Web Scraping and APIs

DSIER [/dɪ'zaɪər/] — Summer 2023

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What skills are demanded in Germany ?

You can use conventional database, for example:

- Employeer-employee database (access is limited)
- ONET database for skills content
- maps German occupations classes (KdB) to ONET classes

And look at the skill-content of newly created jobs

Job offers online

You can create your own data starting from job posting online



Right click the page and "Inspect" the page

Type of occupations HTML source of this link

```
<diy class="heading4 color-text-primary singleLineTitle tapItem-gutter">
   <h2 class="iobTitle iobTitle-color-purple">
     <a aria-label="full details of RN Specialty Practice Clinic" class="jcs-JobTitle" data-hide-spinner="true" data-hiri</pre>
       <span title="RN Specialty Practice Clinic">
         RN Specialty Practice Clinic
<div class="heading6 company_location tapItem-gutter companyInfo">
  <span class="companyName">
    Androscoggin Valley Hospital - NURSING - PHYS...
<div class="companyLocation">
  Berlin. NH 03570
 <div class="heading6 tapItem-gutter metadataContainer noJEMChips salarvOnlv">
  <div class="metadata estimated-salary-container">
    <span class="estimated-salarv">
     <svg aria-hidden="true" aria-label="Estimated $63.9K to $80.9K a year" fill="none" role="presentation" yiewbox="0 0</pre>
```

Look across divs (generic block element) and within "h2" match the attribute "class":"jobTitle jobTitle-color-purple" and extract content in the "span" (in-block element)

> jobs %>% head()
[1] "RN Specialty Practice Clinic" "Communications Assistant"
[3] "Stocker" "Director of Rehabilitation/DOR - Gorham, NH"
[5] "Nursing Unit Aide" "Administrative Assistant to the Superintendent of School

Strengths Weakness

Strengths

- You can better identify demand (matches confounds supply characteristics)

Strengths

- You can better identify demand (matches confounds supply characteristics)
- Rich and customizable



Weakness

- Incomplete and Non-Representative



Weakness

- Incomplete and Non-Representative
- Time dimension
- Unless you are Google, might not be easy to web scrape

Find data that does not exist elsewhere

- 1. Data is generated by contributions from large user base (Uber, Amazon)
- 2. Data is itself just measurement of activity on website (forums like Reddit) or network (Facebook, LinkedIn, WeiBo)

Re-arrange data in more convenient format

- 1. Data from many sources aggregated on one site (Wiki on Civil Wars)
- 2. Parsing techniques of webscraping can also be used when data provider gives you data in inefficient form (ex: max 1000 spreadsheets)

Literature using online data I

- Job posting:
 - Kuhn, P., Shen, K. (2013). Gender discrimination in job ads: Evidence from China. QJE
 - Deming et al. (2018). Skill requirements across firms and labor markets: Evidence from job postings for professionals.
 - Javorcik et al. (2019). The Brexit vote and labour demand
 - Acemoglu et al. (2020). Al and jobs: Evidence from online vacancies.
- Rental and real estate:
 - Halket and Pignatti (2015): scrape Craigslist to study US rental market
 - Horn, K., Merante, M. (2017). Is home sharing driving up rents? Evidence from Airbnb in Boston. Journal of Housing Economics
 - Yilmaz, O., Talavera, O., Jia, J. (2020). Liquidity, seasonality, and distance to universities: The case of UK rental markets

Literature using online data II

- Online vs offline prices:
 - Chevalier et al. (2003). Measuring prices and price competition online: Amazon.com and BarnesandNoble.com.
 - Ellison, G., Ellison, S. F. (2009). Search, obfuscation, and price elasticities on the internet. Econometrica
 - Cavallo and Rigobon (2015): "Billion Prices Project"
 - Cavallo, A. (2017). Are online and offline prices similar? Evidence from large multi-channel retailers. (AER)
 - Gorodnichenko, Y., Talavera, O. (2017). Price setting in online markets: Basic facts, international comparisons, and cross-border integration. American Economic Review,
 - Cavallo, A. (2018). Scraped data and sticky prices. RESTAT
- Consumption behaviors:
 - Baye, M. R., Morgan, J. (2009). Brand and price advertising in online markets. Management Science
 - Davis and Dingell (2016): use Yelp to look ethnic segregation in consumption

Where to start

- Does this data already exist?
- Would the site be willing to give you the data or partner with you?
- Do they have an API?
 - .. if not, extract website data yourself!

How to continue

- If the data is user-contributed, who are the users?
 - Is selection bias going to be a big problem? (eg: which houses are rented on craigslist, who lists on eBay, who posts on social media?)
- Does the site customize the data based on characteristics of the browser? Can you deal with this ?
 - location of IP address, time of day, frequency of visits, ...)? Fake cookies?
- Do you need a panel?
 - If the website changes or is pulled down, could you write a paper with just a few periods?
- How much measurement error can you tolerate in your research design?
 - if you assemble a panel and a few observations per period fail due to impartial scrapes, is this manageable?

Overview of today

- 1. Main economic data sources available
- 2. How to use an API to access data
- 3. Basics of web scraping

Applications

1. The billions Prices Project

Conventional Sources of Data in Economics

- IMF data World Economic Outlook database, time series on a wide number of countries for macro aggregates.
- World Bank WDI the World Development Indicators
- FRED US economy, such as GDP, interest rates, financial indicators and monetary aggregate
- OECD: data from the Organization for Economic Cooperation and Development.
- UNCTAD: trade and development data, including COMTRADE
- Eurostat aggregates data from European stats offices and more
- CEPII: trade related database: BACI better version of COMTRADE, MACMAP for tariffs, Geography variables (gravity etc)

- EUKLEMS: it is a project that provides industry-level time series data for developed countries in a consistent accounting framework.
- Penn World Table: Real national accounts converted in dollars to provide unified framework and comparability.
- Policy Uncertainty: the Economic Policy Uncertanty index for developed countries, for US it provides also components of the series, which is both news- and data-based. Authored and maintained by Baker, Bloom and Davis.
- Real-time data: the Philadelphia Fed provides real-time data for a number of policy-relevant variables, good for estimations of policy rules in the US economy.

- BIS: the Bank of International Settlements provides financial data on a set of countries, along a wide range of dimensions.
- BLS: data on the US economy, also providing granular breakdowns at occupational and frequency levels
- Groningen Data: The GGDC 10-Sector Database provides a long-run internationally comparable dataset on sectoral productivity performance in Africa, Asia, and Latin America.

API

Application Programming Interface: online tool to access info or download raw data



API Data format

- 1. XML
- 2. JSON
- 3. CSV, RSS, etc.

API Data format

1. XML (Extensible Markup Language) - Node structure

```
<job-offers>
<job>
<job-title> Data Analyst </job-title>
<location> Berlin </location>
<benefits>
<salary> 50k </salary>
<remote> yes </remote>
<type> full-time </type>
</benefits>
</job>
</job-offers>
```

<iob-title> Data Analyst </iob-title> value Node closing tag Node opening tag

API Data format

1. XML

2. JSON - Key-value pairs structure

```
{"job-offers": [{
    "job-title": "Data Analyst",
    "location": "Berlin",
    "benefits": {
        "salary": "50k"
        "remote": "yes"
        "type": "full time"
    }
]}
```



- List of Economic Institutions providing APIs
- Financial data: Tiingo, Bloomberg
- Github page with all sort of free (at least partially) APIs

 API
 Description
 Auth
 HTTPS
 CORS

 API Title(Link to API documentation)
 Description of API
 Does this API require authentication? *
 Does the API support CORS? *

- Auth = OAuth, apiKey, no

- CORS = Without proper CORS configuration an API will only be usable server side.

US Census API R Consortium Census Working Group makes it easier via packages on CRAN (here)

| Census | | | | | | |
|---|-----------------|---|--|---|--|--------------|
| BROWER BY TOPIC | DOK ONE DATA | LEINITY | BURNEY'S PROBABLE | INFORMATION FOR | FRIE A CODE | |
| My Community Explore | r is now availa | ble. Explore select demogra | this, business, and resilient | e dala la help blentity pot | ientially underserved co | reneratives. |
| WITHIN DEVELOPERS About | f | Available | APIs | | | |
| App Gallery Anallable APIs Geography Guidance for Developers | in | We plan on adding more many data sets are curre of datasets, please sign to NEW. We now have a mi- release. Usit our Discov Disco ML 1 record to | of our publicly available ently available via APL To ap and solvenit your requi- achine-readable dataset ery Tool page to learn re | datasets, here you'll make specific request ents on our Developer discovery service and ore | ind which of our is for the release Perum, able in beta | |
| Nows Terms of Service Updatus | | | unity Survey (ACS) s | | | |
| | | ✓ Economic Censu ✓ Population Estim | s nates and Projections | | | |
| KEY | | Health Insurance Poverty Statistic | s statistics | | | |
| | | Annual Survey of Annual Survey of | Entrepreneurs (ASE |) | | |
| | | Dusiness Dynam County Designers | ics Statistics (BDS) |) Cadas Basisons Pa | Herns (NBP) | |
| | | and Nonemploye Longitudinal Employee | r Statistics (NES) ployer-Household Dy | namics (LEHD) | | |
| | | Planning Databa Public Sector | se (PDB) | | | |
| | | Census Microdal Economic Indica | tors | | | |
| | | Survey of Busine International Pro | iss Owners (SBO) gram | | | |
| | | Geography Progr | an nografi | | | |

Many institutions provide an Open API or access via a Key (here key for the Census)

Add key to .Renviron
Sys.setenv(CENSUS_KEY=yourkey)
Reload .Renviron
readRenviron("~/.Renviron")
Check to see that the expected key is output in your R console
Sys.getenv("CENSUS_KEY")

censusapi. A wrapper for the U.S. Census Bureau APIs that returns data frames of Census data and metadata

| <pre>> censusapi::listCensusApis()</pre> | | |
|---|--------------|---------|
| title | name | vintage |
| Economic Surveys: Annual Business S | Survey abscb | 2017 |
| Economic Surveys: Annual Business S | Survey abscb | 2018 |
| Economic Surveys: Annual Business S | Survey abscb | 2019 |

Trade data in the US Census

exp_monthly_hs <- "timeseries/intltrade/exports/hs" #this is the name censusapi::listCensusMetadata(name = exp_monthly_hs, type = "variables")

label name NT WGT YR 15-digit Year-to-Date Containerized Vessel Shipping Weight DF 2-character Domestic or Foreign Code MONTH 2-character Month 0TY 1 M0 15-digit Ouantity 1 4-character aggregation levels for commodity code. COMM LVL UNIT OY2 3-character Export Unit of Ouantity 2 UNIT QY1 3-character Export Unit of Quantity 1 CNT VAL MO 15-digit Containerized Vessel Value CTY CODE 4-character Country Code DIST NAME 50-character District name VES VAL YR 15-digit Year-to-Date Vessel Value

Trade data in the US Census

- > exports <- censusapi::getCensus(</pre>
- + name = "timeseries/intltrade/exports/hs",
- + key = Sys.getenv("CENSUS_KEY"),
- + vars = c("E_COMMODITY","CTY_CODE","CTY_NAME","ALL_VAL_MO","ALL_VAL_YR"),
- + YEAR=2020,
- + MONTH="05",
- + COMM_LVL="HS6")
- > head(exports)

| E COMMODITY | CTY CODE | CTY NAME | ALL VAL MO | ALL VAL YR | YEAR MONTH | COMM LV |
|-------------|----------|----------|------------|------------|------------|---------|
| _ | — | _ | | | | _ |

| | 091012 | 0025 | EUR0 | AREA | | 47317 | 2020 | 05 | HS6 |
|---|--------|------|------|------|-------|--------|------|----|-----|
| | 401694 | 0025 | EUR0 | AREA | 34429 | 110219 | 2020 | 05 | HS6 |
| | 610210 | 0025 | EUR0 | AREA | | 571110 | 2020 | 05 | HS6 |
| | 030692 | 0025 | EUR0 | AREA | | 596724 | 2020 | 05 | HS6 |
| 5 | 160419 | 0025 | EUR0 | AREA | | 10133 | 2020 | 05 | HS6 |
| 6 | 843930 | 0025 | EUR0 | AREA | | 19500 | 2020 | 05 | HS6 |

WEB SCARPING

Definitions

- Scraping: Using tools to gather data you can see on a webpage
 - Parsing: The act of analyzing the text (HTML, ...) to collect the data you need
 - Crawling: Moving across or through a website to gather data from multiple URL/pages
- 2 main technologies to build a webpage:
 - HTML (the Hypertext Markup Language) structure of the page
 - CSS (Cascading Style Sheets) visual and aural layout, for a variety of devices.



- "q=" query for type of job, separating search terms with "+" (i.e. "school+teacher" jobs)
- "&I=" begins the string for location, again "North+Westphalia"
- "&start=" index the number of item you want to see

HTML

- HTML: similar to XML, both use tags and node structure
- different functions: HTML displays content on a web page, XML represents data in a hierarchical structure
- XML is case-sensitive while HTML is not
- Link here to tags in html



• in HTML you can leave tags open, in XML not

HTML vs CSS

Save the following in a file .html and open via the browser

```
Hello World!
These paragraphs are styled with CSS.
```

Web Scraping without getting blocked

- Check website's ToS: limit the number of requests? size?
- try to emulate human-like browsing behavior by adding random pauses
 - scraping tools/ library: Scrapy, Beautiful Soup, rvest, Selenium
- yse proxies from different IP addresses, making it harder for the website to track your activity.

THE BILLION PRICES PROJECT

"By 2010, we were collecting 5 millions prices every day." Alberto Cavallo and Roberto Rigobon 2016

- Institutions: Inflacion Verdadera, MIT, PriceStats
- Daily price data since 2008
- From hundreds of large multi-channel retailers
- In over 60 countries

How did it start?

- Argentina's inflation data (2007-2015) was widely questioned
- CPI inflation remained below 10% for many years
- Survey inflation expectations consistently above 25%



• Calculating the CPI for a single item

consumer price index = $\frac{\text{market basket of desired year}}{\text{market basket of base year}} \times 100$

• Calculating the CPI for mulitple items $i = 1, \ldots, n$

$$\mathsf{CPI} = rac{\sum_{i=1}^n \mathsf{CPI}_i imes \mathsf{weight}_i}{\sum_{i=1}^n \mathsf{weight}_i}$$

Ideally, the weights would relate to the composition of expenditure during the time between the price-reference period and the current period.

How representative is the online basket?

- On average, prices from about 60% of CPI expenditure weights can be found online
- All kinds of goods, including food and fuel
- Relatively few services (improving)
- Housing/rents information online, but not directly included the indices



Comparing Data Sources

Table 1 Alternative Micro-Price Data Sources

| | Online data | Scanner data | CPI data |
|-----------------------------------|-------------|--------------|-----------|
| Cost per observation | Low | Medium | High |
| Data frequency | Daily | Weekly | Monthly |
| All products in retailer (Census) | Yes | No | No |
| Uncensored price spells | Yes | Yes | No |
| Countries with research data | ~ 60 | < 10 | ~ 20 |
| Comparable across countries | Yes | Limited | Limited |
| Real-time availability | Yes | No | No |
| Product categories covered | Few | Few | Many |
| Retailers covered | Few | Few | Many |
| Quantities or expenditure weights | No | Yes | Yes |

Source: Table 1 from Cavallo (2015).

Notes: The Billion Prices Project (bpp.mit.edu) datasets contain information from over 60 countries with varying degrees of sector coverage. Nielsen US scanner datasets are available at the Kilts Center for Marketing at the University of Chicago. Klenow and Malin (2010) provide stickiness results with Consumer Price Index data sources from 27 papers in 23 countries. See Cavallo (2013) for more details.

Data Collection

- a random set of goods
- at the website and any physical store of a given retailer
- in a similar time span (7-day window)
- 10 countries, 5-10 retailers in each
- Retailers included:
 - top 20 largest retailers by market share
 - Sell both online and offline
 - Availability of a product id (UPC)

Data Validation

Short-run discrepancies (mainly in developing c.) but medium/long-term co-movement

Developing vs Developed Countries



What is new with Online Data? Anticipation of changes in inflation trends



Figure 3: US Price Index around Lehman Brother's Bankruptcy

Source: Cavallo & Rigobon (2016) "The Billion Prices Project", Journal of Economic Perspectives, Spring 2016, Vol 30(2):151-78.

It took more than two months after Lehman's disaster for the official Consumer Price Index numbers to reflect the full impact on price levels!

Figure 7 Cumulative Impulse Response of the US Consumer Price Index (CPI) to an Online Price Index Shock

(response to a 1% shock in the online index)



Source: Authors using online data computed by PriceStates and US Consumer Price Index. Notes: The Consumer Price Index is a US city average, all items non-seasonally adjusted from the Bureau of Labor Statistics. Data from July 2008 to January 2015. Apart from measurement issues, online prices allowed to offer new light on

- price stickiness
- Law of One Price (LOOP)

Price Stickiness?

With offline data, no evidence of menu pricing... price stickiness (Woodfrod 2009, Midrigan 2011)?



Source: Cavallo (2015).

Notes: Online and scanner data was collected from the same retailer, zip code, and time period. Weekly averages were computed using the daily online data. Nielsen Scanner Data provided by the Kilts Marketing Genter at Chicago Booth. The law of one price is the theory that an economic good or asset will have the same price in different markets (controlling for transaction costs).

Issue: comparing the same good in different countries (barcodes differ, id names). Solution: global retailers IKEA, Zara etc.

 \rightarrow LOOP is valid within countries that use the same currency

Law of One Price

Inflation with Covid Consumption Baskets^{*}

Alberto Cavallo Harvard Business School & NBER

December 2020

Abstract

The Could Ploadness is in the summarized Counser (New Isolator, Clinicator, Statisticator, Stat

JEL-Codes: C43,821,831. Keywords: COVID, consumer expenditures, CPI, inflation.

⁻¹I use provide to Foreneois Hallo for excellent research andreses, to John Friedman for sharing du Opportunit benjden data, to Condine Completion and Manuel Benchtain for help with the CPI state, and to Robel ED Fell Marshall Brinnbert, Das Robel, Xavier Jararel, and Pelo Nicoso for helpful comments and suggestions. Financisupport for this paper was provided by Harvard Bensiens Robel

Inflation with Covid Consumption Baskets

Alberto Cavallo

NBER Working Paper Series, No. 27352

Download Paper | Download Data

The Covid-19 Pandemic led to changes in expenditure patterns that can introduce significant bias in the measurement of Consumer Price Index (CPI) inflation. Using publicly-available data on card transactions, I update the official CPI weights and re-calculate inflation with Covid consumption baskets. I find that the US CPI underestimated the Covid inflation rate, as consumers spent relatively more on food with positive inflation, and less on transportation and categories experiencing deflation. The bias peaked in May, when US Covid annual inflation was 0.95% compared to just 0.13% in the CPI and low-income households were experiencing nearly twice as much inflation as those at the top of the income distribution. I find similar evidence of higher Covid inflation in 12 of 19 additional countries.

Law of One Price



Brent Neiman Federal Beserve Bank of Boston

Abstract

Joney Trees

Tariff Passthrough at the Border and at the Store: Evidence from U.S. Trade Policy

Alberto Cavallo, Gita Gopinath, Brent Neiman, and Jenny Tang American Economic Review: Insights, Vol 3 Issue 1, March 2021

Download Paper | Download Data

We use micro data collected at the border and at retailers to characterize the effects brought by recent changes in US trade policy -- particularly the tariffs placed on imports from China -- on importers. consumers, and exporters. We start by documenting that the tariffs were almost fully passed through to total prices paid by importers, suggesting the tariffs' incidence has fallen largely on the United States. Since we estimate the response of prices to exchange rates to be far more muted, the recent depreciation of the Chinese renminbi is unlikely to alter this conclusion. Next, using product-level data from several large multinational retailers, we demonstrate that the impact of the tariffs on retail prices is more mixed. Some affected product categories have seen sharp price increases, but the difference between affected and unaffected products is generally quite modest, suggesting that retail margins have fallen. These retailers' imports increased after the initial announcement of possible tariffs, but before their full implementation, so the intermediate passthrough of tariffs to their prices may not persist. Finally, in contrast to the case of foreign exporters facing US tariffs, we show that US exporters lowered their prices on goods subjected to foreign retaliatory tariffs compared to exports of non-targeted goods.

Access to the project

- data and results available at the link webpage (bpp.mit.edu)
- ...also script to replicate the results!
- data are not pretreatred
- The US and Argentina inflation indexes used in this paper are published with a 30-day lag on the Billion Prices Project websit
- PPP exchange rate information discussed in the previous section are currently published with a one-year lag on the PriceStats website
- raw micro data collected by PriceStats are not publicly available but can be shared with academic researchers who collaborate with the Billion Prices Project and sign a data-access agreement.