Statistical theory intervenes at that point: the more values k can take, and the more observations of k we have, the better we can predict it. This is applicable to coin flipping as it is to human rights donations, and derives from the **Central Limit Theorem**, which can predict the value of k among all Russian citizens from just a sample of them, even if we do not know how many Russian citizens actually exist.

For our purposes, the population of Russian citizens is the sum of individual preferences about human rights donations, P = { k1, k2, …, kN }. Each item kn is a value: the amount of money one Russian citizen would be willing to donate. In this population, there is a mean value of k. In parallel, if we draw a sample of that population, we can calculate its mean value, and its standard deviation.

When the population is unobservable as a whole, our objective becomes to estimate a **population parameter**, the true mean value of k, from **sample parameters**, by observing the mean value of k in a smaller population of n respondents to a survey that was designed to reach Russian citizens and measure the extent of their willingness to donate to human rights organizations.

The amount of craft and technique that goes into **survey design** is immense, and the amount of bias that can be generated at that stage is too substantial not to mention it. Hopefully, there are thousands of well-run surveys with careful sample design, and the stability of some results is another way to gain confidence in our ability to measure the real world, even in its most intricate aspects.

which has interesting properties for building probabilities to estimate a population parameter from its sample parameter.

Regarding normality, the **summarize** command run with the **detail** option gives you several indications that serve to understand the distribution of your variable.

As far normality goes, you should concentrate on two indicators:

- **Skewness** is an indication of how close to being symmetrical the distribution of your variable is. **Skewness should approach 0**, since the normal distribution is itself perfectly symmetrical.
- **Kurtosis** is an indication of how "thick" the tails of your variable distribution are. **Kurtosis should approach 3**, since that number approximates the tails of a normal distribution.

Remember that the normal distribution is a **theoretical construct**: deviations to it are hence natural. You should, however, assess the extent of the deviation from normality, to know how theoretical assumptions apply to your work.

Example 9f. Normality of the Body Mass Index — Data: NHIS 2009

In the example below, continued from Example 9a, the skewness statistic of the BMI variable deviates from 0. Its positive sign indicates that the right-hand-side of the distribution is causing that deviation:

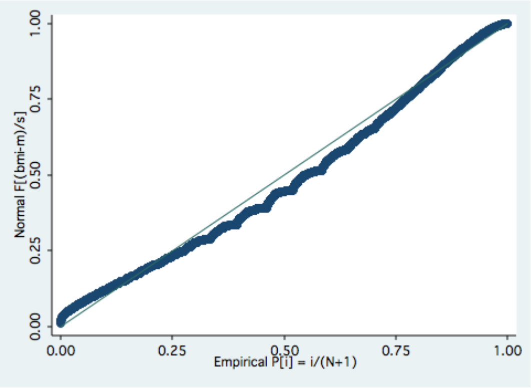
```
. su bmi, d

                        Body Mass Index
-------------------------------------------------------------
      Percentiles      Smallest
 1%     18.30729       15.20329
 5%     20.11707       15.20329
10%     21.26276       15.20329       Obs               24291
25%     23.51343        15.5041       Sum of Wgt.       24291

50%     26.57845                      Mean              27.27
                        Largest       Std. Dev.      5.134197
75%     30.22843       49.60056
90%     34.32617       50.38167       Variance       26.35998
95%     36.91451       50.48837       Skewness       .7207431
99%     41.59763       50.48837       Kurtosis       3.463278
```

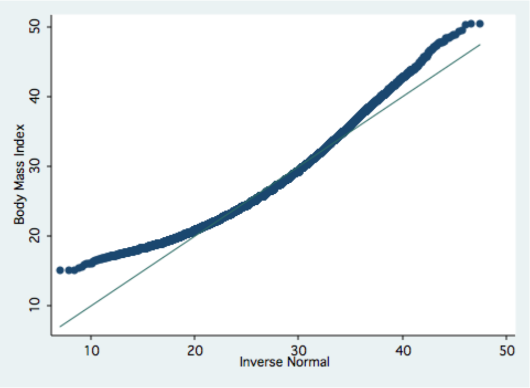
There are more complex ways to assess normality: some statistical tests apply, such as the Shapiro-Francia test with the **sfrancia** command if your data is made of less than 5,000 observations of ungrouped – 'unpaired' – data. These tests, however, are eventually less useful than graphic assessment with distributional diagnostic plots: the symmetry plot (**symplot**), which tests for symmetry, the normal quantile plot (**qnorm**) and the normal probability plot (**pnorm**) all work towards that end.

The last two plots are shown below: what they respectively show is that the BMI variable is deviating from the normal distribution both in its central values (as shown in the **pnorm** plot) and at its tails (as shown in the **qnorm** plot):

```
. pnorm bmi
```

```
. qnorm bmi
```





9.4. Transformations

The tools that are used to find possible transformations of a variable are:

- The ladders of powers (**gladder**) and ladder of quantiles (**qladder**), which provide visual guides to common variable transformations;
- The **ladder** command, from which the best transformation can be chosen by selecting the one with the lowest Chi-squared statistic in the table.

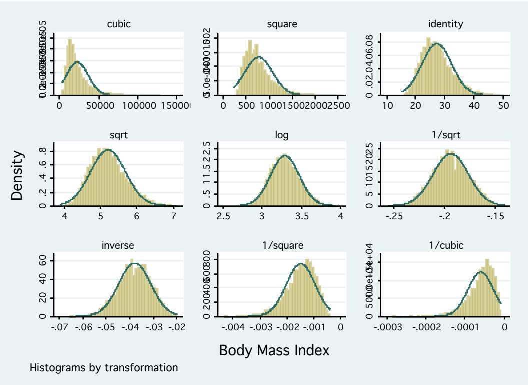
Some common transformations apply to macro-data: country population and GDP per capita are better expressed in logarithmic units. Others apply to micro-data: the distribution of age, for instance, is often better captured in squared units. Transformations are generally theoretically informed and will matter when interpreting your data.

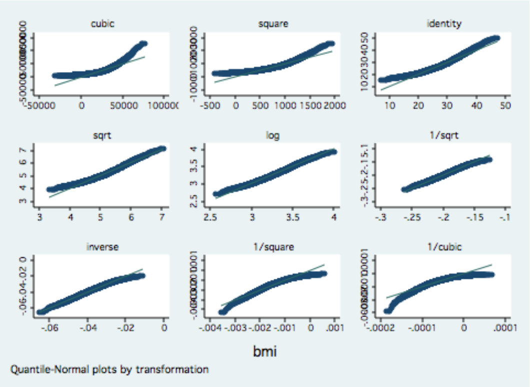
Example 9g. Transforming the Body Mass Index — Data: NHIS 2009

Running the commands above suggest that BMI approaches normality when measured on a logarithmic scale (middle graphs):

```
. gladder bmi
```

```
. qladder bmi
```





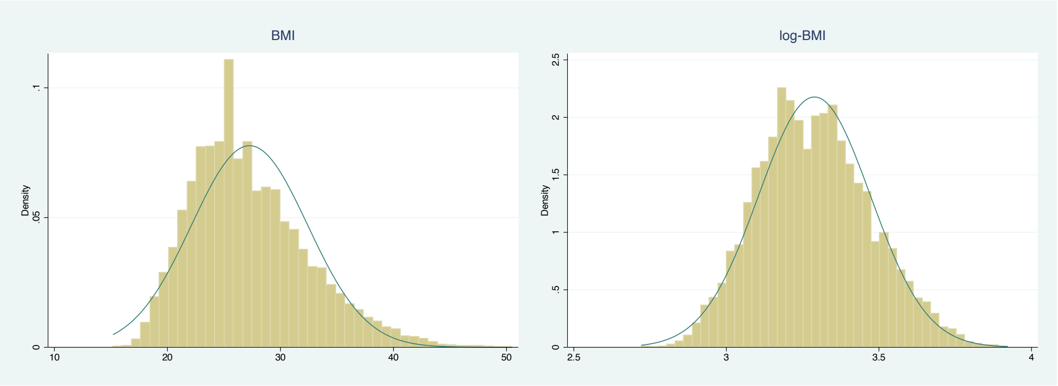
Performing a logarithmic transformation in Stata requires to use the **ln()** function to calculate the natural logarithm of the original BMI variable:

```
. gen logbmi = ln(bmi)

. la var logbmi "Body Mass Index (log-units)"
```

We can now check that the skewness and kurtosis of BMI are closer to 0 and 3 than they previously were, by displaying the histograms for both ‘raw’ and ‘transformed’ BMI side by side with the **graph combine** command:

```
. hist bmi, normal ///
>         title("BMI", margin(medium)) xtitle("") name(bmi, replace)
(bin=43, start=15.203287, width=.82058321)

. hist logbmi, normal ///
>         title("log(BMI)", margin(medium)) xtitle("") name(logbmi, replace)
(bin=43, start=2.7215116, width=.02791236)

. gr combine bmi logbmi, ysize(2)
```

A visual check is usually enough to observe whether a transformation effectively brings a variable closer to normality, as it does here:



We can finally check for skewness and kurtosis in both variables, in order to see how much more symmetrical the transformed variable is (skewness ≈ 0), and how its tails match the tails of the normal distribution (kurtosis ≈ 3):

```
. tabstat bmi logbmi, c(s) s(skew kurt)

    variable |  skewness  kurtosis
-------------+--------------------
         bmi |  .7207431  3.463278
      logbmi |  .2346392  2.762445
----------------------------------
```

In this example, both aspects of the distribution are now closer to normality: the rest of our analysis might hence use the transformed BMI variable. Note that the transformation only affects the unit of measurement for BMI: it does not imply modifying the actual data beyond that characteristic.

9.5. Outliers

Your data might contain outliers, such as a small number of people who earn salaries that are very, very far above the median income, or a small number of states with excessively small populations. **What to do with outliers is primarily a substantive question that depends on your research design**.

Conventionally, **mild outliers** are observations identified by a value located over 1.5 times the interquartile range (IQR) of the variable under examination, and **extreme outliers** by a value over 3 times the same measure. Refer to the course material for details on how box plots are constructed.

The examples below use box plots and the **extremes** package to detect outliers. More advanced techniques for detecting outliers, either before analysis – using graph matrixes – or during regression analysis – using leverage-versus-residual-squared plots – are beyond the scope of this course.

Example 9h. Inspecting outliers — Data: NHIS 2009

When we plotted Body Mass Index in the United States, the presence of a large number of outliers was graphically observable on the right-hand side of the box plot distribution (Example 9a).

We have no substantial reason to exclude outliers from this distribution, so we will just explore them with the **extremes** command and the **iqr(3)** and **N** options to list and count respondents who are extreme outliers to the BMI distribution (keep in mind that values of BMI over 40 will usually indicate morbid obesity):

```
. extremes bmi sex age raceb health, iqr(3) N
```

```
     +-----------------------------------------------------------------+
     |   obs:    iqr:        bmi      sex   age      raceb      health |
     |-----------------------------------------------------------------|
     | 22943.   3.001   50.38167   Female    30      Black        Good |
     | 17683.   3.017   50.48837   Female    28   Hispanic        Good |
     | 22511.   3.017   50.48837   Female    63   Hispanic   Very Good |
     |-----------------------------------------------------------------|
   N |                3          3        3     3          3           3 |
     +-----------------------------------------------------------------+
```

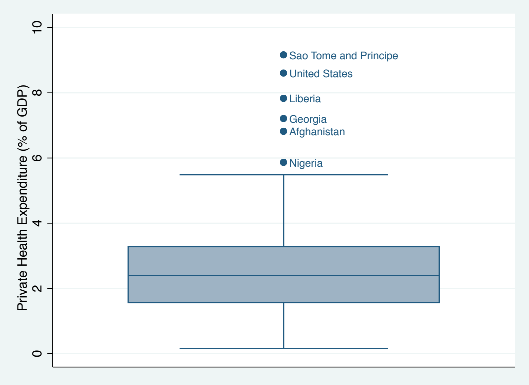
We previously found a transformation of BMI that brought the distribution close to normality, so excluding outliers would make little sense overall. Furthermore, removing mild (*n* = 421) or extreme (*n* = 3) outliers to the BMI distribution in a sample of *N* = 24,491 observations would not make a statistical difference.

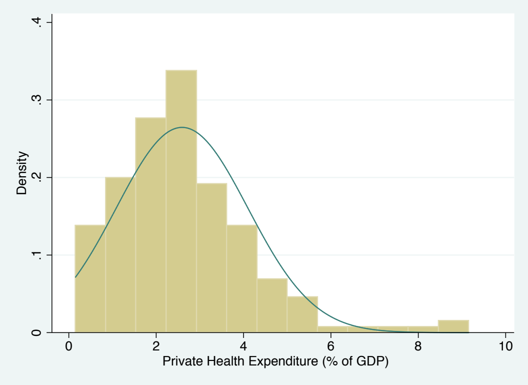
Example 9i. Keeping or removing outliers — Data: QOG 2011

Detecting outliers can serve a purely informative purpose, but you might also want to consider working on a subset of your data to exclude outliers from the analysis. In the example below, we study private health expenditure as a fraction of gross domestic product (variable: **wdi_prhe**). Options passed to the **graph hbox** command will identify the outliers:

```
. gr box wdi_prhe, mark(1, mlabel(cname))
```

The distribution of private health expenditure shows a small number of outliers. Further exploration of the histogram shows that the outliers are creating a clear deviation from normality on the right hand side of the distribution:





Depending on our research design, we might want to get rid of outlier countries spending more than, say, 5% of their GDP on private health expenditure. This would make statistical sense, as the distribution of the variable comes closer to normality when we apply that modification to the data:

```
. gen wdi_prhe2 = wdi_prhe if wdi_prhe < 5
(18 missing values generated)

. tabstat wdi_prhe wdi_prhe2, c(s) s(n mean skewness kurtosis)

    variable |         N      mean  skewness  kurtosis
-------------+----------------------------------------
    wdi_prhe |       188  2.592303  1.337639  5.993119
   wdi_prhe2 |       176   2.33017  .2326665  2.370385
```

The commands above created a **wdi_prhe2** variable by copying values of private health expenditure from the **wdi_prhe** variable when these were inferior to 5. The operation excluded a few countries, and the distribution of the new variable now better satisfies the normality criteria.

Statistically, it would make sense to stick with the **wdi_prhe2** variable for the rest of the analysis. However, excluding data points (observations) requires a substantive justification: we would thus have to document the exceptionality of health expenditure in the outlier countries prior to their exclusion.

10. Association

The section should be rewritten to merge the two first subsections and to treat t-tests and correlation in a closer way, as to reflect their parametric nature and how they help understanding regression afterwards. Moving correlation here makes sense since the subsection on controls can introduce multicollinearity with correlation and graph matrixes. Possible structure: (1) theory (2) crosstabs with all nonparametric tests (3) parametric: *t*-test (4) correlation (5) controls. A brief note about ANOVA could perhaps be made in the last section.

In this section, you will **test your variables for independence**, that is, you will assess whether you should reject or retain the null hypothesis that states an absence of association between two variables, such as income and education or population density and GDP.

These tests are useful to your analysis because they will suggest whether your independent variables are suited for inclusion in your regression model. The tests will also allow to identify some of the interactions that might exist between your independent variables.

At that stage, you should make sure that you understand the statistical terms that relate to probability distributions. Remember, for example, that you have to determine the 'alpha' level of significance that you will be using before looking at *p*-values and other elements of your tests.

You might also want to check that you understand the core logic of association. The key problem with understanding causal inference in observational (i.e. non-experimental) settings is **confounding**, and **crosstabulation** is a simple method to minimize confounding. We will later learn about simple and multiple linear regression modelling, other statistical methods developed with a similar purpose.

10.1. Tests

At that stage of your analysis, you will be running **independence tests**, which by definition contain two groups (and usually two different variables) to compare. Choosing which test to apply depends primarily on the type of your variables:

- When both variables are categorical, the test will operate on a table with a few rows and columns, called a **crosstabulation** or a **contingency table**.
- When the dependent variable is continuous and the independent variable is dichotomous, different tests will operate by comparing **differences in means** or **differences in proportions**.

- These tests do not cover all possible situations and form only a preliminary step to regression, which allows analysing two or more variables of any type. We also leave correlation aside for Section 11.

Bivariate tests introduce some important caveats of statistical tests:

- **Association is not causation:** finding that an association exists between two variables does not imply that the variables are causally related. Both variables can be – weakly, moderately or strongly – associated, but moving from association to causation requires a theoretical and substantive understanding of the variables that no statistical test can provide on its own. The same is true of correlation, which we will restate in Section 11.1 before writing our linear regression models.

  For example, an association between the level of income and the level of education of individuals does not provide any information on the causal links that relate income to education: we need a theory of how, for instance, the income of a household influences the educational attainment of its children, and how, in turn, the level of education of these children will determine their income when they start to work. The statistically significant association of education and income itself contains, in itself, none of these explanatory, theoretical elements. The same would be true of an association between music tastes and political ideology: the direction of the causal link between those characteristics is not situated in the association itself, but in the theoretical understanding of their interplay. Jumping from association to causation with no explanatory theory would be premature. It is also sadly common.

  A more complex example is religion and life expectancy. An association between these variables might seem to indicate a 'direct' link at the individual level, where religion affects life expectancy positively or negatively; the same association, however, might also indicate a more 'indirect' link at the collective level, where religion correlates, for instance, with socioeconomic groups of individuals who enjoy higher or lower life expectancy for reasons (like income) other than religious beliefs. In this case, jumping from association to causation would have erroneously advanced a micro-level interpretation to explain a macro-level phenomenon. The mistake of considering individual-level characteristics as explanatory of group-level ones is called the 'ecological fallacy' and is also relatively common.

- **Statistical significance is not substantive significance:** finding a statistically significant association between two variables does not imply that there exists a substantively significant association between them. Some associations can be statistically significant but devoid of any substantive significance, and conversely.

  For example, if a statistical test shows that countries where people drive on the right-hand side have higher fertility rates, it seems safe to state that this statistically significant association corresponds to no substantive phenomenon occurring in the real world. Conversely, the substantively significant association that exists between former colonial occupation by European countries and the side on which people drive might not yield a statistically significant association, for several reasons such as small sample size, coding errors or unobserved changes in traffic policy.

Identically, statistical significance does not provide an order of magnitude to the substantive significance of the association. The statistical strength of an association relies on data and sample size, and does not indicate that the association is theoretically more important. A study could find a weak association (p < .1) between dictatorship and civil war, and also find a strong association (p < .001) between oil resources and civil war, and still conclude that dictatorship is a more important explanatory factor of civil war than the presence of oil. The significance levels of data analysis are frequently confused with theoretical results, which is why it is crucial to remember that statistical significance only stands for a conventional indication of significance, usually based on the p < .05 level. Any further interpretation of significance will have to be theoretically, not statistically, driven.

Example 10a. Trust in the European Parliament

The following examples measure the average trust in the European Parliament. We use the measures available for the populations of three peripheral European countries, Portugal, Ireland and Greece, which became infamously known as the 'PIG' countries during the current financial crisis (study: **ESS**, variable: **trstep**).

We start by subsetting the data to these countries:

```
. keep if inlist(cntry,"GR","PT","IE")
(44939 observations deleted)
```

Within these countries, we will look at average trust in the European Parliament of citizens and non-citizens, using the same **ctzcntr** binary variable for citizenship that we used in Example 9e. The **ctzcntr** variable needs to be binary if we are to run a *t*-test on its two groups (citizens and foreigners).

The command to run a separate *t*-test for each country runs as follows:

```
. bysort cntry: ttest trstep, by(ctzcntr)
```

The results of the first *t*-test (a test that we explain further in Section 10.4) show that, in Greece, citizens are less inclined to trust the European Parliament than non-citizens. The test compared the average trust score of both groups, which was measured on an ordinal scale of 0 (no trust) to 10 (complete trust), and found out that the **diff**erence is negative: the "Yes" group of citizens shows less trust in the European Parliament (4.3) than the "No" group of foreigners (5.8):

```
-> cntry = GR

Two-sample t test with equal variances
------------------------------------------------------------------------------
   Group |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
     Yes |    1929    4.341109    .0570617     2.50617      4.2292    4.453018
      No |      72    5.888889    .3055022    2.592272    5.279735    6.498043
---------+--------------------------------------------------------------------
combined |    2001    4.396802    .0564503    2.525167    4.286094    4.507509
---------+--------------------------------------------------------------------
    diff |            -1.54778    .3011897               -2.138458    -.957101
------------------------------------------------------------------------------
    diff = mean(Yes) - mean(No)                                   t =  -5.1389
Ho: diff = 0                                     degrees of freedom =     1999

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.0000         Pr(|T| > |t|) = 0.0000          Pr(T > t) = 1.0000
```

The latter group includes only a few observations (*n* = 72), and the standard error for their average trust in the European Parliament is therefore higher (.30) than it is for Greek citizens (.05). The standard deviations further indicate that the groups have a relatively similar underlying distribution of trust scores. Still, the confidence intervals do not overlap, and the *t*-test concludes that the –1.54 points difference in average trust scores is statistically significant with only a very, very small risk of error, denoted by the probability level of the alternative to the null hypothesis being close to, but not equal to, "0.0000" (middle value).

The 'lateral' probabilities confirm the direction of the relationship: the **diff**erence in scores between average trust among citizens, **mean(Yes)**, and average trust among foreigners, **mean(No)**, is highly likely to be negative and highly unlikely to be positive, indicating higher trust among the latter group. To observe this difference and reach that conclusion, two conditions are met: average trust is effectively different in both groups, and the sample size of each group is large enough to establish that the difference is statistically significant.

Depending on the actual difference and on the number of observations available in each group, the *t*-test might have a harder time at identifying any statistically significant difference, as shown in the results for Ireland:

```
-> cntry = IE

Two-sample t test with equal variances
------------------------------------------------------------------------------
   Group |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
     Yes |    1486    4.635262    .0589952    2.274187     4.51954    4.750985
      No |     184    5.195652    .1675218    2.272377     4.86513    5.526175
---------+--------------------------------------------------------------------
combined |    1670    4.697006    .0557944    2.280073    4.587572     4.80644
---------+--------------------------------------------------------------------
    diff |           -.5603897    .1777167               -.908961   -.2118185
------------------------------------------------------------------------------
    diff = mean(Yes) - mean(No)                                   t =  -3.1533
Ho: diff = 0                                     degrees of freedom =     1668

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.0008         Pr(|T| > |t|) = 0.0016          Pr(T > t) = 0.9992
```

In these results, the difference in trust is still negative, confirming that foreigners are more trustful of the European Parliament than citizens in Ireland too; the gap in average trust is smaller than it is in Greece, but the confidence intervals still do not overlap, and the higher number of observations for foreigners allow the test to work with a lower standard error for that group. The other results of the t-test are quite similar, including the still very, very low probability levels.

Portugal offers a different picture. The gap in average trust is smaller, and the number of foreigners in the sample data is very low. As a consequence of both factors, the confidence intervals overlap and no statistically significant difference comes out of the test:

```
-> cntry = PT

Two-sample t test with equal variances
------------------------------------------------------------------------------
   Group |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
     Yes |    1897    4.355825    .0554851    2.416629    4.247007    4.464643
      No |      47    4.659574    .3777784    2.589919    3.899146    5.420003
---------+--------------------------------------------------------------------
combined |    1944    4.363169    .0549027    2.420704    4.255494    4.470843
---------+--------------------------------------------------------------------
    diff |           -.3037495    .3574689              -1.004813    .3973136
------------------------------------------------------------------------------
    diff = mean(Yes) - mean(No)                                   t =  -0.8497
Ho: diff = 0                                     degrees of freedom =     1942

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.1978         Pr(|T| > |t|) = 0.3956          Pr(T > t) = 0.8022
```

Example 10b. Female leaders and political regimes

Consider the following example, where we test the average level of democracy (on a 0–10 scale) between two groups of countries, governed respectively by male and female leaders (study: **QOG**; variables: **p_democ** and **m_femlead**).

The command and its results follow:

```
. ttest p_democ, by(m_femlead)

Two-sample t test with equal variances
------------------------------------------------------------------------------
   Group |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
 0. Male |     149    5.228188    .3218452    3.928621    4.592182    5.864193
1. Femal |       8       8.125    .5153882    1.457738    6.906301    9.343699
---------+--------------------------------------------------------------------
combined |     157    5.375796    .3106018    3.891829    4.762268    5.989324
---------+--------------------------------------------------------------------
    diff |           -2.896812     1.39774               -5.657889   -.1357348
------------------------------------------------------------------------------
    diff = mean(0. Male) - mean(1. Femal)                         t =  -2.0725
Ho: diff = 0                                     degrees of freedom =      155

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.0199         Pr(|T| > |t|) = 0.0399          Pr(T > t) = 0.9801
```

The results of the *t*-test seem to indicate that countries run by female leaders are significantly likely to be more democratic at the 95% confidence level (p < .05). What shall we conclude from this test? In a nutshell, nothing:

- The dataset includes only 8 countries with female leaders, which leads to high standard errors, wide confidence intervals, and makes the statistical significance of the test misguiding. Maximising **sample size** would be a prerequisite to any further tests using this variable.

- Furthermore, there is no **theoretical support** for drawing any form of conclusion from these tests: for instance, female leaders like German Chancellor Angela Merkel or Brazilian President Dilma Rousseff have not made these countries dramatically more or less democratic, and while democratic elections might have made their rise to power possible, so many other factors than regime type are at play in selecting female heads of state that the test in itself is devoid of analytical substance.

- Identically, the **statistical significance** of the test cannot be taken as proof that autocracies are equally likely to be ruled by male or female leaders: even a cursory account of 20th century history will show that autocracies are very unlikely to be led by female rulers, who are almost systematically excluded from the social groups that provide autocrats, such as high levels of military hierarchies. The absence of female autocrats in recent history (one has to go back to 18th century Russia to find a genuine female autocracy) makes the test even more absurd.

- Finally, the democracy and autocracy indexes, despite the fact that they originally come from the canonical Polity IV dataset, are criticisable (more precisely, the intermediate levels of democracy and autocracy that they provide are highly problematic). Additional flaws in the data, such as **measurement error**, are thus likely to affect independence tests, which makes the jump from association to causation a rather arbitrary one.

The few remarks above make an important point: if you cannot substantively justify your test to match its statistical significance results, you will eventually fall short of saying anything relevant about the independence of its groups. This situation, and many others, fall under what is sometimes jokingly referred to as a **"Type III" error**, which consists in giving the right (statistical) answer to the wrong (substantive) question. The conventional "Type I" and "Type II" errors are addressed below.

10.2. Independence

Statistical tests provide **proof by contradiction**. Their logic consists in assuming that we are *wrong* to assume any association between our variables, and that the two variables are in fact unrelated—free of any association. This assumption is referred to as the **null hypothesis**, noted "H_0". It would be absurd to think, for example, that voters or political leaders who drink herbal tea are more likely to support racist ideologies: herbal tea consumption and racism are (hopefully) independent from each other.

Consider a less absurd example: does religion have an effect on political support for democracy? Hypothetically speaking, holding religious beliefs might affect political views by increasing individual self-confidence and providing beliefs that either support or reject democratic rule. The hypothesis might verify any side of the relationship: at that stage, there is no support for a particular direction. Furthermore, holding religious beliefs is not just an individual factor: when large groups of individuals hold religious beliefs, other factors will come into play, such as group persecution or collective dominance, which might also affect how each individual then views democracy. When working with so many known unknowns, the only safe line of reasoning actually consists in suspending all our former beliefs and… stay agnostic. The null hypothesis thus states that religion and democratic support have no relationship whatsoever. More substantially, what the null hypothesis means is that virtually 100% of democratic support can be explained by factors other than religion, such as socioeconomic factors and other contextual elements like the ones cited above.

Example 10c. Religiosity and military spending

Is the average level of religiosity in the population associated to the percentage of gross domestic product spent on military expenditure? Before jumping to any conclusion, consider the following:

- You *might* have good reasons to think that there is a positive association, if the question reminds you of how particularly bellicose countries invoke religious motives to justify, for example, some forms of 'holy war'—but you already realise, at that point, that 'holy wars' can explain only a tiny fraction of military spending by states worldwide.
- You *might* also have good reasons to think that most practices of religion actually preach non-aggressiveness, and would therefore drive states to bring military expenditure down in absence of popular support for it. At that stage, you

also realise that military expenditure is not necessarily subject to public opinion pressures, and that even if it is, other factors are likely to come at play, with possibly greater explanatory power.

- Finally, you will probably conclude that military expenditure and religion should *not* be assumed to be associated by default: the most reasonable approach, and the statistically correct one, is to adopt an agnostic stance by stating the null hypothesis, which basically means that "we cannot know from the start, and that there might just be an association, but only by rejecting the absence of any relationship can we establish that."
- Just for the kicks, you can open the **QOG** data and try to find a statistically significant association between the **wvs_rel** variable (an average measure of "how important God is" to the population) and the **wdi_megdp** variable (national military expenditure as a % of GDP). It will quickly appear that any categorisation of either variable is going to distort the data to the point where finding an association will primarily rely on your own manipulations.

You should **mentally start any bivariate test with a null hypothesis**: even when you are testing a plausible association, such as between education and racism, you should consider the null hypothesis: these variables are independent from each other, no association exists between education and racism, virtually 100% of racism can be explained by factors other than education (and vice versa).

Your test then proceeds by **trying to reject the null hypothesis**. More precisely, it will provide a probability for the null hypothesis to be verified. That probability is expressed as the ***p*-value**, which varies between 0 to 1. In order to reject the null hypothesis, you will read the *p*-value: a *p*-value close to 0 indicates that the likelihood for the null hypothesis to be verified is weak, whereas a *p*-value close to 1 indicates that there is high likelihood for the null hypothesis to be correct.

Consequently, a bivariate test that reveals a statistically significant association will come with a low *p*-value. The level below which you can reject the null hypothesis is called the **(alpha) level of significance**. By convention, $\alpha = 0.05$ in most circumstances, for no other reason than the practical convenience of that decision rule. If $p < 0.05$, assuming an association between your two variables comes with less than a 5% risk of assuming an association where there is actually none—a situation called a **"Type I" error**, where you reject the null hypothesis even though it is actually true. The reverse situation, where you retain the null hypothesis while it is actually false, is called a **"Type II" error**, and is frequent in small samples on which statistical tests produce less reliable results.

Note that this explanation confuses significance testing with hypothesis testing, which is theoretically inaccurate, but acceptable for our purpose here. If you find a statistical textbook that correctly reports the difference between Fisher's *p* and Neyman-Pearson's α, then you are reading quite advanced textbooks. The small confusion made here is technically mistaken in statistical reasoning, but it should reveal as problematic as other confusions addressed elsewhere in this guide.

Based on what has just been outlined, you should try to **minimize "Type I" and "Type II" errors** in your tests. If you need to establish higher certainty about an association, as is often the case in studies involving chemicals because the consequences of a "Type I" error might carry dramatic consequences for the people exposed to them, you will use $\alpha = 0.01$ and reject the null hypothesis only if $p < 0.01$, or even a lower threshold such as $p < 0.001$ or $p < 0.0001$. In parallel, if you fear missing an association by retaining the null hypothesis when you should have rejected it, thereby making a "Type II" error, then you should maximize sample size and reduce the number of missing observations, in order to maximize the number of observations for each variable of interest.

Example 10d. Religion and interest in politics

The Chi-squared tests below test for a relationship between having an interest in politics and belonging to a religion (data: **ESS**, variables: **polintr** and **rlgblg**). The tests are respectively applied to French and Russian respondents:

```
. keep if inlist(cntry,"FR","RU")
(46557 observations deleted)
```

```
. bysort cntry: tab polintr rlgblg, chi2
```

As running the tests and reading the results will show, the association of both variables is statistically significant in France (p < .05), but not in Russia (p > .05). We should hence reject the null hypothesis for French respondents, and consider that a relationship exists in this country between the two factors. In the case of Russia, however, we cannot reject the null hypothesis and retain it. There is a small probability that we are wrong in both cases: in the French case, rejecting the null hypothesis while it is actually true would lead to a "Type I" error, and in the Russian case, retaining the null hypothesis while it should have been rejected would lead to a "Type II" error.

Statistical tests such as the Chi-squared test operationalize the **probabilistic** logic described above. Take, for example, the results of the above Chi-squared test for French respondents, showing column percentages instead of frequencies:

```
. tab polintr rlgblg if cntry=="FR", col nofreq chi2
```

```
                      |    Belonging to
                      | particular religion
 How interested in    |   or denomination
          politics    |       Yes         No |     Total
----------------------+----------------------+----------
   Very interested    |     13.57      17.62 |     15.66
  Quite interested    |     38.72      33.55 |     36.06
 Hardly interested    |     35.33      33.65 |     34.46
Not at all interested |     12.38      15.17 |     13.81
----------------------+----------------------+----------
             Total    |    100.00     100.00 |    100.00

          Pearson chi2(3) =  12.5681   Pr = 0.006
```

The null hypothesis states that interest in politics is independent from religion. In that case, there should be as many "very interested" respondents among French religious believers and non-believers, but this is not the case: very high interest in politics (15.06% of all observations) is over-represented among non-believers and under-represented among believers.

Using the frequencies of each variable, the hypothetical frequencies of their crosstabulation in absence of any relationship between them can be calculated; these **expected** values are then computed against the **observed** frequencies to calculate the Chi-squared statistic. This statistic is then combined to the **degrees of freedom**, which corresponds to the number of cells in your crosstabulation of ethnicity and party preference, minus one row and one column.

Your handbook details both computations, and will also give you a table which crosses the Chi-squared statistic with its degrees of freedom to obtain the *p*-value of the association between both variables. The underlying logic of the Chi-squared test (which is also called the 'goodness of fit' test) is essential to your understanding of how hypothesis-testing works: make sure that you are familiar with it before moving on to further techniques.

This short example yields a Chi-squared of 12.5 against 3 degrees of freedom, with a corresponding *p*-value of "0.006" that really means "below 0.006". The small p-value allows us to reject the null hypothesis with great certitude, as there is less than a 0.6% risk that we are making a "Type I" error. We can therefore reject the null hypothesis and confirm our **alternative hypothesis**, which states that interest in politics and religion are not independent but significantly associated in the French sample of respondents.

At that stage, however, we still lack a plausible theory to explain that association substantively. Even if we find an explanation, reading the whole crosstabulation will show that the relationship seems more complicated than expected: religion does not increase or decrease interest in politics uniformly across all groups. We will also want to make sure that the effect of religion on interest in politics is not cancelled by, for example, the average age of respondents in each group. The Chi-squared test leaves these questions unanswered: more sophisticated tests will (start to) address them in Section 11.

10.3. Crosstabulations

Most bivariate tests combine **two categorical variables**, such as income groups, levels of education, geographical regions or regime types. Crosstabulations of such variables are especially frequent with survey data, where the answers given by the respondents are coded as nominal variables, such as religion, or as ordinal variables on 'short' scales, such as agreement scales that usually range over 3 to 12 items, from "Strongly agree" to "Strongly disagree".

These tests combine variables in a "r x c" (rows by columns) **contingency table**. The intersection of each row with each column forms a **cell** that contains the number of observations (called a **cell count**) for that intersection. Tables can be made easier to read with row and/or column percentages, but the type of test to use ultimately relies on cell counts, as shown in the examples below.

Example 10e. Legal systems and judicial independence

An ever larger number of countries is running elections, but fraud or candidate intimidation was reported in at least a fifth of the cases reported between 2001 and 2008 (study: **QOG**, variable: **dpi_fraud**). Among the countries affected by electoral fraud, some are also former colonies of Western imperial powers:

```
. tab fcol dpi_fraud, exact

           |   Fraud or Candidate
           |      Intimidation
    Former |       Affection
    colony |         0          1 |     Total
-----------+----------------------+----------
         0 |        76         23 |        99 
         1 |        53         11 |        64 
-----------+----------------------+----------
     Total |       129         34 |       163 

           Fisher's exact =                 0.431
   1-sided Fisher's exact =                 0.234
```

The results above show **Fisher's exact test**, which is superior to the Chi-squared test on '2 x 2' contingency tables like the one above. The test produces a unique statistic that can be read as a *p*-value for the likelihood of an accidental association to exist between the variables. Here, the risk of a coincidental association between former colony status and electoral fraud is far from meeting any reasonable level of significance. We can retain the null hypothesis and look for other explanatory factors of electoral fraud.

The Chi-squared test is also inferior to Fisher's exact test when some cells in the cross-tabulation hold less than five observations. When that '5+' convention is violated, Fisher's exact test is recommended over the Chi-squared test.

There are many more tests available to test for association in categorical data. **Cramér's V**, for instance, is a test that complements the Chi-squared test by providing a measure of strength for the association. More **nonparametric tests** were also designed to test for particular associations:

- **When both variables are ordinal**, Spearman's rho is a ranked correlation coefficient that better captures association than the tests mentioned above. An equivalent test, Kendall's tau, uses a different computational logic (closer to the Gamma test) to achieve similar results.
- **When both variables are interval/ratio** (more simply: continuous), Pearson's *r* provides a correlation coefficient that we will explore in Section 11, where we cover correlation and regression as stronger analytical tools that go beyond testing for independence.

10.4. Comparisons of means

A common approach to some quantitative indicators will involve measuring a continuous variable in two discrete groups, such as males and females. When a difference appears between these groups, it is often measured as a difference in means. This setting is common in experiments, such as when we measure the average literacy of a group of children who were given free schoolbooks against the average literacy of another group of children whose parents had to pay for the same schoolbooks.

The comparison of means works by running a ***t*-test**, which computes the mean of a continuous variable over two groups provided by a categorical or binary (dummy) variable. The test compares the means by estimating whether their difference is statistically significant. This method also appears in other tests, especially when the two groups can be paired, as in the case of control and treatment groups. When conditions are met for running an analysis of variance (ANOVA), as is common in psychological and clinical studies, comparing means of a continuous variable (such as blood pressure) across two groups of patients (e.g. those who received some medication and others who received a placebo) is a standard technique to establish the causal effect of a given treatment.

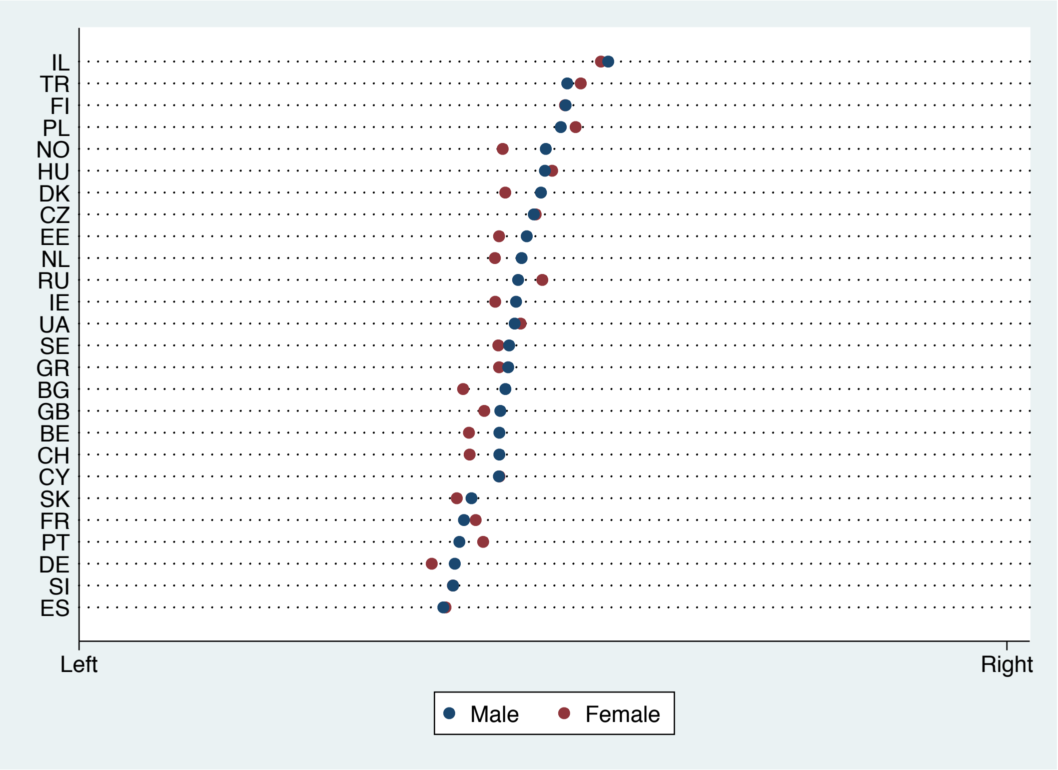
Note: if your continuous variable is in fact coding for a binary outcome such as the result of a medical procedure that succeeds (1) or fails (0) to cure a patient, then the distributional assumption of normality on which the *t*-test relies will be violated. In that case, you should use the **prtest** with exactly the same syntax as the **ttest** command, as in **prtest cure, over(gender)**. In the social sciences, this is relevant to dummy variables coding for dichotomous outcomes such as the fact of being divorced (1) or not (0).

Example 10g. Gender and left-right political positioning

Political parties rely on different electoral clienteles and sometimes assume that positioning on the left–right spectrum significantly differs for men and women. A simple test thus consists in measuring the mean left–right positioning of men and women for several countries. We will start by looking at aggregate scores of left–right positioning at the country level (data: **ESS**, variables: **lrscale** and **gndr**):

```
. gr dot lrscale, over(gndr) asyvars over(cntry, sort(1) des) ///
>        exclude0 ylab(1 "Left" 10 "Right") ytit("") scale(.85)
```

The graph, which was slightly scaled down with the **scale** option for cosmetic reasons, ranks countries by the left–right score of males. It shows no consistent pattern for the average scores of males and females at the macro level:



The *t*-test then indicates an interesting result, which deserves some attention. In the results below, the *t*-test is indeed statistically significant, but substantively insignificant. We will read through each part of the test to reach that conclusion:

```
. ttest lrscale, by(gndr)

Two-sample t test with equal variances
------------------------------------------------------------------------------
   Group |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
    Male |   20620    5.211397    .0158609    2.277571    5.180308    5.242485
  Female |   22682    5.119566    .0146951    2.213164    5.090763     5.14837
---------+--------------------------------------------------------------------
combined |   43302    5.163295    .0107862    2.244507    5.142154    5.184436
---------+--------------------------------------------------------------------
    diff |            .0918305    .0215926                .0495087    .1341524
------------------------------------------------------------------------------
    diff = mean(Male) - mean(Female)                              t =   4.2529
Ho: diff = 0                                     degrees of freedom =    43300

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 1.0000         Pr(|T| > |t|) = 0.0000          Pr(T > t) = 0.0000
```

The interpretation of the t-test goes as follows:

- WRITE.

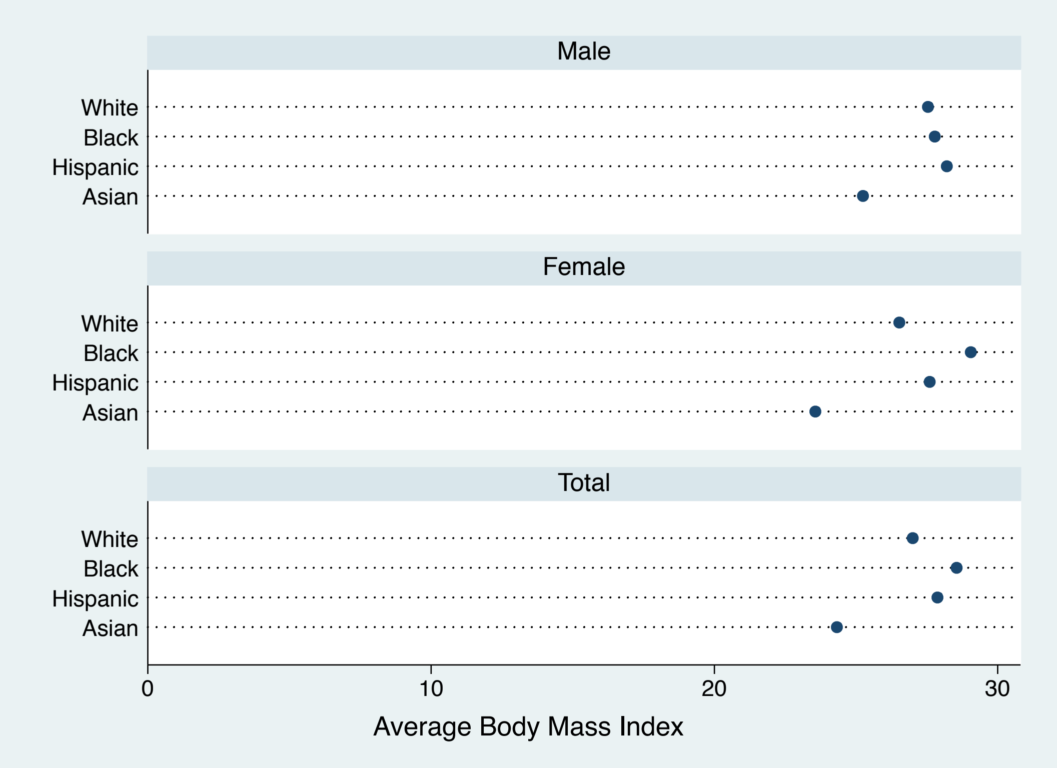
- From the theoretical part of the course, you should remember at that point that the *p*-value for the alternative hypothesis is derived from the *t*-statistic, and that the sum for both directional hypotheses **diff < 0** and **diff > 0** will always be 1).

Example 10h. Obesity and racial-ethnic profiles

We continue to explore the Body Mass Index of U.S. respondents (study: **NHIS**, variable: **sex**, **raceb** and **bmi**, as previously calculated in Example 9a), by looking at the breakdown of BMI by gender groups and four main racial-ethnic profiles. We start by plotting the average BMI for four ethnic groups (variable **raceb**). Graphically, we want three separate dot plots showing the average BMI for each racial-ethnic profile among males and females separately and for both sexes:

```
. graph dot bmi, over(raceb) ///
>         by(sex, rows(3) total note("")) ytit("Average Body Mass Index")
```

In this presentation, the three graphs are horizontally aligned by using the **rows** option to fit them into a single column of three rows. The plot for both gender groups is further generated by the **total** option. Through visual inspection of the variables of interest, we can establish whether gender and race might account for some variation in the Body Mass Index of U.S. respondents:



The sum of observations that could be derived from this graph cannot be brought together into a single bivariate test; instead, multiple linear regression will be used to describe the joint effects of gender and race on BMI (Section 11). A single comparison can focus, however, on the markedly lower BMI of Asian respondents in reference to all other racial-ethnic profiles.

The *t*-test will not accept more than two values for the independent categorical variable, so we had to create a dichotomous (or binary) variable, coding "1" for "Asian" and "0" for any other racial-ethnic profile. As we do so, we must be careful to prevent missing data from being coded as "0", as it would distort the data if some respondents did not report their racial-ethnic profile.

We do not need to use **recode** to generate a full-fledged variable with proper labels at that stage: a dummy that we will create on the fly is enough. A single line of code generates that dummy through the logical statement **(raceb==4)**, which returns 0 when false and 1 when true. Where the **raceb** variable indicates the value for "Asian" **(raceb==4)**, it will code 1 and 0 otherwise.

Using this statement, we create the dummy variable **asian** for all non-missing observations of **raceb,** using the additional logical statement **if !mi(raceb)** to that effect, and then finally check our operation with the **su** command, for which the mean indicates the percentage of Asians in the sample:

```
. gen asian=(raceb==4) if !mi(raceb)

. su asian

    Variable |        Obs        Mean    Std. Dev.       Min        Max
-------------+---------------------------------------------------------
       asian |      24291    .0564407    .2307754          0          1
```

We then run a *t*-test for BMI between Asians and non-Asians:

```
. ttest bmi, by(asian)

Two-sample t test with equal variances
------------------------------------------------------------------------------
   Group |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
       0 |   22920    27.44618    .0340063     5.14833    27.37953    27.51284
       1 |    1371    24.32456    .1037125    3.840163    24.12111    24.52801
---------+--------------------------------------------------------------------
combined |   24291       27.27     .032942    5.134197    27.20543    27.33457
---------+--------------------------------------------------------------------
    diff |            3.121622    .1413385                 2.84459    3.398654
------------------------------------------------------------------------------
    diff = mean(0) - mean(1)                                      t =  22.0861
Ho: diff = 0                                     degrees of freedom =    24289

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 1.0000         Pr(|T| > |t|) = 0.0000          Pr(T > t) = 0.0000
```

The interpretation of the *t*-test goes as follows:

- Out of N = 24,291 respondents for which we could calculate a Body Mass Index, the average BMI approaches 27.4 for n = 22,920 non-Asian respondents and 24.3 for n = 1,371 Asian respondents. The standard error is larger for Asians, since we have less observations for that group.

The difference in means shows that the BMI of Asians is inferior by roughly 3 points to the BMI of non-Asians in the United States. Furthermore, the standard deviation of BMI within the Asian group is smaller than for the rest of the sample, indicating that the distribution of BMI among Asian respondents around its mean is more compact.

Pause at that stage and interpret substantively the difference. Body Mass Index follows an international standard, where a BMI of 25 indicates overweight. Therefore, the sample average respondent is overweight by our results. However, this does not to Asian respondents, who are slightly below, but not that much below, that conventional threshold.

- The null hypothesis (**Ho**) predicts that the difference in means between Asian and non-Asian respondents is null (**Ho: diff = 0**). If the difference is non-null, the null hypothesis further estimates the probability for that difference to be due to sampling error (although it naturally cannot correct for measurement error).

  The null hypothesis hence tests the following statement: "If the Body Mass Index is strictly independent from race, then any difference in means between Asians and non-Asians is accidental." Rejecting the null hypothesis amounts to rejecting that statistical statement, which concerns statistical significance; additional observations about the causes and reasons of that difference will require a substantive theory, such as a difference in physiological and nutritional determinants among Asian respondents.

  The *t*-test actually shows a difference, noted **diff = mean(0) – mean(1)**, that appears to be statistically robust, therefore contradicting the null hypothesis. In this example, on average, the Body Mass Index of Asians (the group for which the **by** variable, **asian**, takes the value **1**) is lower to the BMI of non-Asians (group **0**) by approximately 3 points (**diff** = 3.12, 95% CI = 2.84–3.39).

- The alternative hypothesis (**Ha**) predicts that there is a meaningful association between race and Body Mass Index, which should cause the average BMI of Asians to differ substantively from the average BMI of non-Asians. This hypothesis implies that the difference in average BMI between both racial-ethnic profiles should be significantly different from zero (**Ha: diff != 0**).

  The *p*-values for the *t*-test (**Pr**) indicate that we can reject the null hypothesis **Ho** because the *p*-value for **(Ha: diff !=0)** is inferior to our level of significance, $\alpha = 0.05$. At that stage, we gain empirical confirmation of what we previously observed graphically. More precisely, the test shows that subtracting the mean BMI of Asians to the mean BMI of non-Asians is very likely to give a positive result: the probability level for **Ha: diff >0**, is highly significant ($p < .01$).

Interpreting a *t*-test requires reading all the information used in this example, but reporting a t-test is usually much quicker. Comparing means between groups that fit with reasonable theoretical expectations generally just requires reporting the existence of a significant difference. Other results are less important, given that we will obtain more precise estimates of the difference by including racial-ethnic profiles with other variables into our regression model.

Example 10i. Political regime and female legislators

The *t*-test can quickly run into issues of statistical significance if it is run on a low number of observations. The following example tests the hypothesis according to which federal regimes lead to higher representation of women in parliaments. The hypothesis could be tested only a small group of countries for which the data were available (data: **QOG**, variables **m_wominpar** and **pt_federal**):

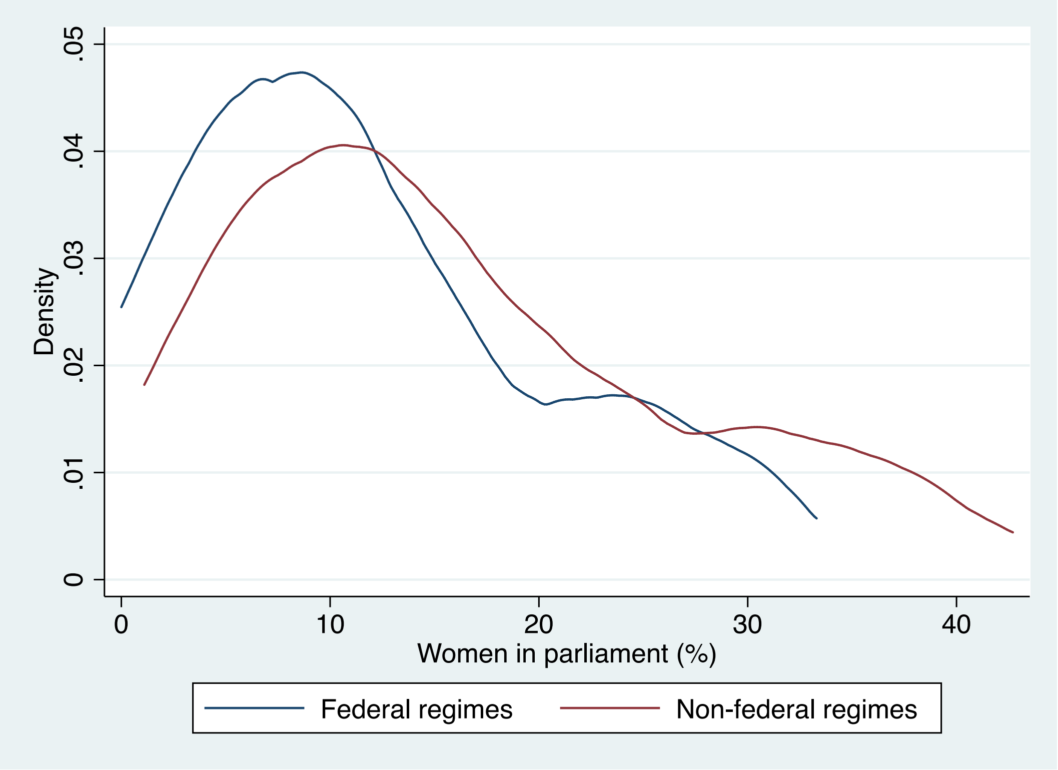
```
. ttest m_wominpar, by(pt_federal)

Two-sample t test with equal variances
------------------------------------------------------------------------------
   Group |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
0. No fe |      68    16.06029    1.284192    10.58972    13.49704    18.62355
1. Feder |      13    18.42308    2.879484    10.38213    12.14922    24.69693
---------+--------------------------------------------------------------------
combined |      81    16.43951    1.169831    10.52848    14.11147    18.76754
---------+--------------------------------------------------------------------
    diff |           -2.362783    3.196071               -8.724404    3.998838
------------------------------------------------------------------------------
    diff = mean(0. No fe) - mean(1. Feder)                        t =  -0.7393
Ho: diff = 0                                     degrees of freedom =       79

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.2310         Pr(|T| > |t|) = 0.4619          Pr(T > t) = 0.7690
```

A first issue here has to do with the large standard errors caused by the low number of observations, but we have no other choice of data. A second issue then has to do with the large standard deviations, which indicate that the mean does not capture well the distribution of women in parliament. Finally, an issue here could be that both variables were measured at different points in time, but we expect regime type to be stable.

The last issue is serious, as shown by two kernel density plots that show the distribution of the **m_wominpar** variable for each regime type. The code for the graph is pretty esoteric, as it involves combining two graphs with the cryptic **tw** ("two-way") operator, using additional operators **() || ()** to separate them:

```
. tw (kdensity m_wominpar if pt_federal) || ///
>         (kdensity m_wominpar if !pt_federal), ytit("Density") ///
>         xtit("Women in parliament (%)") ///
>         legend(lab(1 "Federal regimes") lab(2 "Non-federal regimes"))
```

Against our initial insight, the resulting graph indicates that non-federal regimes actually reach into higher values of women in parliament, whereas the rest of the distribution is pretty similar for each regime type:



The interpretation of the t-test goes as follows:

- In the *N* = 81 countries for which we have data for the year 2008, women occupy an average of 18% of parliamentary seats in federal regimes, and an average of 16% in non-federal regimes. The difference in means hence shows that the percentage of women in parliaments is inferior by roughly 2 percentage points in non-federal regimes.
- The null hypothesis (**Ho**) predicts that the observed difference is caused by sampling error, and is therefore accidental (or coincidental) rather than significant (**Ho: diff = 0**). The alternative hypothesis (**Ha**) states that the difference reflects a significant association, and that the difference in the average number of women in parliament is not null (**Ha: diff != 0**) but rather corresponds to a substantive difference between both regimes.
- The last lines of p-values (**Pr**) indicate that we cannot reject the null hypothesis, as the p-value for **Ha: diff !=0** is highly superior to any reasonable level of significance. We should conclude that, for the countries under examination, federal rule has no significant incidence on the representation of women in parliaments.

10.5. Controls

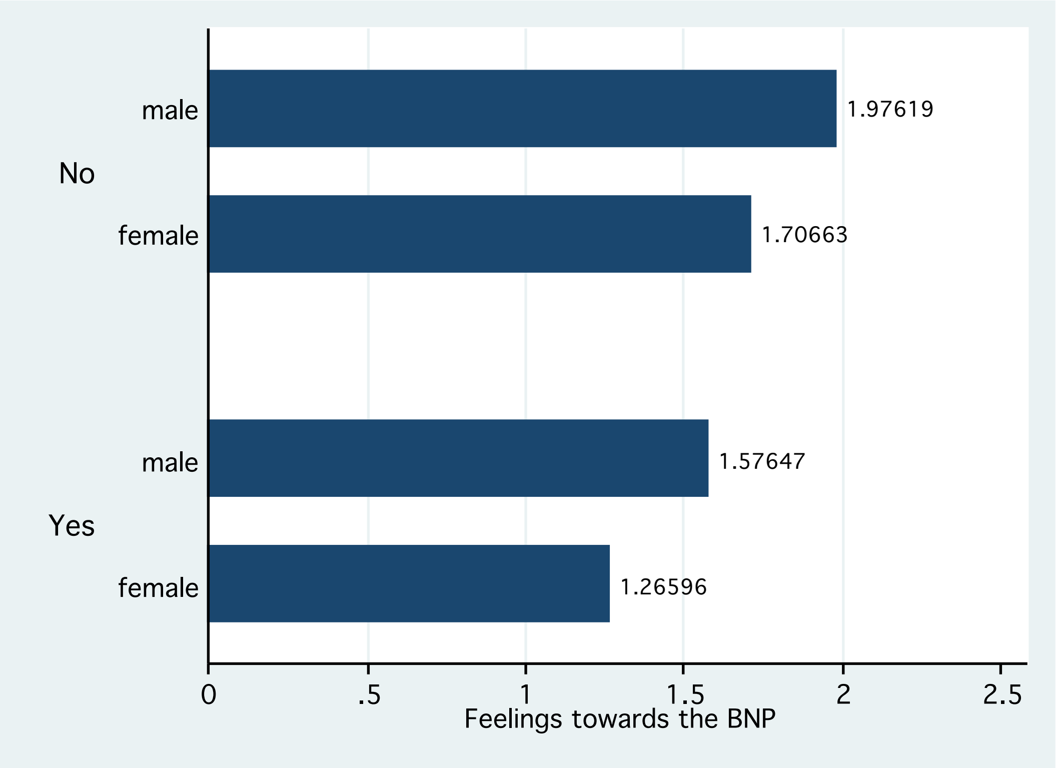
An interesting use of bivariate tests resides in identifying control variables, which are independent variables that might have affect other independent variables, therefore mitigating the interpretation of the relationships that you might come to observe between your variables.

Example 10f. Party support (with controls)

The test featured in Example 10c has confirmed an association between party support for the British National Party (BNP) and gender, with men being more likely to support the BNP than women (study: BNP, variable:). Other factors come into play: for instance, a *t*-test would reveal that members of trade unions are less likely to support the BNP than non-members.

If, in turn, women are more likely to be members of trade unions, it is difficult to know if BNP support is influenced by gender or by trade union membership. Similarly, men who are members of trade unions might be even less supportive of the BNP than females who are also trade union members, which would make the relationship more complex.

Using the **graph hbar** command with two **over** options, we can plot BNP support over both gender and trade union membership. In the resulting graph below, it becomes apparent that gender still influences BNP support, even when *controlling* for trade union membership:

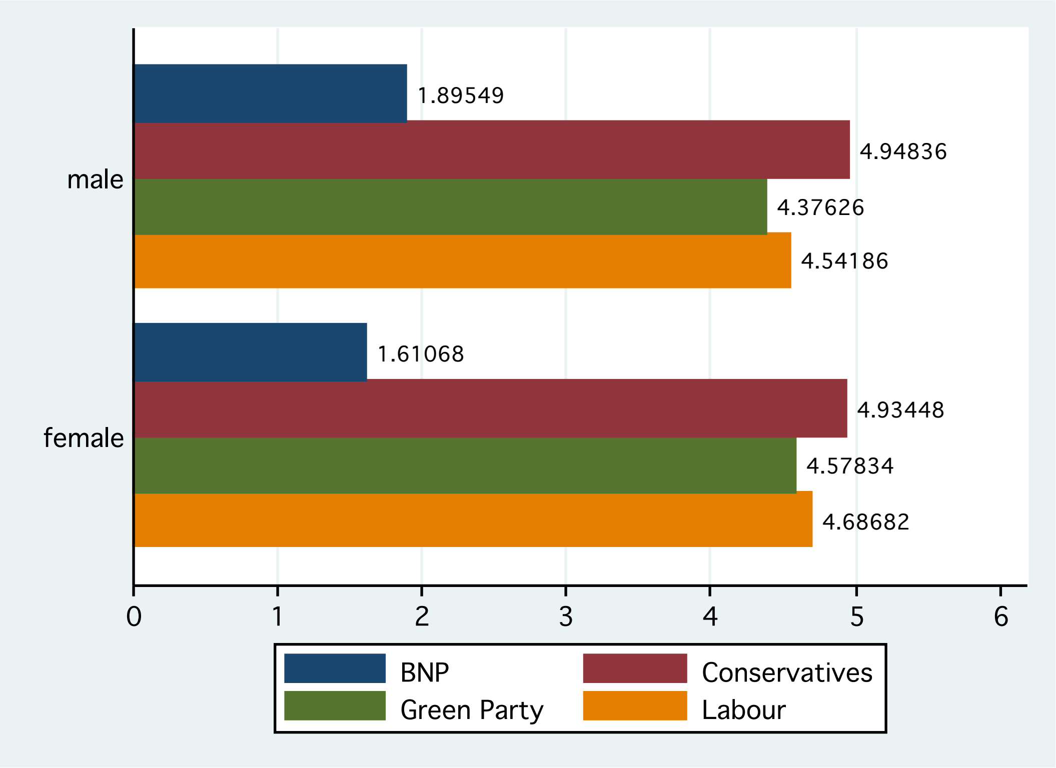


The code for the graph shows that we modified several things (we added bar labels, and we also modified the title and scale of the axis):

```
graph hbar bnp, over(sex) over(union2) ylabel(0(.5)2.5) yti-
tle("Feelings towards the BNP") blabel(bar)
```

We could also 'control' for the effect of gender on party support by verifying that, if men tend to be more supportive of the BNP, an extreme-right party, they also tend to be less supportive of political parties on the opposite end of the right/left spectrum.

The graph below shows support for the BNP and for several other parties, still broken by gender. As it *appears*, men are indeed less politically supportive of parties situated on the left; the difference in support becomes negligible on the right, and becomes *visible* again on the extreme-right.



Once again, the code for the graph comes with different modifications of the axis, bar labels, and legend:

```
graph hbar bnp con green lab, over(sex) legend(label(1 "BNP")
label(2 "Conservatives") label(3 "Green Party") label(4 "La-
bour")) blabel(bar) ylabel(0(1)6)
```

As the language above suggests, the differences and interpretations that we have given are entirely tentative, since they are based on graphical comparison. By running the 95% confidence intervals for the average support of men and women to each party (displayed below), we can see that the differences are not actually robust to the standard error of the mean: the confidence intervals for male and female BNP supports overlap, which means that the difference in support between males and females might be attributable to sampling error.

```
. bysort sex: ci bnp con green lab

--------------------------------------------------------------------------------
-> sex = male

    Variable |        Obs        Mean    Std. Err.       [95% Conf. Interval]
-------------+---------------------------------------------------------------
         bnp |        842    1.895487     .088887        1.72102    2.069953
         con |        852    4.948357    .0850586       4.781408    5.115306
       green |        792    4.376263    .0830203       4.213297    4.539229
         lab |        860     4.54186    .0893638       4.366464    4.717257

--------------------------------------------------------------------------------
-> sex = female

    Variable |        Obs        Mean    Std. Err.       [95% Conf. Interval]
-------------+---------------------------------------------------------------
         bnp |        899    1.610679    .0721949       1.468988    1.752369
         con |        992    4.934476    .0796756       4.778124    5.090828
       green |        868    4.578341    .0765306       4.428134    4.728548
         lab |       1009    4.686819    .0847027       4.520605    4.853032
```

Bivariate tests, along with other procedures such as confidence intervals, should hence lead you to think deeper about the possible associations between your variables. Once you have sufficiently explored these relationships, you should move to a statistical procedure that will allow to estimate a particular form of relationship between two variables while controlling for the effect of several other variables: linear regression.

One last word of caution before moving to regression models: remember that **statistical significance is not substantive significance**. More precisely, statistical significance is neither necessary or sufficient for substantive significance: some associations can be statistically significant and yet devoid of substance, whereas others can be substantively significant and yet too weak on independence tests. Types I and II errors stay possible even after all possible tests, due to the fact that you are using probabilities with confidence intervals and standard errors.

Consequently, your own capacity to interpret the data cannot be replaced by a statistical test. Instead, the tests should be used as heuristics: they should lead you to reflect further on the quality and reliability of your data, and on your predictions regarding your dependent and independent variables.

11. Regression

While correlation is enough to establish and qualify a relationship between two variables, linear regression adds some predictive value to your analysis. In statistical analysis, prediction consists in identifying an equation that can predict approximate values of a dependent variable from the values of independent variable(s).

Linear regression is a form of statistical modelling that predicts a dependent variable from a linear, additive relationship between one or more variables. In a simple linear regression, there are two variables, one dependent (explained) and one independent (explanatory). In **multiple linear regression**, there is still only one dependent variable but many more independent variables.

As its name indicates, **linear regression captures only linear relationships**. If your variables are related in any other way, as in exponential or curvilinear relationships (think of the Kuznets curve in environmental economics), your regression will reflect it only very poorly (if at all). Variable transformation as presented in Section 9.3 might or might not solve that issue; other techniques that reach beyond linear regression modelling can then be used to better model quadratic or polynomial relationships.

A final word of caution: **regression is not causation**. While regression allows you to identify predictive relationships between independent and dependent variables, it does *not* allow you to identify a causal link between them. Only a substantive theory can causally relate, for instance, income with life satisfaction, or gross domestic product with low prevalence rates of HIV/AIDS. With linear regression, you will find coefficients to *relate* both variables, but the *causal* link that might exist between them is a matter of interpretation at that stage.

11.1. Theory

The steps followed by regression modelling are fairly identical to those that you followed when you analysed the distribution of your variables:

- **Start by plotting your data** to understand what you are working with. When working on a single variable, you used histograms and frequency tables (Section 9). With two variables or more, you will be looking at **scatterplots** and **scatterplot matrixes** to look for linear relationships.
- **Continue by summarizing your data** using numerical measures. When working on a single variable, you used central tendency and dispersion. These measures are still relevant at that stage. You will add **correlation** measures to identify patterns between pairs of variables.
- **Finish by testing a model.** When looking at a single variable, you tested the *normality* of the variable (Section 9.3). When looking at several variables using

regression modelling, you will be testing the existence of a *linear relationship* between them.

Note that you will not be able to read regression results properly without a clear understanding of what the standard deviation is. You will also need to read p-values as well as F and t statistics. This guide does not cover the full detail of the theory behind regression. Thus, you should turn to the corresponding handbook chapters before going further with the analysis.

Identically, prior to reading regression results *per se*, you will need to read some correlation coefficients, which are quite straightforward: Pearson's r is a number ranging from -1 to +1, with proximity to either -1 or +1 indicating a linear relationship; the correlation itself can be significant or not, and therefore also comes with a p-value.

Finally, some caveats related to those mentioned in Section 10.1 apply:

- **Correlation is not causation**. Correlation is *symmetric*: it tests for the strength of *any* relationship between two variables, and the relationship can theoretically go both ways. It is only by substantive interpretation that you can make an *asymmetrical* causal claim, as in "age causes religiosity", because the causal arrow between these two variables can go only one way (i.e. the *counterfactual* is impossible: religiosity cannot influence age, whereas it is possible for age to influence religiosity).
- **Beware especially of the ecological fallacy**, which might wrongly lead you to make inferences about the individuals of your sample while looking at group-level data. For instance, the high life expectancy in France is a group-level characteristic that does not apply at the individual level—otherwise, speaking French while smoking and drinking would protect you from developing cardiovascular disease or cancer. Similarly, a U.S. Republican candidate can come first in poor U.S. states even if poor voters tend to vote for the Democrat candidate.

11.2. Assumptions

For the linear regression model to run properly, it should be applied to a **continuous dependent variable**. If your dependent variable is categorical, you can still run your regression as long as the variable has a scale: you can typically treat an ordinal variable as numeric (continuous).

All kinds of variables can be used as your dependent variable: gross domestic product, an electoral score, a scale of life satisfaction or level of education, even a binary outcome, such as "democratic or not" (0/1)—can all be submitted to regression analysis.

There are other assumptions and techniques that apply to regression but that we will ignore, because the course is introductory and limited in scope:

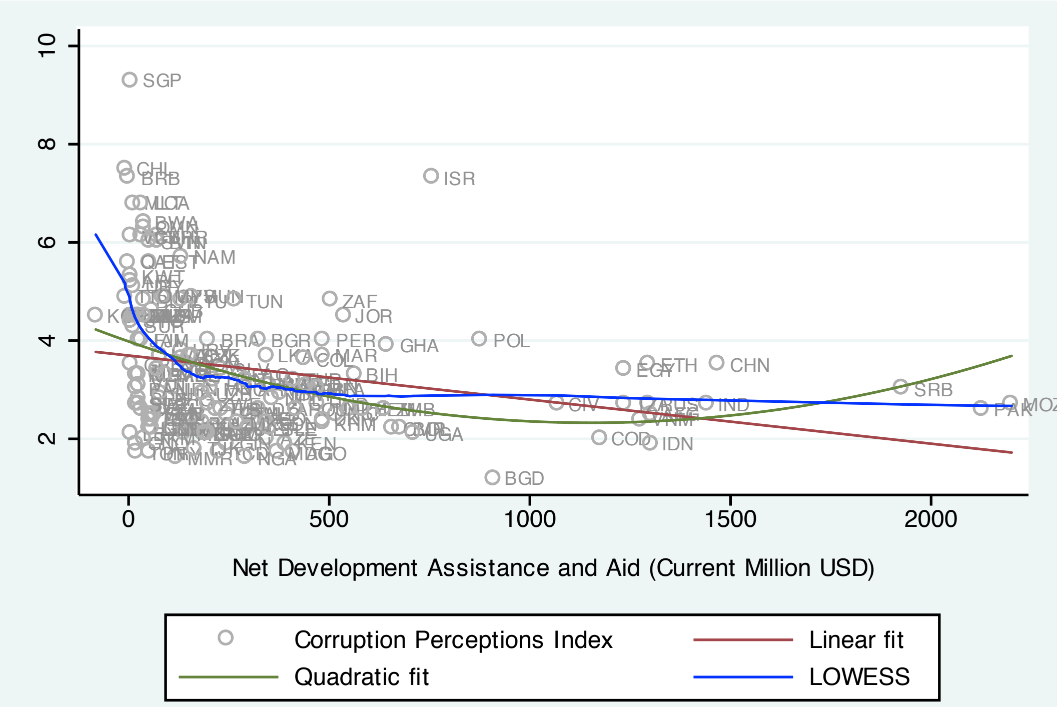
- We will not cover **selection techniques** (such as nested regression) that can be used to pick the right independent variables for your regression to reach its highest predictive value. Instead, we will stick with the independent variables that you chose by intuition and prior knowledge.
- We will not go in depth into **categorical regression models** that apply specifically to binary outcomes (logit and probit), nominal dependent variables (multinomial), and so forth. Regression with categorical data can use very sophisticated models, taught in intermediate courses.
- Finally, we will not run **regression diagnostics** [actually, we just might] which consist in studying the residuals of your regression model in order to validate the other assumptions to regression analysis.

The fact that we will not take these assumptions and techniques into account does not invalidate your regressions straight away. Even if the predictive value and precision of your final model could have been improved, your work will still yield interesting results.

Linear regression knows many variants. Ordinary Least Squares (OLS) is only one method, as is its expanded version, Generalized Least Squares. Another version, **two-step least-squares regression** (2SLS regression), is equally useful. [Explain these briefly. Handbooks rarely provide such an overview.] Another very useful one, weighted least squares regression, can be used to detect nonlinear relationships in scatterplots by fitting a **locally weighted scatterplot smoothed curve** (LOWESS curve).

Example 11a. Foreign aid and corruption

This example uses several graph options and combines a linear fit to a quadratic fit and LOWESS curve, in order to show the many problems that a simple linear regression can obscure (study: **QOG**, variables: **ti_cpi** and **wdi_aid** with some light recoding). The correlation between foreign aid distributed as development assistance and an index of corruption is indeed satisfying ($r = -0.265$, $p < 0.01$), but a graphical look at the linear fit shows that it poorly represents the data. Furthermore, the quadratic fit and LOWESS curve show a nonlinear relationship that we would miss with a simple linear regression. Finally, the scatterplot also reveals several outliers, like Singapore, Israel and Bangladesh.



Sources: Transparency International, World Bank. Lowess curve bandwidth = 1.

This example illustrates the many difficulties of regression modelling: even at the level of two variables, providing a faithful account of a relationship can require complex transformations or fairly advanced techniques. It can take a very long time to produce a satisfying model, and even longer to produce a meaningful interpretation based on its statistical results.

Once you also begin to consider measurement issues, omitted variable biases and possible variations over time, the analysis reaches a level of complexity that requires full-time specialization in quantitative methods.

11.3. Correlation

Correlation is the most straightforward way to test for independence between two continuous variables, by looking for a pattern in their covariance. Stata lets you build **correlation matrixes**, from which you can read correlation coefficients for any number of variables. Correlations can be partial or 'semipartial' and can be computed onto different subsamples, and each method comes with strengths and weaknesses.

When running a correlation, use the **pwcorr** command to select all observations for which the values of *both* variables are available. The 'pw' prefix in the name of the command stands for **pairwise deletion of missing data**: it means that this command will calculate each correlation coefficient by using all the observations for which the pair of variables used by the calculation are available.

An important problem with pairwise deletion is that each correlation coefficient ends up being calculated on a different part of the sample held by the dataset, i.e. on a different subsample. This creates serious **issues of external validity**: it not only limits the ability to compare correlation coefficients obtained under that method, but it also threatens the possibility to generalize them to the population represented by the sample.

When building a correlation matrix, it is generally more reasonable to deal with missing observations by excluding all observations for which *any* of the variables are missing. This method, called **casewise, or listwise, deletion of missing data**, is implemented by the **corr** command. Still, depending on your data structure, this method might result in excluding a very large fraction of the observations contained in your dataset when calculating correlation coefficients, which again threatens the representativeness of your sample.

The problems outlined above are critical when your data contains many missing observations, which might excessively distort the correlation coefficients and limit generalization. There is no statistical solution to these issues because they emerge at the level of data collection and might only be solved at that stage. An acceptable procedure consists in adding the **obs** option to the **pwcorr** command, in order to get the number of observations used in calculating each correlation coefficient. Any important variation in these numbers should be interpreted as a threat to external validity, which you should take into account while interpreting the correlation matrix.

Add the **sig** option to your **pwcorr** command to obtain significance levels in your correlation matrix. For improved reading, use the **star(.05)** option to add a star next to statistically significant correlations at $p < .05$. The strength at which you should start considering a correlation is a substantive question that depends on your research design, but a value of 0.5 is usually a good start to identify strong correlations, and a value of 0.25 might identify moderate correlations.

Due to their multiple issues of validity, you should refrain from drawing strong inferences from correlation matrixes. Use correlation coefficients for explorative purposes, to refine your intuitions and hypotheses. Once you have understood Pearson's *r* and the explorative potential of correlation matrixes, more robust results will be provided by linear regression.

Example 11b. Trust in institutions

Trust is a common measurement in social surveys that usually applies to either people in general or to specific social and political institutions like parliaments, politicians or the police force. We decided to focus on institutional trust (study: **ESS**, variables: all starting with **trst**, which is coded with an asterisk: **trst***) to illustrate how trust correlates between institutions:

```
. pwcorr trst*, star(.05)

             |  trstprl  trstlgl  trstplc  trstplt  trstprt   trstep   trstun
-------------+---------------------------------------------------------------
     trstprl |   1.0000 
     trstlgl |   0.6674*  1.0000 
     trstplc |   0.5527*  0.6813*  1.0000 
     trstplt |   0.7005*  0.5745*  0.5051*  1.0000 
     trstprt |   0.6657*  0.5499*  0.4667*  0.8691*  1.0000 
      trstep |   0.4776*  0.4240*  0.3576*  0.5307*  0.5418*  1.0000 
      trstun |   0.4441*  0.4354*  0.4199*  0.4888*  0.4961*  0.7175*  1.0000 
```

The correlation matrix reproduced above shows moderate-to-strong correlations between many institutions. For instance, there is a strong association between the trust scores of two supranational organizations with ruling parliaments, the European Parliament and the United Nations (r = 0.72). That association is actually less intense between the European Parliament and national parliaments (r = 0.48). Identically, there is a remarkably strong correlation of trust scores for politicians and for political parties (r = 0.87), but the associations between these two scores and the trust score for the legal system are less marked, despite the importance of the rule of law in guaranteeing democratic electoral competition.

All observations drawn from correlational analysis are tentative. The most robust findings actually come from the absence of any significant correlation, which can designate mutually exclusive situations, as in a measure of voting preference for several political candidates: if constitutional rules are set to organise a uninominal ballot, then the election is a zero-sum game between the candidates and voters are likely to polarise their opinions and reject all candidates but one.

However, when the correlation matrix shows very strong associations between two or more independent variables, then you can start diagnosing potential issues of multicollinearity in your future regression model. Multicollinearity is the situation where independent variables influence each other in a significant way that is not captured in your model, where the focus is instead set onto the dependent variable. Section 11.5 covers multicollinearity in more detail.

11.4. Interpretation

Linear regression in Stata uses the **regress** command, followed by two variables for a simple linear regression and any number of variables for a multiple linear regression. The list of variables depends on your research design and on the results of your previous bivariate tests.

To interpret correctly a linear regression model, you should use robust standard errors (using the **robust** option) and then focus on the following results:

- The **number of observations** reflects the subsample used to perform the regression. This subsample is created by casewise deletion, as explained above. A low number of observations will limit the validity of the model.

  If you are facing a very low number of observations, you will need to remove the variables that are causing that number to drop, to increase the validity of the model for your sample population. If one of your independent variables is available for less than 30 observations, remove it and run your regression without it.

- The **p-value** of the model (**Prob > F**) should be below your alpha level of significance. The separate p-values for the coefficients in your model should obey the same rule.

  The p-values can be read independently: if a categorical variable returns both high and low p-values on its dummies, interpret them separately. For instance, if your model includes a variable that defines religious denomination, it might happen that the variable produces a significant effect only for some religions and not others.

- The **R-squared** statistic indicates the predictive value of your model. It can be read as a percentage: an R-squared value of .08 indicates that your model predicts the variance of your dependent variable by only 8% (whereas efficient models will usually predict over 80%).

  An issue with the R-squared statistic is that it will mechanically increase with the number of variables included in the regression model. To control for that effect, you should read the adjusted R-squared (**Adj R-squared**) if your model includes a large number of independent variables. This issue disappears with standardised coefficients, as explained below.

- Finally, the **coefficients** for both your variables and your constant (noted **_cons** and also known as the intercept) are the parts of the model that you will interpret. To make them comparable, you need to standardise them across variables, using the **beta** option.

  Technically, the coefficients establish the amount of variation in your dependent variable that occurs for a variation of one unit in each of your independent variables. This variation can be interpreted straightforward only for continuous data, and requires more thought for categorical data.

[Example suggested by Dawn Teele] AJR's *Colonial Origins of Comparative Development*, p.1378: "To get a sense of the magnitude of the effect of institutions on performance, let us compare two countries, Nigeria, which has approximately the 25th percentile of the institutional measure in this sample, 5.6, and Chile, which has approximately the 75th percentile of the institutions index, 7.8. The estimate in column (1), 0.52, indicates that there should be on average a 1.14- log-point difference between the log GDPs of the corresponding countries (or approximately a 2-fold difference-e1.14-12.1). In practice, this GDP gap is 253 log points (approximately 1-fold). Therefore, if the effect estimated in Table 2 were causal, it would imply a fairly large effect of institutions on performance, but still much less than the actual income gap between Nigeria and Chile."

Example 11c. Subjective happiness

The Quality of Government dataset includes a series of indicators that report self-assessed happiness. One these indicators consists in a mixed measure that combines life satisfaction and a subjective assessment of one's life, from "best possible" to "worst possible". Both measures use standardised psychometric scales that provide an indicator of individual happiness in the 0–1 range, multiplied by life expectancy at birth (study: **QOG**, variable: **wdh_lsbw95_05**, renamed **life** for convenience).

The steps that we took prior to running the linear regression model include data preparation, description and visualization. Each step is covered, with comments, in the **qog_reg.do** file provided in **Appendix A**. We then thought of a list of potential predictors for this dependent variable, which can be summarised along the following categories:

- **Security,** measured as the absence of social, economic or political crisis
- **Wealth**, measured as national affluence, free markets and low corruption
- **Freedom**, measured as free speech, gender equality and democratic life
- **Health**, measured as high life expectancy and low infant mortality
- **Education**, measured as high educational attainment among both sexes

Looking at the variables in the Quality of Government dataset, we found many variables that could fit each part of the model, which is far from perfect—for example, the 'Health' component is partly redundant (or **collinear**) with the dependent variable, since the happiness indicator is already calculated against life expectancy. Identically, infant mortality, life expectancy and educational attainment (measured as average schooling years) are heavily correlated, which would lead to measure the same variable twice, and since corruption is an obstacle to free markets, it is likely to be measured twice if we include it as two separate independent variables. Consequently, we removed some variables from the model after looking at a few correlations.

The final model tests three series of variables, corresponding to our three models of happiness as Security, Wealth and Freedom. The table below summarises the respective results of the models, and as shown, each of them carry statistically significant results that can be substantively interpreted. Improvements of the model would include normalizing some of the variables and applying some other diagnostics, quickly reviewed in the next section.

Table 1. Estimated Effects of Security, Freedom and Wealth on Subjective Happiness

	Model 1 Security	Model 2 Wealth	Model 3 Freedom	Model 1+2	Model 1+2+3
Failed state	– 0.69*** (0.03)			0.02 (0.05)	– 0.05 (0.05)
Gross domestic product		0.39*** (0.00)		0.40** (0.40)	0.39** (0.00)
Market governance		0.45*** (2.37)		0.47*** (2.38)	0.46*** (2.26)
Freedom of speech			0.28** (2.38)		0.25** (1.91)
Freedom of the press			– 0.25 (0.11)		0.39** (0.09)
Women's social rights			0.31** (1.35)		0.00 (1.10)
Electoral process			0.30 (0.91)		0.52** (0.77)
Political process			– 0.39 (0.81)		– 0.31 (0.66)
Constant (or "Intercept")	63.16*** (1.65)	35.93*** (1.62)	37.49** (11.56)	35.23*** (4.32)	17.00* (9.03)
Observations (or just "N")	93	91	94	90	90
R-squared	0.48	0.66	0.45	0.66	0.73

Standardised beta coefficients; robust standard errors in parentheses.

Significance levels: * significant at 10%, ** significant at 5%, *** significant at 1%.

[WRITE: Dummy variables] We might finally want to add a dummy variable to Western countries to see whether Western democracy really has an advantage over the rest of the world in terms of the subjective happiness of its citizens. The simplest way to do this consists in using the **xi: reg** command with **i.ht_region**, but the **tab ht_region, gen(region_)** command will also work.

[WRITE: Interactions]

11.5. Diagnostics

Linear regression models have the capacity to reveal many different aspects of your data, such as **multicollinearity** when several independent variables in the model all revolve around the same factor, and thus lead to estimating the same factor several times through different measurements. For instance, if you include monthly *and* annual income in your model, you are controlling twice for a single factor, measured in two different ways. Multicollinearity will affect your model by calculating separate coefficients for "independent" variables that are actually correlated, hence creating an issue in your linear model by including redundant information about your dependent variable.

Variance inflation factors (VIF) obtained with the **vif** command allow to assess for multicollinearity. As a rule of thumb, the factors should stay below 10 (or, alternatively, their tolerance should stay above 0.1). If your VIF diagnosis finds multicollinearity, your independent variables include some collinear ones, which will affect the measure of regression coefficients.

Another issue that might affect your regression model is **heteroscedasticity**, which designates a violation of the normality assumptions under which linear regression operates. Specifically, linear regression posits *homoscedasticity*, which stands for equal (or constant) variance in your independent variables. This is an important dimension of any regression model.

Under equal variance, a plot of your regression residuals should show no pattern among them. If a nonlinear pattern appears, or if the distribution of the residuals around the fitted values is simply not close to uniformity, then the data violates the linear assumption of your model. The **rvfplot** command diagnoses that issue by producing a plot of residuals-versus-fitted values.

Finally, some formal tests exist to detect heteroscedasticity. The imtest hottest [WRITE]

Each issue will have different consequences on your linear regression model. Multicollinearity will increase the standard error of your coefficients and obscure the interpretation of the results. Heteroscedasticity indicates that a linear model is not reflecting the data correctly, and that a *nonlinear* model should be used.

At that stage, you should also detect **influential observations** using a measure called Cook's *D*, and **outliers**, using tools akin to those described in Section 9.4. The studentized residuals [WRITE]

[EXAMPLE CONTINUING 11.4]

12. Cheat sheet

This section summarises the most useful commands used during the course and in this guide to produce the kind of statistical analysis that is expected to appear in your final research paper. Part 3 will further explain how to write your draft and final papers.

12.1. Theory

Colour codes: You need to understand these notions for Assignment No. 1; You need to understand these notions for Assignment No. 2; You need to understand these notions for the final paper. Each topic is featured at various places in the Stata Guide, and the theoretical notions are explained in depth in your handbook.

- **Datasets:** survey design, sampling strategy, sample size, units of observation, variables, missing observations, categorical (ordinal, interval, nominal) and continuous (ratio, count) variables.
- **Normal distribution:** standard error (of the mean), skewness and kurtosis, probability distribution, (standardized) z-scores and 'alpha' levels of precision, other distributions (binomial, Poisson).
- **Univariate statistics:** number of observations, mean, median, mode, range, standard deviation, percentiles, quartiles, graphs (histograms, kernel density, bar, dot and box plots).
- **Estimation and inference:** point estimates, confidence intervals, *t* distribution, null and alternative hypothesis testing, *p*-values, one-sided and two-sided/-tailed tests, Type I (false positive) and Type II (false negative) errors.
- **Bivariate tests:** *t*-tests (means comparison), proportions tests, Chi-squared tests and Cramér's V (independence or association), correlation (Pearson and Spearman), Gamma test.
- **Regression:** simple and multiple linear regression, unstandardized and standardized 'beta' coefficients, *F*-statistic, *t*- and *p*-values, R-squared, dummies, interactions, diagnostics (residuals, multicollinearity, homoscedasticity, influence).
- **Statistical issues:** sampling frames, survey weights, variable measurement and bias, normality assumptions, correlational ≠ causal analysis, statistical ≠ substantive significance.
- **Scientific writing:** research design, paper structure, scientific style, tables and graph formatting, referencing (sources and citations), discussion.

12.2. Data

Data management is covered in Sections 5–8. Transforming variables needs to be done carefully, and takes a lot of time, especially when you are new to the data that you are analysing. Some general advice applies:

- **Use the datasets that we recommend for this course.** If you do not have a dataset ready well in advance for Assignment No. 1, fall back on ESS, GSS, WVS and QOG data to find variables of interest.
- **Your dependent variable is a single, continuous measurement**, such as the average Body Mass Index of American adults or the percentage of women in national parliaments around the world.
- **Your independent variables are possible predictors of your dependent variable.** Select a handful of 'IVs' of any type, such as age, gender, GDP per capita or welfare regimes, that you think can explain the distribution of your 'DV'.
- **Never save over a clean dataset.** Do not save your changes to the data! This makes them impossible to retrace properly. Instead, post all information you need to *get replicated*—rather than *published*—in the do-file.

Unabbreviated commands for these tasks:

- **drop** and **keep** (to select observations and variables)
- **generate** (to create new variables like sums or indices)
- **rename** and **label variable** (to rename your variables with convenient names that are short and understandable, and to assign them labels)
- **recode** and **replace** (to recode data into simpler categories, such as dichotomous variables with binary outcomes)
- **encode** and **destring** (to convert string data into numeric format)
- **label define** (to create value labels), followed by **label values** (to assign label to the values taken by your variables)

Remember: poorly prepared datasets are much more complex to analyse, and even harder to understand for others. As a rule of thumb, try to apply these principles:

- **Renaming your variables** to humanly understandable words or acronyms is very helpful, as long as you keep the new names short and to the point;
- **Proper labels** should be assigned to both variables and values, so as to make sense of categories, cut-off points and so on.
- **Survey weights** should be documented, even if we do not use extensively. Your do-file should include the **svyset** command documented in the 'readme' text file distributed with each course dataset.

12.3. Distributions

Start by describing your variables as sown in Section 9. Univariate descriptions of your data will appear in your table of summary statistics. Some commands follow:

- **tab**, **tab1** or **fre** (to tabulate *categorical* variables; the additional command **fre** is recommended because of its better handling of missing observations)
- **summarize** (to produce a five-number summary for *continuous* data: number of observations, mean, standard deviation, min and max)
- **summarize** with the **detail** option (to further summarize *continuous* data with quartiles and percentiles as well as skewness and kurtosis)
- **tabstat** with the **n mean sd min p25 p50 p75 max** options (to further summarize *continuous* data with quartiles); alternative command: **univar**.

Continue by **graphing the distribution** of your variables when you are able to comment meaningfully on the distribution in your paper:

- **graph hbox** (to describe the distribution of *continuous* data, showing quartiles and outliers)
- **histogram** with the **kdensity** and **normal** options (to describe the distribution of *continuous* data; use other units if relevant)
- **histogram** with the **discrete** option (to describe the distribution of *categorical* data that support an *interval* or *ordinal* scale)
- **catplot** (to describe the distribution of *categorical* data; this additional command is rarely more useful than a frequency table obtained with **tab1** or **fre**)

Remember: significant labels (usually percentages) will make your graphs much more informative, so use **xtitle** and **ytitle** to assign titles to axes, **ylabel** to modify the units and labelling of the y-axis, and specify **frequency** or **percent** to use these units of measurement instead of density in histograms.

Finally, since independence tests are generally based on the presumption that your variables are normally distributed, you should test this distributional assumption by looking for possible transformations of your variable, using **diagnostic plots**:

- **symplot** (to assess symmetry)
- **qnorm** and **pnorm** (to assess normality at the tails and at the centre)
- **ladder**, **gladder** and **qladder** (to compare transformations)

The **summarize** command with the **detail** option provides skewness and kurtosis: zero skewness denotes a symmetrical distribution, and normal kurtosis is close to 3. A variable might approach normality when transformed to its logarithm (**log** or **ln**), or sometimes its square root (**sqrt**) or square (**^2**). Only a full, visual check using the commands above can determine the relevance of a transformation.

12.4. Association

Your paper is articulated around rejecting the null hypothesis about the absence of association between your dependent and independent variables. There are many tests available to do so, but you will use a short list of **independence tests**:

- **ttest** with the **by** option (to compare two means, using continuous data)
- **prtest** with the **by** option (to compare two proportions, using discrete data)
- **tab** with the **chi2** option (to crosstabulate categorical data)
- **tab** with the **exact** option (to crosstabulate on low cell counts or '2 x 2' tables)
- **pwcorr** with the **obs**, **sig** and **star** options (to build a matrix of significant correlations at a certain level of significance)

The tests do not use the same method: comparison tests use confidence intervals, as also provided by the **ci** or **prop** commands.

You should represent significant relationships graphically:

- **sc** with two continuous variables; use the **mlab(country)** option to label data points with the values of the **country** variable, as you might want to do with country-level data or other data with identifiable observations.
- **spineplot** for two categorical variables; make sure that you install this additional command and train yourself to read it correctly, as it is arguably the most useful way to plot two categorical variables against each other.
- **gr dot** or **gr hbar** for a continuous dependent variable and a categorical independent variable; do not publish these graphs unless you have solid grounds to think that a categorical plot can convey more information than a table.

12.5. Regression

You can use linear regression as long as your dependent variable is continuous. If your dependent variable represents a binary outcome, another model applies, using the **logit** command. The most useful commands for linear regression are:

- **sc** with two continuous variables (to visualize a possible *linear* correlation)
- **tw (lfitci dv iv) (sc dv iv)** with two continuous variables (to visualize correlations with their linear fit and confidence intervals)
- **reg dv iv1 iv2, ...** with 2+ continuous variables (to run simple or multiple linear regression models)
- **reg dv i.dummy** (to add dummy categorical independent variables; add **xi:** in front of the command if running Stata 10 or below)

- **char dummy[omit] value** (to set the baseline, or reference group, for dummy categorical variables; a **recode** is usually simpler/better, though)

In your regression output, you should concentrate on reading:

- the **number of observations** (the data on which the model ran)
- the ***t*-values** and ***p*-values** (whether the model is statistically significant)
- the ***R*-squared** (a gross measure of the predictive value of the model)
- the **coefficients** (the amount of variance predicted by one unit of the predictor)
- the **standard errors, *t*-values, *p*-values and confidence intervals** (the reliability of the coefficients produced by the model)

12.6. Programming

Remember some very basic Stata operating procedures:

- **Setting the working directory is not an option.** For this course, always check that you have selected the **SRQM** folder as your working directory.
- **Remember to install additional packages** like **fre**, **spineplot** or **tabout**, or you will run into errors when calling these commands.
- **The commands of a do-file should be run in sequential order:** if you try to execute line #30 before line #10, you are likely to encounter an error.
- **Get used to running multiple commands at once:** select them and use Ctrl-D on Windows or Cmmd-Shift-D on Mac OS X to run them altogether.

The following tricks are for readers who have little or no experience with programming languages. Skip them if you are acquainted to programming environments.

- **To execute a command and ignore breaks in case of an error**, use the **capture** prefix command (shorthand **cap**), as in **cap drop age** (which will drop the **age** variable and just do nothing if the variable does not exist).

  This option will come in handy with lines such as **cap log close**, which will return an error if no log file is open. Using **cap** is then a safety net to ensure that the do-file will run regardless of a log file being open.

- **Run all adjacent commands connected with '///' together.** To break long commands onto several lines, use **///** or set a line delimiter with the **#delimit**, or just **#d**, function; for instance, type **#d ;** to write in pseudo-C++ syntax.

  The first option is very useful when you are dealing with code that extends beyond the limits of your do-file editor window. This will happen often if you are coding graphs with many options.

- **To apply a command to several variables with a wildcard operator, use the * symbol**, as in **su trst*** if you want to summarize all variables starting with the

trst prefix, or **destring party*vote** to convert all variables named **party1vote**, **party2vote**, …

  This trick comes in handy if you have created binary variables from a categorical one. For instance, the **tab relig, gen(relig_)** command to create dummies of religious beliefs, the relig_1, relig_2,… relig_*n* variables can be designated together by typing, for example, **ci relig_***.

- **To use loops**, read the **foreach** and **while** documentation. Stata code is Turing complete, so it handles your needs. Use them if you know how loops generally function in programming environments; ignore them otherwise.

  The simplest use of a **foreach** loop is when you are recoding a bunch of variables that all follow the same coding rules. In that case, you can place the recoding operations in a **foreach** loop to save time and code.

- **To use 'macros'**, read the **local** and **global** macros help pages. Use macros only if you have sufficient programming experience in another language where you already learned to use macros, constants or scalars.

  A basic example of a **global** macro is one that stores recurrent graph options, which you can then call in only one word. A basic example of a **local** macro involves counters, which should not come up in this course.

Examples of each trick will show up in portions of the course do-files that are not shown in class, but included for you to explore while replicating the session. None of these tricks are part of the course requirements.

*

My tentative conclusion to the course follows.

For empirical social scientists, statistical reasoning and quantitative methods provide an additional layer of theory and methods to their sociological skill set, which also includes a fair share of history, philosophy and various forms of intuition.

This layer is meant to enhance their capacity to make causal claims about observable relationships in the social, material world. Just like any compound of theory and methods, the 'SRQM' layer is a thick one that is not easily digested: in fact, you will have to ruminate it a lot, in the same way that you should be feeding on data and secondary analysis to ground your own work.

You can be an intellectual fox or hedgehog, as Isaiah Berlin once offered to, but if you want to be an empiricist, you will have to be a ruminant too. Please do not be offended when I say that this guide is actually a cookbook for hungry sociological herbivores.

And remember: your input to improve this guide is needed!

Part 3

Projects

The Assignments for this course will lead you towards submitting your final paper, in which you will expose your research project. During the weeks of class, you will write up two Assignments and one final paper, following instructions that are carefully described in this section. **Read these in detail.**

The grades assigned to your Assignments should be read as a measure of your progress towards producing your final paper. The grading ranges from 1 (critical revisions needed) to 5 (cosmetic revisions needed).

The table below shows how Assignments progressively lead to your final paper.

Assignment 1	Assignment 2

1. Research question

Identify a research topic, a dataset, and select some variables.

2. Univariate tests

Identify the values and distributions of the variables used in the research.

Revise and update Assignment No. 1 before moving to steps 3 and 4.

3. Bivariate tests

Crosstabulate the variables and run significance tests for the crosstabs.

4. Regressions

Run regression models, report their output, and discuss the results.

13. Formatting

Section almost entirely consistent with the course in its current form. Review. Notably, Tables and Graphs could be presented in another division, "Exports" and "Presentation".

Applying the formatting conventions below will ensure that your paper uses a presentational standard that comes close to academic practice. Do not consider your paper an academic one without some attention to presentation, which are necessary to help the reader with understanding your work.

Intelligent formatting will require exporting, styling and commenting on tables and graphs. This will make up for a substantial fraction of your word limit, and of your paper overall. If followed, these recommendations will hence help you build your paper methodically, which also helps with reasoning. QED.

13.1. Communication

When sending your Assignments, you must carefully respect some conventions that apply to your email and attached files. Your Assignment emails should be structured as in the following example:

From	Use your Sciences Po or Gmail email address.	
To	Always email to both course instructors.	
Subject	SRQM: Assignment No. 1, Briatte and Petev	
Body	Insert your comments and questions about your work.	
Attachments	**Assignment**	BriattePetev_1.pdf
	Do-file	BriattePetev_1.do
	Dataset (optional)	Attach your data in DTA format if you chose to work with a dataset outside of recommended ones.

13.2. Files

Your Assignment is a text file written following a set of scientific conventions. Follow the instructions provided in class to format your document, and print it as a PDF file using any common utility to do so.

Your do-file must be executable: try running them to make sure that they do not produce errors. Use the template provided in class to do so, and do not hesitate to imitate the do-files from the course sessions.

Your dataset must be provided for replication purposes: if it does not feature in the datasets recommended for the course, send it along as a Stata data file with a '**.dta**' extension, converting it to that format if needed (Section 5), and making sure that it is ready for cross-sectional analysis (Section 7).

Important: if your dataset ranges over ~ 5MB, compress it as a ZIP or RAR file, without any form of password encryption. If your data still ranges over ~ 10MB after subsetting and compression, use sendspace.com to email it over. Please do not use any other format or service, as to avoid unnecessary confusion.

13.3. Text

Your Assignment is not a string of Stata output pasted into a text file. The last sections of this guide (and Section 16 in particular) set out instructions to format your final paper as a scientific one, but more generally, remember that academic writing involves using precise, unambiguous terms in correct, simple sentences. Beyond issues of vocabulary, grammar and syntax, you should also use a text structure made of a small number of balanced paragraphs and sections.

Data and procedures that come with no explanation are useless to the reader. In your work, tabular and graphical data visualizations (tables and figures) should be supported by substantive text, including a title, a legend and some explanatory notes, either in your main text or as captions. More on this below.

In many ways, the same recommendations apply to the code in your do-file. As mentioned in Section 2, computer languages work a lot like human languages. For instance, linguistic diversity also applies to programming languages: Stata code is only one of thousands of different ones, each of which possess their own syntax rules and end up forming 'families' of languages, with shared properties and a more or less dynamic community of more or less proficient users, etc.

Code is fundamentally text, and computer code obeys common linguistic rules. For example, you have noticed that Stata code supports abbreviations, with some commands coming in two forms (a 'full form,' such as **summarize**, and a shorthand form, such as **su**). Pushing that observation further implies that there such a thing as writing 'clear' code, just like there is 'clear' writing.

This notion is often called 'literate programming', as computer scientist Donald Knuth termed in 1984. Knuth offered to "change our traditional attitude to the construction of programs: Instead of imagining that our main task is to instruct a computer what to do, let us concentrate rather on explaining to human beings what we want a computer to do."

Quoting again from Knuth, that mind-set carries one important lesson: "The practitioner of literate programming can be regarded as an essayist, whose main concern is with exposition and excellence of style." Breaking it into simple rules that fit this course, the three most important ideas of 'literate programming' that apply to your work and will convey sense to your code go as such:

- **Syntax and vocabulary are (almost) inflexible**. Computer code is less versatile than human language, and deviations in the syntax or terms that you use will generate errors. Eliminating these errors are the first aspect of 'debugging' a program, that is, correcting its content to make it behave properly. Your code should be flawless by that standard.

  Section 2.6 explains how to deal with a command that returns an error caused by faulty syntax or by a spelling mistake. More complex aspects of debugging involve, for example, the precise order in which you execute your commands. Hopefully, the linear structure of Stata code should reduce issues in that category to their minimum.

- **Complexity calls for annotations**. As soon as we express difficult thoughts, we add a 'meta' layer of information to our text, as with side notes in religious texts like the Talmud, stage directions in theatre plays, or bracketed information and footnotes in other kinds of texts.

  In computer code, comments serve precisely the same elucidative purpose. They will be useful to external readers and will also help you to remember why you entered each command. There is no need to add comments on every single command that you use, and you should be able to distinguish which parts of your code needs them.

- **Sectioning is not an option**. Cartesian thought has that in common with playwriting that it uses blocks, like Acts and Scenes. Think of philosopher Ludwig Wittgenstein's *Tractatus Logico-Philosophicus*, which uses hierarchical numbering to outline seven propositions, or just think about the structure of any book or newspaper, with page numbers, paragraph spacing, text columns, sub-heads and running titles.

  Your code should also feature a simple sectioning, with comments and blank lines used to create blocks of code where commands are grouped in relevant conceptual blocks, such as setup, recoding, descriptive statistics, analysis with a first independent variable, and so on.

13.4. Tables

Quantitative evidence requires producing tables of summary statistics for many operations such as variable description, correlation or regression modelling. Stata output can be exported by copying it from the Results window, using the **'Copy as Picture'** function. This method might be acceptable for presenting draft texts, but not for final written communication.

There are two main reasons to this, beyond aesthetic reasons:

- First, Stata output usually contains more information than required for a standard paper. Scientific communication is parsimonious and only requires a selection of summary statistics, while Stata is more exhaustive and sends larger quantities of information for analytical purposes, to help you build your interpretation.
- Second, Stata output reports a high level of precision by including many digits after the decimal point, which is inconsistent with the limited precision of initial measurements. For example, the **height** variable of the **NHIS** dataset is reported by the **su** command as having a mean of 66.68131 inches, a precision level that does not reflect real measures.

It is therefore expected that you do not copy and paste from your Stata output to report your results, but instead convert it to tables that follow some standard formatting conventions:

- **Round all results to one or two decimals:** After exporting your results to a spreadsheet editor like Google Documents, Microsoft Excel or Open Office, use a rounding function to truncate numbers.
- **Ideally, format your table as to align columns to decimal tabs.** Centring your tables on the decimal separator "." helps with reading your results. Unfortunately, not all word processors manage to do this well.
- **Ideally, provide notes with your table.** Your table can use footnotes to comment on its contents. These comments can either appear in your text, or better, as footnotes immediately below the table.

Because word processors are variably competent or explicit about the two latter conventions, they are only optional here. However, for the most dedicated, brief instructions appear in this guide: http://people.oregonstate.edu/~acock/tables/center.pdf.

Start by exporting your tables using the method described below, which deals first with continuous variables, and then with categorical ones:

- First, install the **tabout** command, then run these commands by replacing **dv**, **iv1**, **iv2** and **iv3** with your dependent and independent variables, as long as they are continuous:

```
* Produce a standard summary statistics table.
tabstat dv iv1 iv2 iv3, s(n mean sd min max) c(s)
* Export to CSV file.
tabstatout dv iv1 iv2 iv3, tf(stats1.csv) s(n mean sd min max)
c(s) f(%9.2fc) replace
```

The CSV file, which will require that you import it in a spreadsheet editor like Microsoft Excel, contains a table of summary statistics that can be easily imported or copied and pasted into your text processor.

- Second, run this command on your categorical variables. The command will export a frequency table in percentages:

```
* Export to CSV file.
tabout iv4 iv5 iv6 using stats2.csv, replace
```

The files **stats1.csv** and **stats2.csv** should have been created in your working directory (Section 3.3), and can be imported or copied and pasted into a word processor. Both files are just working files and need not to be sent with your do-file.

A useful way to compact both files into one, in order to produce only one table, is to stick the frequency percentages of your categorical variables into the same column as the mean values of your continuous ones. An example of that arrangement is shown below in Table 3.

The following example describes a **dataset and its main variables of interest** for its units of observation, *N* = 10 African countries, based on a recent journal article: Kim Yi Dionne, "The Role of Executive Time Horizons in State Response to AIDS in Africa", *Comparative Political Studies* 44(1): 55–77, 2011.

Table 1. Countries of analysis

Country	HIV prevalence (2001)	GDP (2001)
Ethiopia	4.1	724.80
Mozambique	12.1	1018.82
Rwanda	5.1	1182.49
Zambia	16.7	816.83
Tanzania	9	547.27
Burundi	6.2	618.10
Uganda	5.1	1336.33
Lesotho	29.6	2320.70
Namibia	21.3	6274.3
Kenya	8	1016.18

Note: inspired from Yi Dionne (2011).

The next examples describe the **summary statistics** for the Quality of Government dataset. By convention, "N" designates the total number of observations, and "SD" is the acronym for the standard deviation.

Table 2. Summary statistics

Variable	N	mean	SD	min	median	max
Infant mortality rate (per 1000 live births)	181	43.30	39.97	2.80	27	166
GDP per capita (logged)[a]	192	84.67	715.84	0.01	1.93	6243.05
Government health expenditure (% GDP)	76	7.57	1.56	4.58	7.44	11.20

Note: data from Quality of Government (2010).

[a] Variable transformed to natural logarithmic scale.

If you need to include categorical variables, use the "Mean" column to indicate the valid percentages for each category, as follows:

Table 3. Summary statistics

Variable	N	mean	SD	min	median	max
Infant mortality rate (per 1000 live births)	181	43.30	39.97	2.80	27	166
Government health expenditure (% GDP)	76	84.67	715.84	0.01	1.93	6243.05
GDP per capita (logged)[a]	192	7.57	1.56	4.58	7.44	11.20
Regime type						
Monarchy[b]	13	6.99				
Military	12	6.45				
One-party	7	3.76				
Multi-party	56	30.11				
Democracy	89	47.85				

Note: data from Quality of Government (2010).

[a] Variable previously transformed to natural logarithmic scale on grounds of normality.

[b] Includes only nondemocratic monarchies; cf. QOG Codebook (2011), p. 34.

The next example describes **crosstabular output**. By convention, independent variables are displayed in rows, with column percentages. The example below provides both frequencies and percentages, but it is common not to indicate the frequencies when these reach high counts.

As you will notice, the table is not very helpful, as it uses the recoded versions of two continuous variables. When the data are available as continuous variables, scatterplots are always preferable to crosstabulations, especially when displayed with the linear fit of a simple linear regression.

Table 4. Crosstabulation of GDP and HIV

	HIV prevalence							
	Low		Medium		High		**Total**	
GDP per capita	*n*	%	*n*	%	*n*	%	*n*	%
Low	1	25.0	3	37.5	0	0.0	4	26.6
Medium	3	75.0	3	37.5	1	33.3	7	46.6
High	0	0.0	2	25.0	2	66.6	4	26.6
Total	4	100.0	8	100.0	3	100.0	15	100.0

Note: adapted from Yi Dionne (2011), replication dataset.

The final example describes **multiple linear regression output**. The important variables to include are coefficients, standard errors, the constant (or intercept), the total number of observations – or *N* – and the R-squared, as well as the starred p-values. The table below reports multiple linear regression for three dependent variables and uses three levels of significance (0.1, 0.05 and 0.01).

Table 4. Estimated Effects of HIV rates and GDP on API policy scores

	API Policy	Health Spending	AIDS Spending
Log HIV prevalence	7.89	5.77	1.67
	(10.03)	(4.25)	(1.28)
Log GDP per capita	-7.59	-2.51	1.97*
	(8.04)	(3.41)	(0.97)
Constant (or "Intercept")	96.97***	12.22	-21.48***
	(21.75)	(9.22)	(2.7)
Observations (or just "*N*")	15	15	14
R-squared (or fancily"R^2")	0.08	0.13	0.52

Note: adapted from Yi Dionne (2011), Table 3. Each column corresponds to a different model, and starts with the name of the dependent variable. Standard errors in parentheses.
* $p < .1$. ** $p < .05$. *** $p < .01$.

As indicated above, it is good practice to add a table summary after your regression output. The summary must report whether the results confirm or contradict the predictions of the models (your hypotheses), as shown by the full table summary written by the author:

> *Table summary:* Contrary to what I hypothesized, longer time horizons are associated with lower values on the API policy and planning score, meaning less AIDS intervention (API Policy). As predicted, longer time horizons are associated with higher government expenditures on health (Health Spending). However, no inferences can be made with this data about the role of executive time horizons on domestic spending for AIDS programs (AIDS Spending).

The extracts I underlined relate to the author's predictions. Her summary not only describes how her hypotheses did against the data, but also describes the parts of her research that did not yield any significant results. Note that the table summary interprets parts of the table that are not reproduced here.

13.5. Graphs

Section 9.1 describes how to add options to your graphs in order to make them more readable. As a rule of thumb, include graphs only when they convey more information than a well-formatted table.

Exported graphs should use either PNG or PDF format. Export can be performed in more than one way, so read carefully:

- The simplest way to produce a graph in Stata is to run a graph command and then save the results of the 'Graph' window by using the Save item of the File menu. Copying and pasting your graphs from Stata to your text directly is not good enough, as it does not create the actual graph file and skips the part where you can choose its format.

  This method is alright if your graph command appears in your do-file, and if the graph is stored in Stata memory along the way. To do so, add the **name()** option with the **replace** sub-option to the graph commands in your do-file that produce a graph included in your paper:

  ```
  * Histogram of the dependent variable, with saving options.
  hist dv, freq normal name(histogram_dv, replace)
  ```

- The safest way to export graphs is to include the **graph export** command instead of copying and pasting, as to create graphs on the fly, when your do-file is running. The example below illustrates the **name(, replace)** and **graph export** commands:

  ```
  * Histogram of the dependent variable, with saving options.
  hist dv, freq normal name(histogram_dv, replace)
  * Exporting histogram_dv.
  gr export histogram_dv.png, replace
  ```

Basic formatting rules then apply:

- **Be parsimonious.** Your do-file will produce more graphs than you will end up including in your final paper: most of these graphs are used for visual exploration, but need not be included in the final stage of analysis. Section 16.2 restates that point.

- **Explain your graph.** Do not consider your job done until the graph has a title, possibly a caption (as with the footnotes in a table), and a clear reference point in your text that cites your graph as either "Figure 1" or "Fig. 1" (use any, consistently), and explains your graphical results.

14. Assignment No. 1

Section almost entirely consistent with the course in its current form. Use the example and template files as well as the course slides for more exhaustive instructions.

Please make sure that you read this instruction sheet in full. The grade for this Assignment will refer to *every* instruction to assess your capacity to work in a quantitative environment, including *both* stylistic and substantive issues. Also read Section 13 on formatting your work before starting this Assignment.

Why work hard, if at all, on your Assignment?

- **Take it as a challenge**. Unlike jazz music, quantitative data are very much inert by nature and will require that *you* put some life into them. Explore, tabulate, describe it… Take possession of your data!
- **Something important is happening**. Quantitative data are currently affecting both our vision of society and the core tenets of social science. Join the scientific revolution!
- **Your work is cumulative**. You will be able to use this Assignment to write up your final paper, which underlines the *absolute* need for *regular* work and practice during this course. Believe me: other methods *will* fail.

Welcome to the world of quantitative methods, and good luck!

14.1. Research design

Start by describing your **research question** and **hypotheses**, using approximately 15 lines of text. While this step would require consulting the scientific literature on your research topic as to derive your hypotheses (or **predictions**) from the findings of previous studies, you do *not* have to produce a literature review for this course, and should instead use your acquired knowledge of the topic as well as your intuitive predictions.

Here are a few examples of potential topics, in addition to those sent by email or mentioned in class:

- Differences across time and/or countries in **attitudes** toward: religion, inequality, homosexuality, marriage, immigration… The European Values Survey and the World Values Survey hold a large sample of questions on these themes and on many others.

  Use your general knowledge and curiosity to come up with questions. Who are the individuals who declare being optimistic about their future? How does income and health influence other aspects of wellbeing? Is public opinion split on topics such as climate change or euthanasia?

- Changes in **political factors** such as party identification and left/right political cleavages, political regimes, voting systems… The political science literature holds virtually thousands of ideas in that domain. Start by checking the ICPSR data repository on such topics.

  Remember that polling data is produced for many political events and policies. Who supported the invasion of Iraq, and who would support military intervention in Iran to stop nuclear proliferation? Is there public support for the use of torture when interrogating terrorists?

- **Social determinants** of income inequality, poverty and crime rates, health, educational attainment and so on, at a geographic scale for which data are available. The European Social Survey documents some of these aspects for Europe, but there are thousands of datasets available.

  As an example, think of how some issues are unequally distributed among age groups and between men and women, such as drug abuse, career advancement, homicide, geographic mobility, traffic injuries, unauthorised digital file-sharing, depression, alcohol consumption, etc.

- **Observed effects**, both positive and negative, of entry in the European Union or transition to democracy, or… on demographics, life expectancy, economic performance, crime rates, green technology, social mobility… Evaluations and experiments are conducted on all sorts of events.

  To take a few examples, fascinating academic studies have documented the effects of the Cultural Revolution on mental stress and cancer rates in China, on the effects of class size on educational performance, or on the benefits and costs of public-private partnerships.

- Be imaginative! For example, Jane Austen wrote in *Pride and Prejudice* (1813): "**It is a truth universally acknowledged**, that a single man in possession of a good fortune, must be in want of a wife." To what extent was Jane Austen right? (Thomas Hobbes is also a great source of research questions, but they tend to be much more pessimistic about human nature than Jane Austen was.)

Again, be imaginative: your personal interest and ideas are crucial to the task. Data are collected and made available at all levels of society, from municipal districts in urban studies to the whole planet in international relations, on all sorts of topics. Try to review a maximum of options, but **know your limits**: some (interesting) questions are out of our range of skills for this course. Do not use time series data, and select a continuous or ordinal dependent variable.

A real-life example of model description goes like this. Take a close look at the scientific style of the description, especially when it comes to the description of predictions and variables, since you will be borrowing from that style of writing in your own Assignment:

> The dependent variable in the model is the size of government. The concept is measured, following the example of several previous studies (e.g., Alesina & Perotti, 1999; Poterba & von Hagen, 1999), by total government outlays as a percentage of GDP. The measure has considerable face value. However, to test the robustness of the findings, a second model will be estimated using total revenue of all levels of government as a percentage of GDP (Cameron, 1978; Huber et al., 1993) as the dependent variable.
>
> … However, there are also several control variables that need to be included in the study. It has been argued that the size of the public economy of a country is determined by its economic openness (see Alesina & Wacziarg, 1998; Cameron, 1978; Rogowski, 1987). A similar statement has also been made in reference to the size of the welfare state (Katzenstein, 1985). The logic behind the argument is the following: If more open countries are more vulnerable to exogenous shocks such as shifts in their terms of trade with world markets and if government spending is capable of stabilizing income and consumption, then more open countries will need a larger government to play a stabilizing role. The economic openness control variable is measured by the ratio of imports and exports to the GDP. Institutional models of the size of the public economy have also stressed the impact of the federal, institutional structure of government (Cameron, 1978; Schmidt, 1996)… Therefore, one might expect nations with a federal structure of government to have larger public economies than countries with a unitary structure. Linked to this explanation is another aspect of the institutional structure of government: the degree of fiscal decentralization (Cameron, 1978). In accord with the previous statement, the relatively decentralized nations should have a larger scope of public economy… In any event, despite the confusion about the direction of the association, federalism has been identified as an important explanatory variable for government size. Lijphart (1999) created an index measure of federalism and fiscal decentralization ranging from 1 to 5. This measure will be included in the analysis as a control for the effects of government structure.
>
> **Source**: Margit Tavits, “The Size of Government In Majoritarian And Consensus Democracies”, *Comparative Political Studies* 37(3): 340–359, 2004 (footnotes removed, highlighted text added).

You should have noticed that the hypotheses are often **directional predictions**, which are often written as positive relationships such as: “if *x* increases, *y* is also likely to increase, and conversely”, or as negative relationships, as in: “*x* and *y* are expected to be inversely related, with *y* being likely to decrease when *x* increases, and conversely”. The course slides hold advice on hypothesis writing.

14.2. Dataset description

Add to your Assignment a description of the **study** and **dataset** that you will be using to address your research question. For example, the sampling strategy and variable description for the NHIS data that we use to inspect the Body Mass Index of U.S. residents would go as such:

> The National Health Interview Survey (NHIS) is a multipurpose health survey conducted in the United States by the National Center for Health Statistics, which is part of the Centers for Disease Control and Prevention (CDC).[1] It uses a multi-stage probability sample that includes stratification, clustering and over-sampling of racial/ethnic minority groups; it forms a representative sample of civilian, non-institutionalized populations living in the United States, and its total sample population is composed of 251,589 individuals from the 2000–2009 survey years, which was reduced to $N = 24{,}291$ by subsetting the data from the 2009 survey year.
>
> The dependent variable will be the Body Mass Index (BMI) of the respondents, which we constructed from available measures for weight and height (variable bmi). We also recoded the BMI variable into its seven official categories, which range from severely underweight to morbidly obese (variable bmi7).
>
> The independent variables are sex, age, education level, health status, physical exercise (vigorous and leisurely activity), race and health insurance status. We expect to find higher average levels of BMI for males, for older and less educated people, as well as for racial groups that are either less educated or less likely to be covered by health insurance, which is why we included race as a control variable. We expect BMI to decrease with wealth, education and frequent physical activity.
>
> [1] Source URL: http://www.cdc.gov/nchs/nhis.htm.

As mentioned in class, data discovery is a skill in itself, and a time-consuming task moreover. Identifying and fully describing a dataset is never a question of a few minutes: you will need at least a couple of hours to locate, download and explore a selection of datasets in order to make your final choice.

If you have absolutely no previous experience with quantitative analysis, you should begin with the European Social Survey (ESS) if you are interested in measuring social attitudes. If you are more interested in country-level data on political and economic topics, the recommended datasets is the Quality of Government (QOG) dataset.

Include some critical perspective on the data. Your data are limited in precision, due to issues of measurement: for instance, gross domestic product (GDP) is a measurement (or proxy) of national wealth that does not reflect inequalities in income concentration.

Briefly document any issues with variables and variable measurement in a few lines, after reading from the codebook.

Check how your dataset is constructed. Typically, your dataset should hold homogenous **units of observations in rows**, **variables in columns**. It should also contain only **one year of cross-sectional data**. Use the subsetting procedures described in Section 7 if your dataset contains data over several years.

Your description should cover the **sampling strategy** used by the survey, its **unit of analysis** and the **size** of the sample (its total number of observations). Additionally, you should provide the full **source** for your data (authors, URL...). All in all, your dataset description should not range over 10 lines of text. Writing these lines will require that you spend some time reading from the documentation that comes with your dataset.

A real-life example of dataset description goes like this. Again, take a close look at the scientific style of the description:

> To investigate the sources of ethnic identification in Africa, we employ data collected in rounds 1, 1.5, and 2 of the Afrobarometer, a multicountry survey project that employs standardized questionnaires to probe citizens' attitudes in new African democracies. The surveys we employ were administered between 1999 and 2004. Nationally representative samples were drawn through a multistage stratified, clustered sampling procedure, with sample sizes sufficient to yield a margin of sampling error of ±3 percentage points at the 95% confidence level. Our data consist of 35,505 responses from 22 separate survey rounds conducted in 10 countries: Botswana, Malawi, Mali, Namibia, Nigeria, South Africa, Tanzania, Uganda, Zambia, and Zimbabwe.
>
> **Source:** Ben Eiffert, Edward Miguel and Daniel N. Posner, "Political Competition and Ethnic Identification in Africa", *American Journal of Political Science* 54(2): 494–510, 2010 (footnotes removed, highlighted text added).

14.3. Variable description

Before starting your variable description, make sure that your dataset holds at least 30 valid (non-missing) observations for your independent and dependent variables, otherwise you will need to identify other variables to run a statistically robust analysis. Use the **su** and **fre** commands to run these checks.

Start by describing your **dependent variable** (the variable that your research will aim at explaining) in detail. Your dependent variable *must* be either continuous or ordinal (or binary if you can handle a bit more theory in later sessions). Check with the codebook of the study for the exact wording of the question if it comes from a social survey, or check for the definition of the indicator if it comes from a country-level study. If the variable is measured on an ordinal scale, describe the range of possible values.

Always check the precise coding of your variables. For example, if you have selected an ordinal variable that is coded in reverse scores, such as 1 for "Best" and 5 for "Worst", you can install and use the **revrs** command to reverse it into an intuitive scale. Also make sure that you how missing values are coded for each of your variables (the natural Stata coding will be "**.**").

A real-life example of dependent variable description goes like this. Again, take a close look at the scientific style of the description:

> The main dependent variable we employ comes from a standard question designed to gauge the salience for respondents of different group identifications. The question wording [is] as follows:
>
> > "We have spoken to many [people in this country, country X] and they have all described themselves in different ways. Some people describe themselves in terms of their language, religion, race, and others describe themselves in economic terms, such as working class, middle class, or a farmer. Besides being [a citizen of X], which specific group do you feel you belong to first and foremost?"
>
> As noted, a major advantage of the way this question was constructed is that it allows multiple answers and thus permits us to isolate the factors that are associated with attachments to different dimensions of social identity. We group respondents' answers into five categories: ethnic, religion, class/occupation, gender, and "other."

Note: in this example (taken from the same source as above), the dependent variable is a nominal variable, which is strictly categorical and not continuous. For this course, you should not use categorical variables, but rather focus on continuous or on ordinal variables (which we will treat as continuous).

Continue your dependent, continuous variable description by **describing its distribution** and potentially transforming it to a more normal distribution, using the procedures shown in class and covered in Section 9.

Finish by briefly describing your **independent variables**, using tables of **summary statistics** (see Section 9). No graphs should be required for these variables.

14.4. Programming

Your first Assignment must come with a do-file. You will have to write the do-file and then run it (execute it) to produce a log file, as described in Section 3 and Section 3.6 in particular.

Your do-file should not contain any errors: it should run until its end without stopping (breaking) because of a mistake in your code. This will require that you test your do-file multiple times to debug it (correct mistakes).

14.5. Reminders

- **Do not panic**. Work regularly, and you should be fine. It is foreseeable that some aspects of either statistical analysis, quantitative methods or Stata procedures will get you lost, especially if you are learning about these topics for the first time. If you work every week along the basic course schedule described in Section 1, you *will* be fine.
- **Always read the replication sets** from each course session, as provided on the course website. The course do-files show you *every single* procedure that you might need to use for your own research, which means that the answers to your problems are probably just a few clicks away from where you are standing right now.
- **Get the formats right.** Your email should contain all your files, and should be sent along the instructions mentioned in Section 13. Following these instructions really is a standalone skill. Basic psychology teaches that grading instructors like it a lot when students follow all instructions, and the reverse statement is likely to be also true.

Again, good luck, and see you soon!

15. Assignment No. 2

Section almost entirely consistent with the course in its current form. Use the example and template files as well as the course slides for more exhaustive instructions.

Please make sure that you read this instruction sheet in full. The grade for this Assignment will refer to every instruction in order to assess your research skills in a quantitative environment, including both stylistic and substantive issues. Also read Section 13 on formatting your work before starting this Assignment.

15.1. Corrections

Assignment No. 1 was composed of a text file and of a do-file, and was the first draft that you submitted towards your final paper. Assignment No. 2 follows the same logic and is as much about extending your analysis as it is about improving your first draft. Assignments in this course are not standalone test grades: they are cumulative writings that monitor your advancement with your project.

Assignment No. 2 builds on your previous Assignment and will bring you just one step from writing up your final paper. Before doing so, **it is essential that you fully revise Assignment No. 1 before 'upgrading it' to Assignment No. 2.** Please refer to Section 14 and to the feedback on your Assignment to make sure that you have done so.

Here are some common mistakes that often appear in early do-files, and which you should immediately correct:

- **Analysing ESS data without survey weights.** If your research design relies on data from the European Social Survey, you will need to weight the data as indicated in its documentation.

  Simply put, you should insert the **svyset [pw=wgt]** command immediately after loading your data with the use command. If your research design covers all European countries, then you need to generate a product of design and population weights to weight respondents properly: insert **gen wgt=dweight*pweight** before the **svyset** command.

  If you are working on only one country, or if population (country) weights are irrelevant to your research design, simply replace **wgt** by **dweight** in the **svyset** command above and ignore the **gen** command.

- **Using fre for continuous variables while you should be using su instead.** The most common mistake at the level of descriptive statistics is to use the **fre** command when the summarize (**su**) command is appropriate.

If you are using **fre** to count valid observations and missing data, you should be using the **codebook** command with the **c** option instead, which also gives you summary statistics and variable labels, as in this example:

```
. codebook agea gndr, c

Variable      Obs Unique      Mean  Min  Max  Label
-------------------------------------------------------------------------------------------------------

agea        50996     87  47.57369   15  123  Age of respondent, calculated
gndr        51123      2  1.541518    1    2  Gender
-------------------------------------------------------------------------------------------------------
```

Note that in this example, the mean value of the **gndr** variable is irrelevant, as it was computed from arbitrary values assigned to gender in this categorical variable.

If you are drowning in more serious problems with missing data than just a few observations to drop, you should turn back to recoding your missing values, as explained in Section 8.2.

Finally, do not forget about the **count** command and the if **mi()** or if **!mi()** logical operators. Those often come in handy when you are thinking about selecting variables for crosstabulation or association tests.

– **Assignment No. 1 should be close to three pages.** Assignment No. 2 will add to them, but before starting, you need to check whether your data and variable descriptions are concise enough. Figures and tables might have pushed you slightly over, up to four pages or even five pages if you chose a large font or have a long table of summary statistics. But there is hardly any reason to push Assignment No. 1 over five pages.

  Limit figures and tables in Assignment No. 1 by using a single table for summary statistics, and a single graph for the histogram of your dependent variable: you are not expected to include other graphs like variable transformations from the gladder command at the level of descriptive statistics. Assignment No. 2 will add more figures and tables.

  Copy-pasted Stata output does not count as text. Your text should not include Stata commands, and your tables should not be Stata output copied and pasted in your text. Section 13.4 explains how to format summary tables, and the tabout, tabstat and mat2txt commands shown in the template do-file for Assignment No. 1 will export your results for formatting with Microsoft Office.

– The following paragraphs summarize what your corrected version of Assignment No. 1 should be telling its reader(s):

  1. Introduction: (i) one or two paragraphs to state clearly the research question, explain its relevance to the general public and with respect to previous literature on the subject; (ii) one paragraph or two to formulate your argument in terms of clear and testable hypotheses along with an explanation/justification for what you predict.

2. Data: one paragraph that describes the dataset used in your study, describes and justifies your choice of countries to compare, and mentions the final sample size after deletion of missing cases.

3. Variables: (i) one paragraph that describes your dependent variable in terms of its summary statistics –mean, standard deviation, median, minimum, maximum– and its distribution, shown by a histogram; (ii) one paragraph or two to cite and explain the relevance to your research question and hypotheses of your choice of independent variables along with a description of their distribution using either proportions–if the variables are categorical (binary, nominal or ordinal)–or summary statistics–if the variables are truly or sufficiently pseudo-continuous.

4. Analysis: one paragraph for every separate association between your DV and each of your IVs. This section is developed in Assignment No. 2.

5. Conclusion: one or two paragraphs that summarize your results with regard to your general argument and research question.

15.2. Association

In this Assignment, you test for independence between your dependent variable and each of your independent variables. The objective is to identify which independent variables are worth keeping for the final regression analysis. The rule of thumb is to keep only variables that have a statistically significant association with your dependent variable.

To that end, you need to review course material on bivariate tests: replicate each session using the do-files, read through the course handbook chapters and slides, and read Section 10 as well as various parts of Section 11 for correlation and simple linear regression.

As you will see, there are different types of tests of bivariate association: chi-squared tests, *t*-tests, correlation and simple linear regression. The choice of the right test depends on the type of the variables. There are three basic cases:

- **When both variables are categorical**, use the Chi-squared test. Produce a table with column or row percentages, comment on the relationship between the variables, and interpret the statistical significance (*p*-value) of the Chi-squared statistic.
- **When one variable is continuous and the other is categorical**, use the *t*-test. To that purpose, the categorical variable needs to be recoded into a binary (0/1) variable in order to compare the mean value of the continuous variable in each group. Comment on the differences in means by interpreting the *p*-value for the null and each directional hypothesis.

- **When both variables are continuous**, use a simple linear regression. After looking at the number of observations used in the model, interpret the *F*-statistic, its *p*-value and the *R*-squared. This first step establishes how much statistical power and fit your model provides.

  When you are done understanding the overall fit of your model, turn to the independent variable: identify significant coefficients by looking at standard errors, *t*-values and *p*-values, and read their direction and magnitude, as covered in Section 11.

Note the following special cases:

- **The Chi-squared test requires a minimal number of cells counts:** if your cross-tabulation shows a table where some cells fall below 5 observations, you should use the Fisher's exact test instead, as you should with '2 x 2' contingency tables, regardless of the cell counts. Fisher's exact test will be computationally more correct in both cases. Its test statistic reads as if it were a *p*-value.
- **Interval or ordinal categories offer you a choice of strategies:** you can treat them either as categorical or continuous data. However, if you decide to treat them as continuous and wish to measure the association of that variable with another continuous variable, you need to first make sure that there is a linear relationship between the two variables. To check this, you need to display the relationship using a scatter plot. If it shows an approximately linear relationship, you can then use a simple linear regression.

Interpret, usually in two or three sentences at most, each of the tables where you detected a statistically significant relationship between two variables. Report relevant statistics in brackets within your sentences, such as the *p*-value for a Chi-squared test, Fisher's exact statistic (which reads as a *p*-value itself), or the *p*-value of a *t*-test or a proportions test. When reporting correlations, report Pearson's *r* and its *p*-value; do not forget to report the intensity and direction of the correlation. If you are dealing with several statistically significant correlations within your choice of variables, use a correlation matrix to present them.

In your do-file, you have to test all your independent variables, but you do not have to produce either tables or graphs in your Assignment for cases where the null hypothesis was retained (when no association can be identified under your alpha level of significance). Identically, you should be selective when testing for interactions between independent variables: produce these tests only if there is a substantive justification to do so, as when you *control* for age while testing the association between an independent – *explanatory* – variable like household income and a dependent variable like the number of children in the household.

Remember to discuss the statistical significance and substantive importance of all bivariate associations. If you are comparing the behaviour of your DV across countries, regions or socio-demographic groups, then you should focus here on discussing differences across those groups. Use as many separate tables as needed for crosstabulation and, if useful, use figures to illustrate your results.

15.3. Regression

Assignment No. 2 also covers simple linear regression, which comes as a natural complement to correlation. Section 11 covers both simple and multiple linear regression, but you should limit yourself to simple linear regressions with only two variables at play for this Assignment.

Contrarily to the methods we used while covering association and correlation, regression goes beyond merely detecting relationships between variables: it is a modelling technique that provides estimations of the model parameters. When reporting on the regression coefficients and intercept, you should provide your own interpretation of that model, as illustrated in class.

Including a scatterplot showing the linear fit between your dependent and independent variables can serve to display your simple linear regression. The graph should not be used as mere illustration: it refines the analysis by providing an informative visualization of the relationship between your variables, from which you can extract additional observations: is the relationship truly linear, or is it curvilinear like an exponential (quadratic) relationship? Does the scatterplot reveal visually identifiable outliers, what observations do they stand for, and can you explain why they deviate so much from the linear fit? (A classical example is Luxembourg, which always stands out as soon as GDP per capita is involved as an independent or dependent variable, because its residents are outstandingly wealthy in comparison to virtually any other country.)

15.4. Reminders

Here are a few reminders as to how you should be organising your work. Most of it will sound like old news to many of you.

- **Replicate, replicate, replicate the course sessions.** To minimize the risk of using the wrong command, test or graph, the easiest thing is to replicate the last course session every week. The course website provides every single file used in class, so that you can run the do-files again.

- **Your do-file should be replicable.** When grading, we must be able to run your analysis again, by running (executing) the do-file. This implies that you send a do-file that contains no errors, along with your original dataset, just as the course website provides both so that you can replicate course sessions at home.

- **Write as if you are writing a research paper.** Your Assignment is the draft for your final paper: it should be written as an 'advance copy' of it, with correct English, full sentences, and clear explanations about what you are doing, what you are finding, and what you think about it.

If you follow these instructions, bits and pieces of your paper should read as this completely fictional example, which illustrates how to translate a battery of tests into tables, figures and, most importantly, interpretations:

> The association between income and age groups, which reported a statistically significant relationship with the Chi-squared test ($p < 0.01$), was also observable when using continuous measures of both variables. Specifically, the correlation matrix (Table 1) reports a strong, positive correlation ($r = 0.45$, $p < 0.05$) that confirms their interplay within the sample population. Furthermore, as shown in Figure 1, their relationship is quasi-linear, except at the highest values of both, where the linear fit is slightly less truthful to the data. The regression coefficient can be understood as follows: from the age of 25 onwards (the minimum age of the respondents in our sample), income, starting at approximately at $22,000 per year, increases quasi-linearly by $700 each year on average, which reflects the effect of career advancement and enhanced employment opportunities on wages, as well as other factors that might have to do with capital accumulation.

When you are done with this Assignment, the last step towards your final paper will consist in building a multiple regression model and a final interpretation of your research question, all in the form of a standard research paper. Good luck, and see you soon!

16. Final paper

Section still in draft form, but a good restructuring of all assignment sections will help to make clear what should be mentioned here.

Your final paper is the finish line, the ultimate point, the very last episode of that epic quest of yours. Fortunately, there is no dragon to beat. However, there is a paper to write: if your last draft does not already read like a draft *paper*, you might have several hours of work ahead.

In many ways, you have already cut off many heads off the Stata hydra: by finding and preparing your dataset, by producing descriptive statistics, by running association tests and by thinking, again and again, about your research design. Finally, the one last step that has definitely revealed the worth of your work has consisted in running a linear regression model that has assessed the predictive value of your independent variables over your dependent variable.

Your final paper is primarily a reorganization of your work, which means that you will, again, be revising previous assignments in order to suppress any potential ambiguity in your wording or ideas, add what you might have omitted on first submission, and correct any mistakes that was flagged so far.

Rewriting will represent roughly 75% of your work on your final paper (increase that estimate if your previous assignments came back with a grade below 4 and/or lots of instructions for revision). The last 25% consist in checking your do-file carefully, reorganising it, producing a log file and sending them all by email, as with your drafts.

16.1. Structure

Your paper follows a scientific style of writing as well as a scientific breakdown of sections. Read this section even if you have some experience with writing up under these conventions, and if you do not, read it with extra care, as it will turn out useful not only for this course but also for many others.

First, your paper needs to be written in scientific style, which means that the writing will be as simple as possible and only as complex as necessary. Some additional guidelines apply:

- **Because the paper reflects what you know and did, do not use any term or argument that you cannot explain yourself**. For instance, your paper will not reference "a sensitivity analysis of cluster sampling over high-resolution data".
- **Without exception, reference every single item of your paper that you did not create yourself**. This applies to arguments, observations, and also to data: your dataset needs to be fully referenced. The online source of your dataset will usually give an example citation for it.

- **Just as with any academic work, your paper is expected to have been carefully proofread**, up to the point where the read should not detect more than one occasional spelling mistake on every page or so. Spell-check your paper and check your sources for names, acronyms, etc.

Second, your paper should follow an outline analogous to the 'IMRAD' model, which can be adapted to this course as follows (note that the example extracts are fictional and do not represent any real study; real examples are provided later on in this instruction sheet).

- Your **Introduction** spells out your research question, outlines the variables of interest, and offers your hypotheses (from Assignment No. 1).

  e.g. "I study the relationship between extreme-right voting and socioeconomic status (SES), as measured through occupation, income and educational attainment. I also control for age, gender, ethnic origin and religious beliefs.
  My hypothesis states that extreme-right voters sit at the bottom of social hierarchies within their age and gender groups, and will therefore score lower on all measurements than other members of the social categories to which they belong to."

- Your **Methods** cover your data and variables. The actual method of your paper is ordinary least squares, or OLS, multiple linear regression.

  e.g. "The study uses the last edition of the British Election Study, a survey conducted by […] in May 2010. The dataset, which is available at […], contains […] adult respondents. The data were collected through face-to-face interviews and the method of sampling was […].
  The data were searched for significant correlations, which were then explored through simple and multiple regression analysis in order to identify linear relationships between the variables of interest."

- Your **Results** report your independence tests (from Assignment No. 2) and the results of your linear regression model.

  e.g. "Extreme-right voting does not concern a majority of the population: as Figure 1 shows, only a small fraction of British voters declared voting for any of the extreme right political parties.
  After observing a significant correlation between […] and […], we can state with confidence that extreme-right voting is higher in lower income groups. Figure 2 below plots this relationship for each gender group.

  In parallel, our regression of political participation against income also shows that lower income groups participate significantly less in elections. The results of that regression are reported in Table 1. The high R-squared (.56) suggests that income is a major factor at play here."

- Your **Discussion** concludes on your project, and includes criticism of both your data and your predictions.

  e.g. "Although the project succeeded at showing that income and educational attainment are predictors of extreme-right voting, the weak association suggests that other important factors come into play in explaining this relationship. Furthermore, our hypothesis that religious behaviour would have a significant impact on voting was not confirmed by our analysis. The small sample size for our independent variables measuring religiosity limited the significance of our tests and constitutes an important drawback of our study."

16.2. Limits

- **Paper**. Your research paper should fit on a maximum of 10–12 pages, using the standard format defined during our last course session. There is no length limit for the number of lines of code in your do-file, but anything outside of the 100–400 range will probably indicate something strange.
- **Graphs**. Include only relevant graphs that help to understand the relationships mentioned in your text. Choose the type of graph carefully, as explained in class and in several sections of this guide.

  The feedback on Assignment No. 2 will usually include some notes on which graphs to include, but the simplest way to know whether or not to include a graph in your final paper is to judge whether it brings anything of value to the rest of your analysis; if the answer is anything but 'absolutely yes', do not include the graph.
- **Tables**. Do not include tables except for your most significant outputs: summary statistics, correlation matrix, and regression models. For other significance tests, report the results (and especially the p-value) directly in your text. Presenting and exporting tables is covered in Section 13.4.

16.3. Example

The following extracts are taken from a recent working paper published by the United Nations Development Programme, which is used to illustrate what a research paper using quantitative data and methods should contain.

These are the opening lines of the text:

> **Introduction**[1]
> This paper examines the variation across countries and evolution over time of life expectancy.

> The opening section examines the impact of national income, measured as GDP per capita in PPP, in Preston and augmented Preston regressions. Rather than focus only on recent cross-sections since 1970 or so we use the available historical data going back to the beginning of the 20th century (the data are taken from the series created for the GAPMINDER application and are described in the data appendix). This long-run focus allows us to establish several basic facts about the relationship.
>
> …
>
> [1] Many thanks to comments from…

Source: Lant Pritchett and Martina Viarengo, "Explaining the Cross-National Time Series Variation in Life Expectancy: Income, Women's Education, Shifts, and What Else?" UNDP Research Paper 31, October 2010.

The authors immediately inform the reader about the dependent variable, life expectancy, and then submit the first independent variable, income, and its proxy (the means of measurement for it), which here is GDP per capita in PPP.

The method of analysis – some form of regression – is also mentioned, and the data are described by providing the source and the time period covered. It is good practice to store a detailed description of the data sources in an appendix, which the authors do (see pages 60–63 of their paper).

The first footnote acknowledges some colleagues for their help with writing the paper: if you have received help from anyone else than the course instructors, including other students from the class or people who you might have emailed about accessing your dataset, you should acknowledge their help.

The text continues as such:

> First, there has been a strong cross-national relationship between income and life expectancy for as far back as one can take the data. In the simple double natural log Preston curve (life expectancy regressed on GDP per capita) the R-squared for the 21 countries with data was as high as .8 as early as 1927 and was at that level through the pre-World War II period. The modern data sets with over 150 countries begin in 1952 and have availability every five years and in that data there has been a high and rising R-squared roughly ever since (once one controls for the AIDs affected countries).

This paragraph should be almost fully understandable now that you have completed the course. It mentions the sample size, the variables used by the authors in their hypothesis test (life expectancy and GDP per capita), as well as the shape of the distribution revealed by this hypothesis (a natural logarithm).

The extract also show that important aspects of your analysis should be mentioned directly in the text, like the R-squared or the control variables (here, the authors set aside the units of observation – countries – with high infection rates of HIV/AIDS).

The only part that requires further explanation is the Preston curve, which is a classic finding by Samuel H. Preston: when regressed onto GDP per capita for cross-sectional data, life expectancy follows a natural logarithmic distribution. Learn more on Wikipedia: http://en.wikipedia.org/wiki/Preston_curve.

16.4. Reminders

- **Normalise your files and emails**. Files sent without normalisation at this stage run the unacceptable risk of either delaying the grading process or (even worse) getting lost in dozens of other emails. You have almost all done very well with this, for which you earn infinite gratitude from virtually every grader in the world; please do so one last time.
- **Unlike deadlines for midterm assignments, the deadline for the final paper is completely intangible**, as it corresponds to the last days before which grading can be performed in acceptable conditions for formal submission of the grades to the Sciences Po administrative units. Late work will therefore be dismissed.

The deadline will appear in a class email along with additional guidance.

Good luck, and well done!

We wish you the best of luck in all your future endeavours. Please submit some feedback on the course, and let's meet later on for drinks and/or food.

Datasets:

ESS	European Social Survey (used in Sections 6 and 8) 4th wave (2008) http://ess.nsd.uib.no/
QOG	Quality of Government (used in Sections 9, 10 and 11) Most recent update (6 April 2011) http://qog.pol.gu.se/
NHIS	National Health Interview Survey (used in Sections 7, 9 and 10) Last survey year (2009) http://www.cdc.gov/nchs/nhis/

Commands: (in progress…)

Applied examples:

This version: 23 February 2012.

Written using Stata 11/12 SE on Mac OS X Lion.

Typeset in Linotype Syntax and Menlo.

I rest my head on 115
But miracles only happen on 34th, so I guess life is mean
And death is the median
And purgatory is the mode that we settle in

– Cannibal Ox, “Iron Galaxy”