

Data exploration report

A whiteboard to understand the data, test ideas, and shape our deliverables

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Overview

This document can be considered a whiteboard or a catalog gathering all the insights and ideas we can think of as reflecting on Labor Demand in the South Cone via Online Job postings. Half the effort falls on understanding the data set nuances, while the other half is focused on collecting insights around the **Energy Transition, Remote Work, Knowledge Sectors, Gender Inclusion, The Silver Economy, Immigrant labor assimilation, and Regional Economies.**

It's a work in progress.

Use the table of contents on the right to travel between document sections: TBD stands for To Be Done, while WIP stands for Work in Progress.

I've examined occupational, sector, abilities, sub-abilities, job zones, work schedules, regions, cities, and firm distributions of online job vacancies. I've also looked at the distribution of binary categories like green jobs, remote jobs, and knowledge jobs.

Overall, I can say that:

- The figures presented here are based on a month of data. It goes from September 25 to October 26.
- That amounts to 60.000 job postings. Chile accounts for about 58%, Argentina for 38% and Uruguay for 4%. Remember that Chile, Argentina, and Uruguay account for 39%, 54%, and 7% of formal employment in the South Cone, respectively. See Table 1
- We compared occupations shares in total employment with their share in online job vacancies. The following major occupational groups are over-represented in the latter: “Sales and Related Occupations”, “Healthcare Practitioners and Technical Occupations”, “Architecture and Engineering Occupations”, “Office and Administrative Support Occupations”, “Protective Service Occupations”, “Computer and Mathematical Occupations”, “Production Occupations”, “Management Occupations”, “Business and Financial Operations Occupations,” in that order. See Table 29.
- We obtained similar conclusions at the sector level. The following sectors are over-represented in online job postings: “Real Estate And Rental And Leasing”, “Professional Scientific And Technical Services”, “Finance And Insurance”, Manufacturing, “Retail Trade”, “Educational Services”, “Health Care And Social Assistance”, and “Accommodation And Food Services”. See Table 30. *Note that over represented means more common than would be expected by their share of employment.*
- Regions like Santiago (13000), Buenos Aires (9300), Valparaiso (4900), Concepcion (3774), Rosario (2316), and Gran Temuco (2125) have more online vacancies than Uruguay (2060). See Table 25

Differences between countries:

- Argentina's online job demand aims towards more educated, trained, and technical workers than Chile. This is evident in the job zones, and abilities distributions (see Figure 23 , Figure 12), but also foreseeable from the sector and occupational distributions alone (see Figure 9 , ?@fig-occupation_country). Uruguay mimics that in many ways, but we're always less sure due to its narrow sample size.

- Despite being 1.5x outsized by its' andean neighbor, Argentina has more vacancies in “Financial Operation Occupations” and a similar number of vacancies in “Architecture and Engineering,” “Computer and Mathematical,” “Educational,” and “Construction and extraction” occupations (see [?@fig-occupation_country](#)). It's also remarkably close to Chile in the number of vacancies with “Considerable preparation” (Job Zone 4.)
- When compared with it's region neighbor, Chile has an extraordinary high number of openings asking for “Some Preparation” (Job Zone 2.) Indeed, these account for about 46% of all the sampled vacancies, 10 points more than URY and 11 points more than ARG.

Abilities and sub-abilities

- “Cognitive” and “Sensory” abilities are the most prevalent in online job postings. “Physical” and “Psychomotor” abilities are almost half as required. See Figure 11.
- The most “Cognitive” abilities-intensive sectors are “Professional, Scientific and Technical Services,” “Utilities,” and “Management of Companies and Enterprises.” See Figure 18.
- The most “Sensory” sectors are “Wholesale Trade,” “Management of Companies and Enterprises,” and “Educational Services.” These are sectors demanding many “Sensory” subabilities to a high degree. See Figure 18.
- The “Construction” sector demands “Cognitive,” “Physical,” “Psychomotor,” and “Sensory” abilities similarly. The demand for abilities in the “Accommodation and Food Services” sector is similarly even. See Figure 18.
- Sub-abilities' intensity in Google Jobs data aligns well with O*NET data on Sub-abilities' importance by occupation. Figure 70. There are methods to identify occupations exposed to AI by looking at subabilities (See Felten et. Al. 2018).

Work from Home arrangements (WFH):

- The fraction of remote/hybrid vacancies detected is too low. Chile's share of remote vacancies is 1.3%, while New Zealand's is 10% (see Table 17 and [?@fig-bloom3](#)). However, global surveys say Chileans work from home 0.9 days a week, while New Zealanders do so 1.0 days per week (see [?@fig-bloom3](#)).
- In the Argentinean files reviewed, 85% of vacancies with the word “hybrid” on the description were classified as not remote/hybrid (see Table 21). This evidence suggests a high prevalence of Type II errors. This likely happens in Chile and Uruguay files.
- Type II errors aside, Santiago and Buenos Aires account for 24% and 20% of all remote vacancies, respectively. Regions like Córdoba, Mendoza, Corrientes, and Metropolitana account for 4%, 4%, 2%, and 4% of remote job postings, respectively. These last regions and Buenos Aires account for a more significant share of remote vacancies than expected by chance (See Table 19).

Energy transition:

- Green jobs represent 15% of all online job postings. Argentina has the highest share of green jobs in its' job postings (17%), while Chile has the lowest (13%). See Table 14.

- “Green Increased Demand” accounts for 45% of Green jobs, while “Green Enhanced Skills” and “Green New & Emerging” account for 40% and 14%, respectively. See Table 15.
- Argentina is intensive in “Green Increased Demand” (48%), while Chile is relatively intensive in “Green Enhanced Skills” (43.4%). See Table 15
- Santiago and Buenos Aires account for 18% and 18% of all green online vacancies, while regions like Rosario, Mendoza, and Antofagasta account for 6%, 4%, and 4%, respectively. Buenos Aires, Rosario, Mendoza, and Antofagasta account for a more significant share of Green vacancies than expected by chance. See Table 16.

Job Zones:

- 41% of job vacancies in the South Cone require “(2) Some preparation”, while 25% require “(4) Considerable preparation”, and another 25% require “(3) Middle preparation”. Only 8% of the demand falls on the “(1) no preparation” and “(5) a lot of preparation” extremes. See Figure 19.
- 46% of job postings in Chile demand “(2) Some preparation”. It’s the country most concentrated in that area of demand by a considerable margin. See Figure 23.
- 30.5% of job postings in Argentina demand “(4) Some preparation”. It’s the country most concentrated in that area of demand by a moderate margin. See Figure 23.
- We show sectors’ composition of online vacancies by Job Zone. One of the surprises we found is that Transportation and Warehousing asks for [(4) Preparación Considerable] en around 15% of online vacancies, at least in Argentina. See Figure 24.
- The breakdown of job zones aligns with our understanding of training and preparation requirements by sector. We’re able to spot minor variations within countries.

Firms:

- Chile and Argentina have around 800 firms (see Table 27). The 100 most prominent firms in both countries account for around 40% of all job vacancies. We present a plot to help policymakers spot the hottest demand firms across different periods (see Figure 51).

Ideas moving forward:

- **Automating this report:** We could work on automating updates to this or other similar on a monthly basis by establishing an API connection.
- **Creating a dashboard with dates and country filters:** We could work on a dashboard that allows the user reproduce all these plots and statistics and includes date/country filters. The tool would be connected to the API.
- **Follow developments on Argentina Labor markets:** Data could be used to track the effects of the incoming labor markets de-regulation in Argentina.
- **Discuss the effect of AI on labor demand:** [Acemoglu, Autor, et al 2022](#) have used online job vacancies and AI exposure measures to discuss heterogeneous effects of AI on labor demand. Our data is very similar, only short.

- **Measure labor market tightness:** Geographical granularity offers valuable insights for policy makers. This could allow researchers create estimates of labor market tightness in large regions by calculating the ratio of vacancies to unemployment. On the other end, firm granularity could allow policy makers to reach out to firms leading job demand.
- **Assist green transition efforts:** We could explore other dimensions of “green labor demand.” What sectors and firms are behind it? What abilities are they more reliant on? How does it change following COP28 resolutions?
- Evidence found here suggest there is a possibility of reducing type II error in remote work classification at a low cost. First step would consist on building a simple NLP model for WFH detection and compare it with “human-in-the-loop” classifications of a sub-sample of postings to measure improvements. Algorithms could grow more complex if needed. If that’s the case I suggest using [Taska, Bloom, et. al. 2023](#)) work as guidance.

The IDB online job postings database

Variables

We identify four groups of variables:

- Sector weights: will tell us the sector distribution of firms searching for workers. Each column is named after one of the 20 [NAICS 2-digits sectors](#).

Names in the database
<ul style="list-style-type: none"> – accommodation_and_food_services, administrative_and_support_services, agriculture_forestry_fishing_and_hunting, arts_entertainment_and_recreation, construction, educational_services, finance_and_insurance, government, health_care_and_social_assistance, information, management_of_companies_and_enterprises, manufacturing, mining_quarrying_and_oil_and_gas_extraction, other_services_except_public_administration, professional_scientific_and_technical_services, real_estate_and_rental_and_leasing, transportation_and_warehousing, utilities, wholesale_trade, retail_trade

- Abilities and sub abilities weights: works similar to the sector ones. Each column shows a score associated with that (sub)ability. The raw score apparently lacks any interpretation, but it can be used to either rank items from most to least important, or weight each observations to calculate the aggregate importance of each item. (Sub)Abilities are defined in the [ONET Content Model Ability](#).

Names in the database

- Abilities: Cognitive Abilities, Sensory Abilities, Physical Abilities, Psychomotor Abilities
- Sunbilities: Arm-Hand_Steadiness, Auditory_Attention, Category_Flexibility, Control_Precision, Deductive_Reasoning, Depth_Perception, Dynamic_Strength, Explosive_Strength, Extent_Flexibility, Far_Vision, Finger_Dexterity, Flexibility_of_Closure, Fluency_of_Ideas, Gross_Body_Coordination, Gross_Body_Equilibrium, Hearing_Sensitivity, Inductive_Reasoning, Information_Ordering, Manual_Dexterity, Mathematical_Reasoning, Memorization, Multilimb_Coordination, Near_Vision, Night_Vision, Number_Facility, Oral_Comprehension, Oral_Expression, Originality, Perceptual_Speed, Peripheral_Vision, Problem_Sensitivity, Rate_Control, Reaction_Time, Response_Orientation, Selective_Attention, Sound_Localization, Spatial_Orientation, Speech_Clarity, Speech_Recognition, Speed_of_Closure, Speed_of_Limb_Movement, Stamina, Static_Strength, Time_Sharing, Trunk_Strength, Visual_Color_Discrimination, Visualization, Wrist-Finger_Speed, Written_Comprehension, Written_Expression

- Work related variables: Including the occupation title, the work schedule, training and education requirements (zones), whether remote or not, whether green or not, and whether knowledge activity or not.

Names in the database

- *occupation*: Contains occupation titles according to the ONETSOC19 system. The actual codes aren't available in the table, but titles can be joined to official crosswalks to recover them. Its' spanish version can be found in *onet_job*. **Problem to report: 2.5% of *occupation* records are empty, 0% of *onet_job* are empty.**
- *remote*: Binary indicator on whether a position offers any kind of work from home (WFH) arrangement. Namely remote or hybrid work.
- *area*: Binary indicator on whether a the employer is likely be a knowledge-intensive services provider, as defined by the [Ley de Economía del Conocimiento Argentina](#): ****software; nanotecnología; biotecnología; las industrias audiovisual, aeroespacial y satelital; la ingeniería para la industria nuclear y la robótica, entre otras actividades.***
- *green_job*: Variable showing the [ONET green occupation category](#) a vacancy falls into (Green New & Emerging, Green Enhanced Skills, and Green Increased Demand.)
- *job_zone*: Variable showing the [ONET category of preparation requirements](#) an vacancy falls into. Here, preparation stands for a mix of education, experience, and training.
- *schedule*: Variable showing the contractual arrangement offered in the vacancy. It can take “Internship”, “Contractor”, “Part-time”, “Full-time”, and “other” as categories.

- Origin variables: Including the id of the vacancy, the date, the country code, firm name, platform, and region.

Names in the database
– <i>country_code</i> : The name of the country.
– <i>date_posted</i> : The date the vacancy was posted in yyyy-mm-dd format.
– <i>firm</i> : The name of the firm publishing the post.
– <i>rm</i> : Region Metropolitana. It has 24 unique values for Argentina (equal to Provincia in when the count of vacancies is small, otherwise accounting for important metropolitan areas). Similarly, “rm” has 18 unique values for Chile (two more of what’s supposed to be if the intention is showing Regiones), and 6 unique values for Uruguay (way below the 18 Departamentos).
– <i>city_name</i> : City. Good providing more geographic granularity. A high-level analysis shows that cities like Vicente Lopez and Quilmes have a combined number of vacancies similar to that of Santa Fe and Rosario combined, Córdoba Capital, and Mendoza Capital.
– <i>job_name</i> : The name the employer gave to the vacancy in the posting.
– <i>descrip</i> : The raw text description of the job.

There is an statistical summary of these and other relevant variables in table [Table 2](#).

Database statistics

Here we present the dimension and summary statistics of our dataset:

[1] “There are 60689 postings in our data. Job postings count by country:”

Summary

Table 1: Summary

Overall Statistics
Between 2023-09-25 and 2023-10-29. Population data comes from ILOSTAT

country_code	Online vacancies	Online vacancies (%)	Working Age Pop (Thousands)	Working Age Pop (%)
CHL	35,194	57.99%	15,706	38.69%
ARG	23,435	38.61%	22,049	54.32%
URY	2,060	3.39%	2,837	6.99%

Detailed Summary

Characterizing labor market demand (Work in progress)

This section consists in highlighting vacancy distributions of each country across different indicators (occupational groups, sectors, skills, sub-skills, job zones, work schedule, green jobs, remote jobs, knowledge jobs, regions, and firms). Each indicator will have its own section.

Unless otherwise specified, each section will start with the overall distribution of vacancies across that variable, followed by the same distribution within each country. Each section is then finalized a relative concentration analysis, showing where is each country more specialized vis a vis its' peers.

In other words, analysis will answer the following questions:

- Whats more common?
- What's the most common in each country?
- Which country has more of each group?
- Which country has a higher than average concentration on each group?

Across occupations

We prepare the South Cone data for aggregation at the Major SOC group (2018) level. We first get the ONET SOC 19 code of each occupational title in the data, and then use ONET crosswalk to SOC18.

Summary

- “Sales and Related”, “Office and Administrative Support”, “Production”, “Business and Financial”, “Management”, “Architecture and Engineering”, and “Computer and Mathematical” occupations are the most prevalent occupational groups across all countries. Together they account for about 70% of all vacancies.

Table 2: Detailed summary

(a) Data summary

Name	Piped data
Number of rows	60689
Number of columns	16
Column type frequency:	
character	10
Date	1
logical	3
numeric	1
Group variables	country_code

Variable type: character

skim_variable	country_code	n_missing	complete_rate	min	max	empty	n_unique	whitespace
firm	ARG	0	1.00	0	93	11	6037	0
firm	CHL	0	1.00	2	212	0	9596	0
firm	URY	0	1.00	3	123	0	798	0
source	ARG	0	1.00	15	64	0	200	0
source	CHL	0	1.00	15	120	0	199	0
source	URY	0	1.00	16	53	0	48	0
rm	ARG	0	1.00	5	35	0	24	0
rm	CHL	0	1.00	5	16	0	18	0
rm	URY	0	1.00	3	13	0	6	0
city	ARG	0	1.00	0	89	6	806	0
city	CHL	0	1.00	4	25	0	240	0
city	URY	0	1.00	4	25	0	70	0
city_name	ARG	0	1.00	4	35	0	216	0
city_name	CHL	0	1.00	4	20	0	201	0
city_name	URY	0	1.00	4	22	0	48	0
occupation	ARG	0	1.00	0	97	366	619	0
occupation	CHL	0	1.00	0	94	1025	680	0
occupation	URY	0	1.00	0	94	32	284	0
onet_job	ARG	0	1.00	7	113	0	637	0
onet_job	CHL	0	1.00	7	114	0	703	0
onet_job	URY	0	1.00	7	107	0	292	0
schedule	ARG	0	1.00	5	10	0	5	0
schedule	CHL	0	1.00	5	10	0	5	0
schedule	URY	0	1.00	5	10	0	5	0
green_job	ARG	19330	0.18	20	22	0	3	0
green_job	CHL	30639	0.13	20	22	0	3	0
green_job	URY	1738	0.16	20	22	0	3	0
area	ARG	0	1.00	12	15	0	2	0
area	CHL	0	1.00	12	15	0	2	0
area	URY	0	1.00	12	15	0	2	0

Variable type: Date

skim_variable	country_code	n_missing	complete_rate	min	max	median	n_unique
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- Argentina’s demand is remarkably strong in “Business and Financial Operations”, “Arts, Design, Entertainment, and Media” and “Installation, Maintenance, and Repair” occupations, as well as remarkably in “Transportation and Material Moving”, “Protective services” and “Community and Social Service” occupations. It’s above average in “Computer and Mathematical” and “Architecture and Engineering Occupations”.
- Chile accounts for almost 60% of the sample, so it swings much less from the average than Argentina and Uruguay. Chile’s demand is remarkably strong in “Transportation and Material Moving Occupations”, “Building and Ground Cleaning and Maintenance”, and “Community and Social service” occupations. It’s remarkably in “Business and Financial Operations Occupations” and below average in “Computer and Mathematical occupations”.
- Uruguay’s demand is remarkably strong in “Computer and Mathematical Occupations”, “Educational Instruction and Library Occupations”, “Personal Care and Service”, “Construction and Extraction”, and “Legal” occupations. It’s remarkably in “Management”, “Healthcare Support”, and “Healthcare Practitioners and Technical” Occupations, which was unexpected.

What’s more common?

We calculate the frequency of each Major SOC group in the South Cone as a whole.

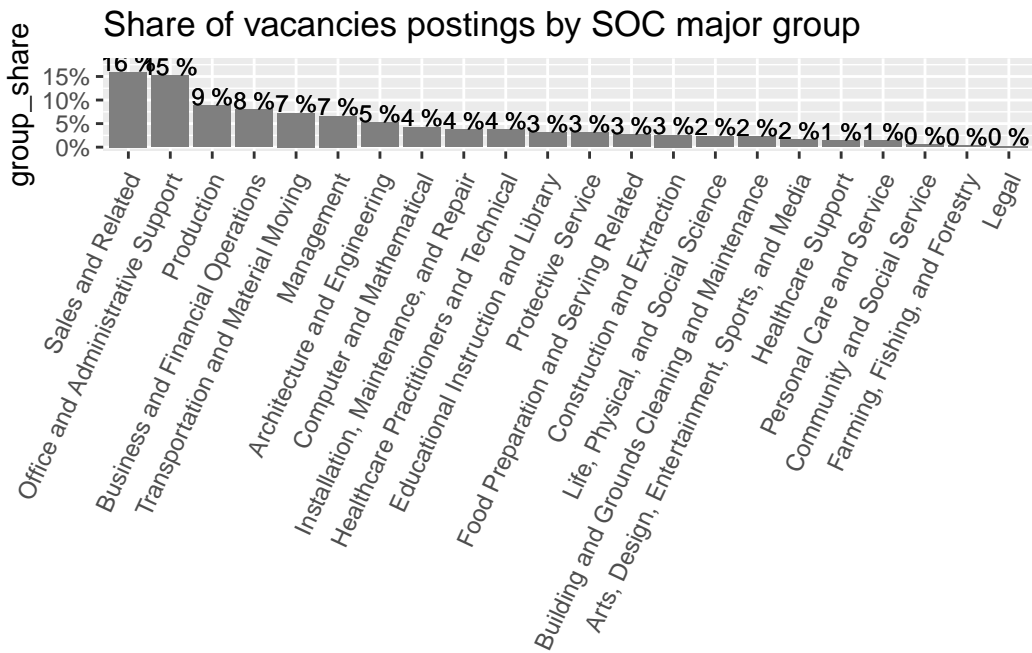


Figure 1: Major SOC group distribution

What's more common in each country?

We calculate the frequency of each Major SOC group in each country. For each row, we calculate the share of that group in the country and the share of the country in the group.

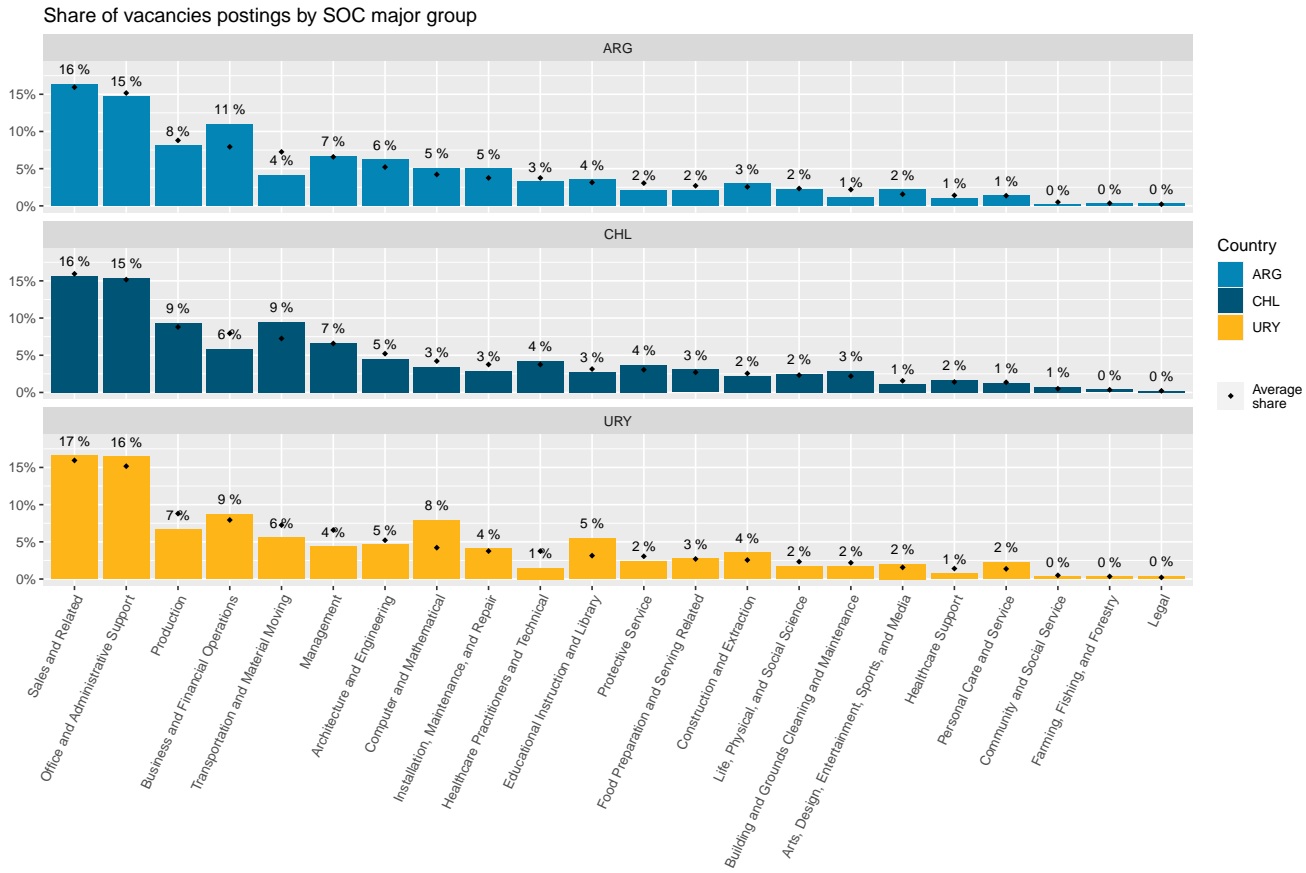


Figure 2: Major SOC distribution, by country

What's the country most specialized in each group?

Which country has the largest number of vacancies in each group?

Table View

Across Sectors (Ramas)

- The sectors demanding more jobs online are “Retail Trade”, “Manufacturing”, “Professional scientific and Technical Services”, “Educational Services”, “Government”, and “Finance and Insurance”. They account for about 83% of all postings.

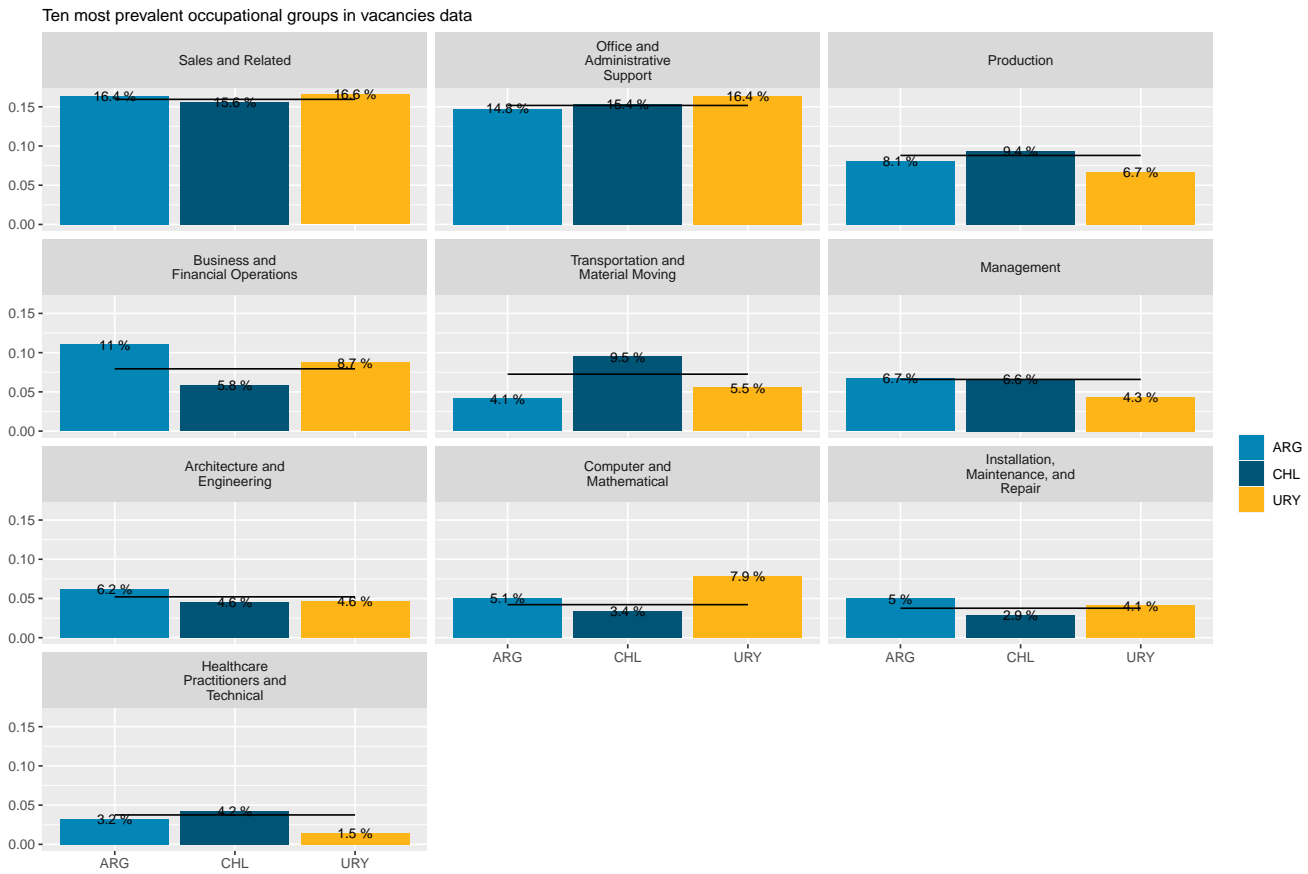


Figure 3: Major SOC distribution by country, side by side

Twelve less prevalent occupational groups in vacancies data

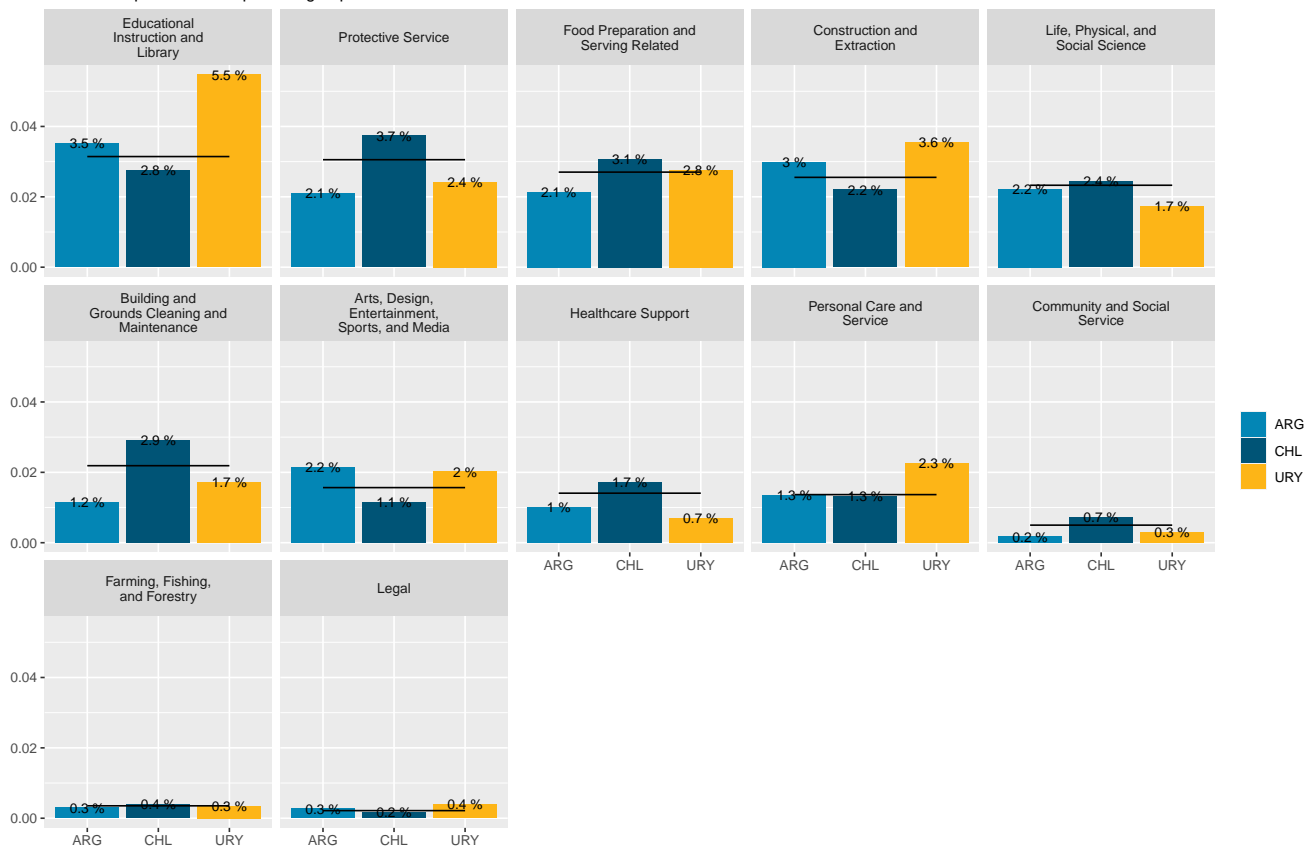


Figure 4: Major SOC distribution by country, side by side

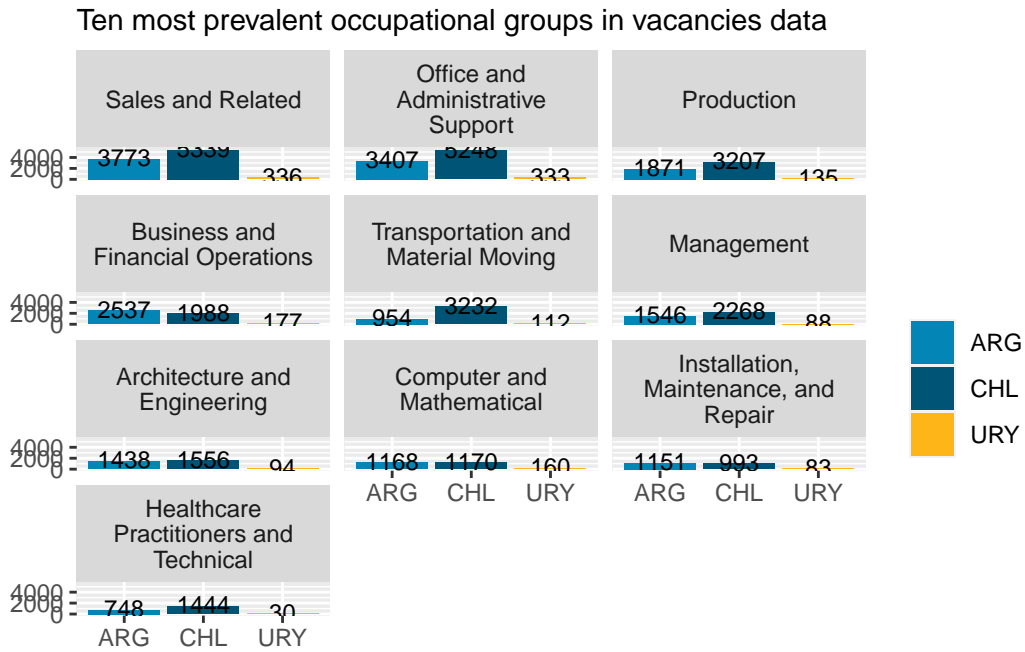


Figure 5: Major SOC distribution, by country

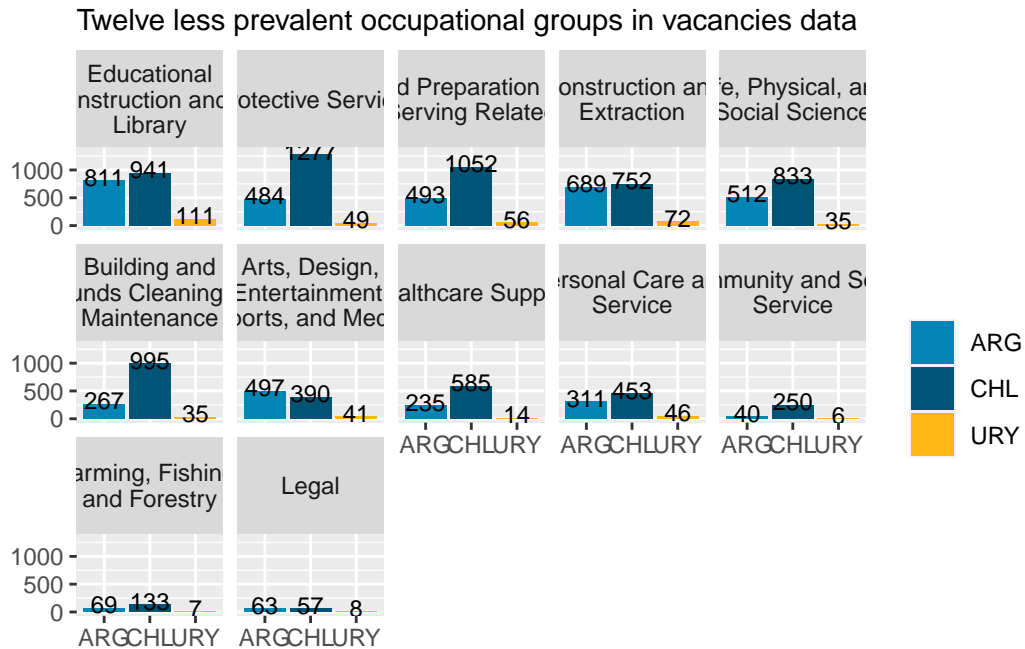


Figure 6: Major SOC distribution, by country

Table 7: ?(caption)

(a)

major_group_title	Vacancies	% of Vacancies	% of ARG	% of CHL	% of U
Sales and Related	9448	15.94%	16.36%	15.63%	16.57%
Office and Administrative Support	8988	15.17%	14.77%	15.36%	16.42%
Production	5213	8.80%	8.11%	9.39%	6.66%
Business and Financial Operations	4702	7.94%	11.00%	5.82%	8.73%
Transportation and Material Moving	4298	7.25%	4.14%	9.46%	5.52%
Management	3902	6.59%	6.70%	6.64%	4.34%
Architecture and Engineering	3088	5.21%	6.23%	4.55%	4.64%
Computer and Mathematical	2498	4.22%	5.06%	3.42%	7.89%
Installation, Maintenance, and Repair	2227	3.76%	4.99%	2.91%	4.09%
Healthcare Practitioners and Technical	2222	3.75%	3.24%	4.23%	1.48%
Educational Instruction and Library	1863	3.14%	3.52%	2.75%	5.47%
Protective Service	1810	3.05%	2.10%	3.74%	2.42%
Food Preparation and Serving Related	1601	2.70%	2.14%	3.08%	2.76%
Construction and Extraction	1513	2.55%	2.99%	2.20%	3.55%
Life, Physical, and Social Science	1380	2.33%	2.22%	2.44%	1.73%
Building and Grounds Cleaning and Maintenance	1297	2.19%	1.16%	2.91%	1.73%
Arts, Design, Entertainment, Sports, and Media	928	1.57%	2.15%	1.14%	2.02%
Healthcare Support	834	1.41%	1.02%	1.71%	0.69%
Personal Care and Service	810	1.37%	1.35%	1.33%	2.27%
Community and Social Service	296	0.50%	0.17%	0.73%	0.30%
Farming, Fishing, and Forestry	209	0.35%	0.30%	0.39%	0.35%
Legal	128	0.22%	0.27%	0.17%	0.39%
sum	—	59,255.00	1.00	1.00	1.00

Major SOC distribution, by country

- Argentina’s demand is strong in “Finance and Insurance”, “Professional Scientific and technical services”, and “Construction”. It’s particularly weak in “Retail”, “Accommodation and food services”, “Administrative and support services”, and “transportation and warehousing”
- Chile’s demand is strong in “Retail trade”, “Manufacturing”, “Health Care and Social Assistance”, “Administrative and Support Services”, “Retail trade”, “Transportation and Warehousing”, and “Wholesale Trade”. It’s particularly weak in “Professional Scientific and Technical Services”, “Finance and Insurance”, “Construction”, “Other Services Except Public Administration”, and “Information.”
- Uruguay is super strong in “Professional Scientific and Technical Services”, “Educational Services”, “Construction”, and “Information”. It’s strong in “Construction”. It’s particularly weak in “Health care and social assistance” and “Manufacturing”.

What’s more common?

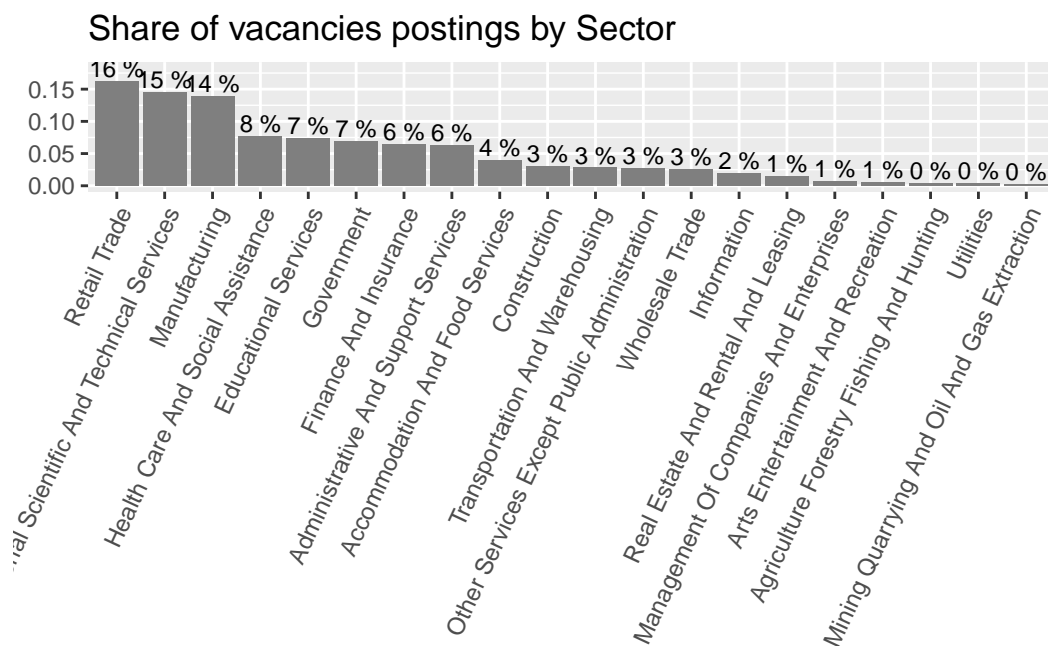


Figure 7: Sector distribution, with number of vacancies weighed by the weight of the sector

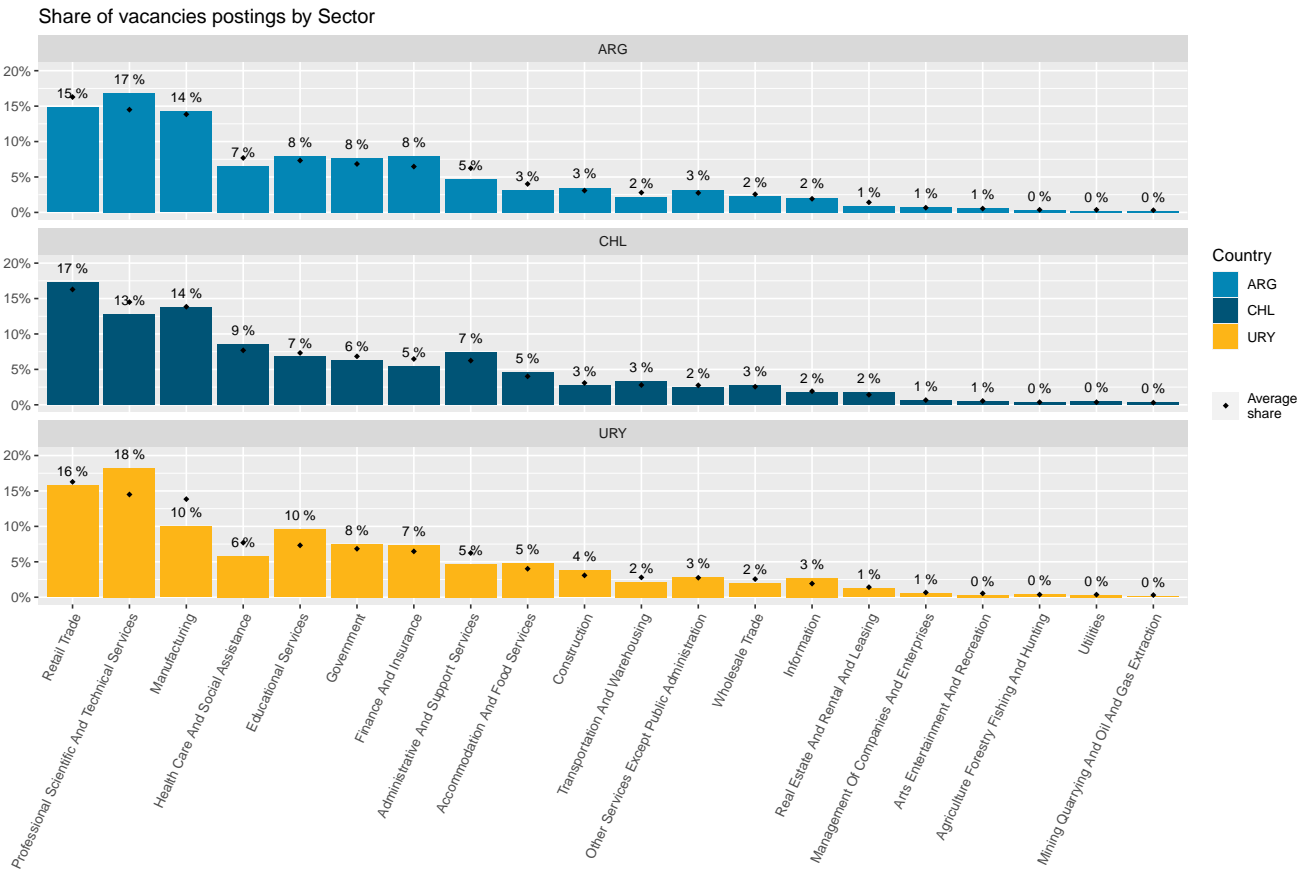


Figure 8: ?(caption)

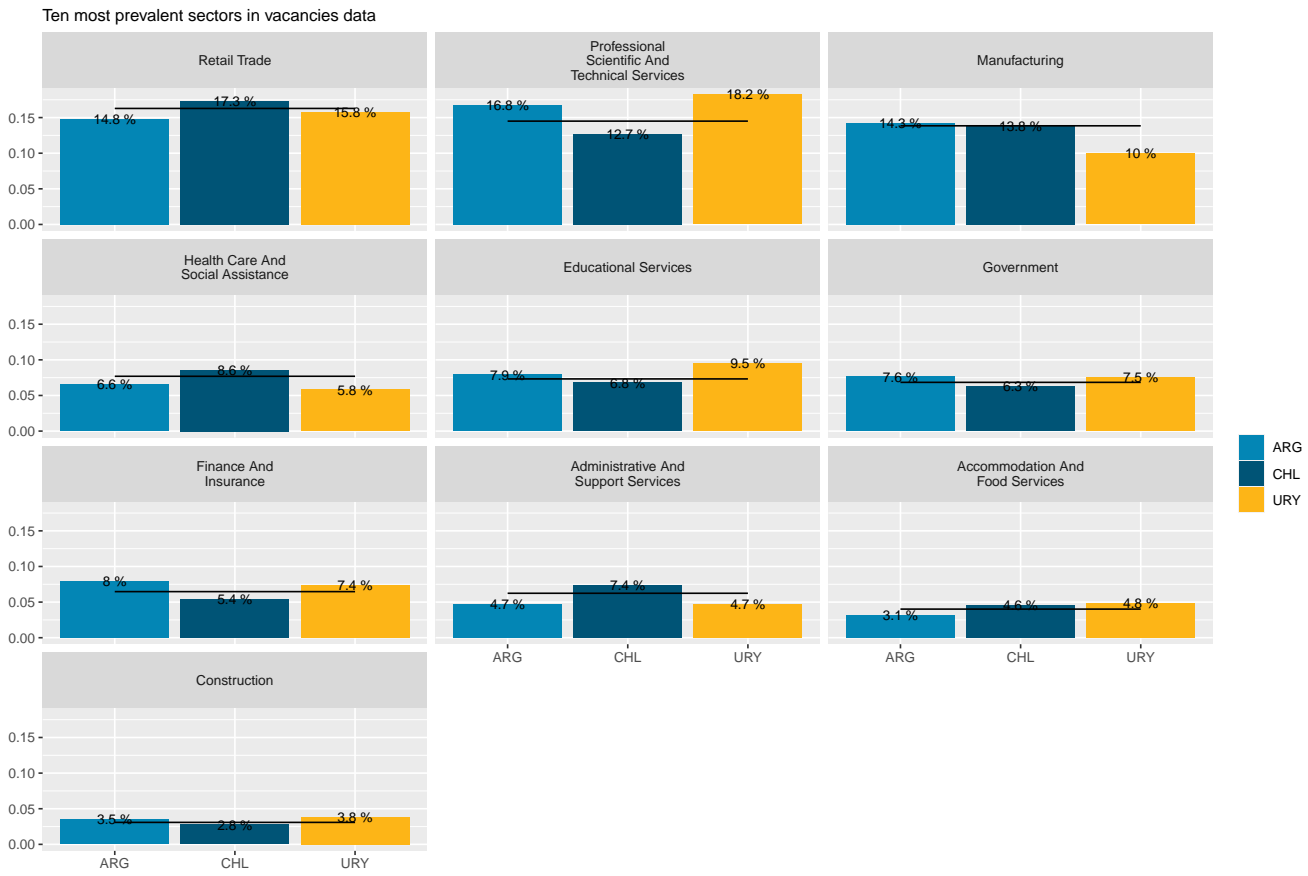
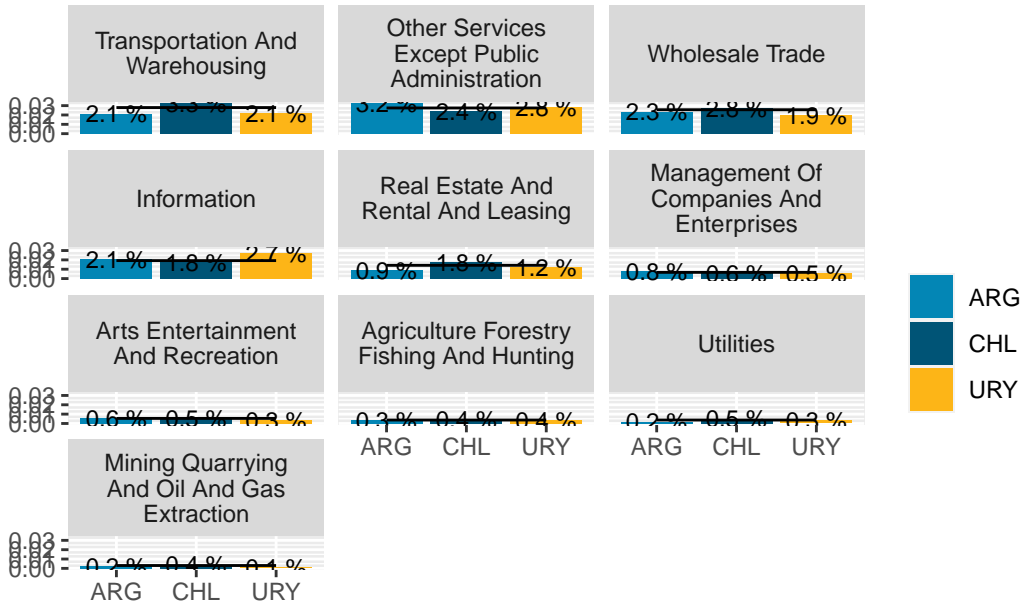


Figure 9: Sector distribution, by country

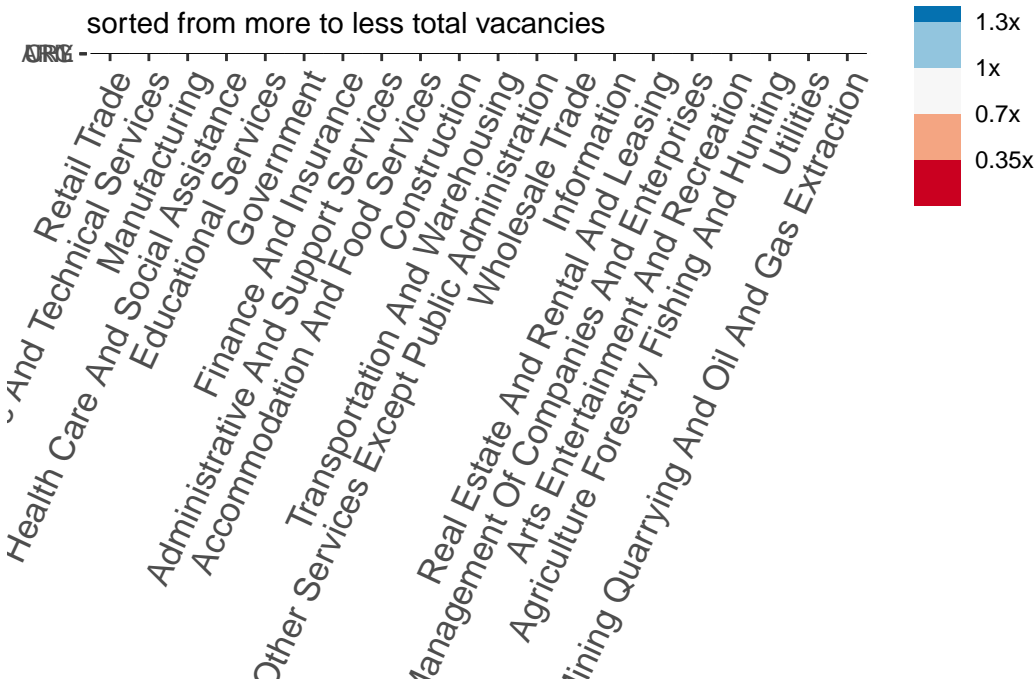
What's more common in each country?

What are countries specialized in?

Ten least prevalent sectors in vacancies data



sorted from more to less total vacancies



Which country accounts for the largest number of vacancies?

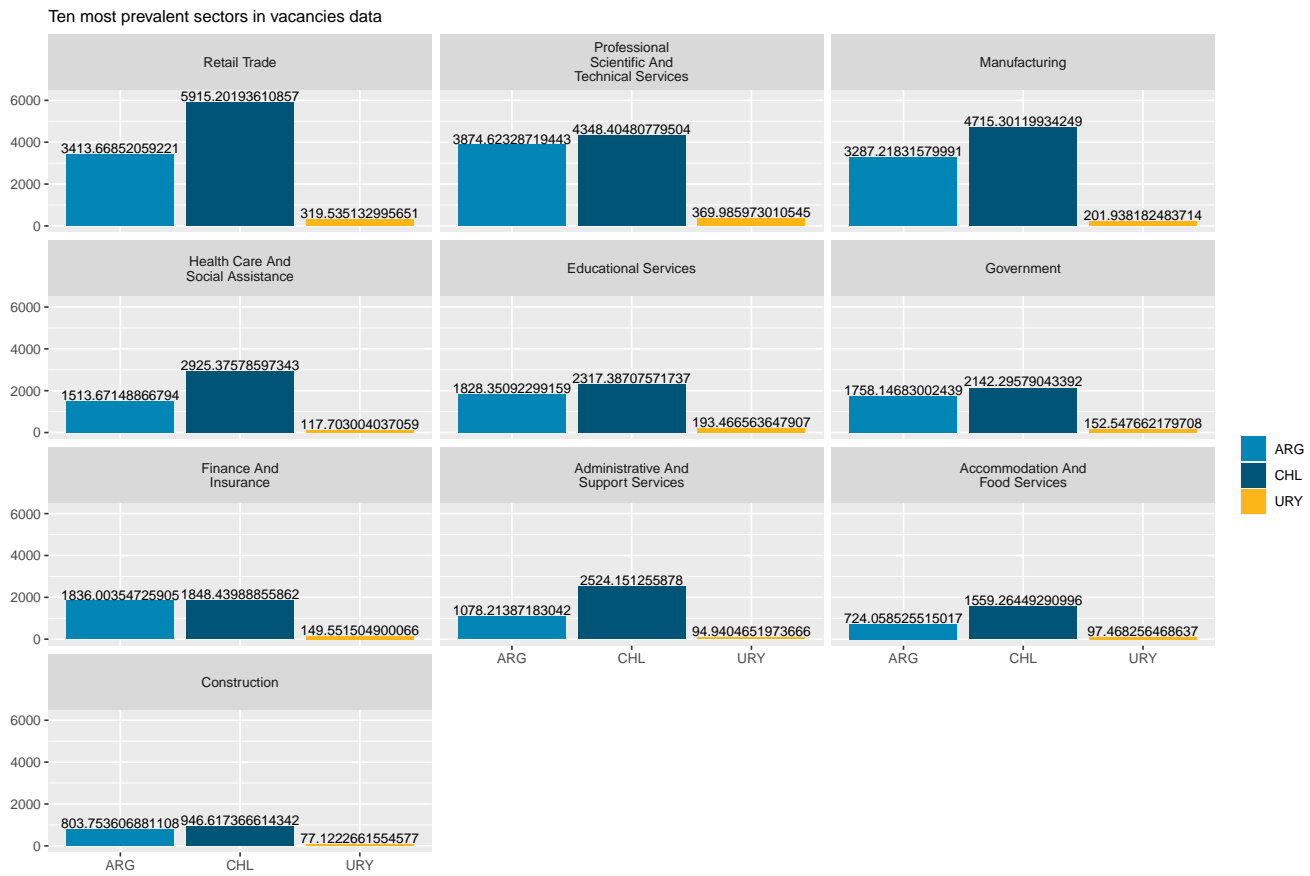


Figure 10: ?(caption)

Ten least prevalent sectors in vacancies data

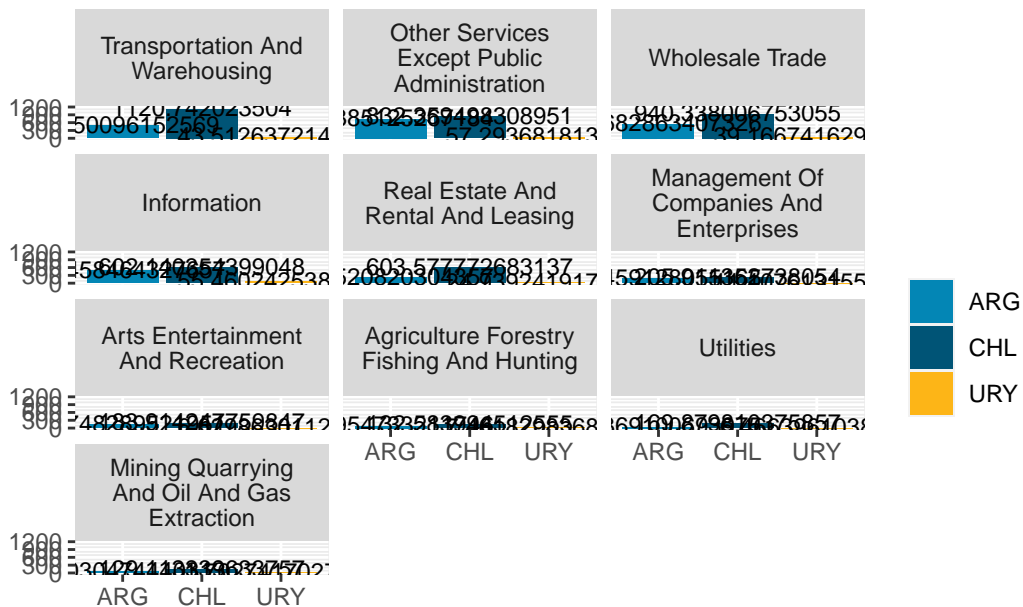


Table View

Abilities

- The most in-demand abilities online are Cognitive (33%) and Sensory (33%). Demand of Physical and Psychomotor activities is almost half of that.

Table 8: ?(caption)

(a)

sector	Vacancies	% of Vacancies	% of ARG	% of CHL	% of URY
Retail Trade	9648.4056	16.28%	14.80%	17.31%	15.76%
Professional Scientific And Technical Services	8593.0141	14.50%	16.80%	12.73%	18.24%
Manufacturing	8204.4577	13.85%	14.25%	13.80%	9.96%
Health Care And Social Assistance	4556.7503	7.69%	6.56%	8.56%	5.80%
Educational Services	4339.2046	7.32%	7.93%	6.78%	9.54%
Government	4052.9903	6.84%	7.62%	6.27%	7.52%
Finance And Insurance	3833.9949	6.47%	7.96%	5.41%	7.37%
Administrative And Support Services	3697.3056	6.24%	4.67%	7.39%	4.68%
Accommodation And Food Services	2380.7913	4.02%	3.14%	4.56%	4.81%
Construction	1827.4932	3.08%	3.48%	2.77%	3.80%
Transportation And Warehousing	1656.7556	2.80%	2.14%	3.28%	2.15%
Other Services Except Public Administration	1631.0383	2.75%	3.21%	2.44%	2.83%
Wholesale Trade	1517.1876	2.56%	2.33%	2.75%	1.93%
Information	1140.0591	1.92%	2.09%	1.76%	2.73%
Real Estate And Rental And Leasing	841.0378	1.42%	0.92%	1.77%	1.23%
Management Of Companies And Enterprises	394.4781	0.67%	0.77%	0.60%	0.55%
Arts Entertainment And Recreation	321.2924	0.54%	0.57%	0.54%	0.33%
Agriculture Forestry Fishing And Hunting	219.8413	0.37%	0.35%	0.39%	0.37%
Utilities	218.2831	0.37%	0.18%	0.50%	0.32%
Mining Quarrying And Oil And Gas Extraction	180.6191	0.30%	0.22%	0.38%	0.08%
sum	—	59,255.00	1.00	1.00	1.00

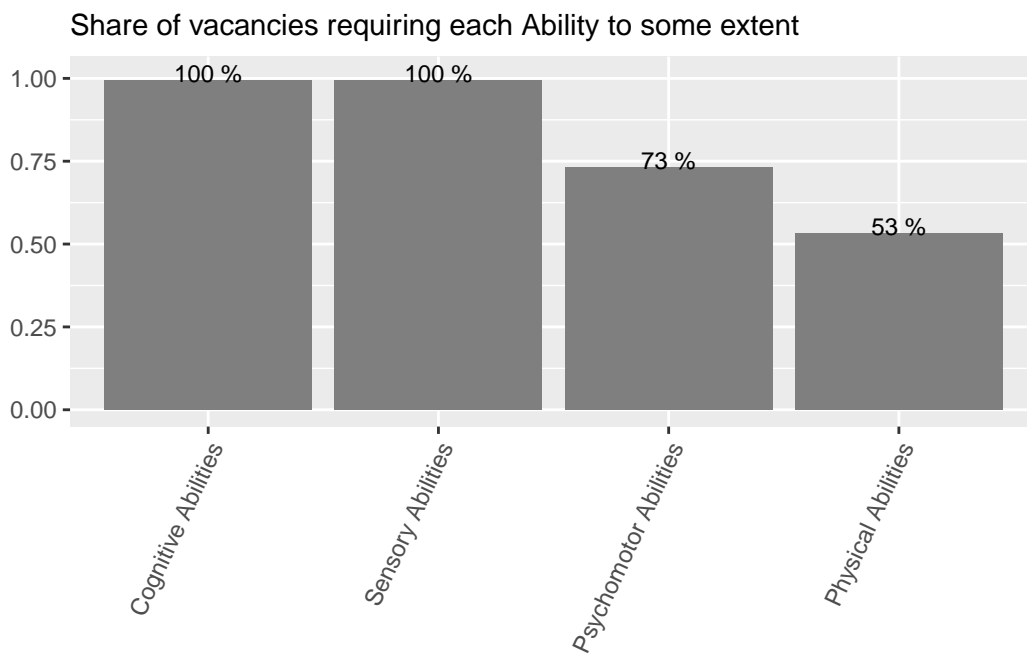
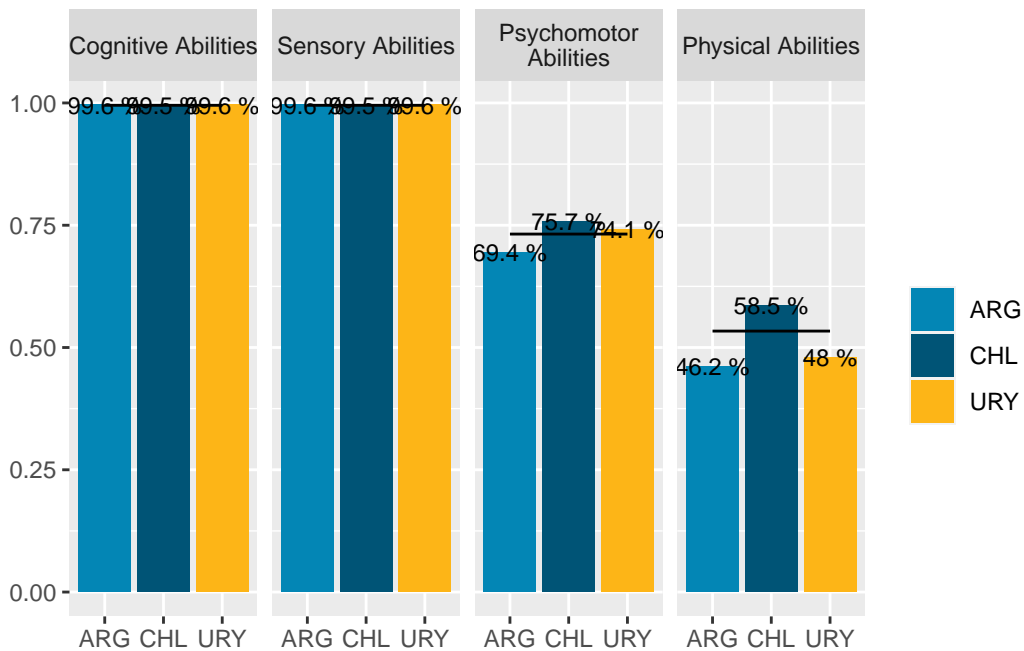


Figure 11: ?(caption)

Charts



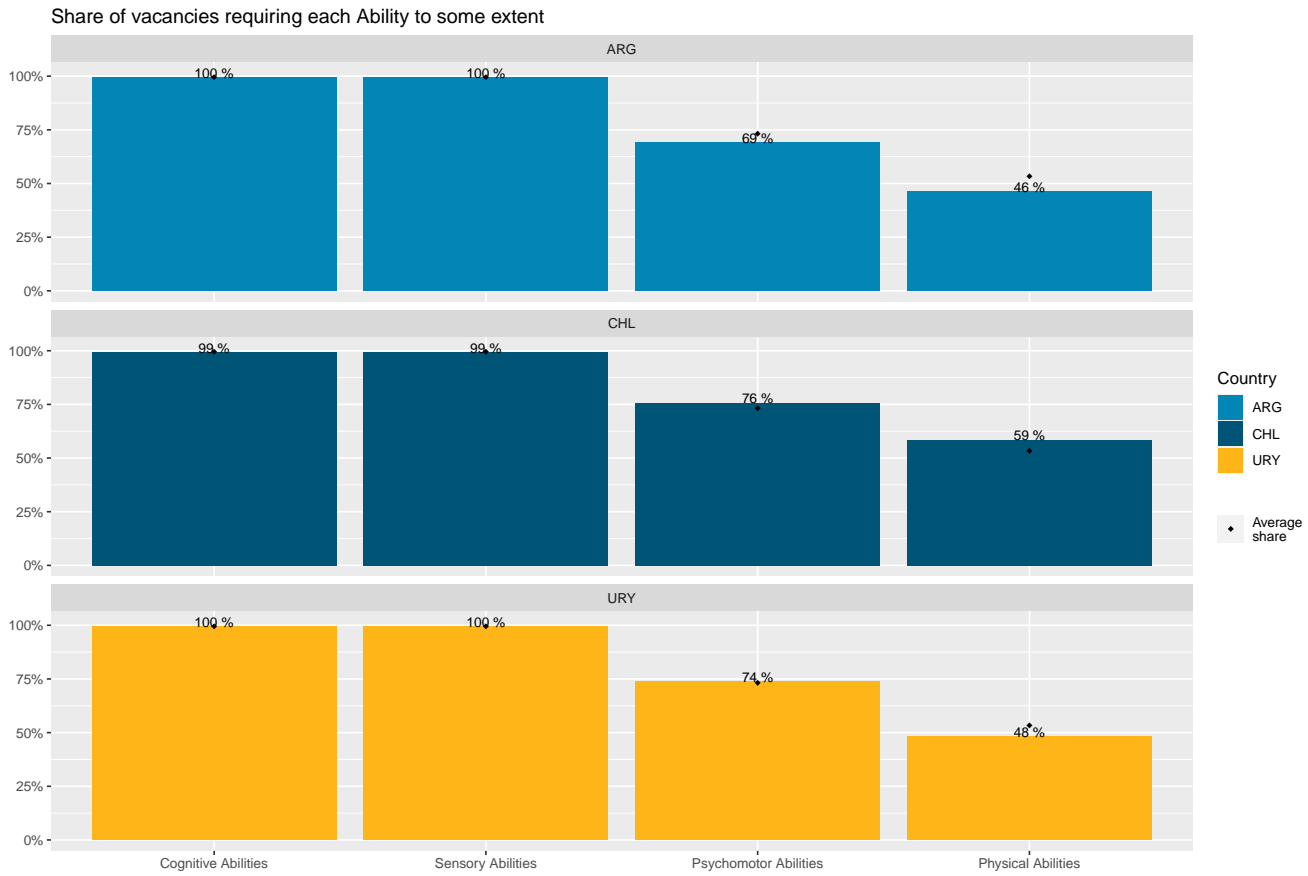


Figure 12: Subabilities by country

Table 9: ?(caption)

(a)

abilities	Vacancies	% of Vacancies	% of ARG	% of CHL	% of URY	
Cognitive Abilities	58971	99.52%	99.61%	99.46%	99.61%	
Sensory Abilities	58971	99.52%	99.61%	99.46%	99.61%	
Psychomotor Abilities	43369	73.19%	69.36%	75.73%	74.06%	
Physical Abilities	31618	53.36%	46.18%	58.52%	48.03%	
sum	—	192,929.00	3.26	3.15	3.33	3.21

Number of vacancies requiring an Ability, by Country

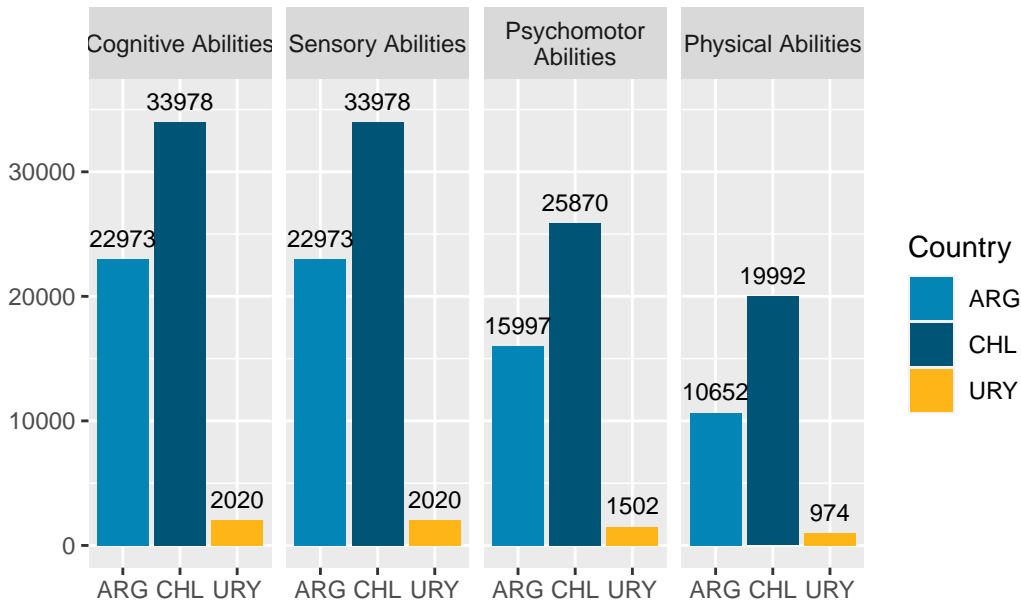


Table View

Sub-abilities

- There are 51 Sub Skills but *Dynamic_Flexibility* is missing from Uruguay. This report shows the remaining 50 until the original data is fixed.
- Oral Comprehension and Oral Expression are the most in-demand sub abilities, followed by Near Vision, Written Comprehension, and Deductive Reasoning. Argentina and Uruguay demand this skills with a higher intensity than Chile.

- Number facility and Mathematical Reasoning rank 21th and 22th in the ranking of most demanded sub abilities. Argentina and Uruguay demand this skills with a higher intensity than Chile.
- We compared the prevalence of sub-abilites job postings contrasted it what O*NET experts think are the typical importance and mastery levels of each skill within an occupation. We got a strong positive correlation, which suggests our text mining algorithms were able to capture some of the knowledge occupational experts have.

Charts

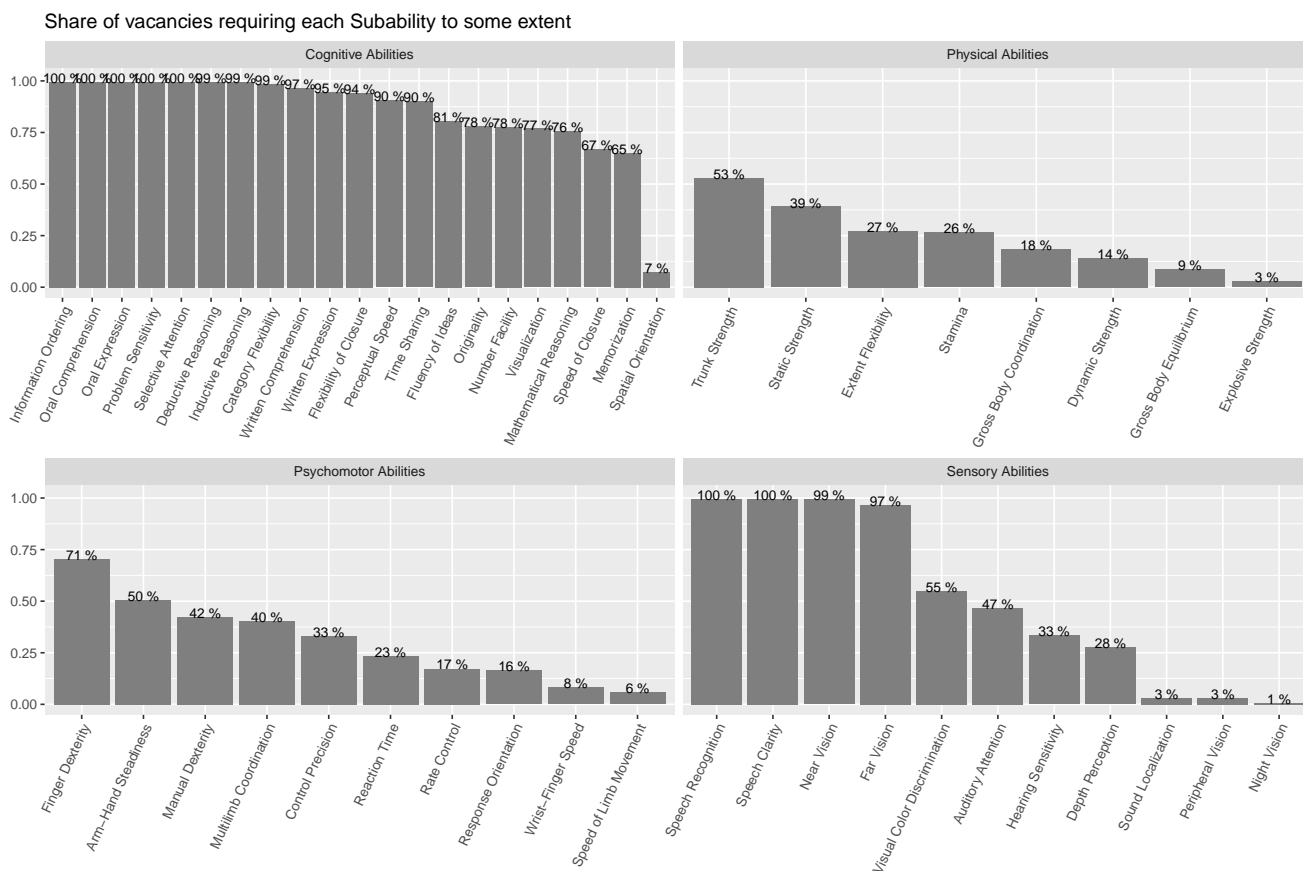


Figure 13: ?(caption)

[[1]]

[[2]]

[[3]]

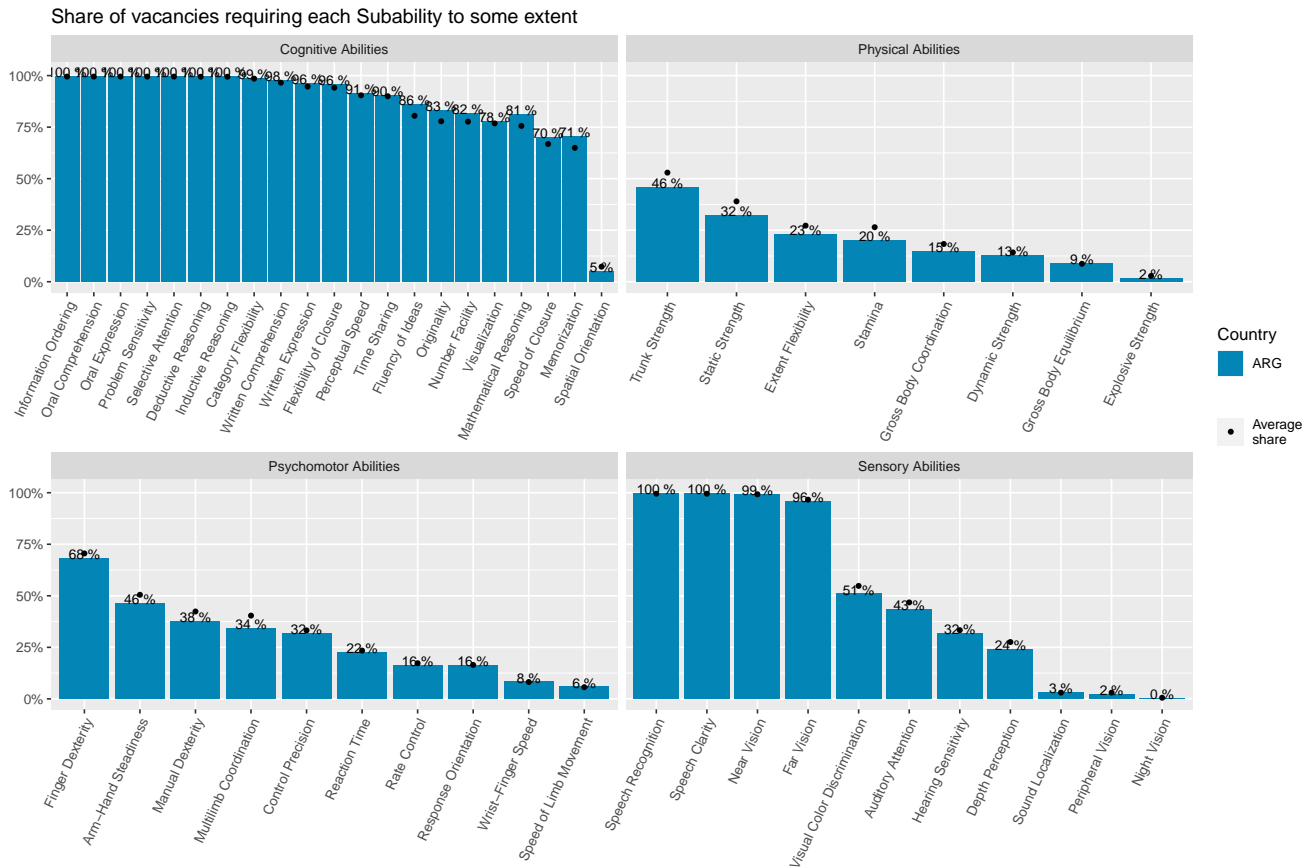


Figure 14: ?(caption)

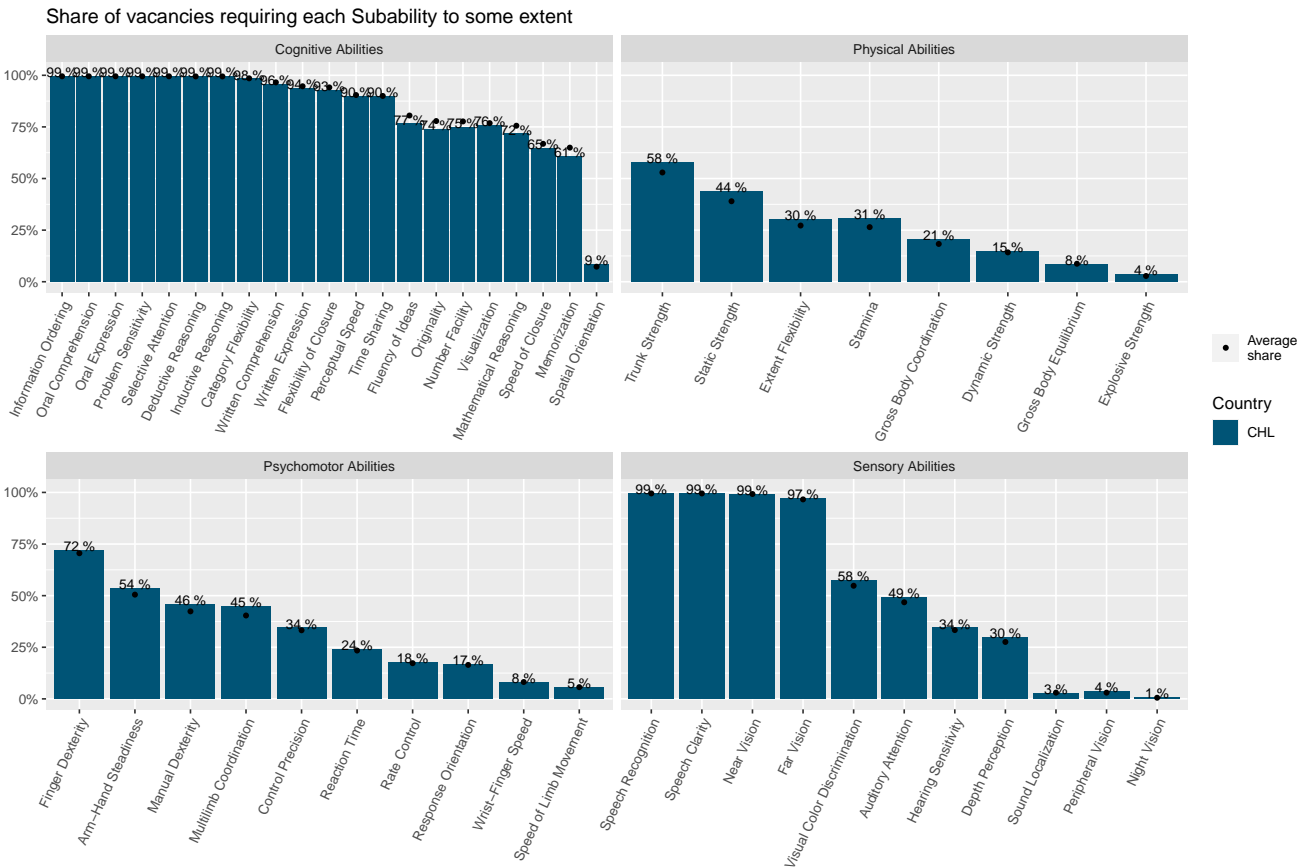


Figure 15: ?(caption)

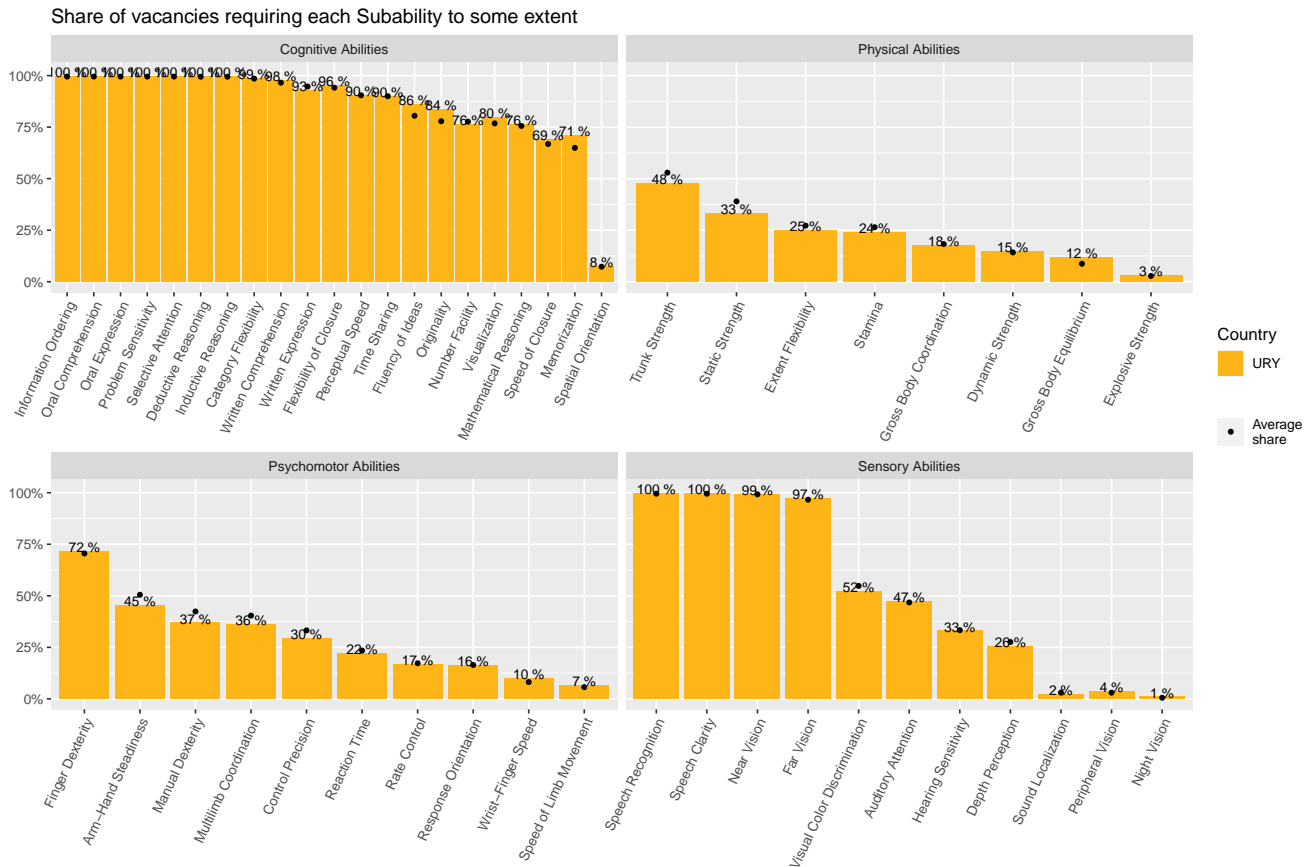
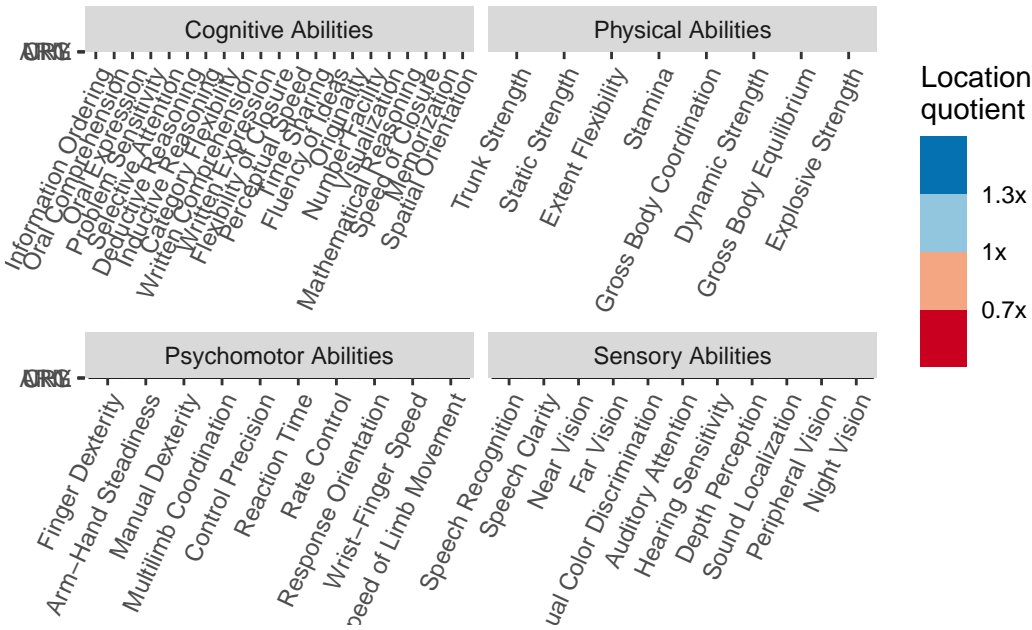


Figure 16: ?(caption)

sorted from more to less total vacancies



Number of vacancies requiring an Ability, by Country

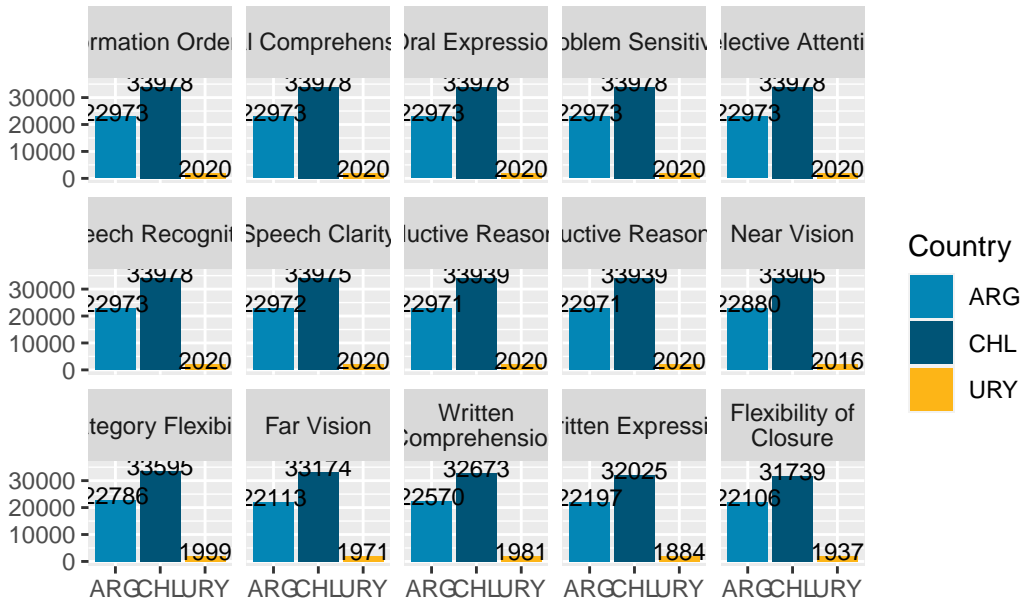


Table View

Table 10: ?(caption)

(a)

subabilities	Vacancies	% of Vacancies	% of ARG	% of CHL	% of URY
Information Ordering	58971	99.52%	99.61%	99.46%	99.61%
Oral Comprehension	58971	99.52%	99.61%	99.46%	99.61%
Oral Expression	58971	99.52%	99.61%	99.46%	99.61%
Problem Sensitivity	58971	99.52%	99.61%	99.46%	99.61%
Selective Attention	58971	99.52%	99.61%	99.46%	99.61%
Speech Recognition	58971	99.52%	99.61%	99.46%	99.61%
Speech Clarity	58967	99.51%	99.60%	99.45%	99.61%
Deductive Reasoning	58930	99.45%	99.60%	99.34%	99.61%
Inductive Reasoning	58930	99.45%	99.60%	99.34%	99.61%
Near Vision	58801	99.23%	99.20%	99.24%	99.41%
Category Flexibility	58380	98.52%	98.79%	98.34%	98.57%
Far Vision	57258	96.63%	95.88%	97.11%	97.19%
Written Comprehension	57224	96.57%	97.86%	95.64%	97.68%
Written Expression	56106	94.69%	96.24%	93.74%	92.90%
Flexibility of Closure	55782	94.14%	95.85%	92.90%	95.51%
Perceptual Speed	53588	90.44%	91.42%	89.78%	90.38%
Time Sharing	53324	89.99%	90.31%	89.77%	90.09%
Fluency of Ideas	47708	80.51%	85.89%	76.55%	86.14%
Originality	46125	77.84%	83.35%	73.78%	83.63%
Number Facility	46016	77.66%	81.81%	74.93%	76.33%
Visualization	45519	76.82%	77.85%	75.93%	79.98%
Mathematical Reasoning	44783	75.58%	81.26%	71.70%	76.23%
Finger Dexterity	41803	70.55%	68.11%	72.13%	71.55%
Speed of Closure	39592	66.82%	69.88%	64.62%	68.98%
Memorization	38493	64.96%	70.53%	60.85%	70.96%
Visual Color Discrimination	32468	54.79%	50.96%	57.53%	52.32%
Trunk Strength	31361	52.93%	45.68%	58.11%	47.93%
Arm-Hand Steadiness	29918	50.49%	46.44%	53.53%	45.32%
Auditory Attention	27724	46.79%	43.45%	49.02%	47.19%
Manual Dexterity	25114	42.38%	37.66%	45.90%	36.88%
Multilimb Coordination	23929	40.38%	34.17%	44.84%	36.00%
Static Strength	23104	38.99%	32.46%	43.74%	33.23%
Hearing Sensitivity	19745	33.32%	31.66%	34.47%	32.99%
Control Precision	19688	33.23%	31.80%	34.41%	29.54%
Depth Perception	16336	27.57%	24.24%	29.93%	25.64%
Extent Flexibility	16130	27.22%	23.01%	30.19%	25.05%
Stamina	15674	26.45%	20.20%	30.81%	24.11%
Reaction Time	13876	23.42%	22.41%	24.18%	22.09%
Gross Body Coordination	10846	18.30%	14.94%	20.62%	17.50%
Rate Control	10240	17.28%	16.47%	17.87%	16.62%
Response Orientation	9749	16.45%	16.17%	16.66%	16.17%
Dynamic Strength	8427	14.22%	13.07%	14.95%	15.04%
Gross Body Equilibrium	51672	8.72%	8.85%	8.45%	11.79%
Wrist-Finger Speed	4841	8.17%	8.26%	8.01%	9.86%
Spatial Orientation	4324	7.30%	5.26%	8.65%	7.69%
Speed of Limb Movement	3363	5.68%	5.90%	5.46%	6.71%
Sound Localization	1791	3.02%	3.34%	2.85%	2.27%

Extension: Sub-Skills by sector

As we said before, sectors and sub-skills aren't discretely assign to each online vacancies. Instead, each sector and skill has a weight on each job vacancy associated with the chances the firm belongs to that sector (or demands that skill).

To offer a tractable measure of the skills demand by sector we're simply going to assign a 1 to the sector with the maximum chances of being the vacancy's sector. Then we either count the number of times an ability (or subability) is required by a vacancy in the chosen sectors, or their average importance within the latter.

Another way is just counting the percentage of all postings within a country in which both the skill and the sector had a higher than average weight. We'll try different specifications and use the most satisfactory one in the final deliverable.

This is the frequency in which each sectors is a vacancy's most-likely sector:

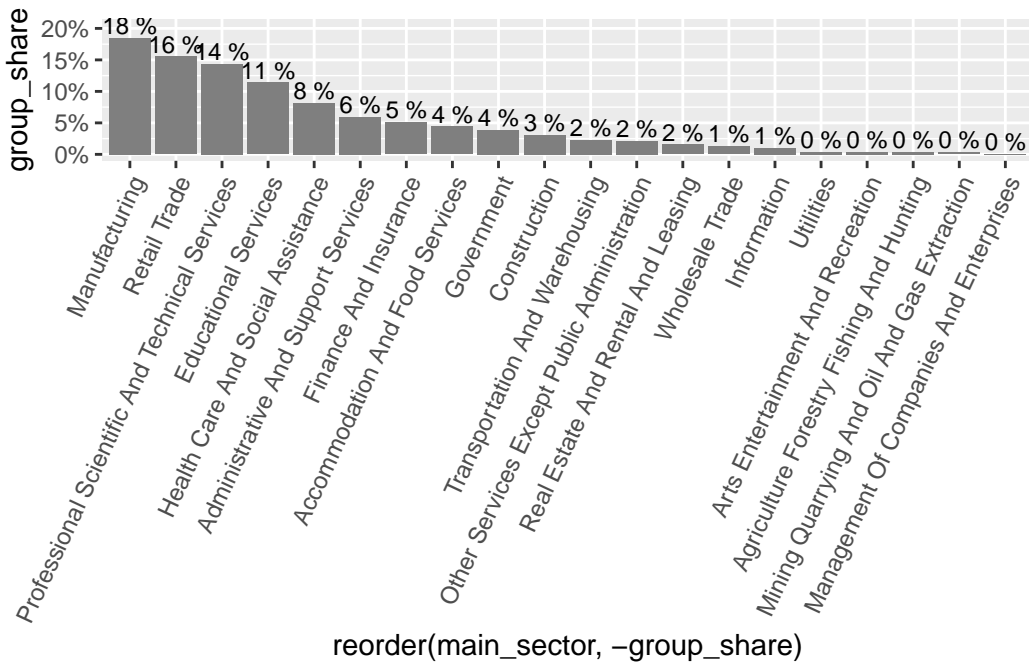


Figure 17: ?(caption)

This is the frequency in which each skill has positive changes of being demanded in a vacancy:

[[1]]

Table 11: ?(caption)

(a)

skim_type	skim_variable	n_missing	complete_rate	logical.mean	logical.count
logical	Information_Ordering	284	0.9952072	1.0000000	TRU: 58971
logical	Oral_Comprehension	284	0.9952072	1.0000000	TRU: 58971
logical	Oral_Expression	284	0.9952072	1.0000000	TRU: 58971
logical	Problem_Sensitivity	284	0.9952072	1.0000000	TRU: 58971
logical	Selective_Attention	284	0.9952072	1.0000000	TRU: 58971
logical	Speech_Recognition	284	0.9952072	1.0000000	TRU: 58971
logical	Speech_Clarity	284	0.9952072	0.9999322	TRU: 58967, FAL: 4
logical	Deductive_Reasoning	284	0.9952072	0.9993047	TRU: 58930, FAL: 41
logical	Inductive_Reasoning	284	0.9952072	0.9993047	TRU: 58930, FAL: 41
logical	Near_Vision	284	0.9952072	0.9971172	TRU: 58801, FAL: 170
logical	Category_Flexibility	284	0.9952072	0.9899781	TRU: 58380, FAL: 591
logical	Far_Vision	284	0.9952072	0.9709518	TRU: 57258, FAL: 1713
logical	Written_Comprehension	284	0.9952072	0.9703753	TRU: 57224, FAL: 1747
logical	Written_Expression	284	0.9952072	0.9514168	TRU: 56106, FAL: 2865
logical	Flexibility_of_Closure	284	0.9952072	0.9459226	TRU: 55782, FAL: 3189
logical	Perceptual_Speed	284	0.9952072	0.9087178	TRU: 53588, FAL: 5383
logical	Time_Sharing	284	0.9952072	0.9042411	TRU: 53324, FAL: 5647
logical	Fluency_of_Ideas	284	0.9952072	0.8090078	TRU: 47708, FAL: 11263
logical	Originality	284	0.9952072	0.7821641	TRU: 46125, FAL: 12846
logical	Number_Facility	284	0.9952072	0.7803157	TRU: 46016, FAL: 12955
logical	Visualization	284	0.9952072	0.7718879	TRU: 45519, FAL: 13452
logical	Mathematical_Reasoning	284	0.9952072	0.7594072	TRU: 44783, FAL: 14188
logical	Finger_Dexterity	284	0.9952072	0.7088739	TRU: 41803, FAL: 17168
logical	Speed_of_Closure	284	0.9952072	0.6713808	TRU: 39592, FAL: 19379
logical	Memorization	284	0.9952072	0.6527446	TRU: 38493, FAL: 20478
logical	Visual_Color_Discrimination	284	0.9952072	0.5505757	TRU: 32468, FAL: 26503
logical	Trunk_Strength	284	0.9952072	0.5318038	TRU: 31361, FAL: 27610
logical	Arm-Hand_Steadiness	284	0.9952072	0.5073341	TRU: 29918, FAL: 29053
logical	Auditory_Attention	284	0.9952072	0.4701294	FAL: 31247, TRU: 27724
logical	Manual_Dexterity	284	0.9952072	0.4258703	FAL: 33857, TRU: 25114
logical	Multilimb_Coordination	284	0.9952072	0.4057757	FAL: 35042, TRU: 23929
logical	Static_Strength	284	0.9952072	0.3917858	FAL: 35867, TRU: 23104
logical	Hearing_Sensitivity	284	0.9952072	0.3348256	FAL: 39226, TRU: 19745
logical	Control_Precision	284	0.9952072	0.3338590	FAL: 39283, TRU: 19688
logical	Depth_Perception	284	0.9952072	0.2770175	FAL: 42635, TRU: 16336
logical	Extent_Flexibility	284	0.9952072	0.2735243	FAL: 42841, TRU: 16130
logical	Stamina	284	0.9952072	0.2657917	FAL: 43297, TRU: 15674
logical	Reaction_Time	284	0.9952072	0.2353021	FAL: 45095, TRU: 13876
logical	Gross_Body_Coordination	284	0.9952072	0.1839209	FAL: 48125, TRU: 10846
logical	Rate_Control	284	0.9952072	0.1736447	FAL: 48731, TRU: 10240
logical	Response_Orientation	284	0.9952072	0.1653185	FAL: 49222, TRU: 9749
logical	Dynamic_Strength	284	0.9952072	0.1429007	FAL: 50544, TRU: 8427
logical	Gross_Body_Equilibrium	34 284	0.9952072	0.0876193	FAL: 53804, TRU: 5167
logical	Wrist-Finger_Speed	284	0.9952072	0.0820912	FAL: 54130, TRU: 4841
logical	Spatial_Orientation	284	0.9952072	0.0733242	FAL: 54647, TRU: 4324
logical	Speed_of_Limb_Movement	284	0.9952072	0.0570280	FAL: 55608, TRU: 3363
logical	Sound_Localization	284	0.9952072	0.0303709	FAL: 57180, TRU: 1791

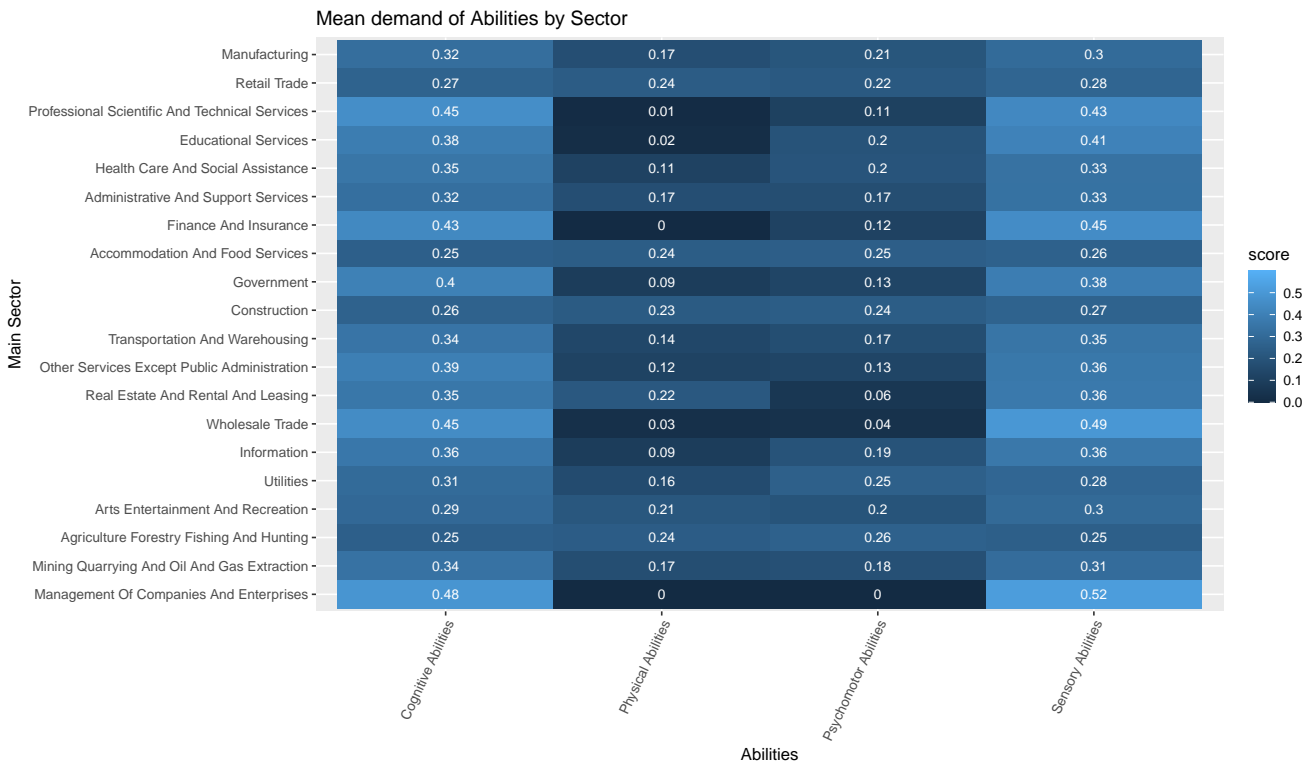
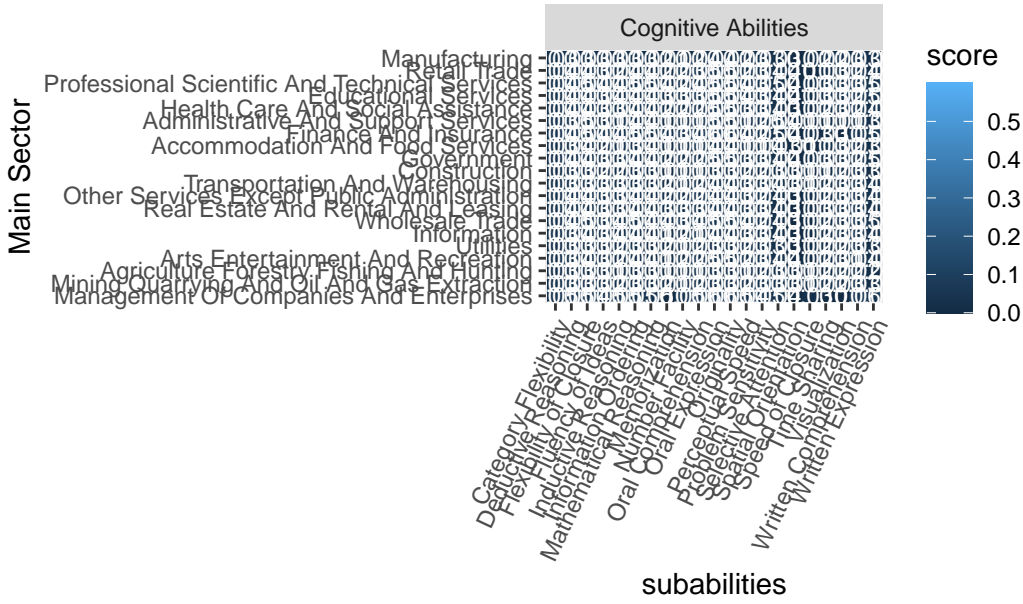


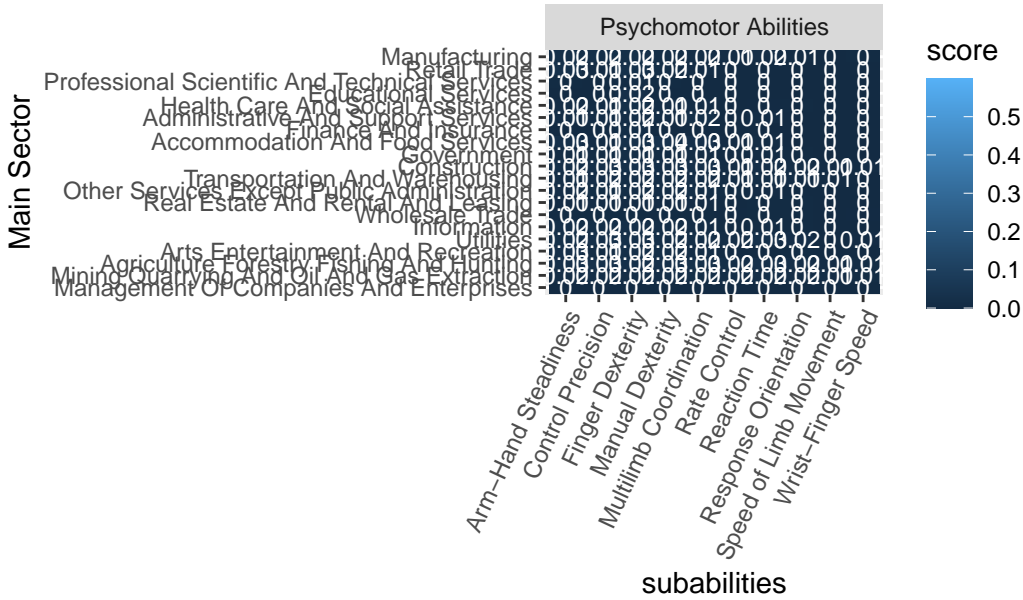
Figure 18: Subabilities by sector

Mean demand of Cognitive Abiliti



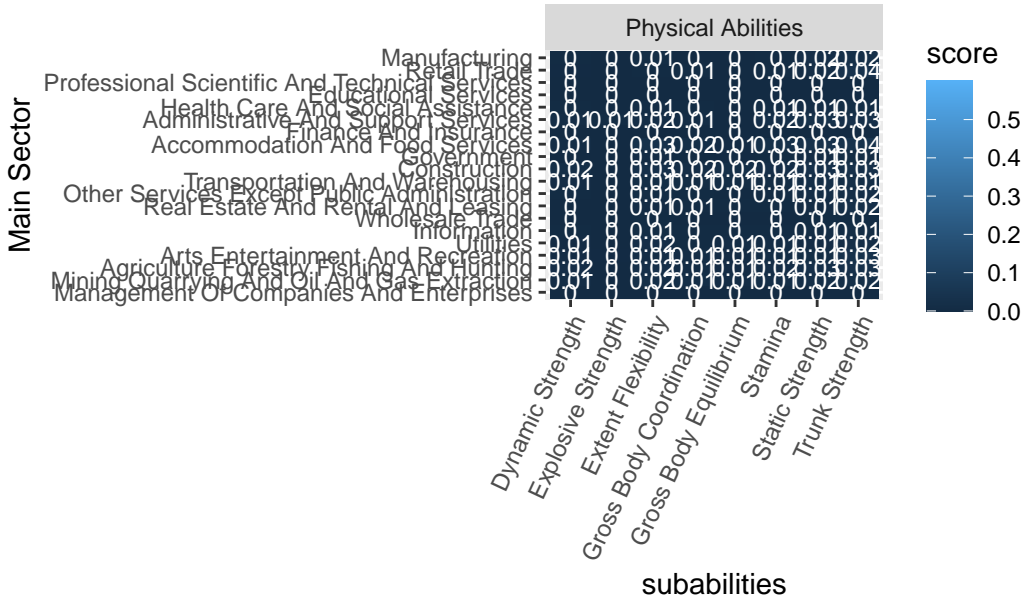
[[2]]

Mean demand of Psychomotor A



[[3]]

Mean demand of Physical Abilitie



[[4]]

Mean demand of Sensory Abilitie



Job zones

- 41% of job vacancies in the South Cone require “(2) Some preparation”, while 25% require “(4) Considerable preparation”, and another 25% requires “(3) Middle preparation”. Only 8% of the demand is focused on the “(1) no preparation” and “(5) a lot of preparation” extremes.
- 46% of job postings in Chile demand “(2) Some preparation”. It’s the country most concentrated in that area of demand by a considerable margin.
- 30.5% of job postings in Argentina demand “(4) Considerable preparation”. It’s the country most concentrated in that area of demand by a moderate margin.
- 29.6% of job postings in Uruguay demand “(3) Middle preparation”. It’s the country most concentrated in that area of demand by a moderate margin.

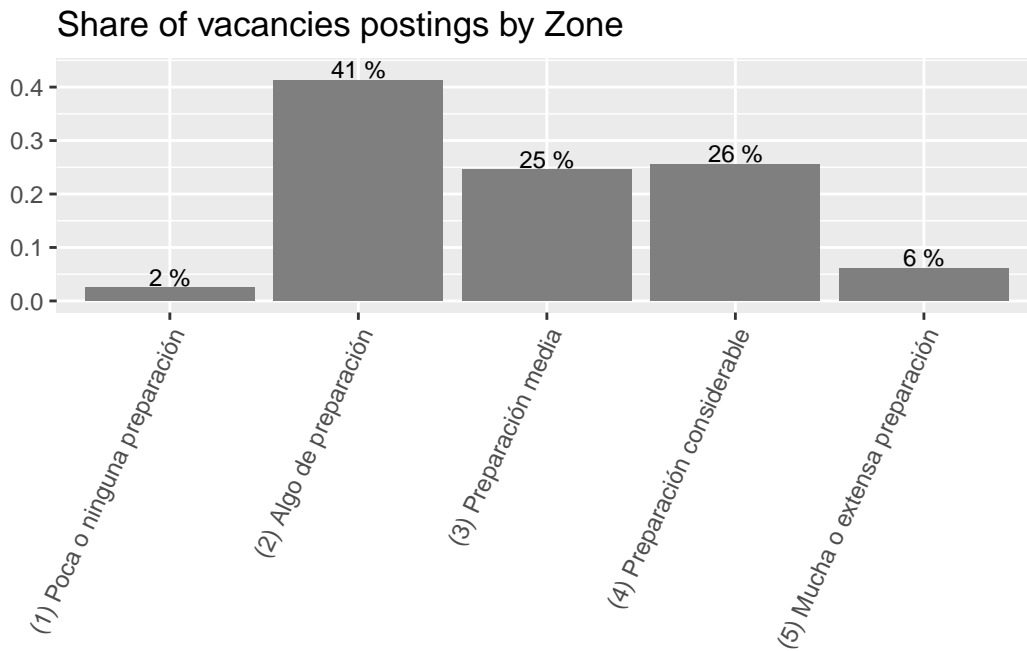


Figure 19: ?(caption)

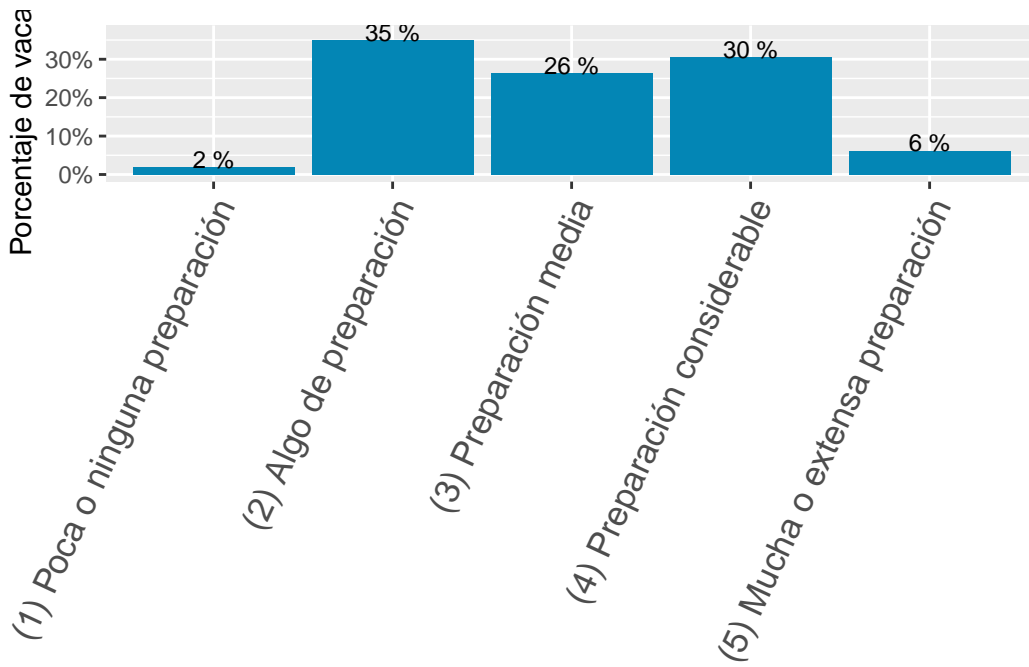


Figure 20: ?(caption)

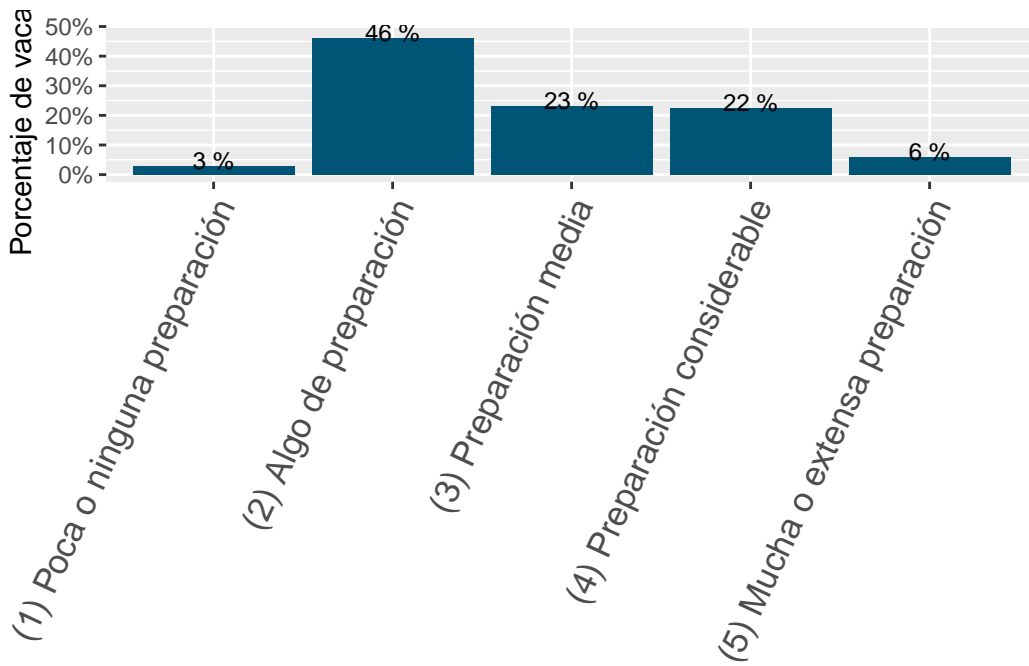


Figure 21: ?(caption)

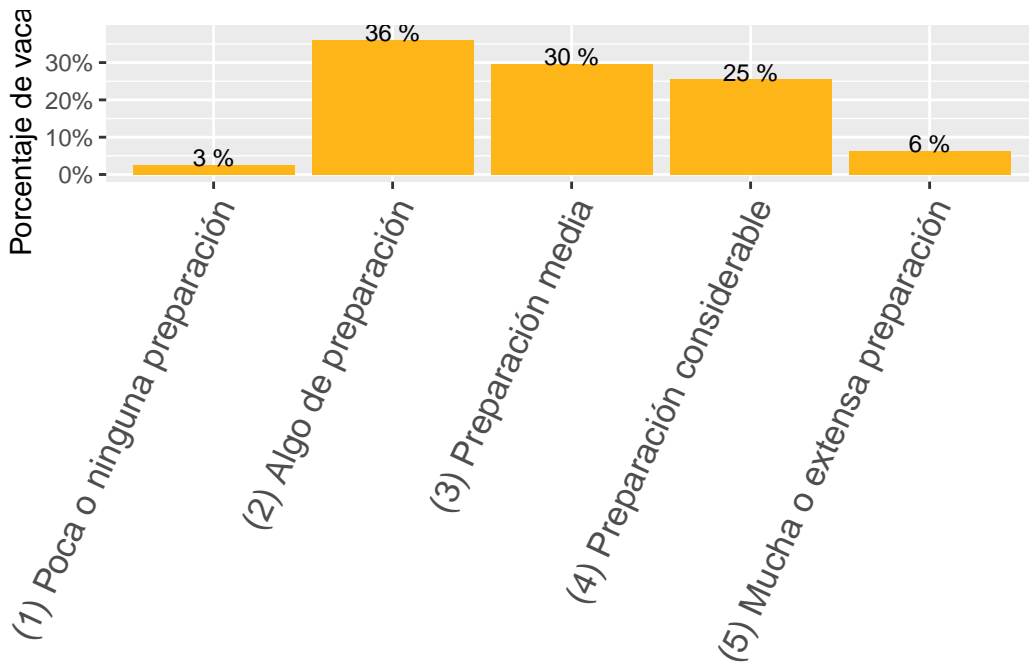


Figure 22: ?(caption)

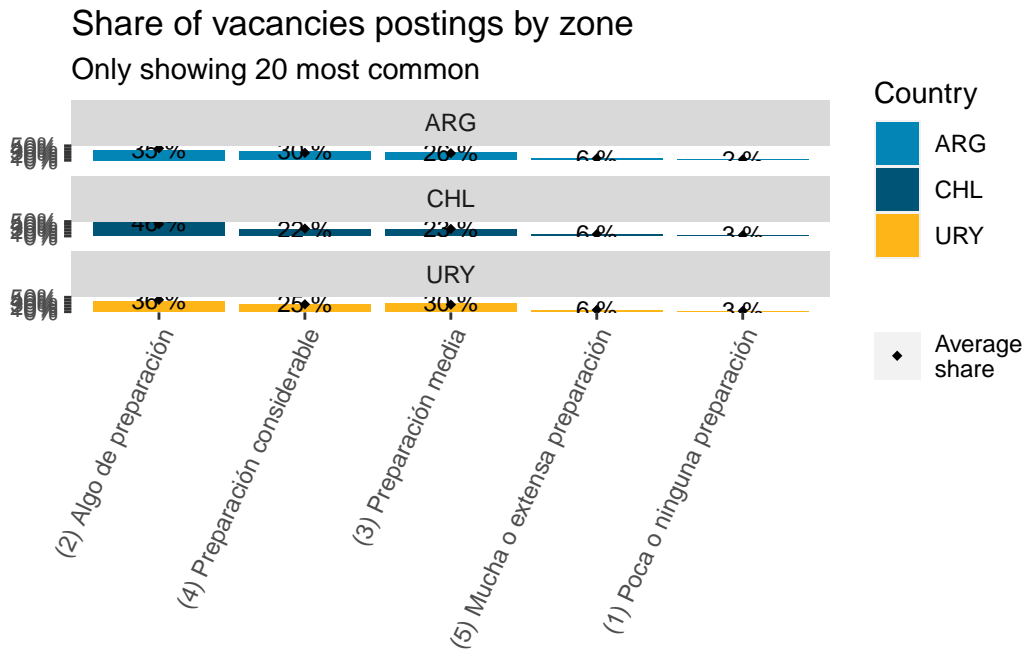
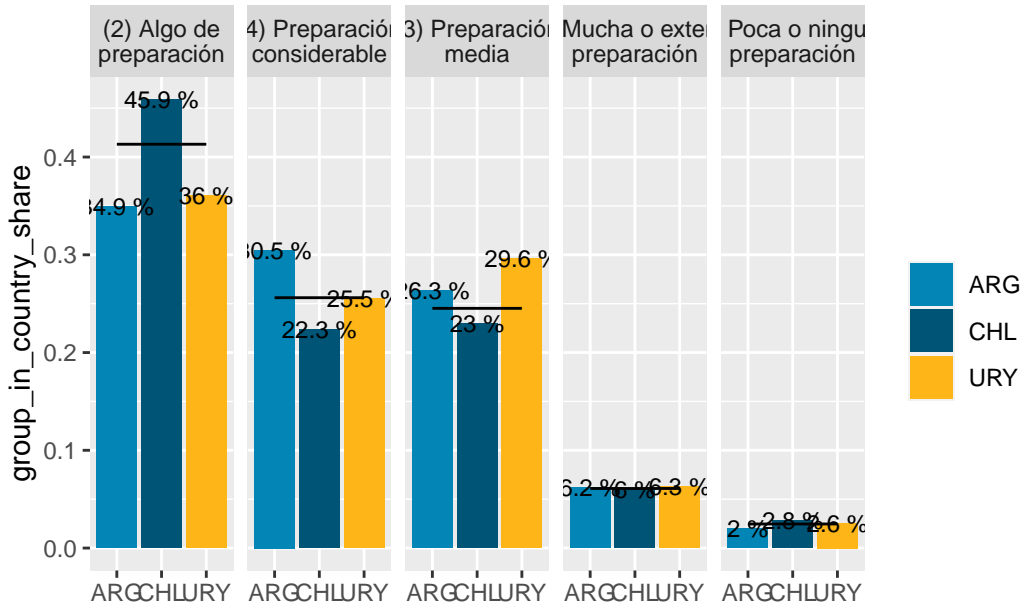
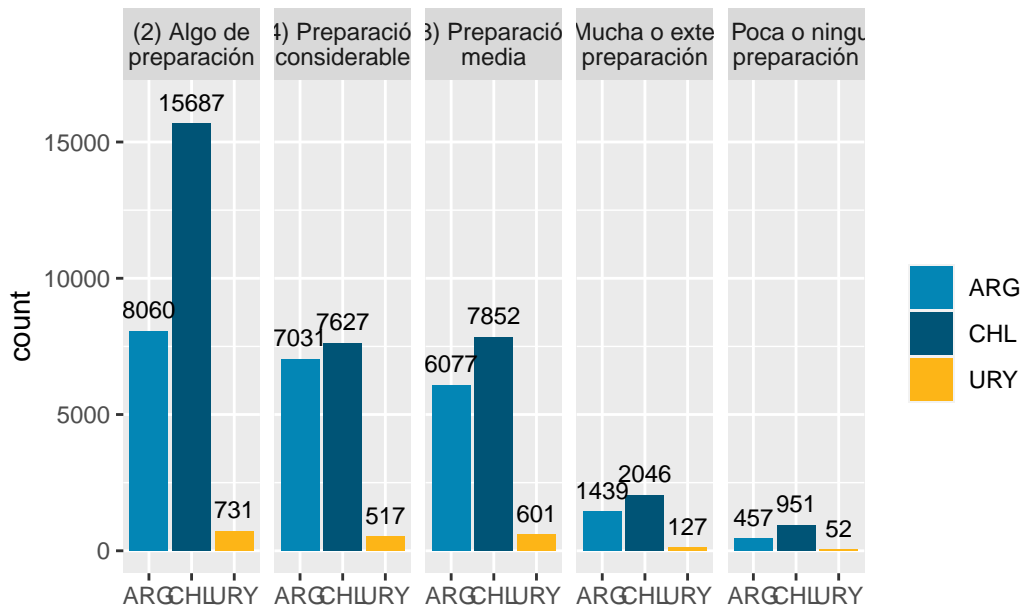


Figure 23: Jobzones

Job zones distribution in online vacancies data



Job zones distribution in online vacancies data



Job zones across sectors

[[1]]

Table 12: ?(caption)

(a)

zones_label	Vacancies	% of Vacancies	% of ARG	% of CHL	% of URY
(2) Algo de preparación	24478	41.31%	34.95%	45.92%	36.05%
(4) Preparación considerable	15175	25.61%	30.48%	22.33%	25.49%
(3) Preparación media	14530	24.52%	26.35%	22.98%	29.64%
(5) Mucha o extensa preparación	3612	6.10%	6.24%	5.99%	6.26%
(1) Poca o ninguna preparación	1460	2.46%	1.98%	2.78%	2.56%
sum	59,255.00	1.00	1.00	1.00	1.00

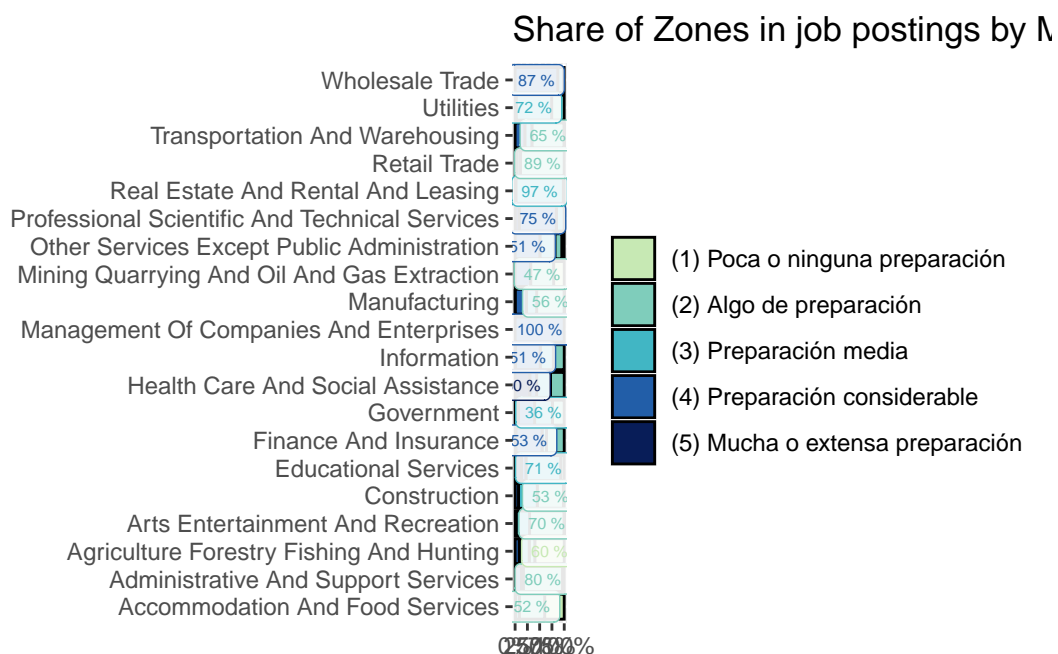
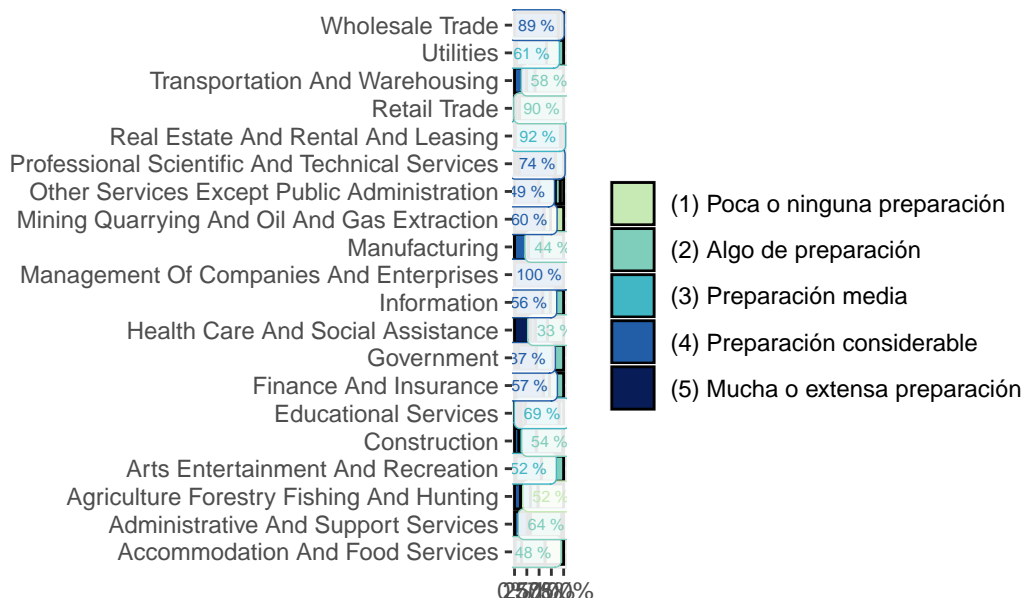


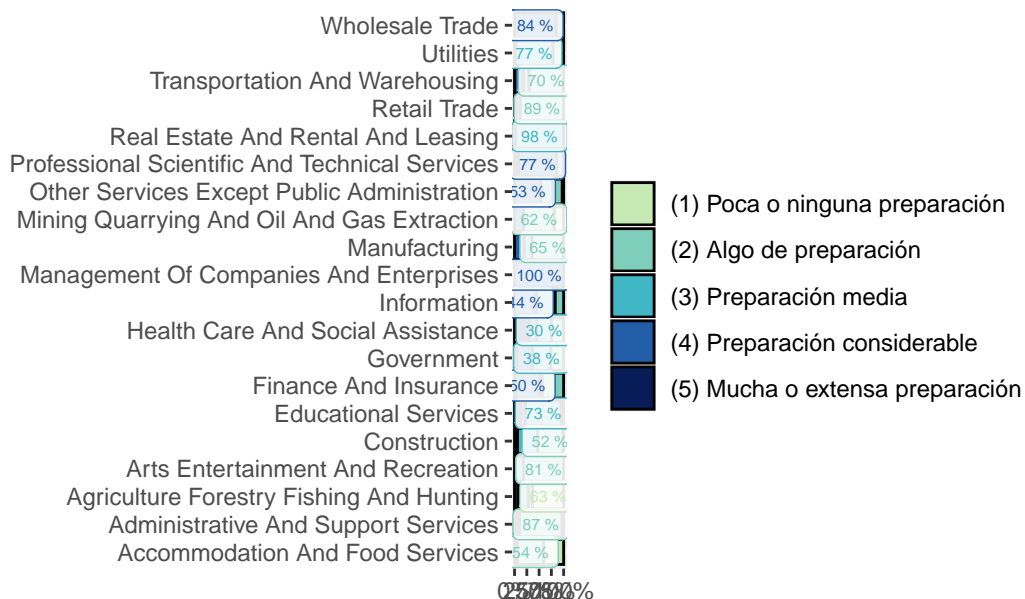
Figure 24: Jobzones by sector

ARG share of Zones in job postings



[[2]]

CHL share of Zones in job postings



[[3]]

URY share of Zones in job postings

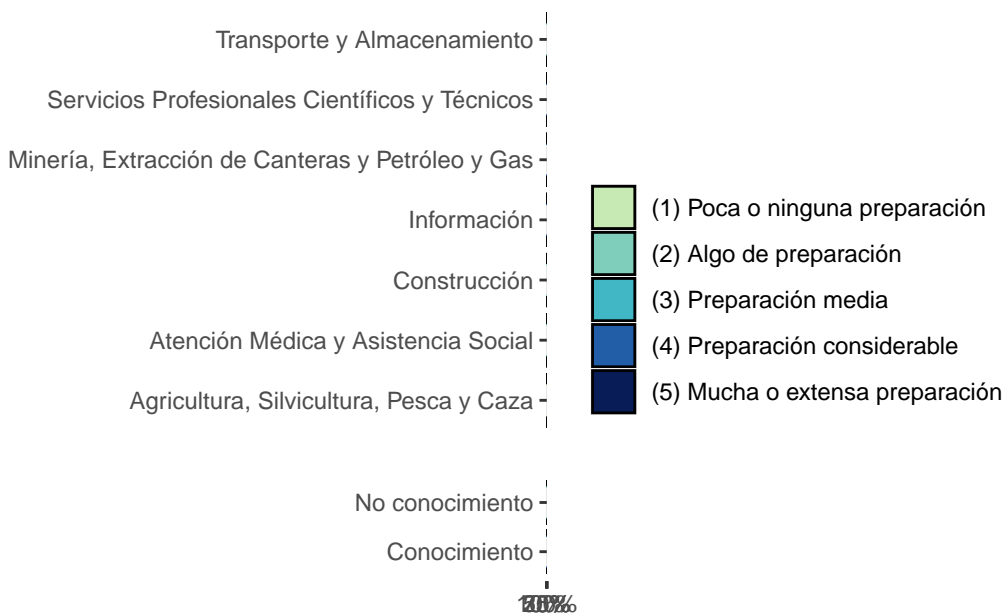


Figure 25: ?(caption)

Job zones across occupational groups

[[1]]

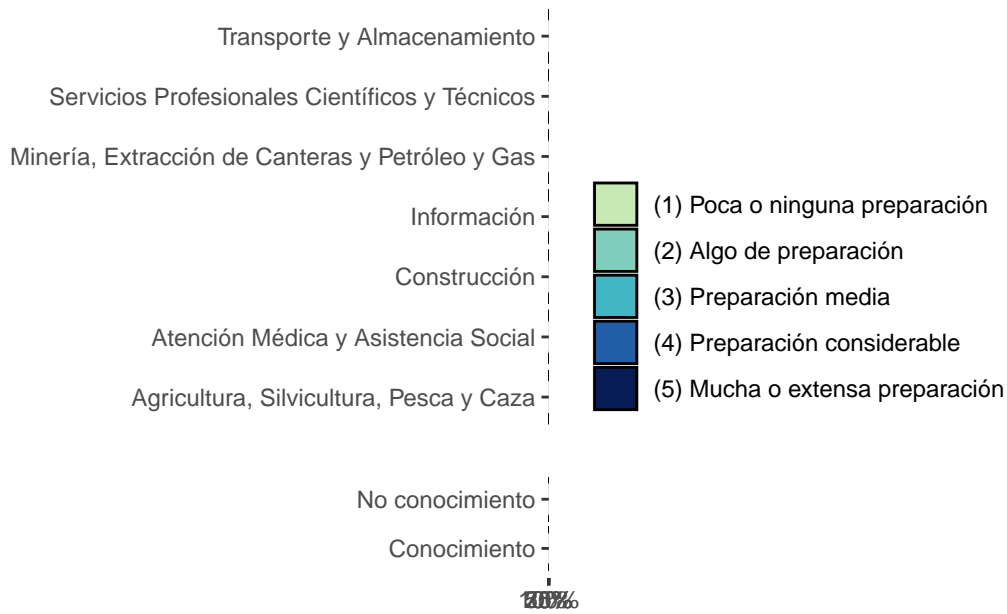


Figure 26: ?(caption)

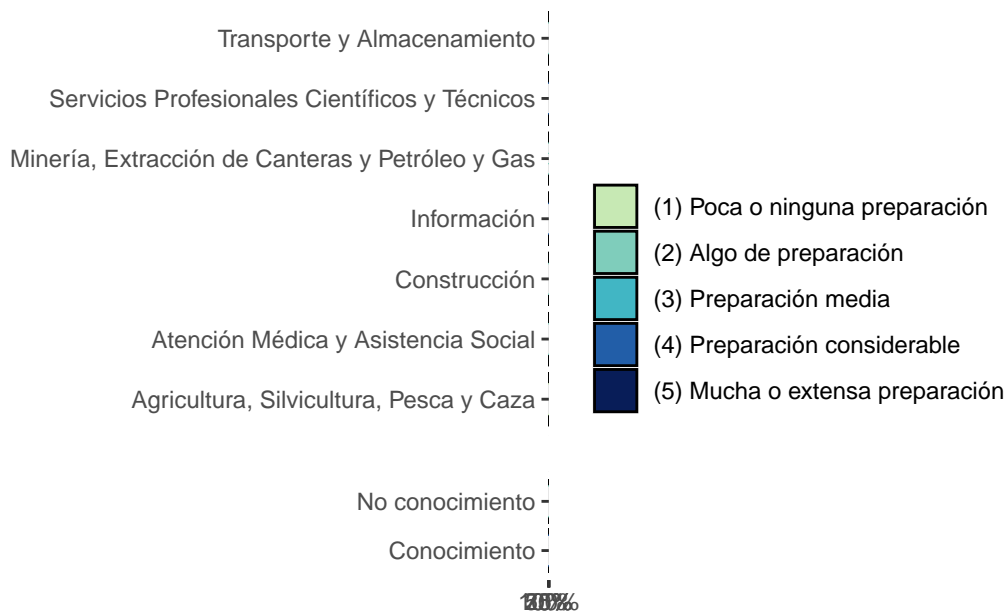


Figure 27: ?(caption)

Share of Zones in job postings by N

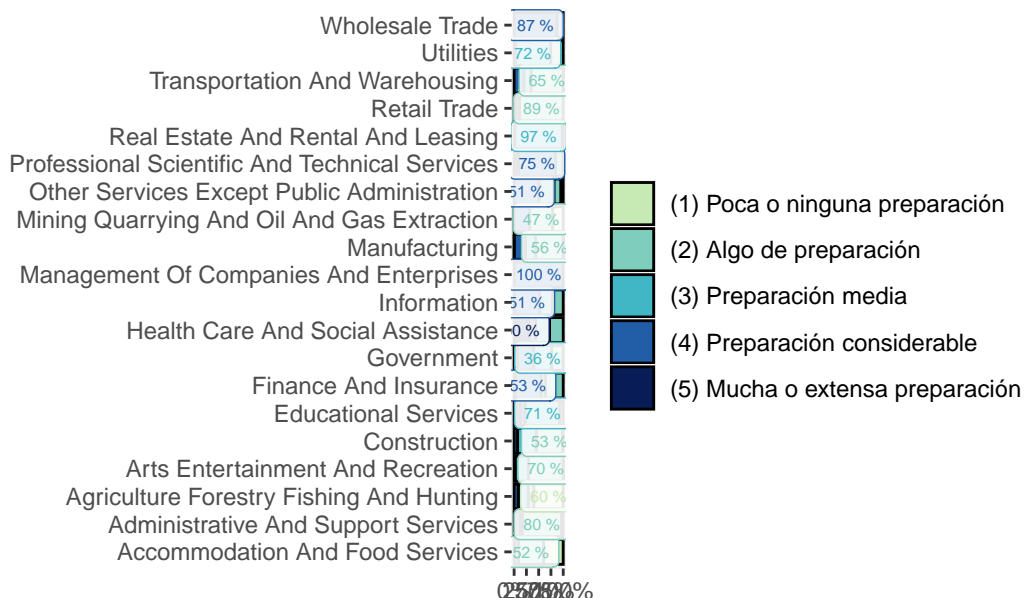
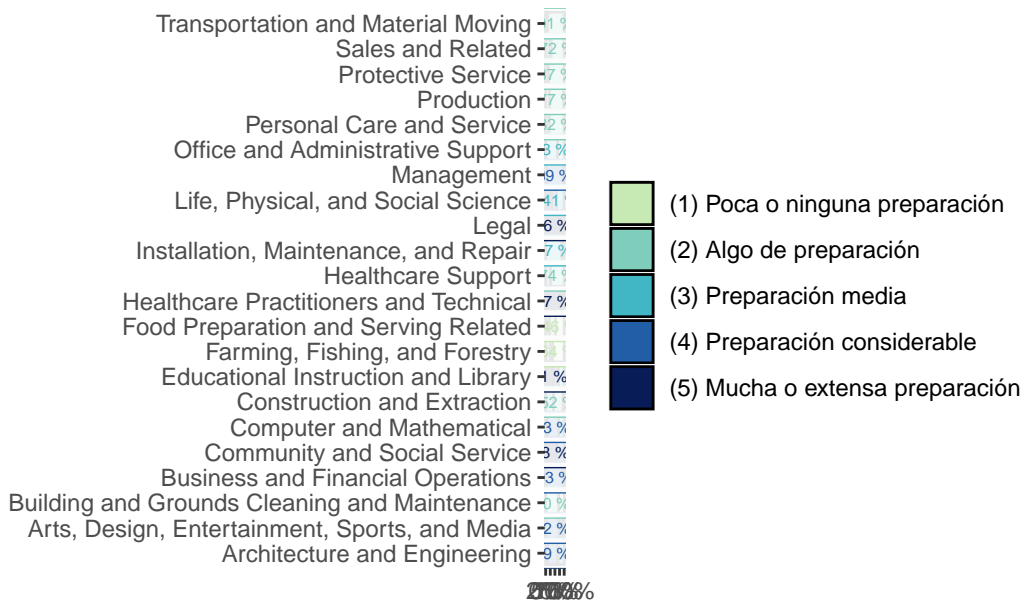


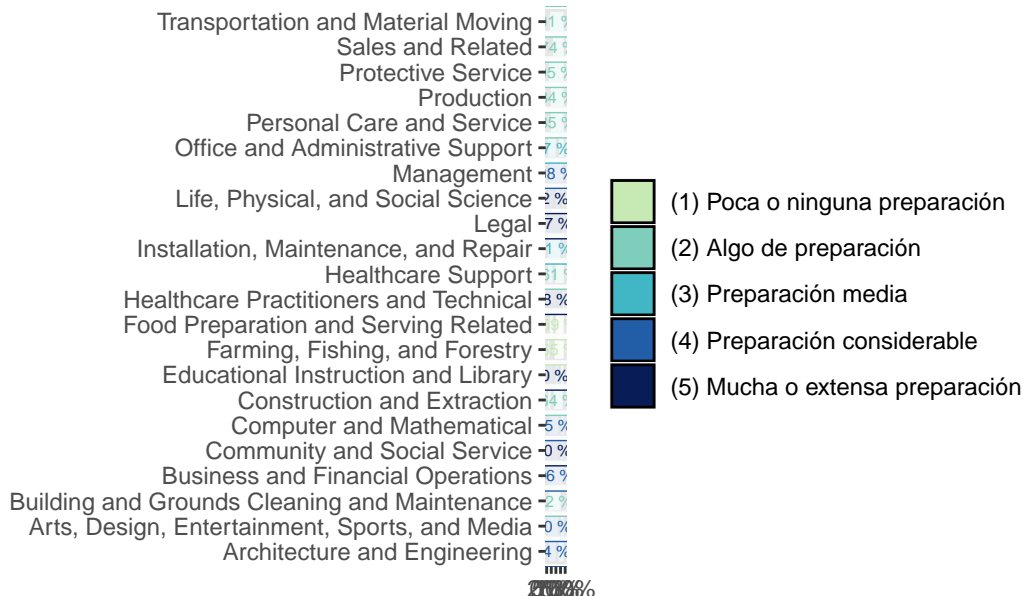
Figure 28: Jobzones by soc

ARG share of Zones in job postin



[[2]]

CHL share of Zones in job postin



[[3]]

URY share of Zones in job postin

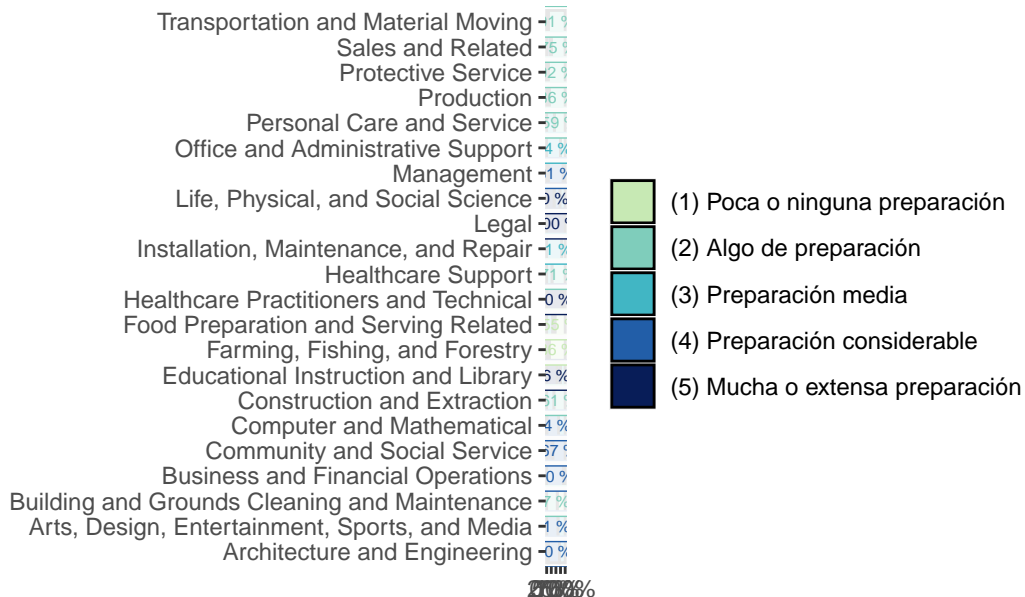


Table 13: ?(caption)

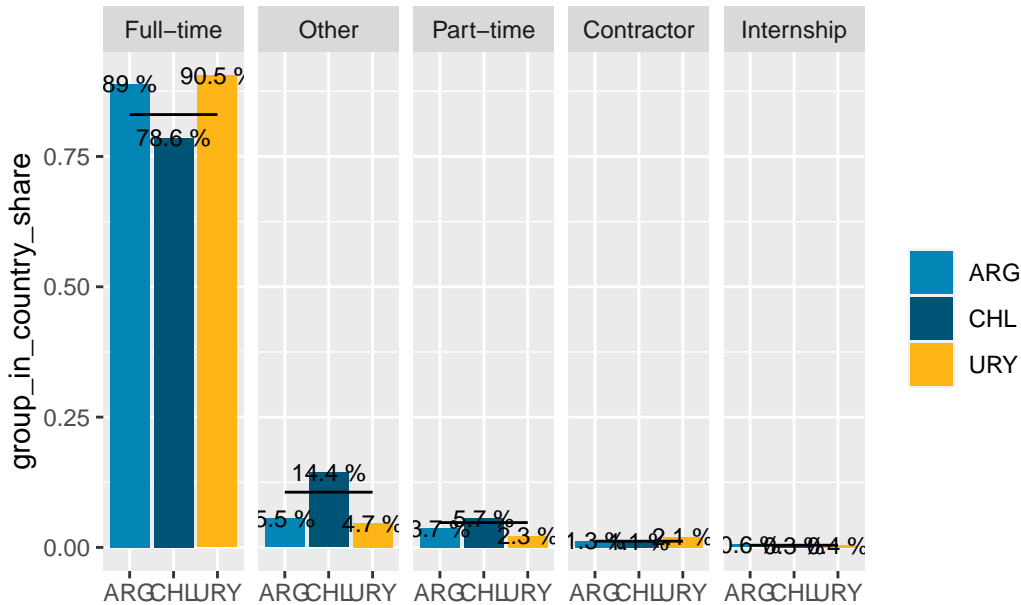
(a)

	schedule	Vacancies	% of Vacancies	% of ARG	% of CHL	% of URY
	Full-time	49201	83.03%	88.97%	78.58%	90.53%
	Other	6278	10.59%	5.54%	14.36%	4.68%
	Part-time	2822	4.76%	3.66%	5.65%	2.27%
	Contractor	705	1.19%	1.26%	1.09%	2.07%
	Internship	249	0.42%	0.56%	0.32%	0.44%
sum	—	59,255.00	1.00	1.00	1.00	1.00

Work Schedule

- 83% of postings seek to fill full-time positions.
- 14% of postings in Chile correspond to “Other”. This needs clarification. This is associated with the lower than average share of full-time positions in Chile.
- 5.7% of Chile job postings correspond to “Part-time” roles (about 1 percent point above average).
- The contractor mode is more prevalent in Uruguay job postings (almost twice the average). This would be consistent with the rumors about many Uruguay firms outsourcing Argentinean workers. This should be corroborated with remote work data.

Schedule distribution in online vacancies data



Share of vacancies postings by Schedule

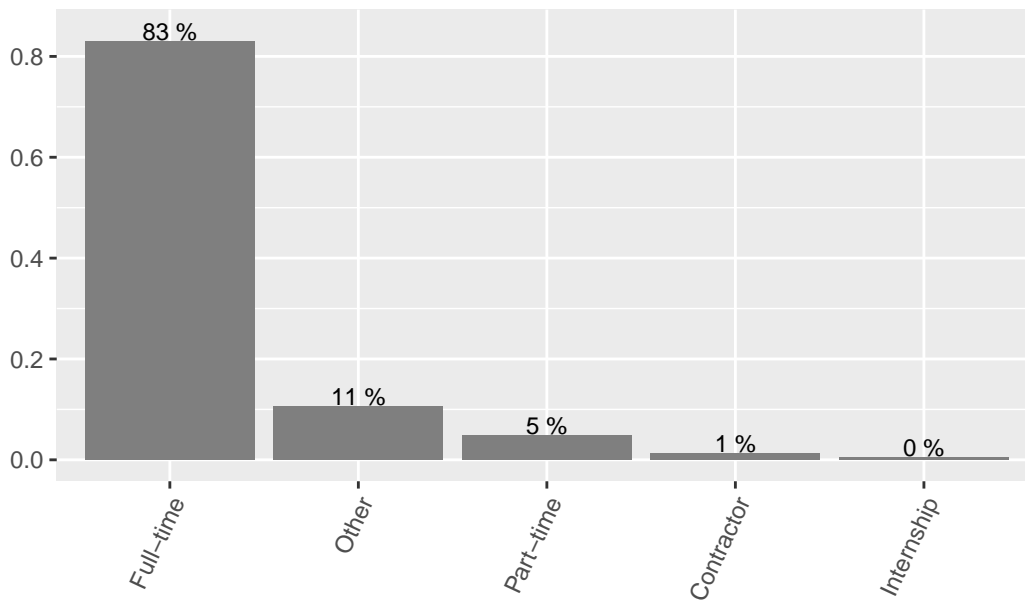


Figure 29: ?(caption)

Share of vacancies postings by Schedule

Only showing 20 most common

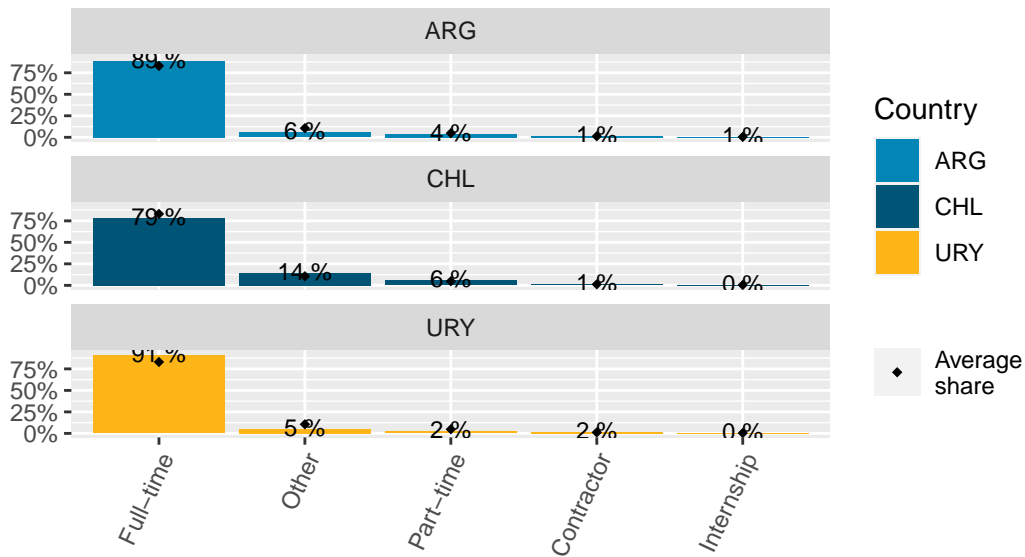
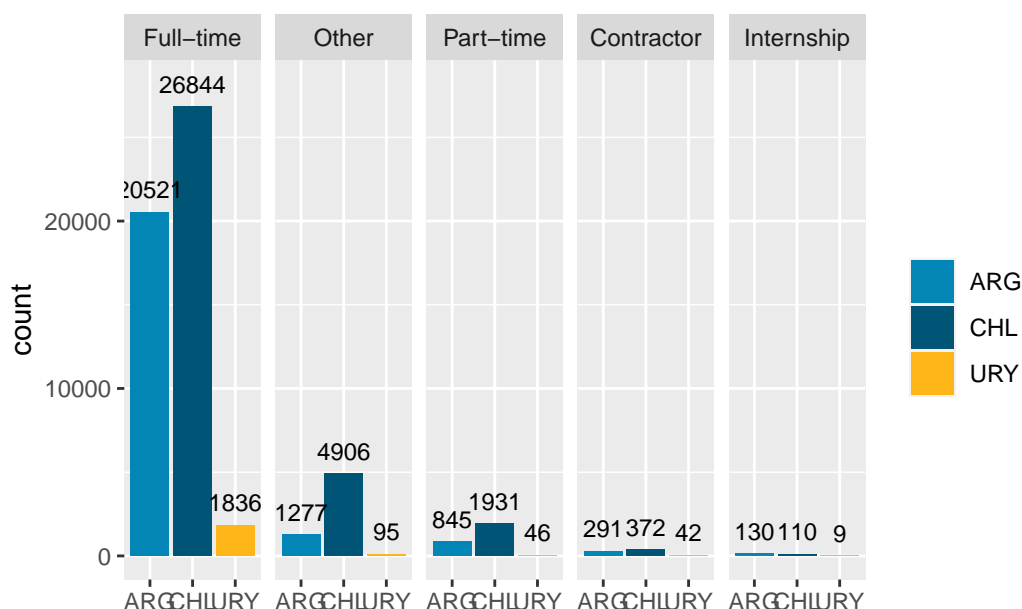


Figure 30: ?(caption)

Schedule distribution in online vacancies data



Green jobs

- Green jobs represent 15% of all online job postings.
- Argentina has the highest share of green jobs in its' job postings (17%).
- Within green jobs, the most demanded are classified as “Green Increased Demand” (45%).
- Green job postings in Argentina are 48% “Green Increased Demand”, 37% are “Green enhanced skills”, and 14% are “Green New & Emerging”.
- Greener regions in terms of online vacancies are Santiago, Buenos Ares, Valparaíso, Concepción, Rosario, Córdoba y Antofagasta. Buenos aires, Concepción, Rosario, Córdoba, and Antofagasta are overrepresented in the sample of green online vacancies.

Table 14: Green jobs distribution

green_job_bin	Vacancies	% of Vacancies	% of ARG	% of CHL	% of URY
FALSE	50273	84.84%	82.20%	86.67%	84.12%
TRUE	8982	15.16%	17.80%	13.33%	15.88%
sum	—	59,255.00	1.00	1.00	1.00

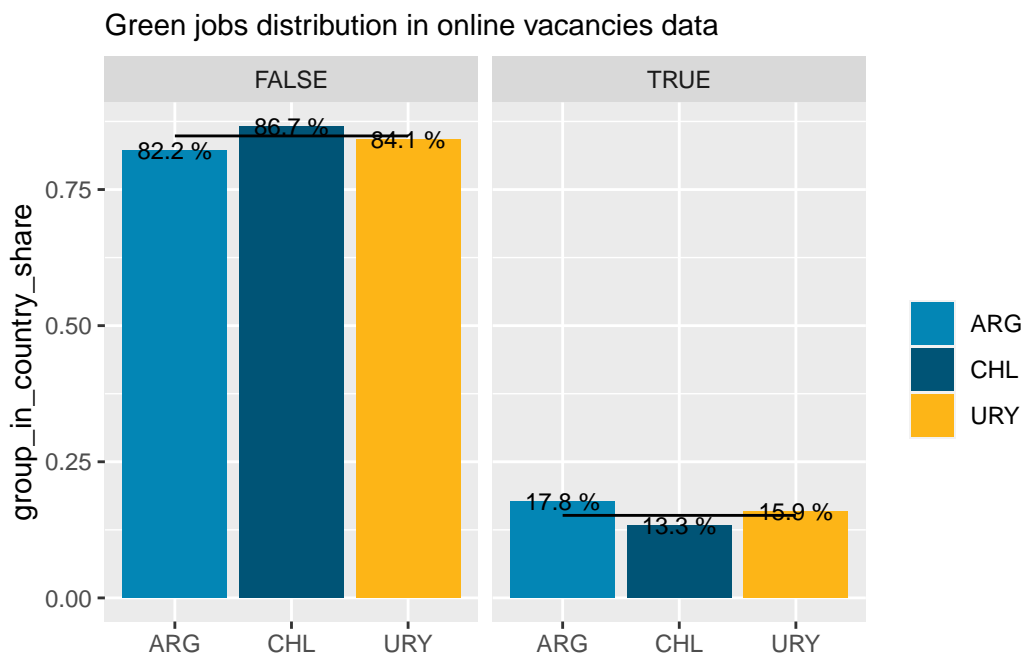


Figure 31: Green jobs distribution, by country

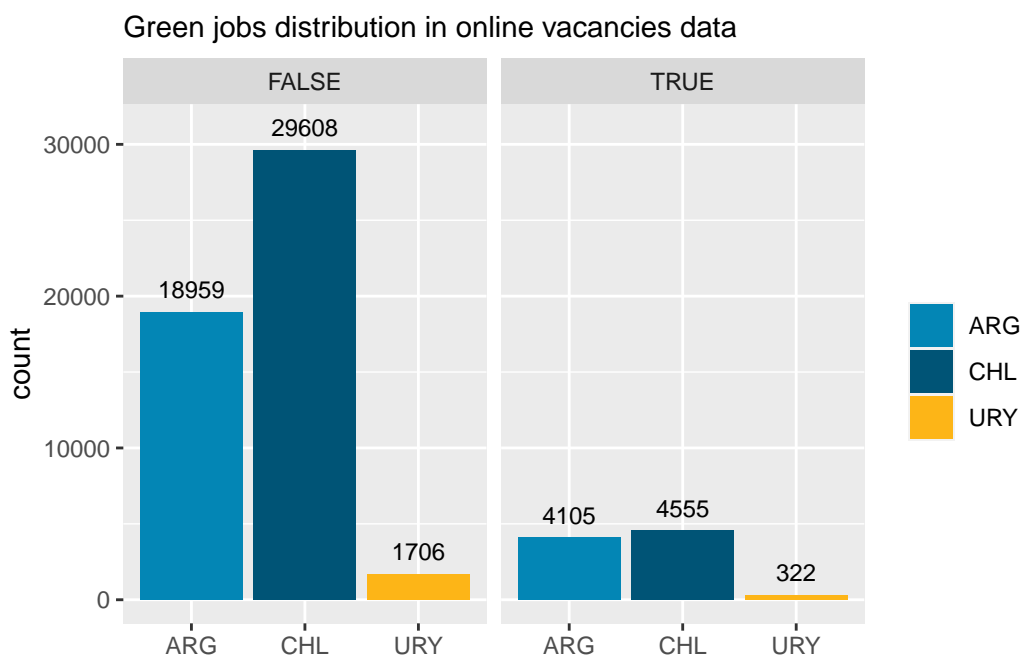


Table 15: Green job types distribution

green_job	Vacancies	% of Vacancies	% of ARG	% of CHL	% of URY
-----------	-----------	----------------	----------	----------	----------

Green Increased Demand	4042	45.00%	48.43%	42.06%	42.86%
Green Enhanced Skills	3654	40.68%	37.59%	43.36%	42.24%
Green New & Emerging	1286	14.32%	13.98%	14.58%	14.91%
sum	—	8,982.00	1.00	1.00	1.00

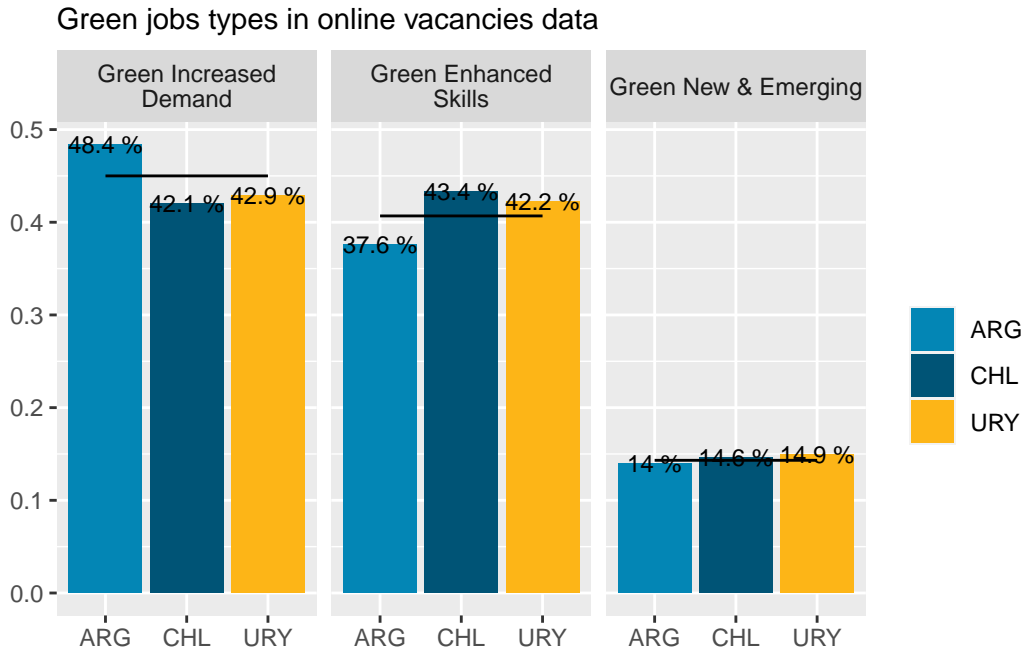


Figure 32: Green job types distribution by country

Green jobs types in online vacancies data

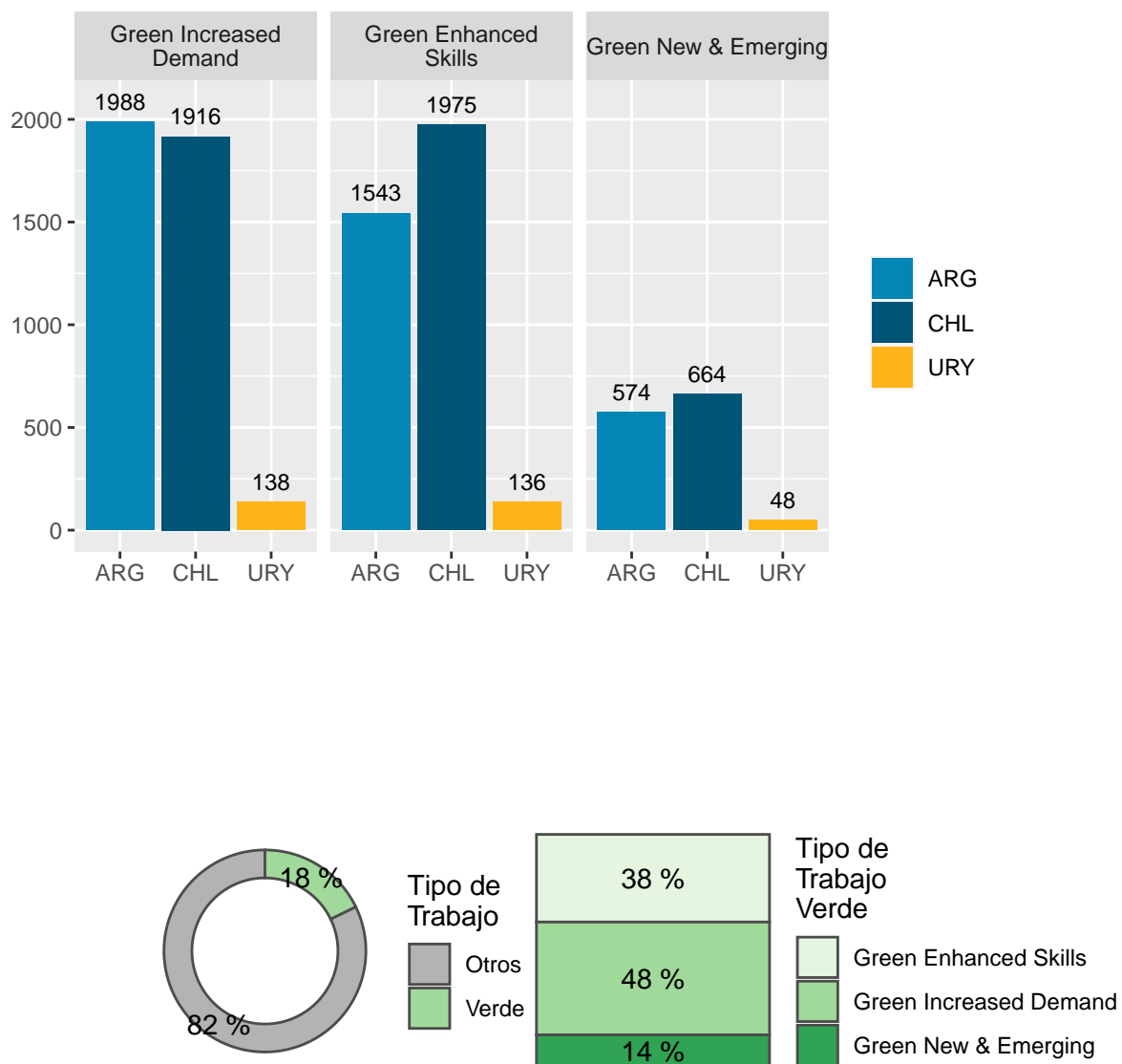


Figure 33: ?(caption)



Figure 34: ?(caption)

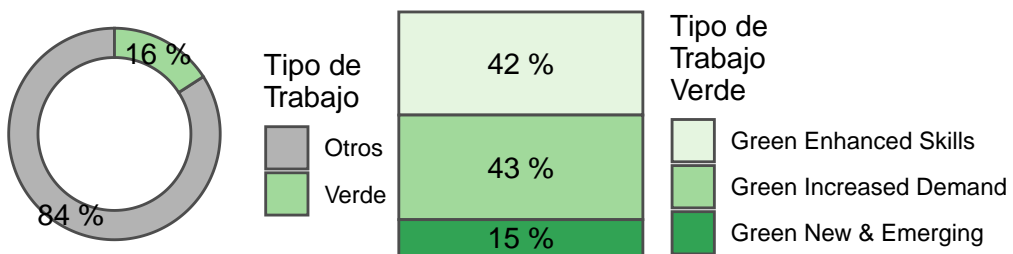
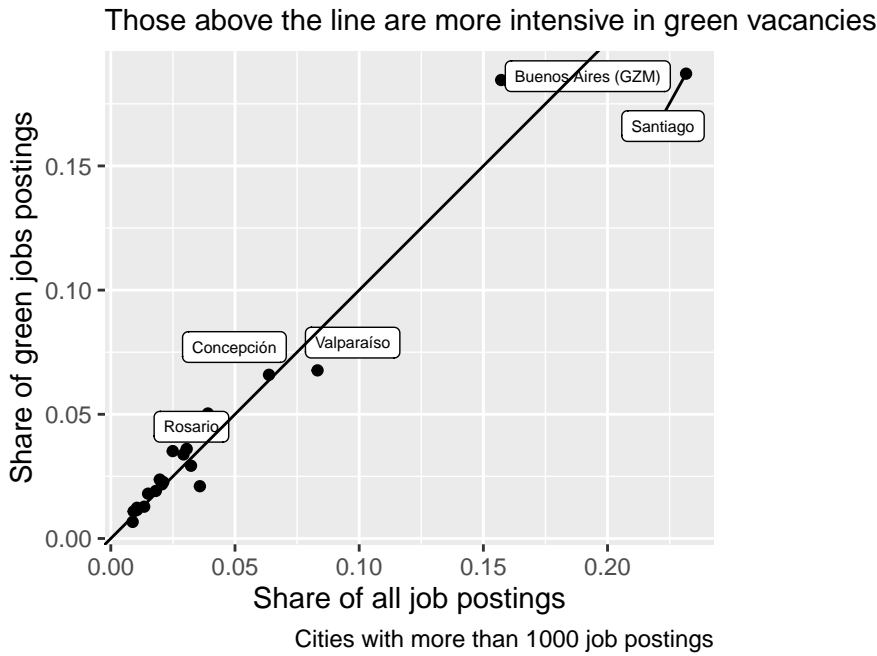


Figure 35: ?(caption)

Table 16: Green jobs distribution, by region

region	Job postings	share in all data	share in green	ratio
Santiago	13725	24%	0.1871521	0.81
Buenos Aires (GZM)	9313	16%	0.1845914	1.17
Valparaíso	4932	8%	0.0676909	0.81
Concepción	3774	6%	0.0659096	1.03
Rosario	2316	4%	0.0503229	1.29
Gran Temuco	2125	4%	0.0210421	0.59
Coquimbo	1913	4%	0.0292808	0.91
Córdoba	1810	4%	0.0360721	1.18
Mendoza	1734	2%	0.0338455	1.16
Antofagasta	1477	2%	0.0351815	1.41
Puerto Montt	1251	2%	0.0227121	1.08
Metropolitana	1220	2%	0.0218214	1.06
Tarapacá	1168	2%	0.0237141	1.20
Corrientes	1074	2%	0.0191494	1.06
Región Metropolitana Confluencia	889	2%	0.0180361	1.20

Location of green jobs across regions



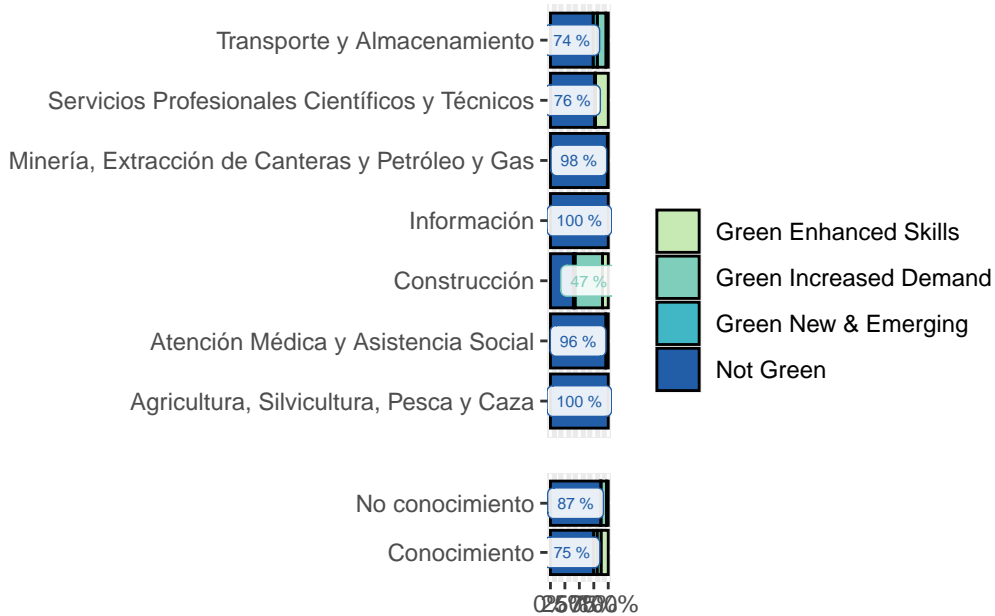


Figure 36: ?(caption)

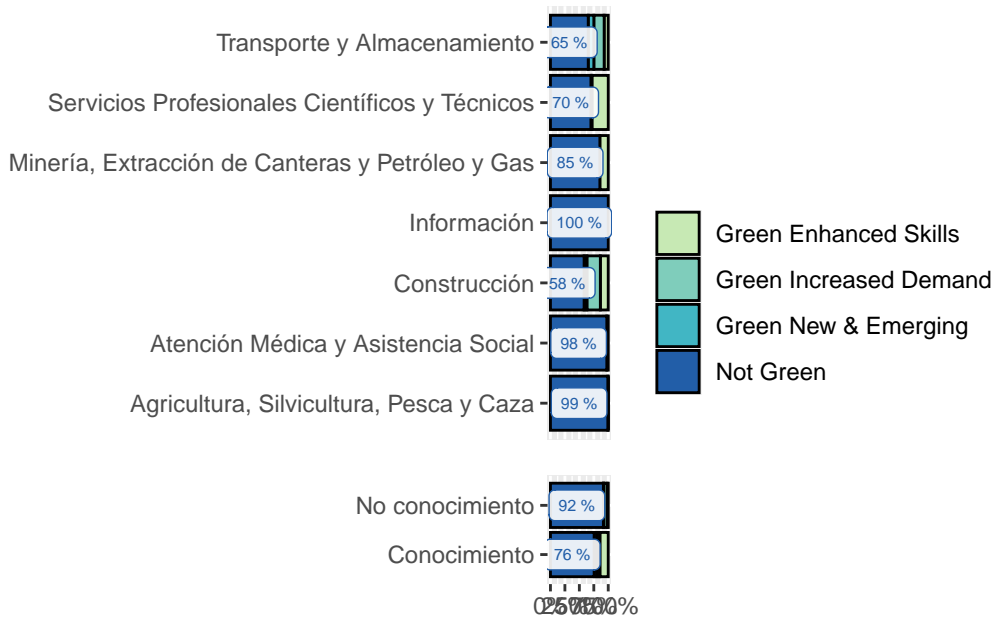


Figure 37: ?(caption)

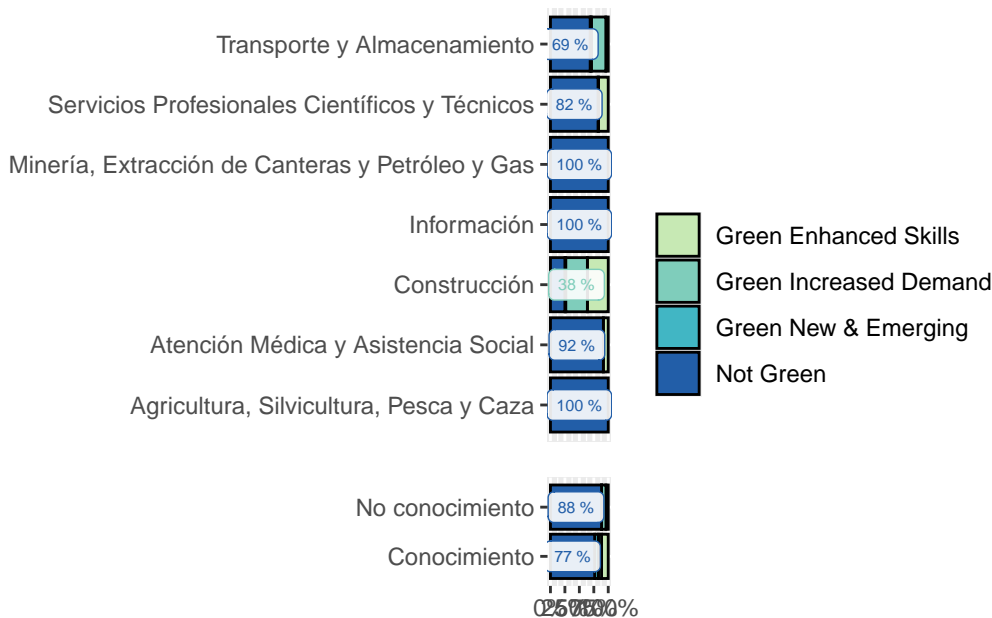


Figure 38: ?(caption)

Green jobs across sectors

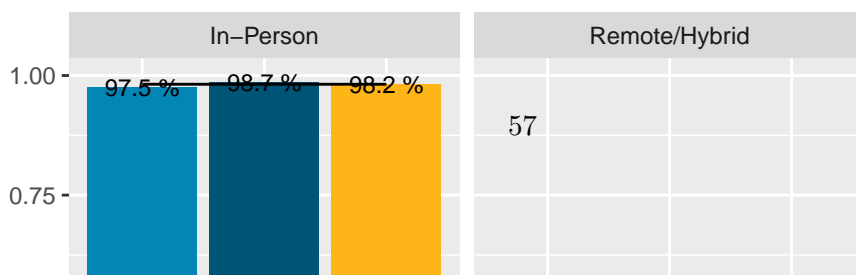
Remote jobs

- Only 1.8% of jobs postings are classified remote. This contrast with 10% and 12% for countries like New Zeland and Australia, which aren't much different than Chile according to remote work surveys at the firm level. This gap is puzzling.
- The occupational major groups with the highest shares of remote postings are “Legal”, “Business and Financial Operations”, “Personal Care and Service” (weird), “Management”, and “Computer and Mathematical” occupations, in that order. This is different from the ranking of remote online vacancies found by Lightcast in English speaking countries: “Computer and Mathematical”, “Business and Financial Operations”, “Legal”, “Management”, and “Architecture and Engineering.”

Table 17: Remote work distribution

remote	Vacancies	% of Vacancies	% of ARG	% of CHL	% of URY
In-Person	58174	98.18%	97.45%	98.67%	98.18%
Remote/Hybrid	1081	1.82%	2.55%	1.33%	1.82%
sum	59,255.00	1.00	1.00	1.00	1.00

Remote/Hybrid jobs distribution in online vacancies data



Remote/Hybrid jobs distribution in online vacancies data

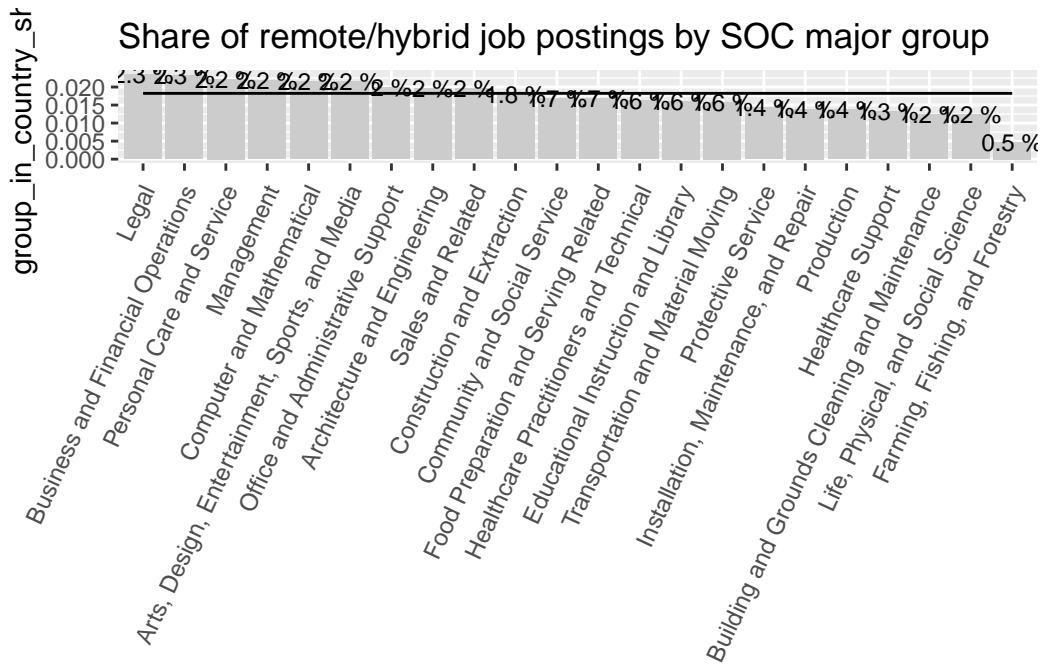
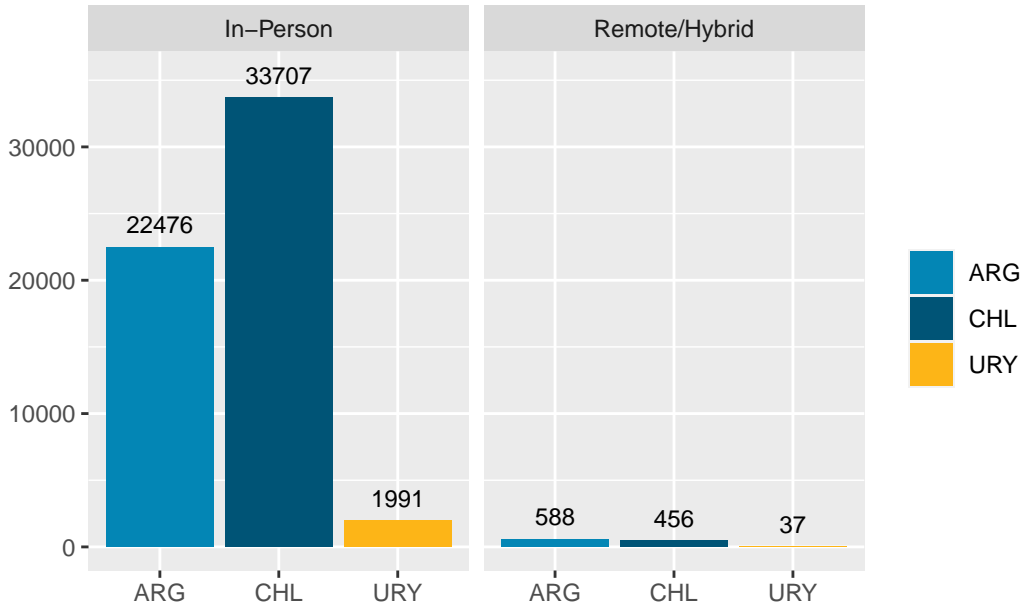


Figure 40: ?(caption)

There are much fewer job vacancies classified as remote than there should be. These charts show it's not consistent with Lighthcast estimates US, UK, Australia and New Zeland markets ([Remote Work across Jobs, Companies, and Space by Stephen Hansen, Peter John Lambert, Nick Bloom, Steven J. Davis, Raffaella Sadun, Bledi Taska :: SSRN](#)).

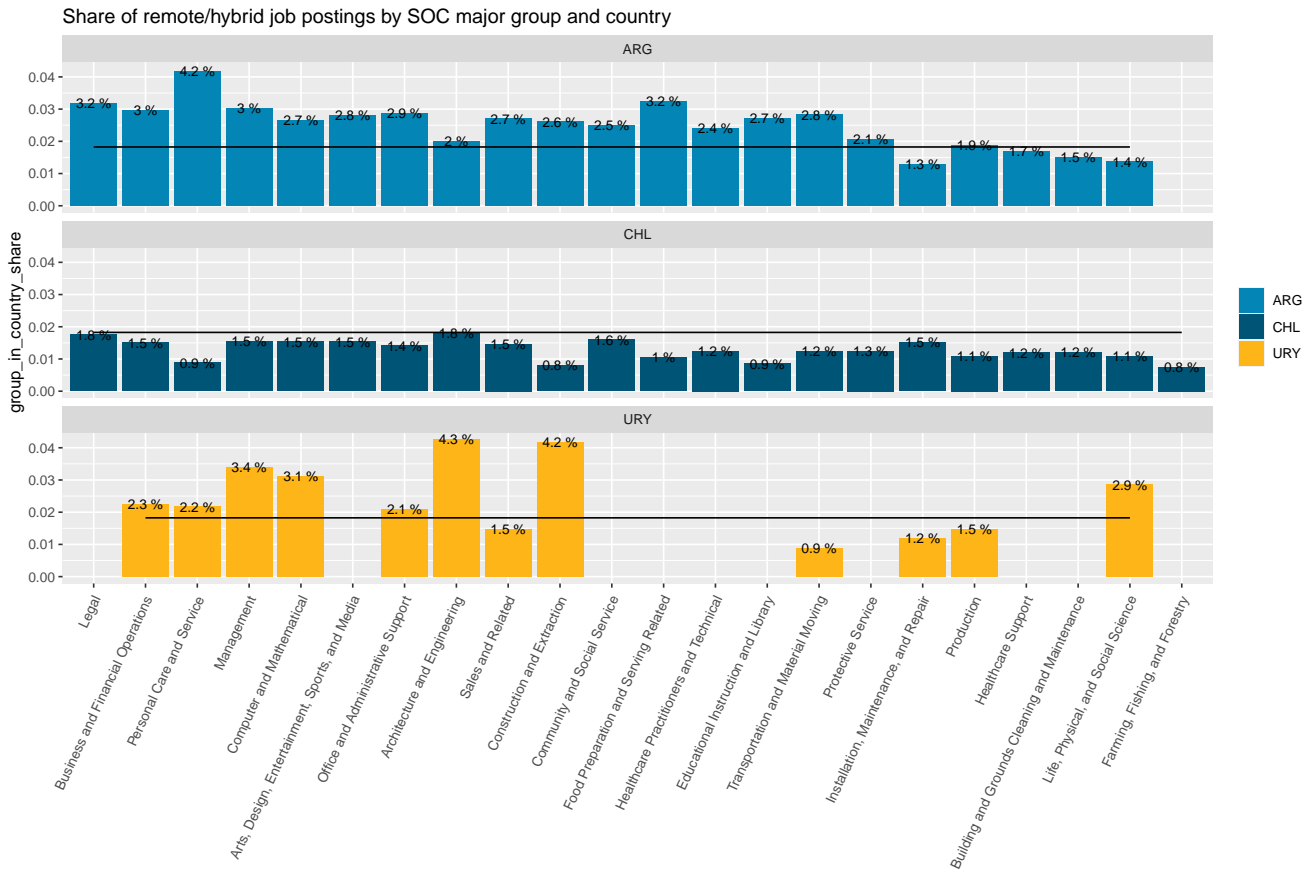


Figure 41: ?(caption)

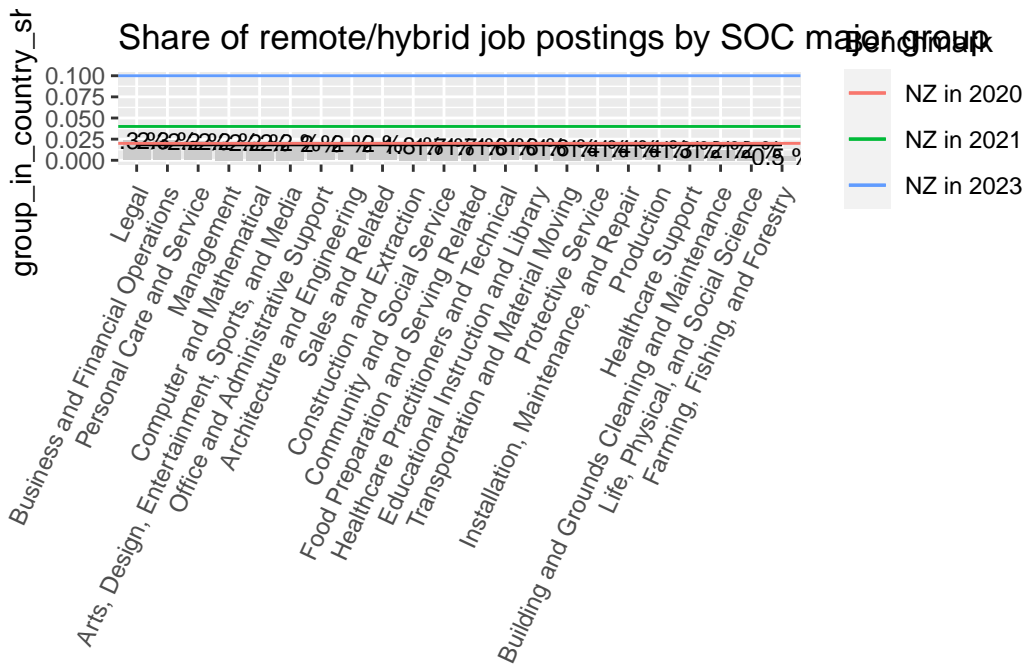
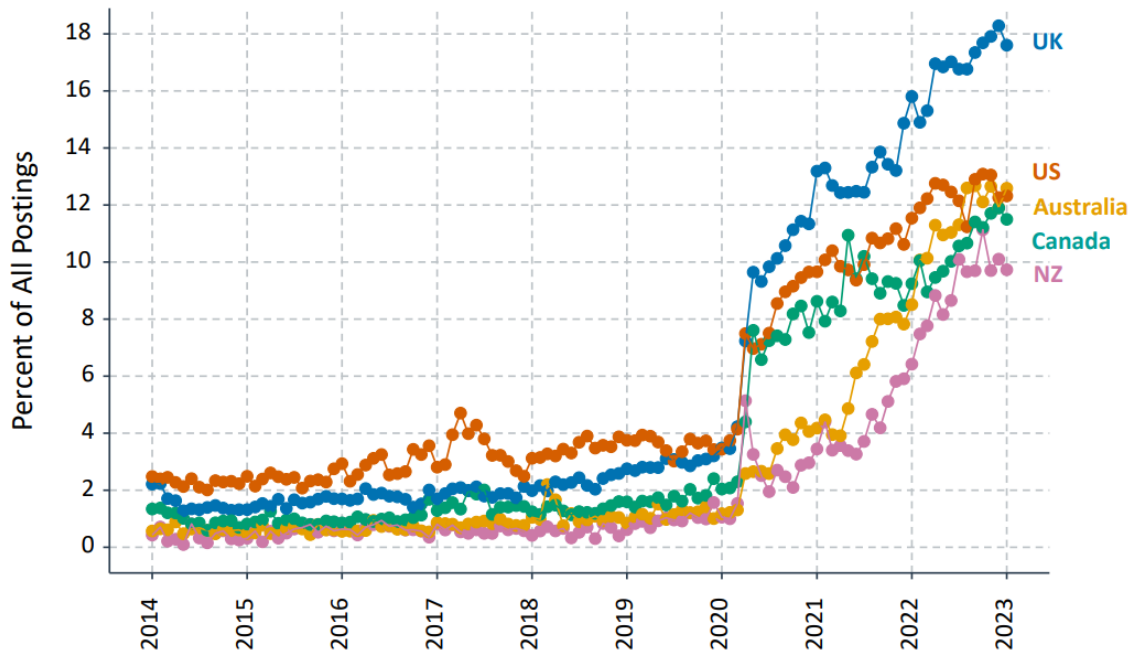


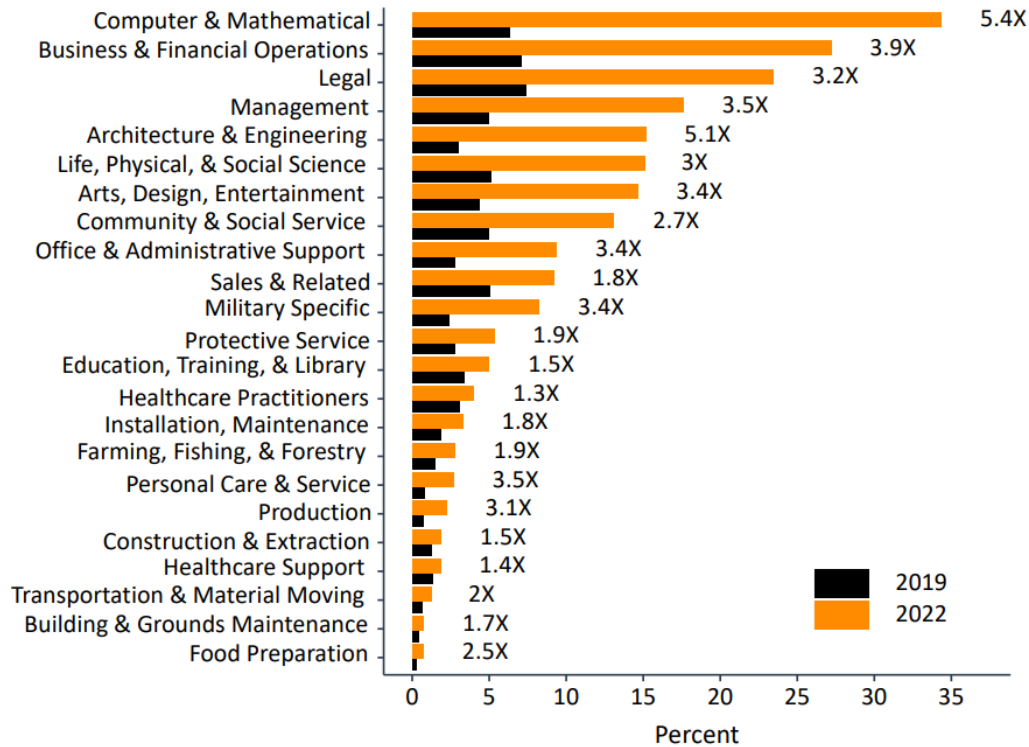
Figure 42: ?(caption)

Figure 3: Vacancy Postings that Explicitly Offer Hybrid or Fully Remote Work Rose Sharply in All Five Countries from 2020



Note: This figure shows the percent of vacancy postings that say the job allows one or more remote workdays per week, encompassing both hybrid and fully-remote working arrangements). We compute these monthly, country-level shares as the weighted mean of the own-country occupation-level shares, with weights given by the U.S. vacancy distribution in 2019. Our occupation-level granularity is roughly equivalent to six-digit SOC codes. See Appendix B for the corresponding raw series and series based on alternative weighting schemes.

Figure 4: Professional, Scientific and Computer-Related Occupations Have the Highest Shares of Postings that Offer Hybrid or Fully-Remote Work, U.S. Data



Note: Each bar reports the percent of vacancy postings that say the job allows one or more remote workdays per week in the indicated period and occupation group (two-digit SOC).

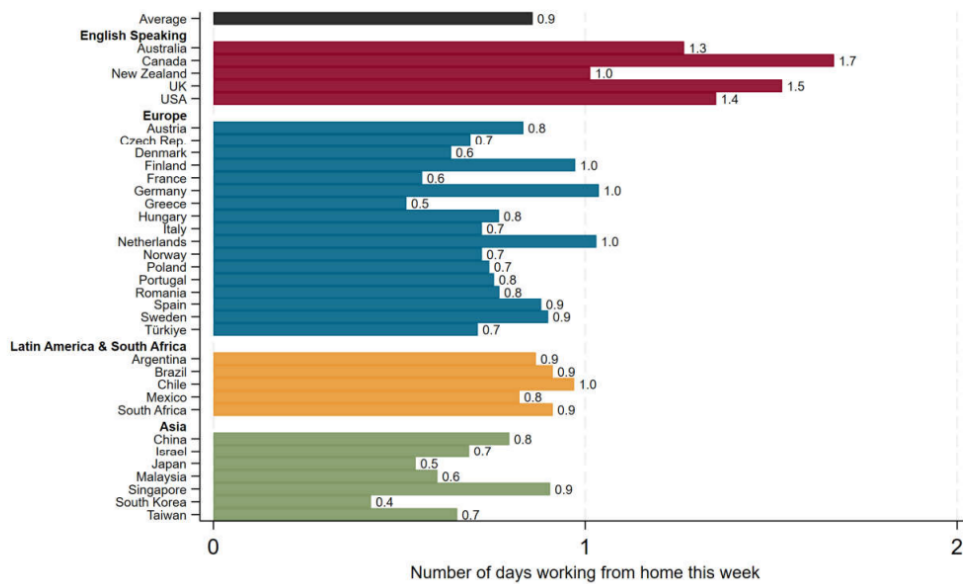
The Global Survey of Work (GSWA) arrangements looked at 34 countries in April-May 2023 and reports that Latin American workers work from home (WFH) 0.9 days a week on average, (which coincides with the global average) while workers in New Zealand and Australia work from home an average of 1 and 1.3 days, respectively. According to this, we should expect job vacancies to show WFH rates in Chile (1.8%) to be at least close to New Zealand (10%).

The GSWA review also shows Chileans work from home more than Argentineans, which refutes our results. Of course, this could be due to the difference in sector compositions between the GSWA and online job vacancies.

How does it align with Dingle & Neiman (2020)?

Does a 1.8% share of remote job vacancies make sense when we take into account the occupations these vacancies are concentrated in? We'll use Dingle and Neiman (2020) definition of teleworkable occupations and calculate the percentage of online job postings that fall in that category and see whether it's lower than the observed in English Speaking countries. Dingle and Neiman (2020) define teleworkable occupations as those not involving evidently 'in-place' activities and can be performed remotely.

Figure 1: Paid Full Days Worked from Home per week (April-May 2023)



Note: Responses to the question “For each day **last week**, did you **work 6 or more hours**, and if so **where**?”. Sample of N=42,426 workers in 34 countries surveyed in April-May 2023. All values are available at <https://bit.ly/Figures-GSWA-2023>

Figure 43: bloom1

Table 18: ?(caption)

(a)

	teleworkable	Vacancies	% of Vacancies	% of ARG	% of CHL	% of URY
	0	34097	57.54%	53.56%	60.41%	54.59%
	1	24874	41.98%	46.05%	39.05%	45.02%
	NA	284	0.48%	0.39%	0.54%	0.39%
sum	1.00	59,255.00	1.00	1.00	1.00	1.00

Take a look at the classification of a few occupations:

[1] “Not-teleworkable occupations in ONET 28.0: 565 (0.65)” [2] “Teleworkable occupations in ONET 28.0: 308 (0.35)”

o_net_soc_code	title	n	teleworkable	physical_activities
11-1011.00	Chief Executives	29.50	1	0
11-1011.03	Chief Sustainability Officers	27.00	1	0
11-1021.00	General and Operations Managers	31.75	1	0
11-2011.00	Advertising and Promotions Managers	20.50	1	0
11-2021.00	Marketing Managers	39.75	1	0
11-2022.00	Sales Managers	23.00	1	0

The table below show the share of online vacancies in occupations that could be performed remotely. 42% of all job vacancies could be feasibly performed from home according the the average work context and activities of the occupations they were assigned on. It’s below the 50% share I spotted on US job postings between 2020-2021, but it’s large considering they only account for 35% of all occupational codes and around 35% of employment in the US at the onset of the pandemic.

Is there any spatial concentration pattern in remote postings?

- Do we see more remote postings in large or small cities? No at a glance. It’d be worth controlling for sectorial composition of employment to test this hypothesis.

Which firms are hiring remotely?

Type II Errors: Classified as non-remote nor hybrid when they are

There are plenty of cases like this. The table below shows the number of type 2 errors we found in Argentinean data:

Below we show the list of some examples:

Table 19: Remote work by Metropolitan Region

region	Job postings	share in all data	share in remote	ratio
Santiago	13725	24%	24%	1.02
Buenos Aires (GZM)	9313	16%	20%	1.22
Valparaíso	4932	8%	4%	0.47
Concepción	3774	6%	4%	0.49
Rosario	2316	4%	4%	0.95
Gran Temuco	2125	4%	0%	0.13
Coquimbo	1913	4%	2%	0.83
Córdoba	1810	4%	4%	1.54
Mendoza	1734	2%	4%	1.52
Antofagasta	1477	2%	2%	0.78
Puerto Montt	1251	2%	2%	0.53
Metropolitana	1220	2%	2%	1.39
Tarapacá	1168	2%	0%	0.47
Corrientes	1074	2%	4%	2.35
Región Metropolitana Confluencia	889	2%	2%	0.74

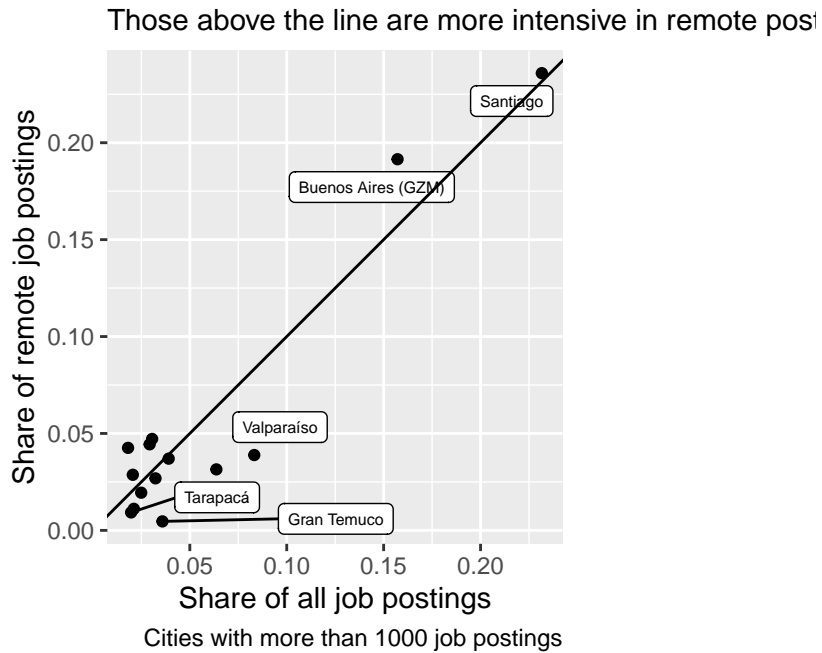


Figure 44: ?(caption)

Table 20: Firms hiring remote or hybrid

Firm	Firm postings	Remote Postings	% Remote
Confidencial	2890	71	2%
Emprego	2447	67	2%
Wurth Argentina S.a	132	24	18%
Mendoza, Capital, Mendoza, Argentina	327	13	4%
Buenos Aires, CABA, Argentina	225	8	4%
Entel Empresa de Contact Center	118	7	6%
ACTIVOS CHILE	448	6	2%
ADN - Recursos Humanos	125	6	4%
Babysits	217	6	2%
Tawa	257	6	2%
Manpower Chile	677	5	0%
ManpowerGroup	308	5	2%
Adecco Chile	678	4	0%
ECRGROUP® Chile	118	3	2%
Emprego CL C2	122	3	2%
Neuquén, Argentina	105	3	2%
Progestion Chile	890	3	0%
Randstad AR	121	3	2%
Cygnus	569	2	0%
Grupo Gestión	259	2	0%

Table 21: Postings mentioning remote or hybrid format but not classified as WFH

Type II Error	Count	Share
FALSE	95	14%
TRUE	553	86%

Table 22: ?(caption)

(a)

area	Vacancies	% of Vacancies	% of ARG	% of CHL	% of URY
No conocimiento	39266	66.27%	61.67%	69.51%	63.86%
Conocimiento	19989	33.73%	38.33%	30.49%	36.14%
sum	59,255.00	1.00	1.00	1.00	1.00

Firma	Position
Umbral Capital Humano	Operador de flota propia (SJ095)
Umbral Capital Humano	Supervisor de Limpieza - Mendoza, Luján de Cuyo
Umbral Capital Humano	técnicos electromecánicos y electrónicos
Umbral Capital Humano	Ingeniero de procesos mendoza
Umbral Capital Humano	MZ534 Mendoza Operario de Mantenimiento Industrial
Umbral Capital Humano	Promotora - Activación en Punto de venta
Camera di Commercio Italiana nella Repubblica Argentina	CDC Personal de Depósito - Zona Oeste
Adlatina Group	EMPLEADO DE MOSTRADOR, LOCAL DE SANITARIO
Grupo Myth	Administrativo Contable
Camera di Commercio Italiana nella Repubblica Argentina	pasante - ingenieria de produccion

Knowledge Jobs

- 33% of all online vacancies were classified as belonging to knowledge sectors.
- Argentina, with a 38% is the country with the highest intensity in these job postings.
- The occupational groups these knowledge vacancies belong to sound like occupational groups a knowledge firm will require to function.

Knowledge jobs across occupations

Knowledge jobs across industries

Location of Knowledge jobs across regions

Regions

There are three geographic aggregation variables in the data. This is the count of unique, missing, and empty values each of these indicator has.

And this is a list of the most frequent regions of each country

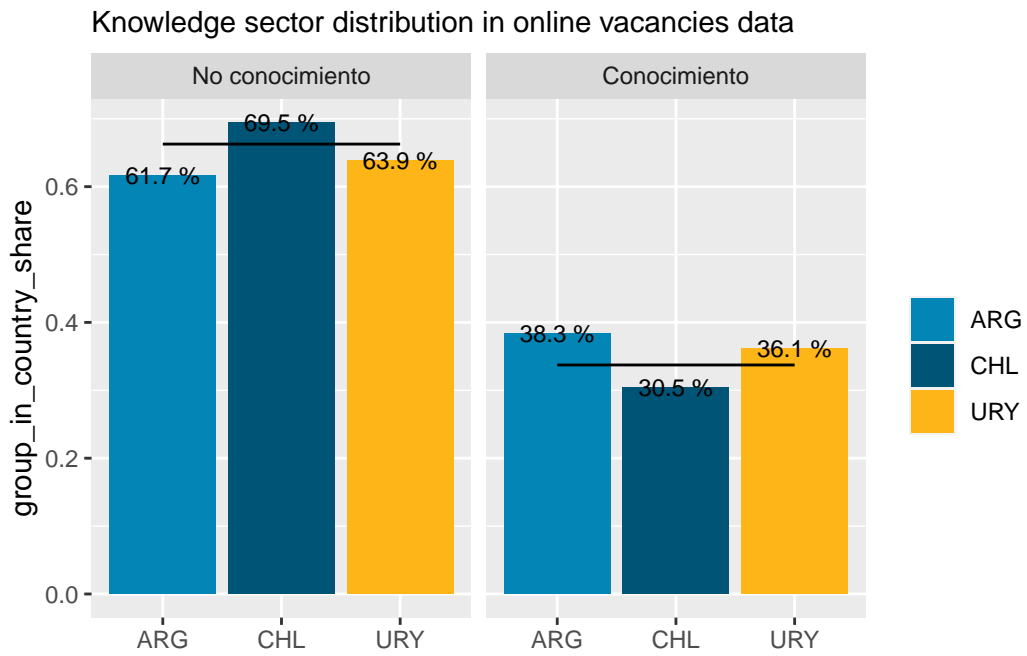


Figure 45: TRUE

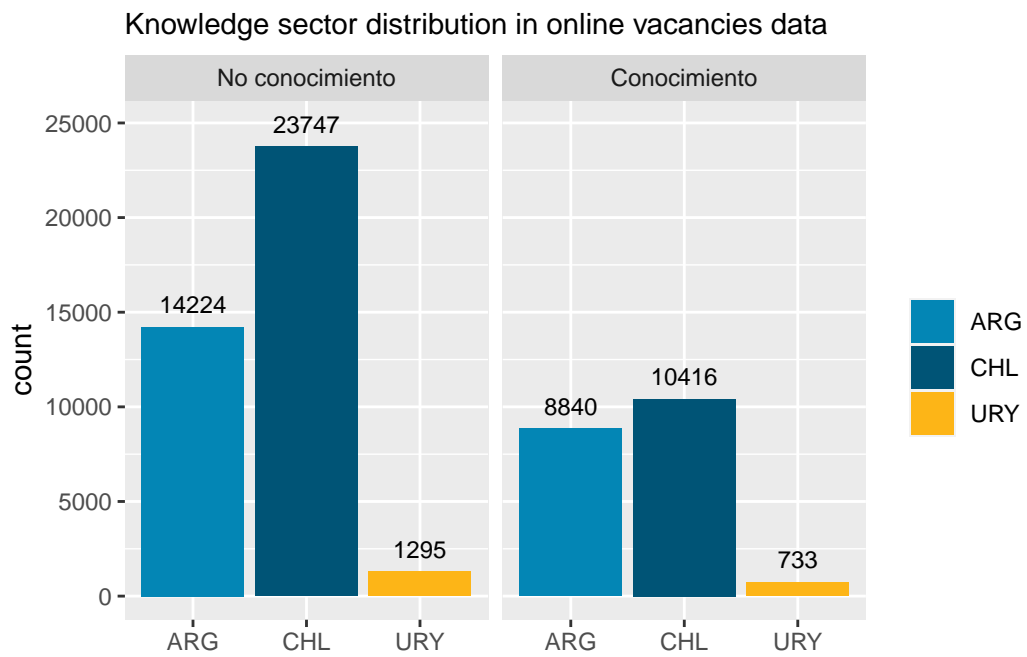


Figure 46: TRUE

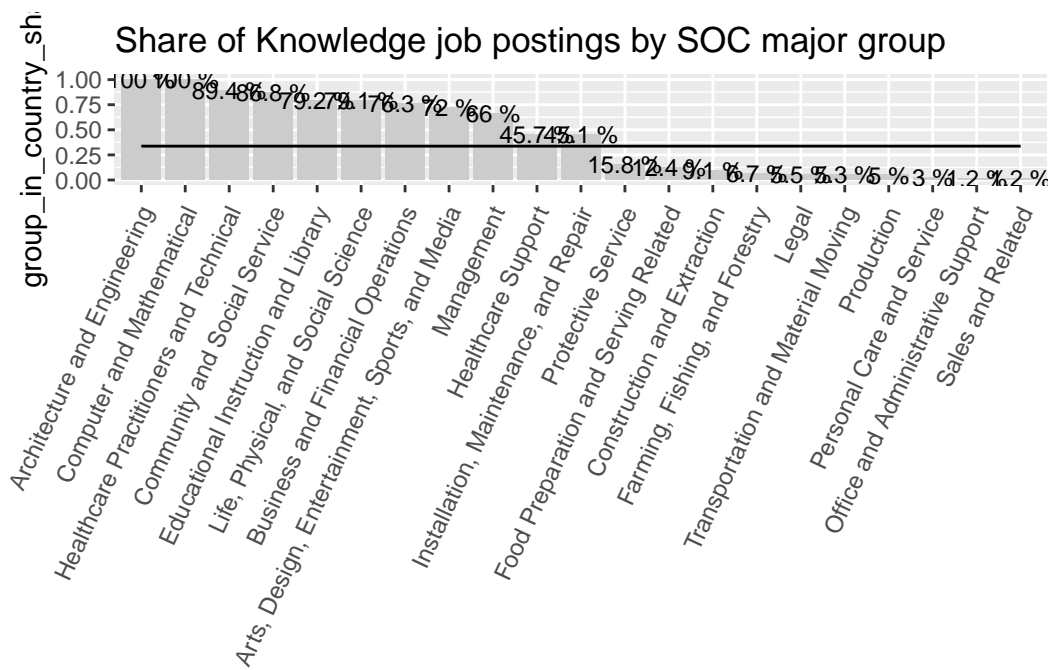


Figure 47: ?(caption)

Table 23: ?(caption)

(a)

Region	Job postings	% in all data	% in knowledge jobs	Ratio
Santiago	13725	24%	20%	0.86
Buenos Aires (GZM)	9313	16%	16%	1.07
Valparaíso	4932	8%	8%	0.88
Concepción	3774	6%	6%	0.93
Rosario	2316	4%	4%	1.14
Gran Temuco	2125	4%	4%	0.91
Coquimbo	1913	4%	2%	0.88
Córdoba	1810	4%	4%	1.17
Mendoza	1734	2%	4%	1.18
Antofagasta	1477	2%	4%	1.27
Puerto Montt	1251	2%	2%	0.97
Metropolitana	1220	2%	2%	1.10
Tarapacá	1168	2%	2%	1.16
Corrientes	1074	2%	2%	1.21
Región Metropolitana Confluencia	889	2%	2%	1.29

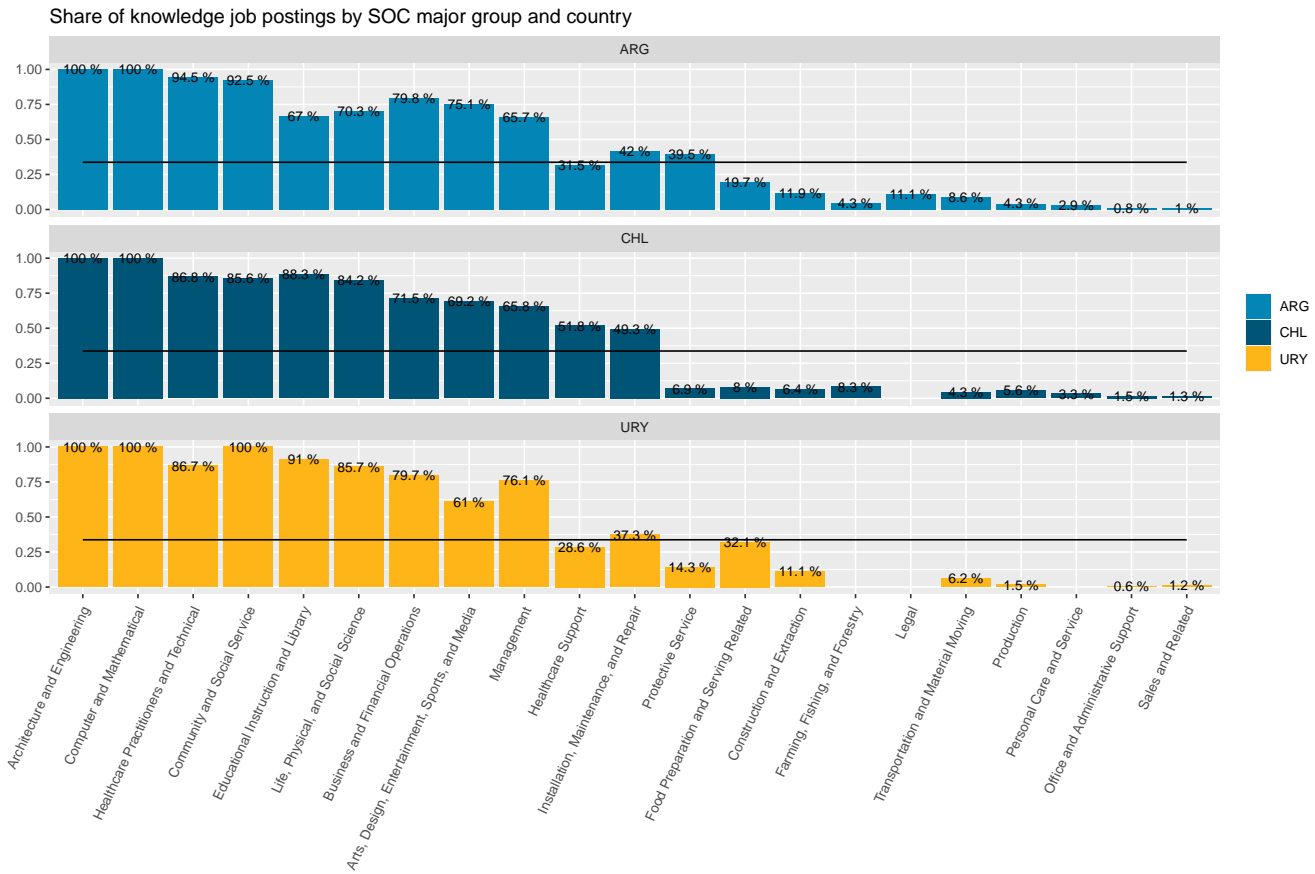


Figure 48: ?(caption)

Table 24: ?(caption)

(a)

skim_type	skim_variable	country_code	n_missing	complete_rate	character.empty	character.n_unique	char
character	rm	ARG	0	1	0	24	
character	rm	CHL	0	1	0	18	
character	rm	URY	0	1	0	6	
character	city	ARG	0	1	6	800	
character	city	CHL	0	1	0	239	
character	city	URY	0	1	0	70	
character	city_name	ARG	0	1	0	216	
character	city_name	CHL	0	1	0	201	
character	city_name	URY	0	1	0	48	

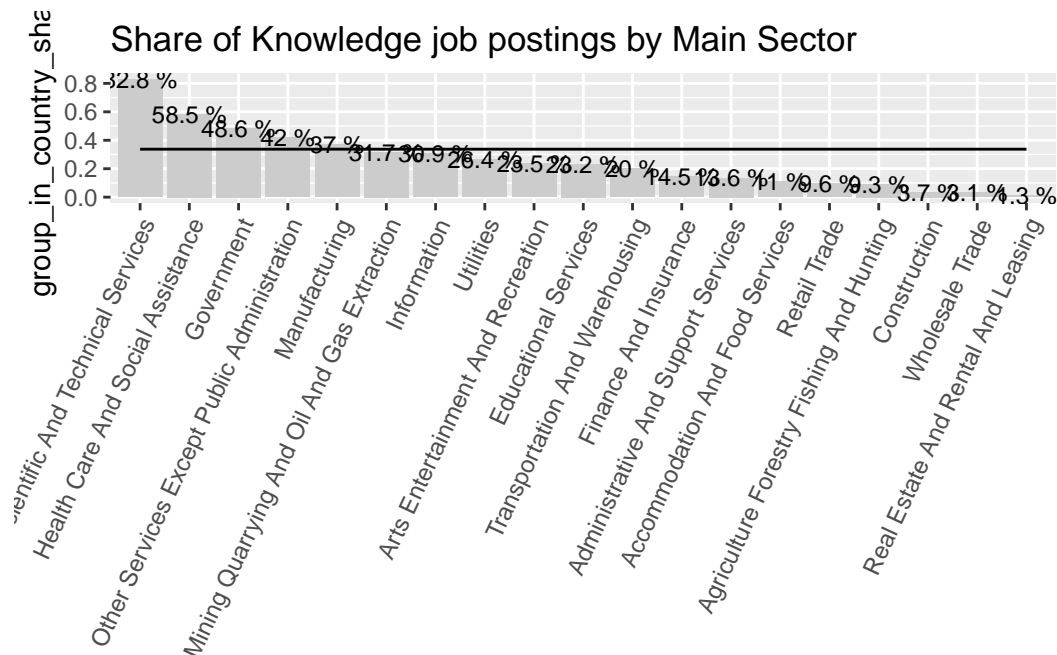


Figure 49: ?(caption)

Table 25: Main regions, by country

rank	ARG	CHL	URY
1	Buenos Aires (GZM), 9313 (40.4%)	Santiago, 13725 (40.2%)	Metropolitana, 1220 (60.2%)
2	Rosario, 2316 (10%)	Valparaíso, 4932 (14.4%)	Este, 347 (17.1%)
3	Córdoba, 1810 (7.8%)	Concepción, 3774 (11%)	Centro, 127 (6.3%)
4	Mendoza, 1734 (7.5%)	Gran Temuco, 2125 (6.2%)	Sur, 117 (5.8%)
5	Corrientes, 1074 (4.7%)	Coquimbo, 1913 (5.6%)	Norte, 111 (5.5%)
6	Región Metropolitana Confluencia, 889 (3.9%)	Antofagasta, 1477 (4.3%)	Noreste, 106 (5.2%)
7	Entre Ríos, 796 (3.5%)	Puerto Montt, 1251 (3.7%)	NA
8	Tucumán, 624 (2.7%)	Tarapacá, 1168 (3.4%)	NA
9	Chaco, 622 (2.7%)	Rancagua, 521 (1.5%)	NA
10	Santiago del Estero, 544 (2.4%)	Copiapó, 399 (1.2%)	NA
11	Valle de Lerma (AMVL), 435 (1.9%)	Valdivia, 396 (1.2%)	NA
12	Chubut, 414 (1.8%)	Calama, 381 (1.1%)	NA
13	San Luis, 376 (1.6%)	Arica-Paranicota, 367 (1.1%)	NA
14	Mar del Plata, 343 (1.5%)	Osorno, 361 (1.1%)	NA
15	San Fernando del Valle de Catamarca, 328 (1.4%)	Punta Arenas, 348 (1%)	NA
16	Posadas-Garupá-Candelaria (AMPGC), 265 (1.1%)	Talca, 347 (1%)	NA
17	San Salvador de Jujuy, 259 (1.1%)	Chillán, 339 (1%)	NA
18	Bahía Blanca, 250 (1.1%)	Curicó, 339 (1%)	NA
19	VIRCH-Valdés, 193 (0.8%)	NA	NA

Cities in Argentina

This is a look at the most frequent values of ‘city’ and ‘city_name’ in Argentina:

- city captures lots of company names and shows low levels of detail within Buenos Aires and other regions.
- I haven’t seen any company names within ‘city_name’ values. It looks like the best variable to use.

Cities in Chile

This is a look at the most frequent values of ‘city’ and ‘city_name’ in Chile:

- city evidently has low levels of details within Santiago and Valparaiso Regions.
- city_name has more granularity, but there are lots of cases where it defaults to region name (when it doesn’t guess a city name, imputes the Region name)

Región Metropolitana	Vacantes	Ciudadades
Santiago	13725	52
Valparaíso	4932	38
Concepción	3774	33
Gran Temuco	2125	32
Coquimbo	1913	15
Antofagasta	1477	8
Puerto Montt	1251	4
Tarapacá	1168	7
Rancagua	521	2
Copiapó	399	1

rank	Concepción	Coquimbo	Gran Temuco	Santiago
1	Concepción, 470 (12.5%)	Coquimbo, 362 (18.9%)	Temuco, 404 (19%)	Ñuñoa, 497 (3.6%)
2	Chiguayante, 435 (11.5%)	Ovalle, 293 (15.3%)	Angol, 229 (10.8%)	Huechuraba, 469 (3.4%)
3	Los Ángeles, 330 (8.7%)	La Serena, 281 (14.7%)	Villarrica, 197 (9.3%)	Renca, 441 (3.2%)
4	Talcahuano, 302 (8%)	Salamanca, 221 (11.6%)	Pucón, 184 (8.7%)	Pudahuel, 419 (3.1%)
5	Coronel, 280 (7.4%)	Illapel, 197 (10.3%)	Victoria, 179 (8.4%)	Santiago, 416 (3%)
6	Hualpén, 240 (6.4%)	Los Vilos, 137 (7.2%)	Lautaro, 150 (7.1%)	Quilicura, 405 (3%)
7	San Pedro de la Paz, 211 (5.6%)	Monte Patria, 107 (5.6%)	Nueva Imperial, 98 (4.6%)	Lampa, 379 (2.8%)
8	Penco, 200 (5.3%)	Canela, 103 (5.4%)	Pitrufquén, 94 (4.4%)	San Bernardo, 377 (2.8%)
9	Tomé, 175 (4.6%)	Vicuña, 63 (3.3%)	Gorbea, 56 (2.6%)	San Joaquín, 364 (2.7%)
10	Lota, 159 (4.2%)	Río Hurtado, 54 (2.8%)	Loncoche, 52 (2.4%)	Cerrillos, 361 (2.6%)
11	Curanilahue, 132 (3.5%)	Andacollo, 35 (1.8%)	Padre Las Casas, 52 (2.4%)	Colina, 350 (2.6%)

12	Lebu, 119 (3.2%)	Punitaqui, 24 (1.3%)	Collipulli, 49 (2.3%)	La Florida, 349 (2.5%)
13	Cabrero, 103 (2.7%)	Combarbalá, 16 (0.8%)	Freire, 46 (2.2%)	La Reina, 341 (2.5%)
14	Cañete, 99 (2.6%)	La Higuera, 12 (0.6%)	Traiguén, 42 (2%)	Recoleta, 341 (2.5%)
15	Arauco, 91 (2.4%)	Paihuano, 8 (0.4%)	Carahue, 41 (1.9%)	Las Condes, 334 (2.4%)
16	Nacimiento, 76 (2%)	NA	Cholchol, 33 (1.6%)	Macul, 324 (2.4%)
17	Mulchén, 50 (1.3%)	NA	Curacautín, 28 (1.3%)	Vitacura, 316 (2.3%)
18	Santa Juana, 40 (1.1%)	NA	Renaico, 27 (1.3%)	San Miguel, 311 (2.3%)
19	Laja, 37 (1%)	NA	Cunco, 24 (1.1%)	Maipú, 304 (2.2%)
20	Florida, 33 (0.9%)	NA	Vilcún, 23 (1.1%)	Melipilla, 293 (2.1%)

Cities in Uruguay

This is a look at the most frequent values of ‘city’ and ‘city_name’ in Uruguay:

- city doesn’t look as bad as in Argentina and Chile.
- city_name offers more granularity within region “Metropolitana”

Región Metropolitana	Vacantes	Ciudadades
Metropolitana	1220	23
Este	347	7
Centro	127	4
Sur	117	7
Norte	111	3
Noreste	106	4

rank	Centro	Este	Metropolitana	Norte	Sur
1	Florida, 77 (60.6%)	Maldonado, 177 (51%)	Montevideo, 388 (31.8%)	Salto, 54 (48.6%)	Co
2	Durazno, 24 (18.9%)	Punta del Este, 83 (23.9%)	Ciudad de la Costa, 151 (12.4%)	Paysandú, 52 (46.8%)	De
3	Flores, 19 (15%)	Minas, 22 (6.3%)	Canelones, 115 (9.4%)	Artigas, 5 (4.5%)	Rí
4	Trinidad, 7 (5.5%)	San Carlos, 22 (6.3%)	Las Piedras, 114 (9.3%)	NA	So
5	NA	Rocha, 16 (4.6%)	Progreso, 98 (8%)	NA	Co
6	NA	Treinta y Tres, 16 (4.6%)	18 de Mayo, 66 (5.4%)	NA	Fr
7	NA	Lavalleja, 11 (3.2%)	Paso Carrasco, 59 (4.8%)	NA	Me
8	NA	NA	Barros Blancos, 55 (4.5%)	NA	NA
9	NA	NA	Santa Lucía, 34 (2.8%)	NA	NA
10	NA	NA	La Paz, 33 (2.7%)	NA	NA
11	NA	NA	Pando, 19 (1.6%)	NA	NA
12	NA	NA	San José, 16 (1.3%)	NA	NA
13	NA	NA	Toledo, 16 (1.3%)	NA	NA
14	NA	NA	Joaquín Suárez, 12 (1%)	NA	NA
15	NA	NA	Ciudad del Plata, 11 (0.9%)	NA	NA
16	NA	NA	Atlántida, 7 (0.6%)	NA	NA
17	NA	NA	Salinas, 7 (0.6%)	NA	NA

18	NA	NA	Libertad, 6 (0.5%)	NA	NA
19	NA	NA	General Líber Seregni, 4 (0.3%)	NA	NA
20	NA	NA	Parque del Plata, 3 (0.2%)	NA	NA
21	NA	NA	Tala, 3 (0.2%)	NA	NA

Firms

How many firms are in each country? 5900 in Argentina, 9400 in Chile, and 789 in Uruguay.

Which are the most important firms across countries and regions?

- Empleo en Argentina, Confidencial en Chile, Gallito Trabajo en Uruguay.
- HR agencies seem to represent most of the postings (at least this month).
- There are many cases where they list the place of the vacancy instead of the company. Mostly in Argentina.

Which are the most important firms in the most demanded roles:

rank	Business and Financial Operations	Computer and Mathematical	Office and
1	Empleo, 251 (5.3%)	Empleo, 116 (4.6%)	Confidencial
2	Confidencial, 212 (4.5%)	Confidencial, 96 (3.8%)	Empleo, 4
3	Progestion Chile, 51 (1.1%)	Recruiting from Scratch, 37 (1.5%)	Progestion
4	Adecco Chile, 47 (1%)	Buenos Aires, CABA, Argentina, 36 (1.4%)	Adecco Ch
5	Mendoza, Capital, Mendoza, Argentina, 45 (1%)	Mendoza, Capital, Mendoza, Argentina, 34 (1.4%)	Fundación
6	Buenos Aires, CABA, Argentina, 40 (0.9%)	Fundación Integra, 25 (1%)	Cygnus, 10
7	Manpower Chile, 37 (0.8%)	Progestion Chile, 24 (1%)	Manpower
8	ACTIVOS CHILE, 34 (0.7%)	Manpower Chile, 23 (0.9%)	ACTIVOS
9	Cygnus, 33 (0.7%)	Adecco Chile, 20 (0.8%)	Eurofirms
10	Adecco Argentina S.A., 28 (0.6%)	Eurofirms Chile, 18 (0.7%)	XinerLink,
11	Fundación Integra, 28 (0.6%)	Inclusion Cloud, 18 (0.7%)	NA

Which are the most important firms in the most active sectors:

rank	Finance And Insurance	Manufacturing	Professional Scientific And T
1	Empleo, 157 (5.2%)	Confidencial, 539 (4.9%)	Empleo, 402 (4.7%)
2	Confidencial, 128 (4.3%)	Empleo, 483 (4.4%)	Confidencial, 367 (4.3%)
3	Mendoza, Capital, Mendoza, Argentina, 35 (1.2%)	Adecco Chile, 168 (1.5%)	Progestion Chile, 97 (1.1%)
4	Progestion Chile, 33 (1.1%)	Manpower Chile, 162 (1.5%)	Buenos Aires, CABA, Argen
5	Adecco Chile, 31 (1%)	Progestion Chile, 149 (1.4%)	Adecco Chile, 90 (1.1%)
6	Cygnus, 23 (0.8%)	ACTIVOS CHILE, 121 (1.1%)	Manpower Chile, 83 (1%)
7	Buenos Aires, CABA, Argentina, 22 (0.7%)	Cygnus, 110 (1%)	Mendoza, Capital, Mendoza,
8	Manpower Chile, 22 (0.7%)	Fundación Integra, 85 (0.8%)	Fundación Integra, 65 (0.8%)

9 Fundación Integra, 21 (0.7%)
 10 ManpowerGroup, 21 (0.7%)

XinerLink, 81 (0.7%)
 Eurofirms Chile, 77 (0.7%)

Eurofirms Chile, 56 (0.7%)
 Recruiting from Scratch, 56

How concentrated are online vacancies within firms across different regions?

Representativity Assessment (Work in progress)

Which occupations and sectors are over(under)represented in each country? We'll compare vacancies data to Employment estimates in employment or household surveys to figure it out.

Comparing against ILOSTAT data by occupation

ILOSTAT data contains tables of employment at the ISCO 08 2-digits level. Samples for Chile and Uruguay managed to classify all occupations from the original surveys, while the Argentina's failed to assign an ISCO 08 code to 16% of employment in the original sample.

The table below shows the correlation between employment and online job vacancies distributions.

Correlation between employment and online vacancies distributions

Estimates correspond to Pearson's correlation coefficientns

estimate	statistic	group
41.28%	3.625998	Total
45.13%	2.261776	ARG
42.50%	2.099956	CHL
41.26%	2.025881	URY

These tables show the detailed distributions behind these correlations.

Regular comparisson

Total

Table 29: Comparisson of employment and postigns distribution

Comparing employment and online vacancies distributions
 All countries

major_group_title	Share of employment	Share of online vacancies	%Vac
Architecture and Engineering Occupations	0.94%	5.21%	
Sales and Related Occupations	3.79%	15.94%	

Healthcare Practitioners and Technical Occupations	1.02%	3.75%
Computer and Mathematical Occupations	1.39%	4.22%
Business and Financial Operations Occupations	4.49%	7.94%
Office and Administrative Support Occupations	8.64%	15.17%
Protective Service Occupations	1.80%	3.05%
Production Occupations	5.81%	8.80%
Installation, Maintenance, and Repair Occupations	2.90%	3.76%
Management Occupations	5.68%	6.59%
Life, Physical, and Social Science Occupations	2.25%	2.33%
Educational Instruction and Library Occupations	3.37%	3.14%
Healthcare Support Occupations	1.76%	1.41%
Transportation and Material Moving Occupations	9.45%	7.25%
Food Preparation and Serving Related Occupations	4.36%	2.70%
Legal Occupations	0.39%	0.22%
Arts, Design, Entertainment, Sports, and Media Occupations	3.12%	1.57%
Personal Care and Service Occupations	2.80%	1.37%
Building and Grounds Cleaning and Maintenance Occupations	5.18%	2.19%
Construction and Extraction Occupations	6.80%	2.55%
Community and Social Service Occupations	3.12%	0.50%
Farming, Fishing, and Forestry Occupations	3.90%	0.35%
Military Specific Occupations	0.10%	NA
Not ISCO classified	16.94%	NA

Argentina

Comparing employment and online vacancies distributions For ARG

major_group_title	Share of employment	Share of online vacancies	%Vac
Architecture and Engineering Occupations	0.60%	6.23%	
Computer and Mathematical Occupations	0.79%	5.06%	
Sales and Related Occupations	3.18%	16.36%	
Healthcare Practitioners and Technical Occupations	0.82%	3.24%	
Business and Financial Operations Occupations	3.64%	11.00%	
Installation, Maintenance, and Repair Occupations	2.19%	4.99%	
Legal Occupations	0.14%	0.27%	
Office and Administrative Support Occupations	9.11%	14.77%	
Life, Physical, and Social Science Occupations	1.41%	2.22%	
Production Occupations	5.32%	8.11%	
Protective Service Occupations	1.49%	2.10%	
Educational Instruction and Library Occupations	2.62%	3.52%	
Management Occupations	5.34%	6.70%	
Arts, Design, Entertainment, Sports, and Media Occupations	2.03%	2.15%	

Healthcare Support Occupations	1.53%	1.02%
Personal Care and Service Occupations	2.16%	1.35%
Construction and Extraction Occupations	5.85%	2.99%
Food Preparation and Serving Related Occupations	4.23%	2.14%
Transportation and Material Moving Occupations	8.62%	4.14%
Building and Grounds Cleaning and Maintenance Occupations	3.83%	1.16%
Farming, Fishing, and Forestry Occupations	2.08%	0.30%
Community and Social Service Occupations	2.40%	0.17%
Not ISCO classified	30.58%	NA

Chile

Comparing employment and online vacancies distributions For CHL

major_group_title	Share of employment	Share of online vacancies	%Vac
Sales and Related Occupations	4.64%	15.63%	
Healthcare Practitioners and Technical Occupations	1.29%	4.23%	
Architecture and Engineering Occupations	1.40%	4.55%	
Office and Administrative Support Occupations	7.22%	15.36%	
Protective Service Occupations	2.19%	3.74%	
Computer and Mathematical Occupations	2.22%	3.42%	
Production Occupations	6.37%	9.39%	
Management Occupations	6.27%	6.64%	
Business and Financial Operations Occupations	5.67%	5.82%	
Transportation and Material Moving Occupations	10.24%	9.46%	
Healthcare Support Occupations	2.01%	1.71%	
Installation, Maintenance, and Repair Occupations	3.80%	2.91%	
Life, Physical, and Social Science Occupations	3.42%	2.44%	
Food Preparation and Serving Related Occupations	4.61%	3.08%	
Educational Instruction and Library Occupations	4.25%	2.75%	
Building and Grounds Cleaning and Maintenance Occupations	6.58%	2.91%	
Personal Care and Service Occupations	3.58%	1.33%	
Construction and Extraction Occupations	7.95%	2.20%	
Arts, Design, Entertainment, Sports, and Media Occupations	4.58%	1.14%	
Legal Occupations	0.68%	0.17%	
Community and Social Service Occupations	4.02%	0.73%	
Farming, Fishing, and Forestry Occupations	6.02%	0.39%	
Military Specific Occupations	0.19%	NA	
Not ISCO classified	0.81%	NA	

Uruguay

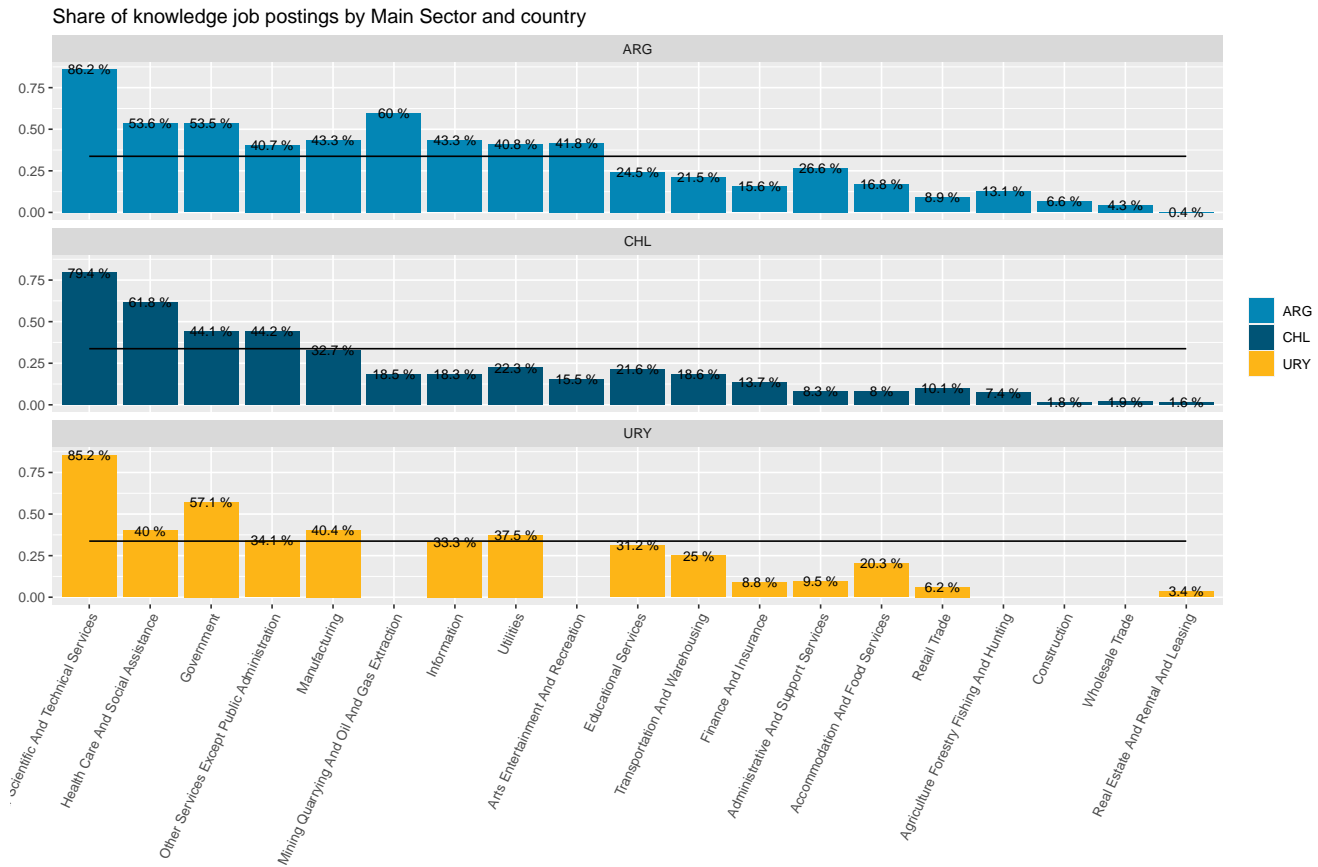


Figure 50: ?(caption)

Table 26: true

(a)

Región Metropolitana	Vacantes	Ciudad
Buenos Aires (GZM)	9313	42
Rosario	2316	25
Córdoba	1810	50
Mendoza	1734	14
Corrientes	1074	9
Región Metropolitana Confluencia	889	11
Entre Ríos	796	14
Tucumán	624	10
Chaco	622	3
Santiago del Estero	544	5

(b)

rank	Buenos Aires (GZM)	Corrientes	Córdoba	Mendoza
1	Buenos Aires, 521 (5.6%)	Corrientes, 306 (28.5%)	Capital, 450 (24.9%)	Mendoza, 306 (16.5%)
2	Vicente López, 417 (4.5%)	Ituzaingó, 276 (25.7%)	Córdoba, 209 (11.5%)	Mendoza C, 209 (11.5%)
3	Quilmes, 390 (4.2%)	Bella Vista, 189 (17.6%)	Río Cuarto, 175 (9.7%)	Luján de C, 175 (9.7%)
4	San Isidro, 349 (3.7%)	Mercedes, 176 (16.4%)	Alta Gracia, 151 (8.3%)	Godoy Cru, 151 (8.3%)
5	La Matanza, 338 (3.6%)	Santo Tomé, 53 (4.9%)	Monte Cristo, 89 (4.9%)	Maipú, 162 (8.9%)
6	Zárate, 336 (3.6%)	Goya, 45 (4.2%)	Malagueño, 83 (4.6%)	San Rafael, 83 (4.6%)
7	Morón, 332 (3.6%)	Paso de los Libres, 14 (1.3%)	Colón, 73 (4%)	San Martín, 73 (4%)
8	La Plata, 331 (3.6%)	Curuzú Cuatiá, 12 (1.1%)	Oncativo, 67 (3.7%)	Las Heras, 67 (3.7%)
9	Avellaneda, 324 (3.5%)	Monte Caseros, 3 (0.3%)	Villa Allende, 67 (3.7%)	Guaymallé, 67 (3.7%)
10	General San Martín, 322 (3.5%)	NA	Villa Carlos Paz, 55 (3%)	Lavalle, 60 (3.3%)
11	Ezeiza, 296 (3.2%)	NA	Jesús María, 47 (2.6%)	Tupungato, 47 (2.6%)
12	Campana, 294 (3.2%)	NA	La Calera, 46 (2.5%)	Tunuyán, 46 (2.5%)
13	Lanús, 279 (3%)	NA	Cosquín, 25 (1.4%)	General Al, 25 (1.4%)
14	Lomas de Zamora, 275 (3%)	NA	Sinsacate, 23 (1.3%)	Malargüe, 23 (1.3%)
15	Almirante Brown, 270 (2.9%)	NA	Mendiolaza, 21 (1.2%)	NA
16	Isidro Casanova, 267 (2.9%)	NA	Estación Juárez Celman, 20 (1.1%)	NA
17	Tigre, 251 (2.7%)	NA	Juárez Celman, 18 (1%)	NA
18	Esteban Echeverría, 246 (2.6%)	NA	Unquillo, 16 (0.9%)	NA
19	Luján, 245 (2.6%)	NA	Cruz del Eje, 15 (0.8%)	NA
20	Escobar, 244 (2.6%)	NA	Calamuchita, 14 (0.8%)	NA

Table 27: Firms by country

skim_variable	country_code	n_missing	complete_rate	character.empty	character.n_unique	character.whitesp
firm	ARG	0	1	10	5983	
firm	CHL	0	1	0	9431	
firm	URY	0	1	0	789	

Table 28: ?(caption)

(a)

rank	ARG	CHL	URY
1	Emprego, 2447 (10.6%)	Confidencial, 2130 (6.2%)	Gallito Trabajo, 88 (4.3%)
2	Confidencial, 748 (3.2%)	Progestion Chile, 890 (2.6%)	ManpowerGroup, 61 (3%)
3	Mendoza, Capital, Mendoza, Argentina, 327 (1.4%)	Adecco Chile, 678 (2%)	Inclusion Cloud, 48 (2.4%)
4	Adecco Argentina S.A., 261 (1.1%)	Manpower Chile, 677 (2%)	Superprof, 33 (1.6%)
5	Grupo Gestión, 259 (1.1%)	Fundación Integra, 575 (1.7%)	Aldeas Infantiles SOS Urug
6	ManpowerGroup, 230 (1%)	Cygnus, 569 (1.7%)	Advice, 26 (1.3%)
7	Buenos Aires, CABA, Argentina, 225 (1%)	ACTIVOS CHILE, 448 (1.3%)	Adecco, 25 (1.2%)
8	Tusclases, 214 (0.9%)	Eurofirms Chile, 432 (1.3%)	confidencial, 24 (1.2%)
9	LatinHire, 198 (0.9%)	XinerLink, 416 (1.2%)	Randstad Uruguay, 22 (1.1%)
10	Wurth Argentina S.a, 132 (0.6%)	Walmart Chile, 296 (0.9%)	Securitas Uruguay, 22 (1.1%)

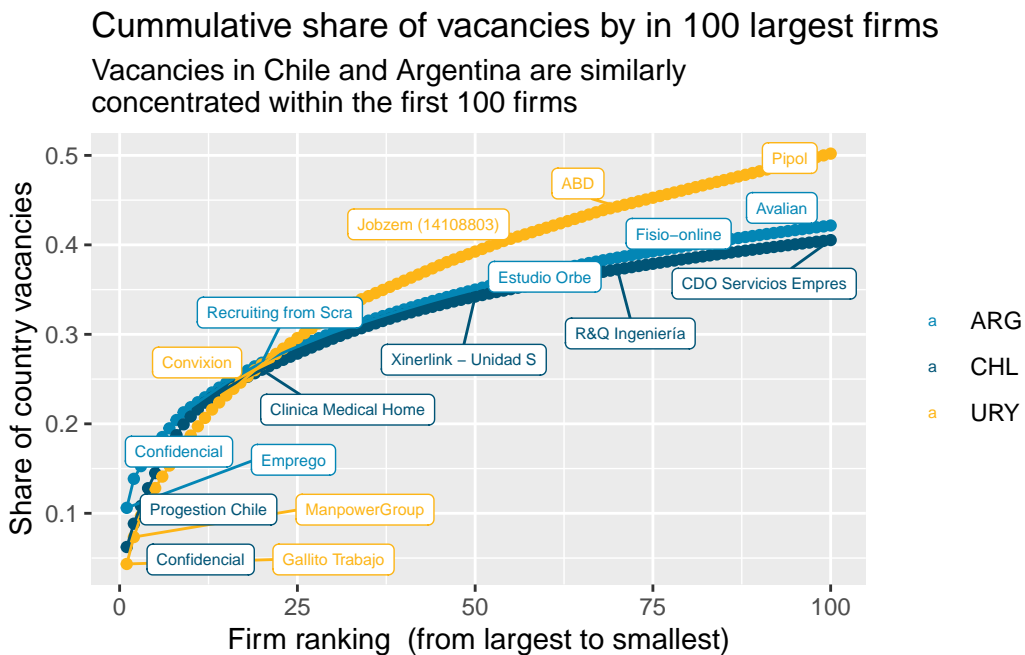
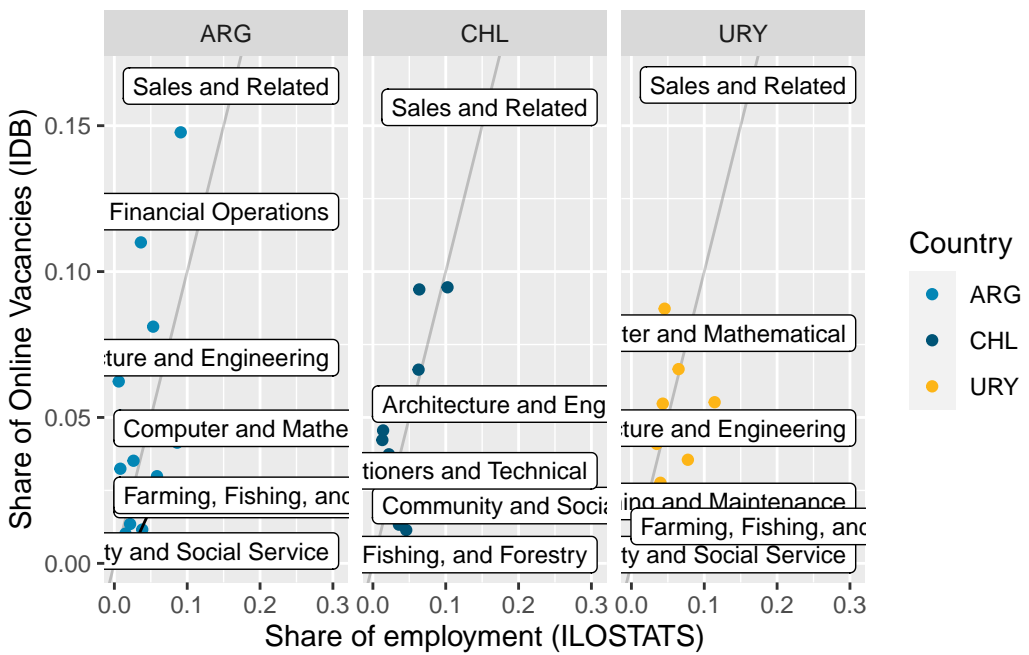
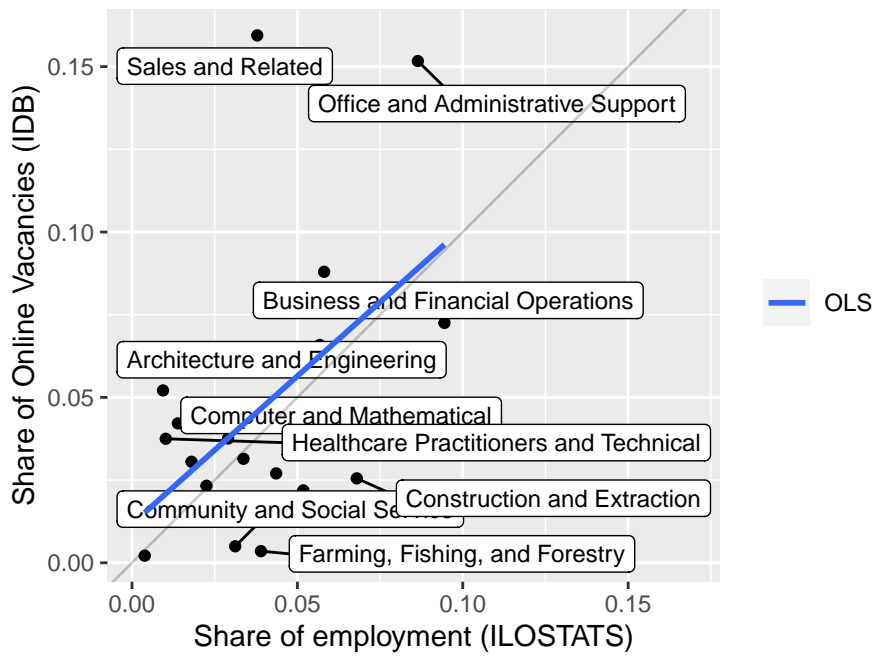


Figure 51: ?(caption)

Comparing employment and online vacancies distributions
For URY

major_group_title	Share of employment	Share of online vacancies	%Vac
Computer and Mathematical Occupations	1.41%	7.89%	
Architecture and Engineering Occupations	0.98%	4.64%	
Sales and Related Occupations	3.75%	16.57%	
Business and Financial Operations Occupations	4.56%	8.73%	
Healthcare Practitioners and Technical Occupations	1.09%	1.48%	
Office and Administrative Support Occupations	12.87%	16.42%	
Educational Instruction and Library Occupations	4.31%	5.47%	
Installation, Maintenance, and Repair Occupations	3.47%	4.09%	
Protective Service Occupations	2.06%	2.42%	
Production Occupations	6.47%	6.66%	
Management Occupations	4.99%	4.34%	
Life, Physical, and Social Science Occupations	2.32%	1.73%	
Food Preparation and Serving Related Occupations	3.98%	2.76%	
Personal Care and Service Occupations	3.56%	2.27%	
Legal Occupations	0.66%	0.39%	
Arts, Design, Entertainment, Sports, and Media Occupations	3.57%	2.02%	
Transportation and Material Moving Occupations	11.42%	5.52%	
Construction and Extraction Occupations	7.75%	3.55%	
Healthcare Support Occupations	2.13%	0.69%	
Building and Grounds Cleaning and Maintenance Occupations	7.92%	1.73%	
Community and Social Service Occupations	3.70%	0.30%	
Farming, Fishing, and Forestry Occupations	6.25%	0.35%	
Military Specific Occupations	0.42%	NA	
Not ISCO classified	0.36%	NA	

These charts give you a straightforward view:

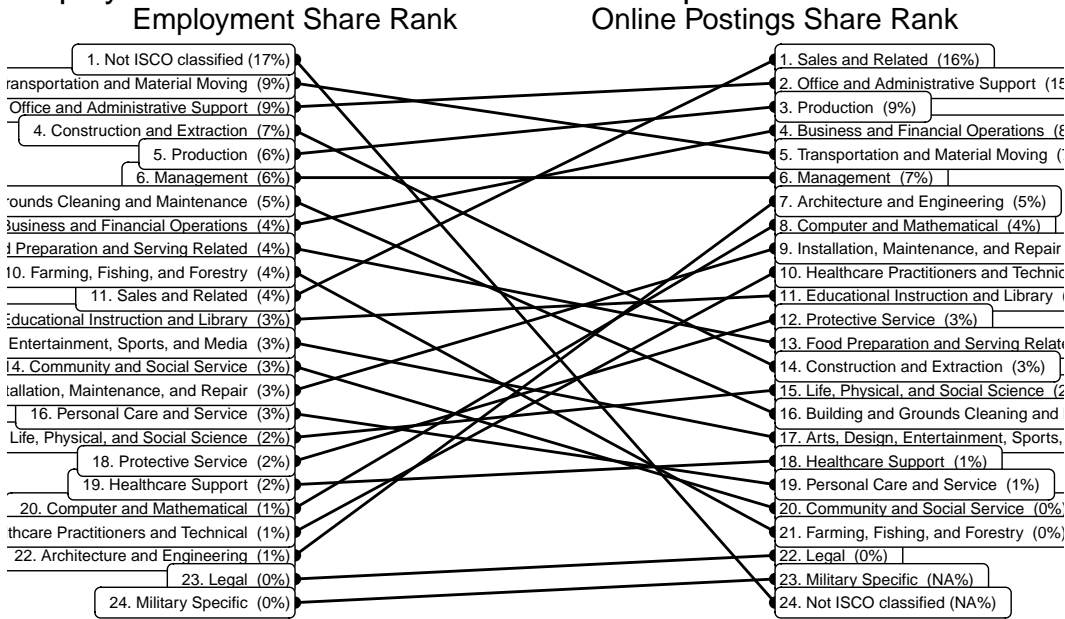


These charts shows the change in rankings from one database to the other:

Rank comparisson

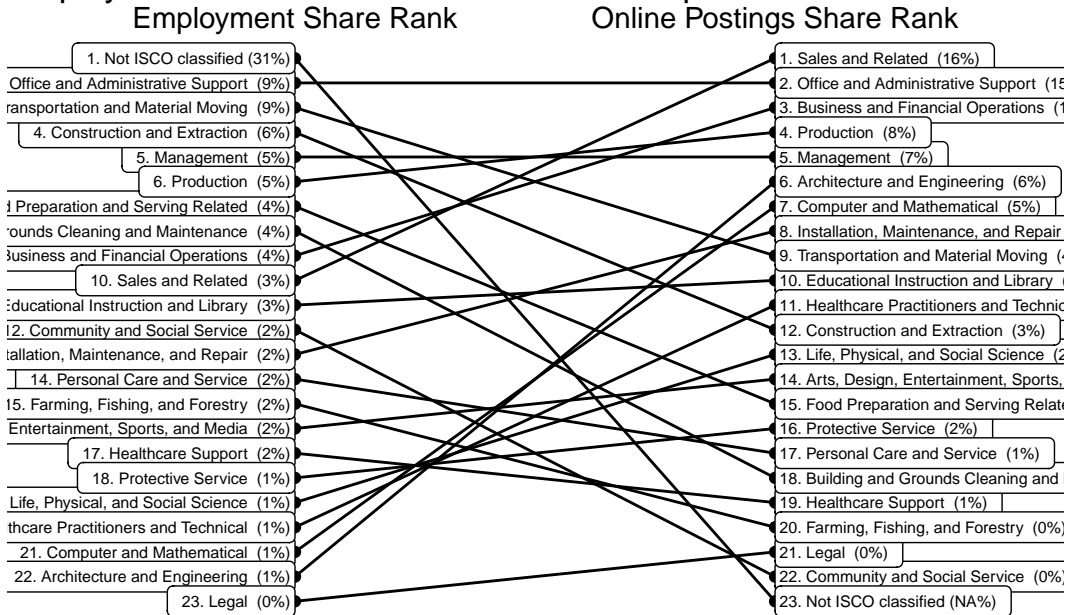
Total

Employment and online vacancies rank comparisson



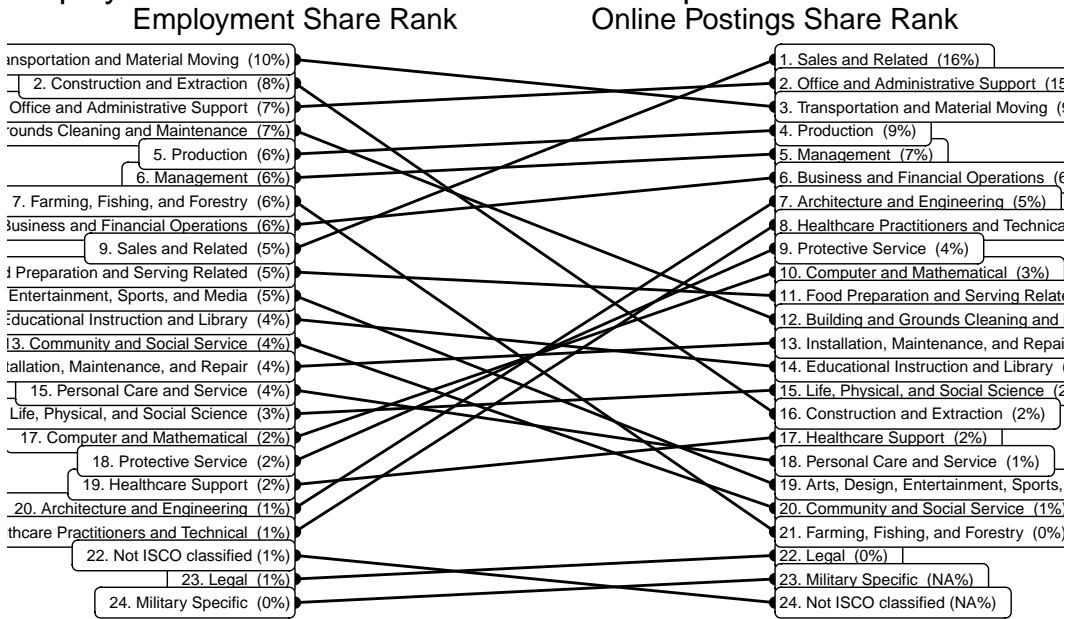
Argentina

Employment and online vacancies rank comparisson for ARG



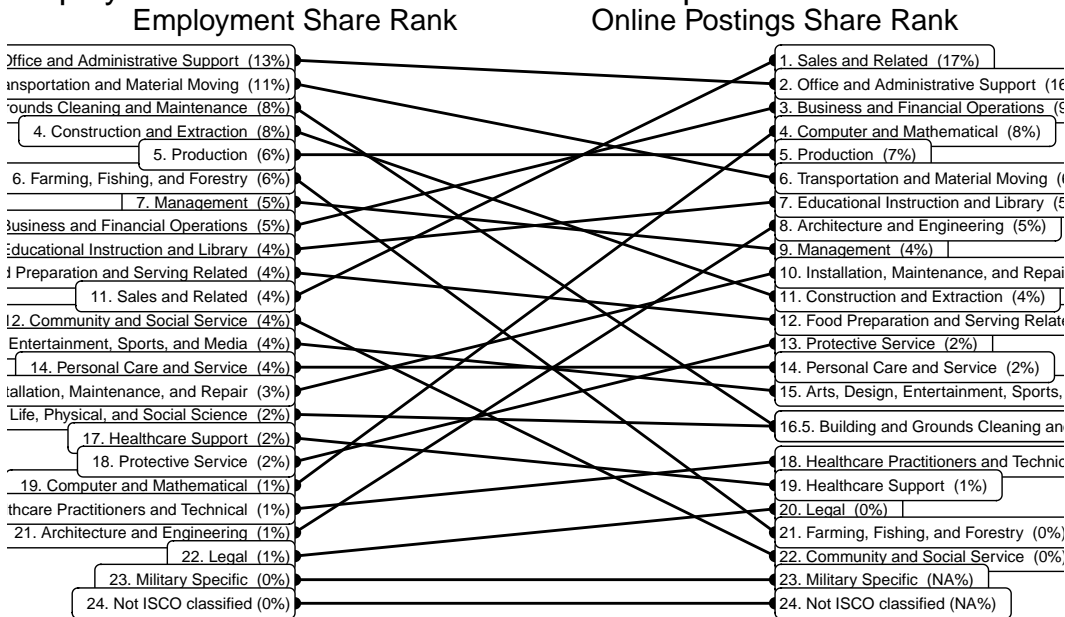
Chile

Employment and online vacancies rank comparison for CHL



Uruguay

Employment and online vacancies rank comparison for URY



Comparing against ILOSTAT data by sector

The table below shows the correlation between employment and online job vacancies distributions.

Correlation between employment and online vacancies distributions

Estimates correspond to Pearson's correlation coefficients

estimate	statistic	group
48.01%	4.131854	Total
33.71%	1.519098	ARG
65.31%	3.659099	CHL
43.44%	1.988377	URY

Regular comparisson

Total

Table 30: Comparisson of employment and postigns distribution

Comparing employment and online vacancies distributions
All countries

main_sector	Share of employment	Share of online vacancies	%Vacancies-%Empl
Real Estate And Rental And Leasing	0.44%	1.55%	
Professional Scientific And Technical Services	4.09%	14.38%	
Finance And Insurance	1.77%	5.07%	
Manufacturing	8.18%	18.48%	
Retail Trade	10.38%	15.54%	
Educational Services	8.31%	11.41%	
Health Care And Social Assistance	6.86%	8.16%	
Accommodation And Food Services	3.83%	4.42%	
Government	3.80%	3.87%	
Administrative And Support Services	7.06%	5.89%	
Transportation And Warehousing	3.12%	2.26%	
Information	1.56%	1.02%	
Construction	7.50%	3.04%	
Utilities	1.68%	0.43%	
Mining Quarrying And Oil And Gas Extraction	1.33%	0.31%	
Other Services Except Public Administration	10.96%	2.11%	
Arts Entertainment And Recreation	2.29%	0.42%	
Wholesale Trade	7.03%	1.26%	
Agriculture Forestry Fishing And Hunting	4.82%	0.38%	
Management Of Companies And Enterprises	0.69%	NA	

NA 4.29% NA

Argentina

Comparing employment and online vacancies distributions
For ARG

main_sector	Share of employment	Share of online vacancies	%Vacancies-%Empl
Professional Scientific And Technical Services	3.62%	16.84%	
Finance And Insurance	2.00%	6.52%	
Real Estate And Rental And Leasing	0.38%	1.15%	
Retail Trade	5.16%	13.64%	
Manufacturing	9.44%	18.44%	
Educational Services	7.97%	12.43%	
Health Care And Social Assistance	6.78%	6.79%	
Government	4.70%	4.30%	
Accommodation And Food Services	3.49%	3.17%	
Transportation And Warehousing	3.00%	2.30%	
Information	2.11%	1.25%	
Mining Quarrying And Oil And Gas Extraction	0.46%	0.26%	
Administrative And Support Services	7.76%	4.36%	
Construction	8.59%	3.17%	
Other Services Except Public Administration	12.43%	2.85%	
Agriculture Forestry Fishing And Hunting	2.41%	0.36%	
Arts Entertainment And Recreation	2.42%	0.34%	
Utilities	1.55%	0.21%	
Wholesale Trade	11.96%	1.61%	
Management Of Companies And Enterprises	0.68%	0.01%	
NA	3.10%	NA	

Chile

Comparing employment and online vacancies distributions
For CHL

main_sector	Share of employment	Share of online vacancies	%Vacancies-%Empl
Real Estate And Rental And Leasing	0.52%	1.83%	
Manufacturing	6.38%	18.76%	
Professional Scientific And Technical Services	4.57%	12.45%	
Finance And Insurance	1.52%	4.09%	
Wholesale Trade	0.51%	1.05%	

Government	2.50%	3.57%
Health Care And Social Assistance	6.64%	9.18%
Accommodation And Food Services	4.38%	5.17%
Administrative And Support Services	6.00%	7.03%
Educational Services	9.06%	10.54%
Retail Trade	17.47%	16.90%
Information	0.90%	0.85%
Transportation And Warehousing	3.24%	2.22%
Construction	6.34%	2.93%
Utilities	1.85%	0.58%
Arts Entertainment And Recreation	2.08%	0.49%
Other Services Except Public Administration	8.83%	1.60%
Mining Quarrying And Oil And Gas Extraction	2.71%	0.36%
Agriculture Forestry Fishing And Hunting	7.26%	0.40%
Management Of Companies And Enterprises	0.67%	0.01%
NA	6.56%	NA

Uruguay

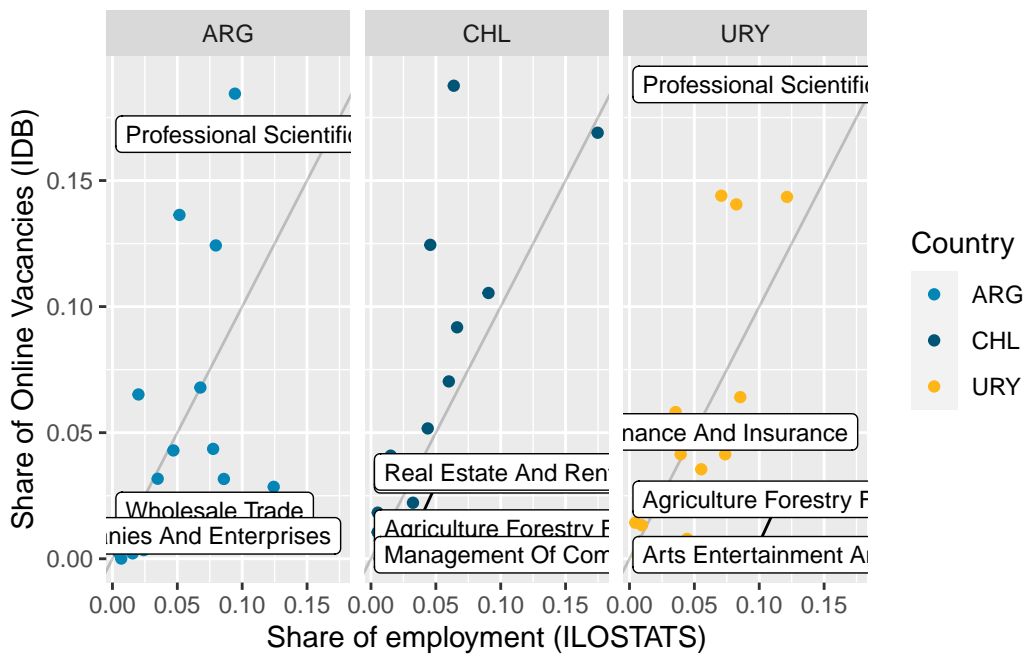
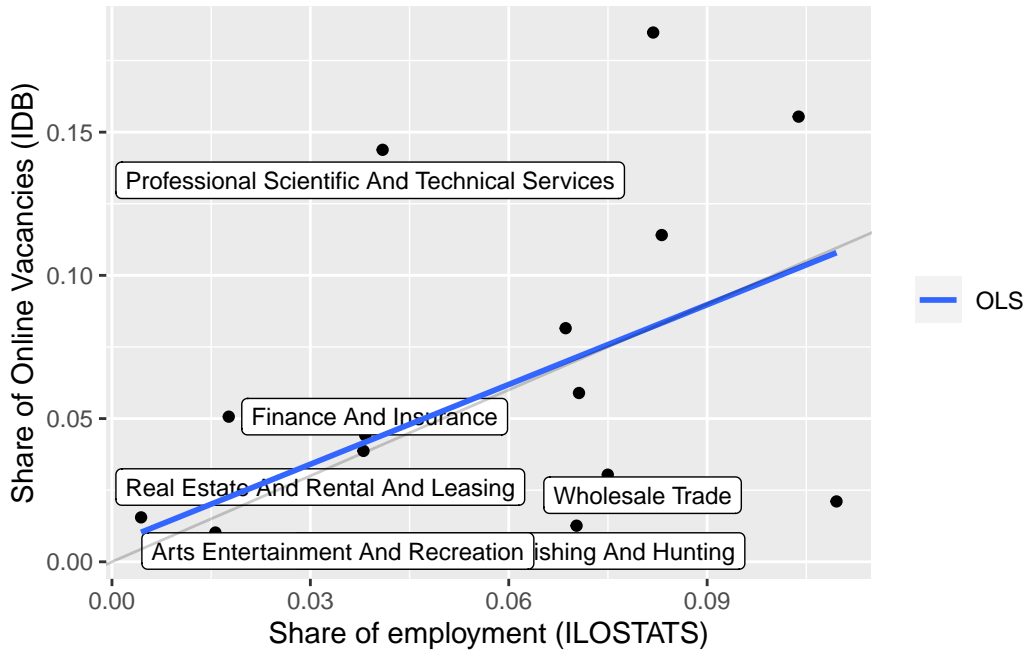
Comparing employment and online vacancies distributions
For URY

main_sector	Share of employment	Share of online vacancies	%Vacancies-%Empl
Finance And Insurance	1.31%	5.03%	
Professional Scientific And Technical Services	5.07%	18.98%	
Real Estate And Rental And Leasing	0.44%	1.43%	
Educational Services	7.08%	14.40%	
Manufacturing	8.24%	14.05%	
Accommodation And Food Services	3.56%	5.82%	
Information	0.96%	1.33%	
Retail Trade	12.14%	14.35%	
Government	3.94%	4.14%	
Health Care And Social Assistance	8.54%	6.41%	
Transportation And Warehousing	3.41%	2.37%	
Construction	5.53%	3.55%	
Administrative And Support Services	7.38%	4.14%	
Utilities	1.78%	0.39%	
Other Services Except Public Administration	11.05%	2.17%	
Wholesale Trade	4.44%	0.79%	
Mining Quarrying And Oil And Gas Extraction	0.64%	0.10%	
Arts Entertainment And Recreation	2.49%	0.20%	
Agriculture Forestry Fishing And Hunting	9.75%	0.35%	

Management Of Companies And Enterprises
NA

0.87%
1.39%

NA
NA



These charts shows the change in rankings from one database to the other:

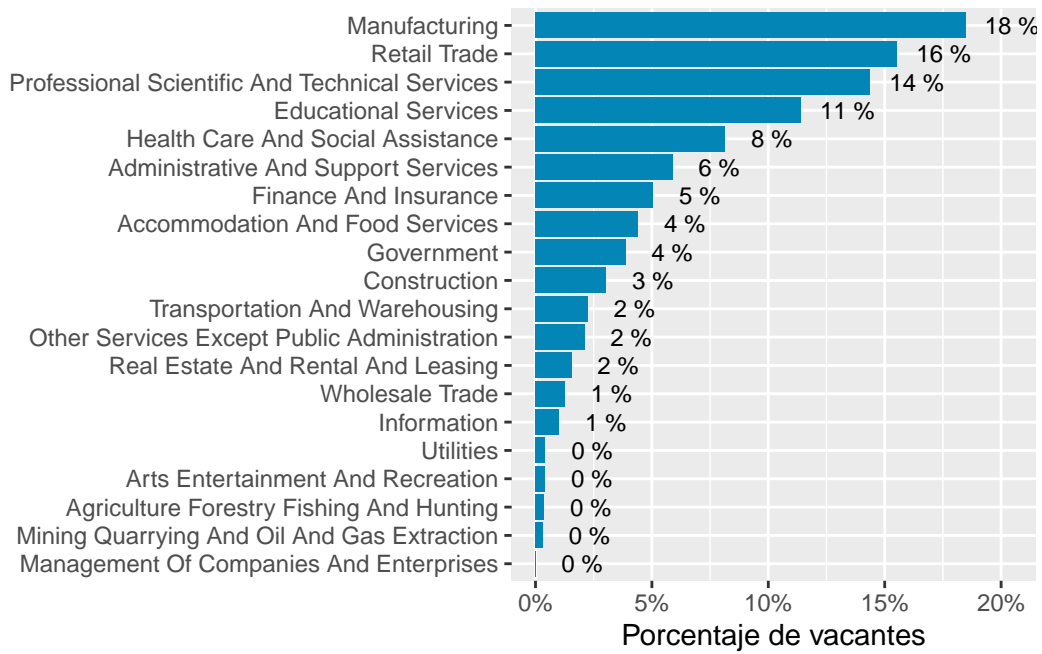


Figure 52: ?(caption)

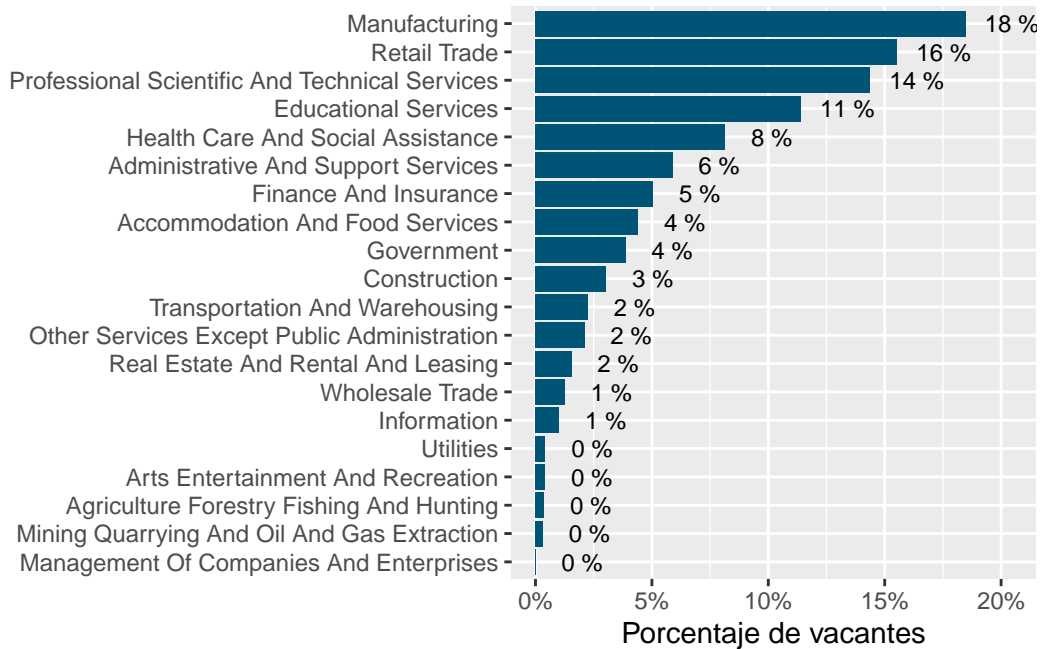


Figure 53: ?(caption)

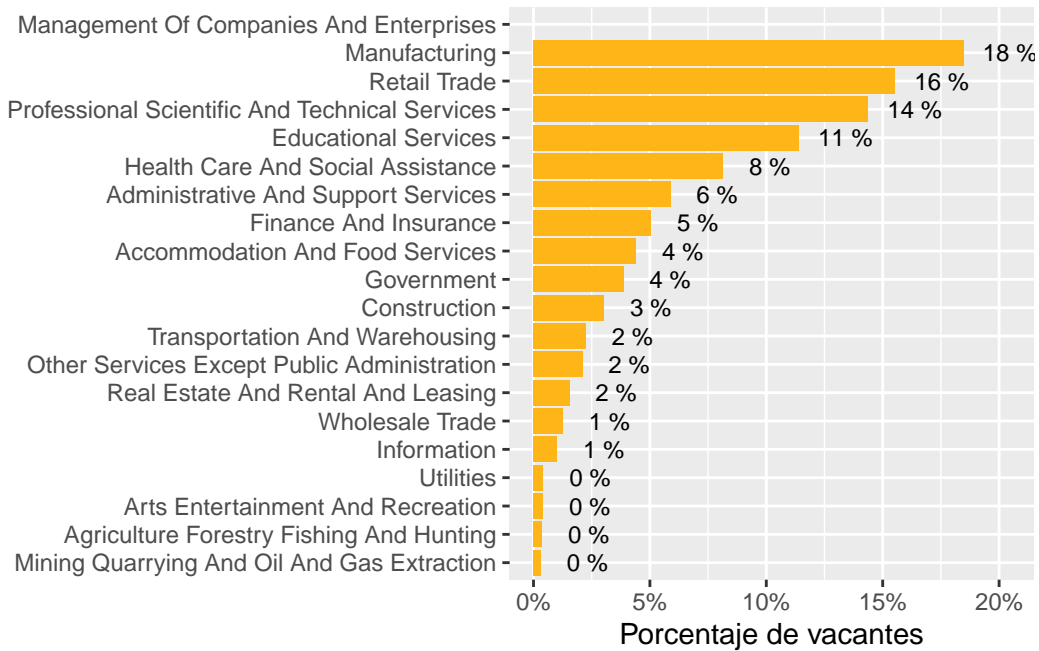
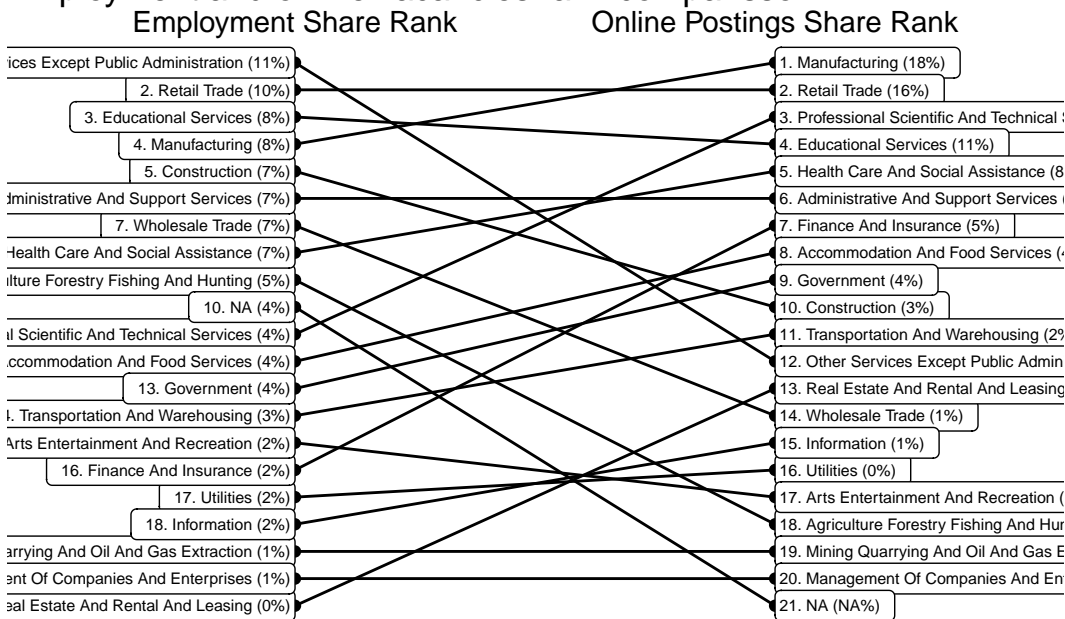


Figure 54: ?(caption)

Rank comparisson

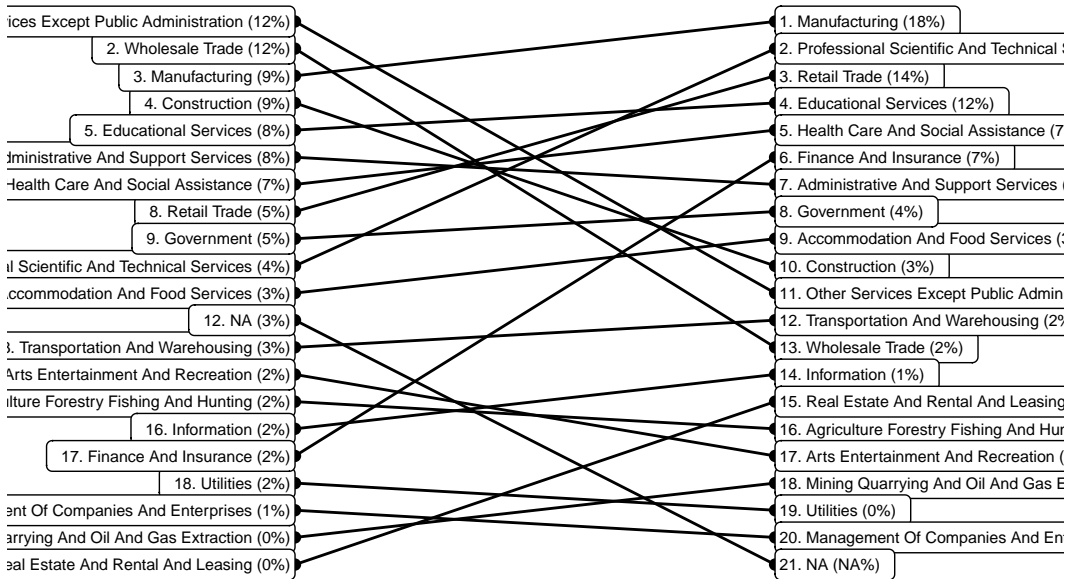
Total

Employment and online vacancies rank comparisson



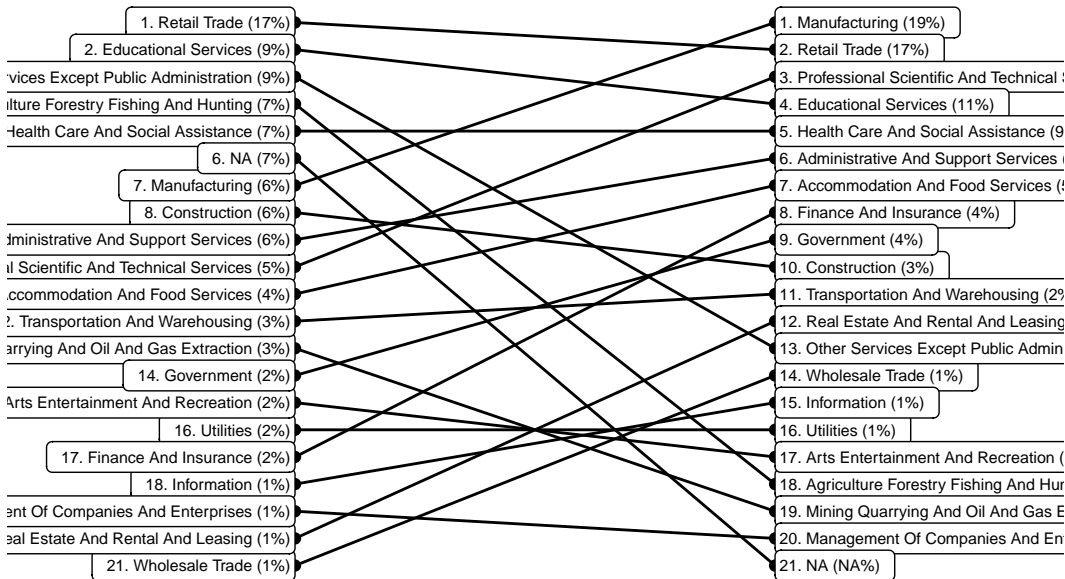
Argentina

Employment and online vacancies rank comparisson for ARG



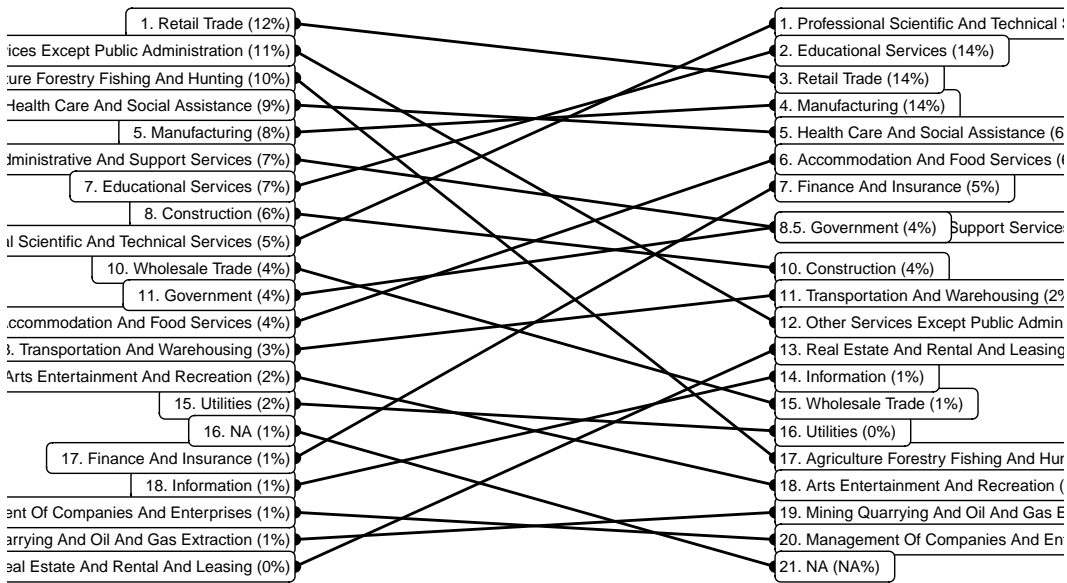
Chile

Employment and online vacancies rank comparisson for CHL



Uruguay

Employment and online vacancies rank comparison for URY



Appendix

Slides

Sectores

Número de vacantes ponderado por la importancia de cada sector

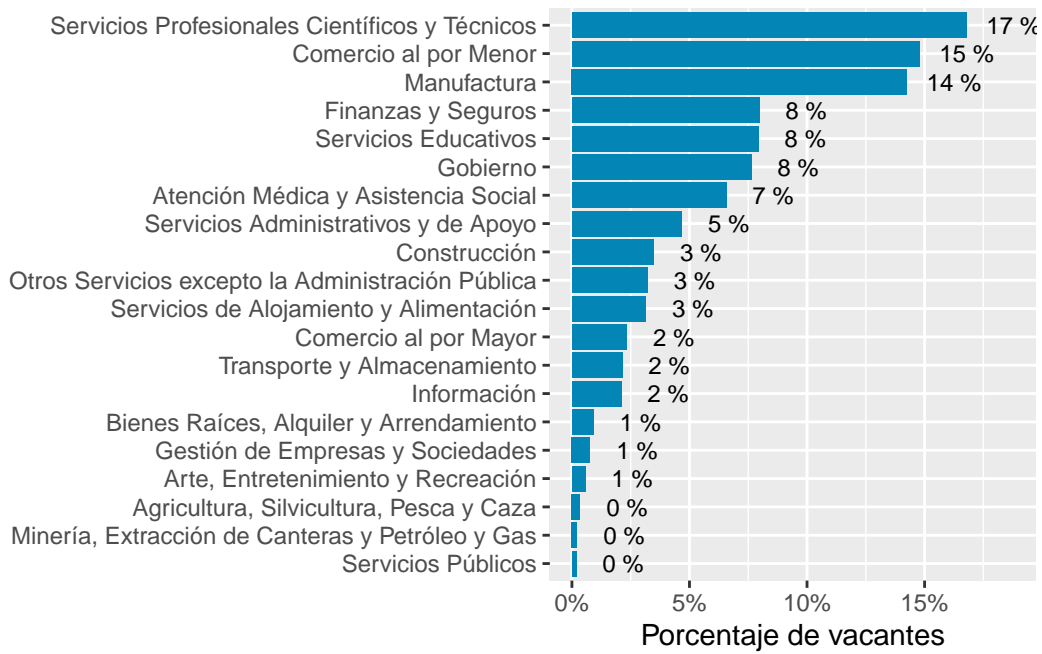
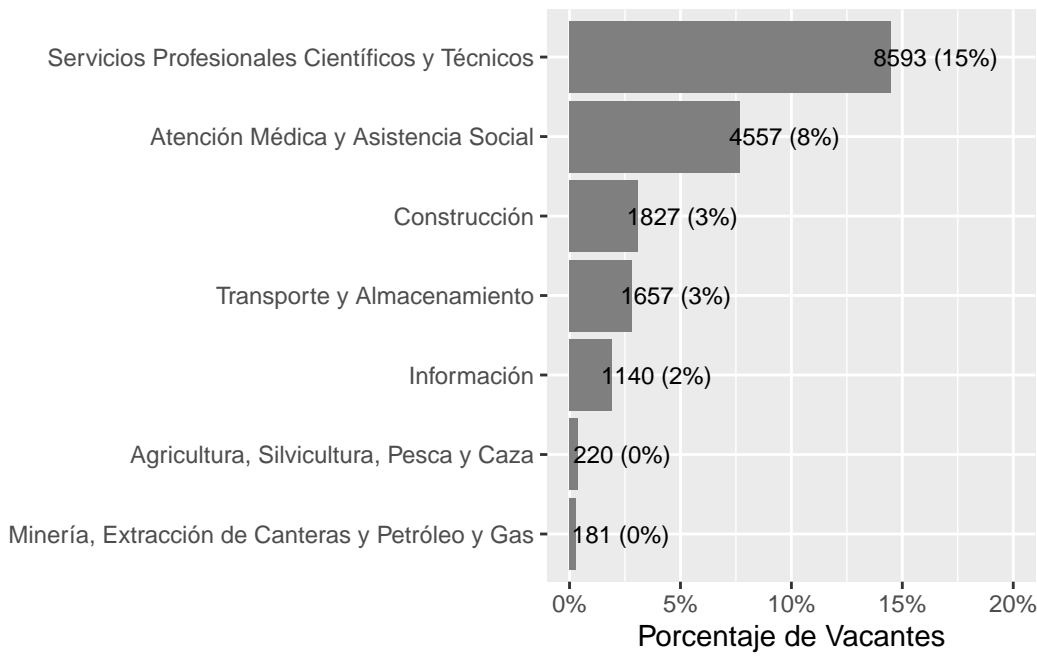


Figure 55: ?(caption)

Porcentaje de vacantes donde cada sector es la más importante.

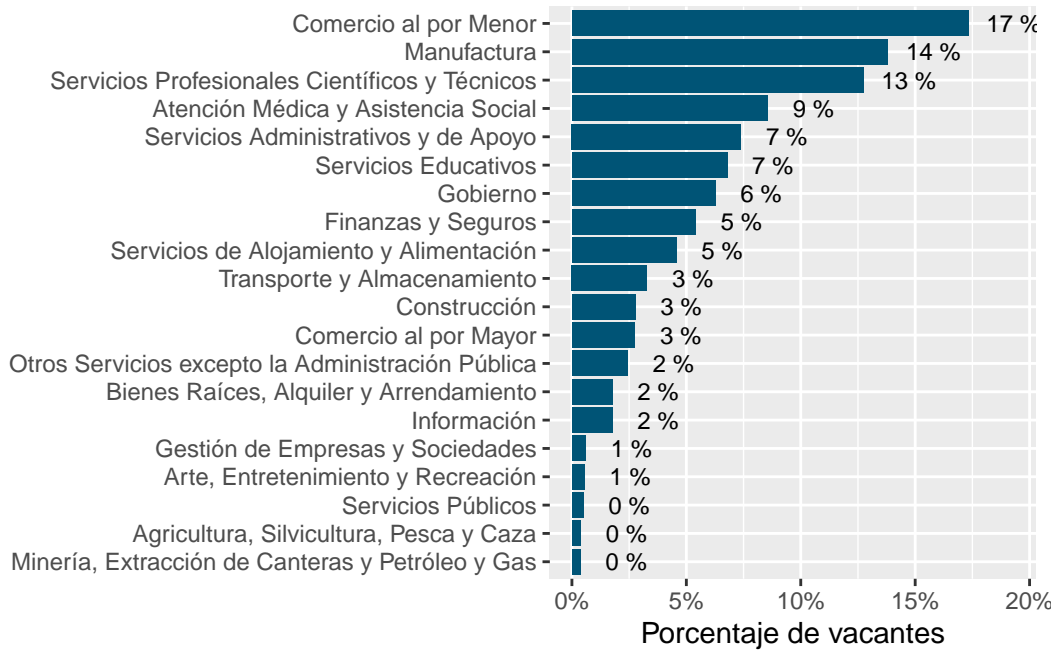


Figure 56: ?(caption)

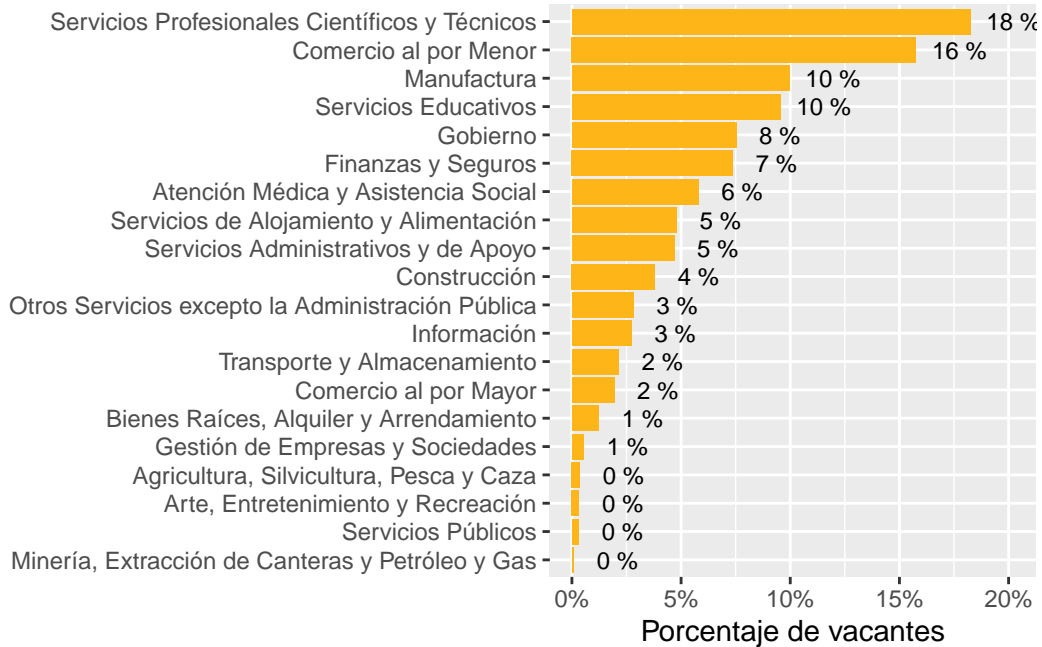
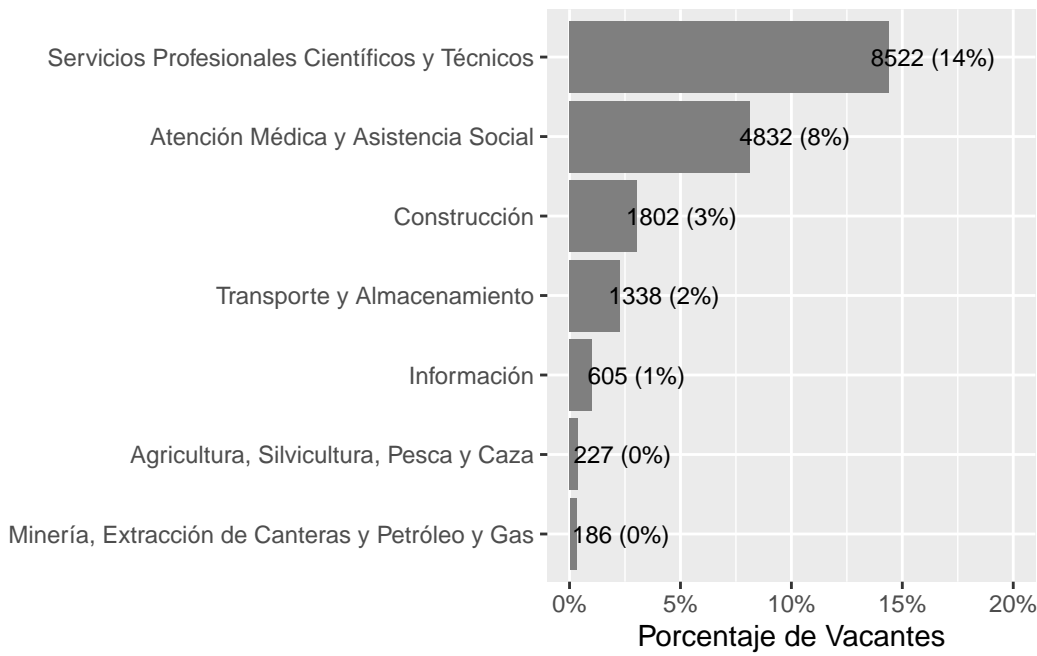


Figure 57: ?(caption)



Ocupaciones

Top Occupational groups

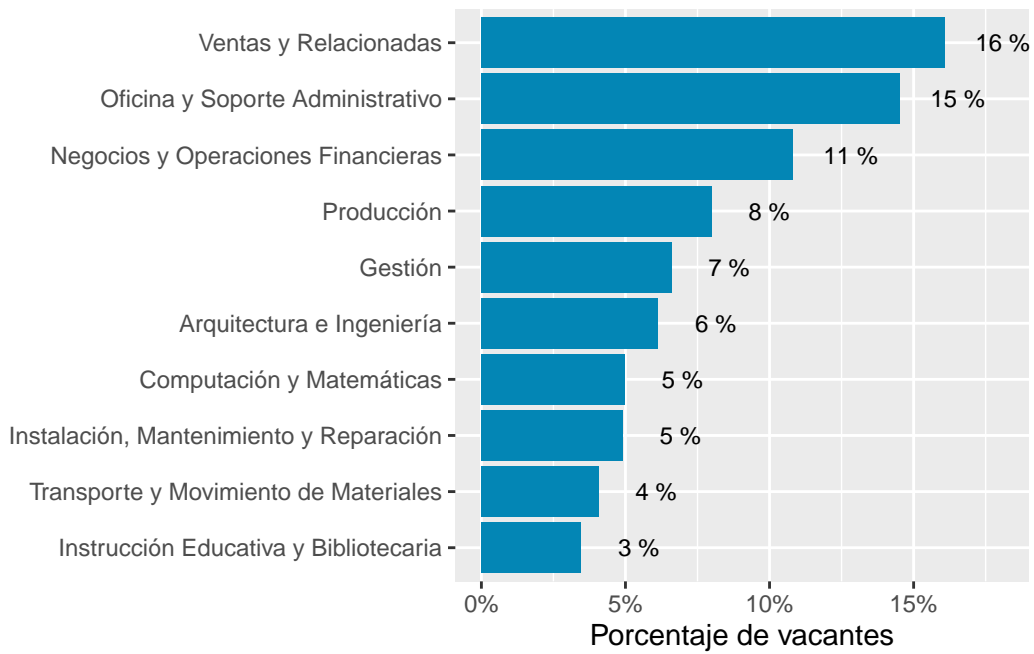


Figure 58: ?(caption)

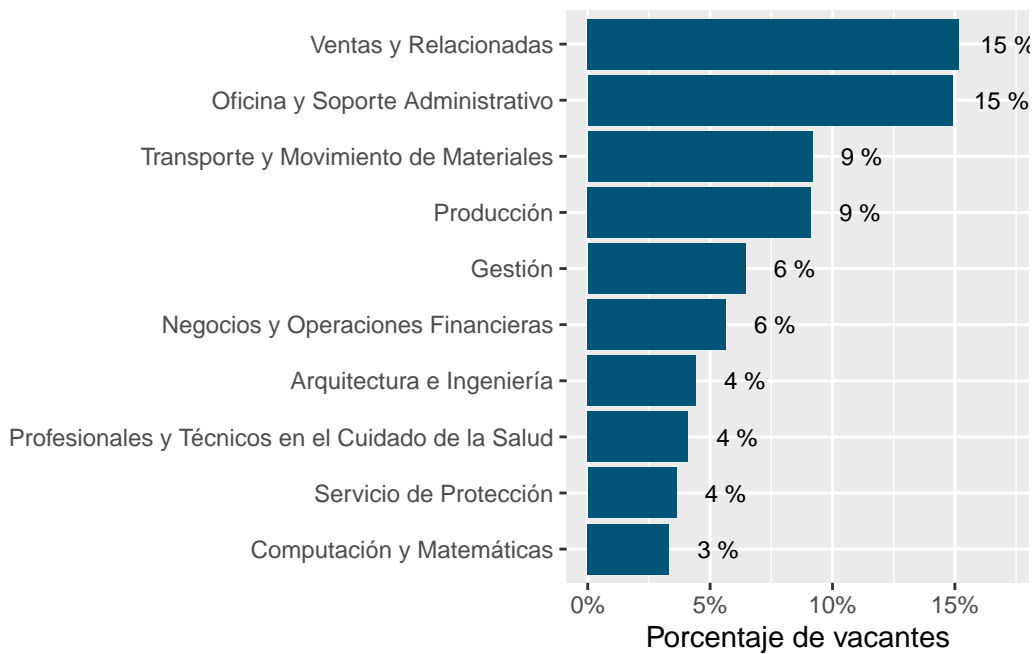


Figure 59: ?(caption)

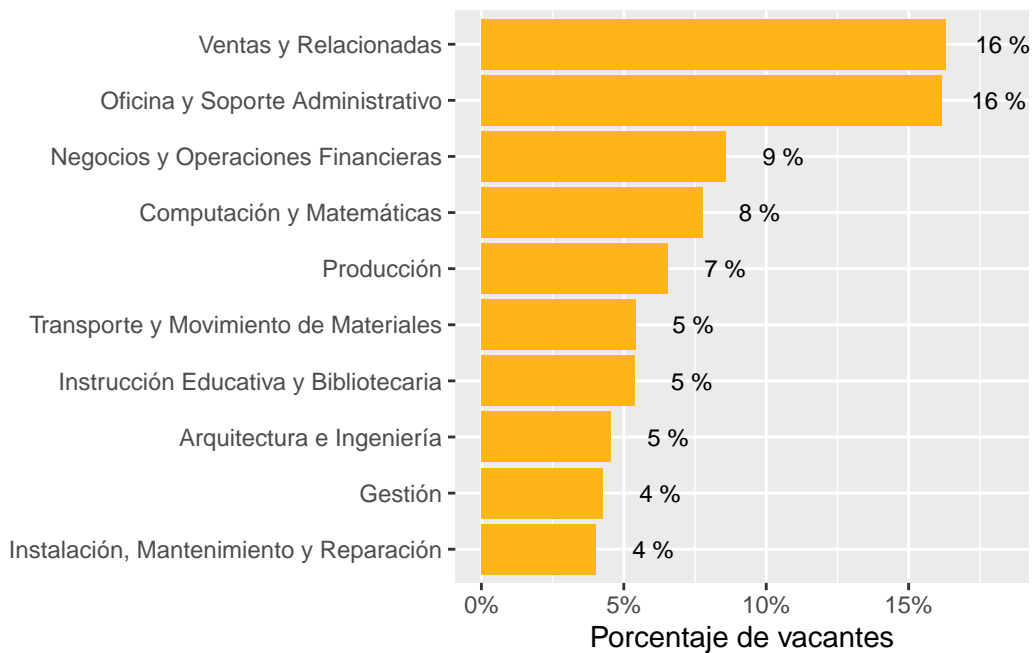
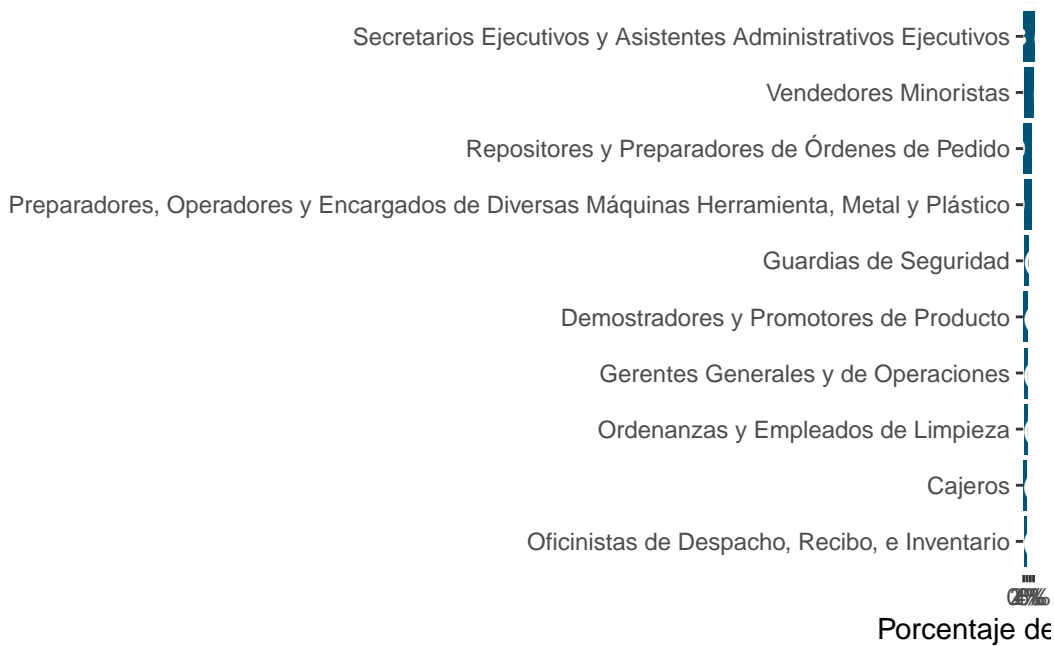
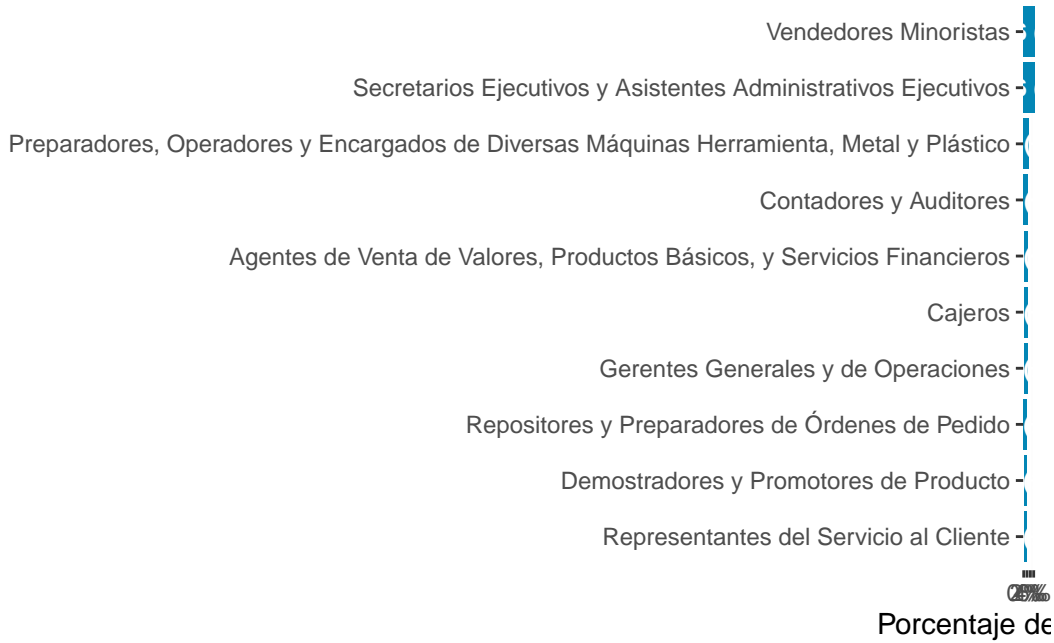
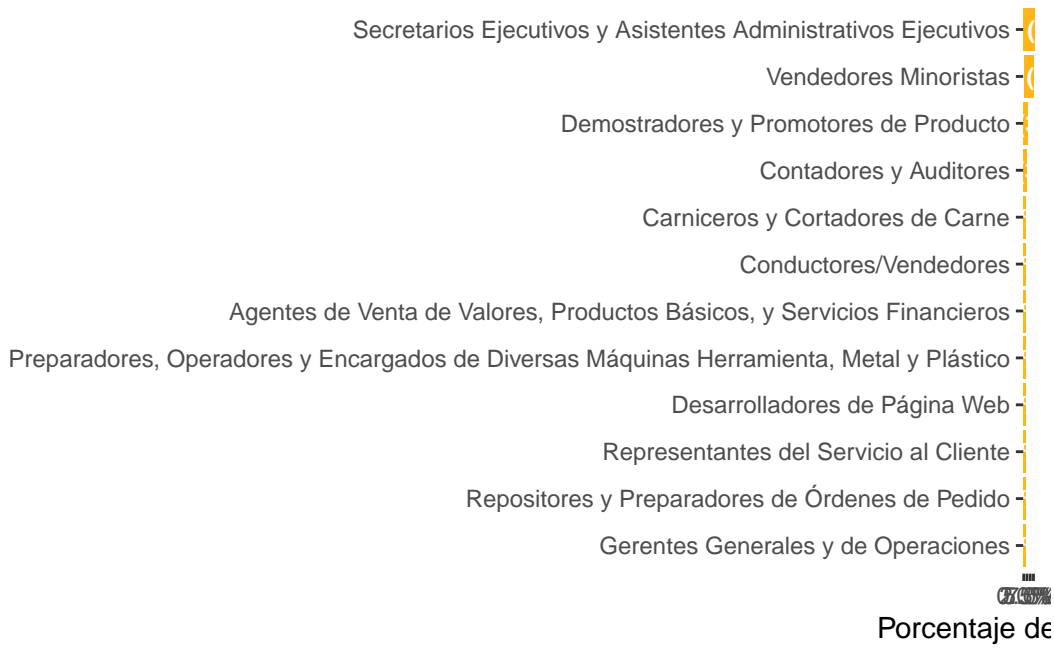


Figure 60: ?(caption)

Top occupations





Habilidades

Número de vacantes ponderado por la importancia de cada habilidad

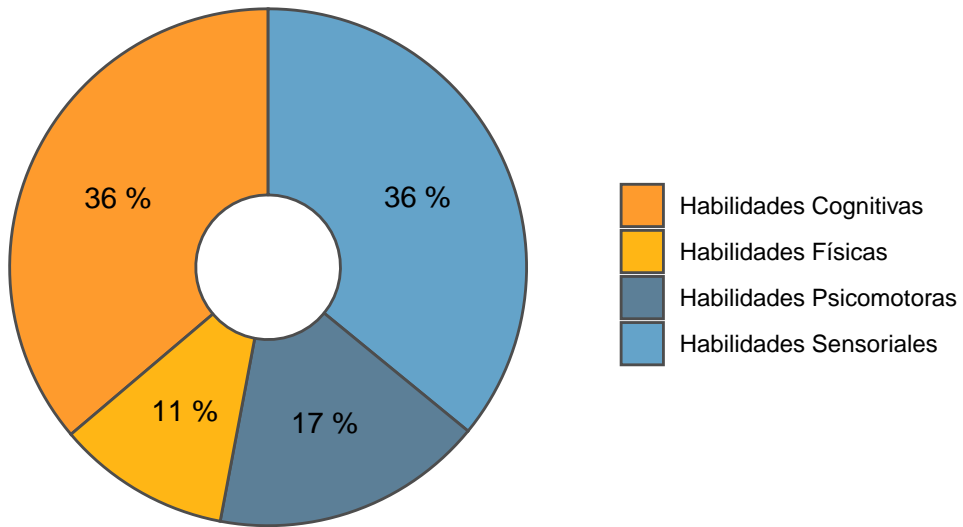


Figure 61: ?(caption)

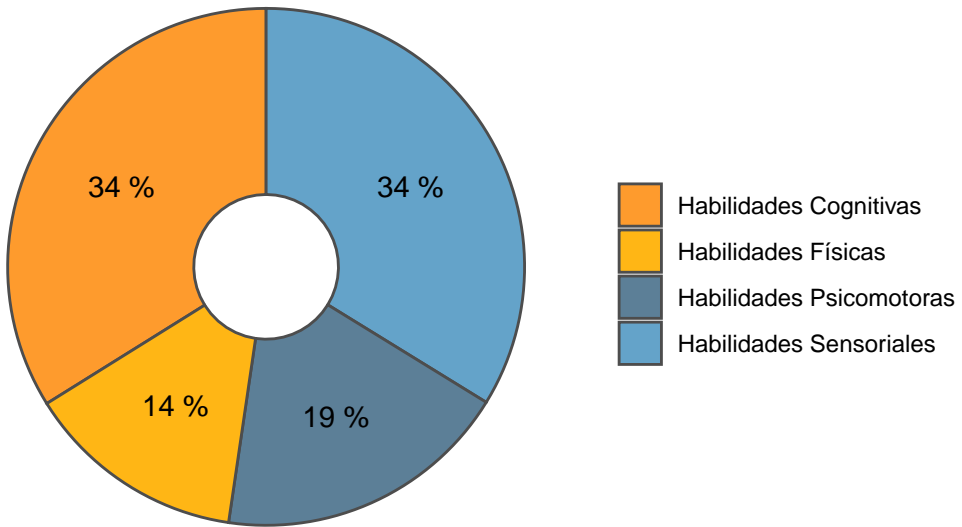


Figure 62: ?(caption)

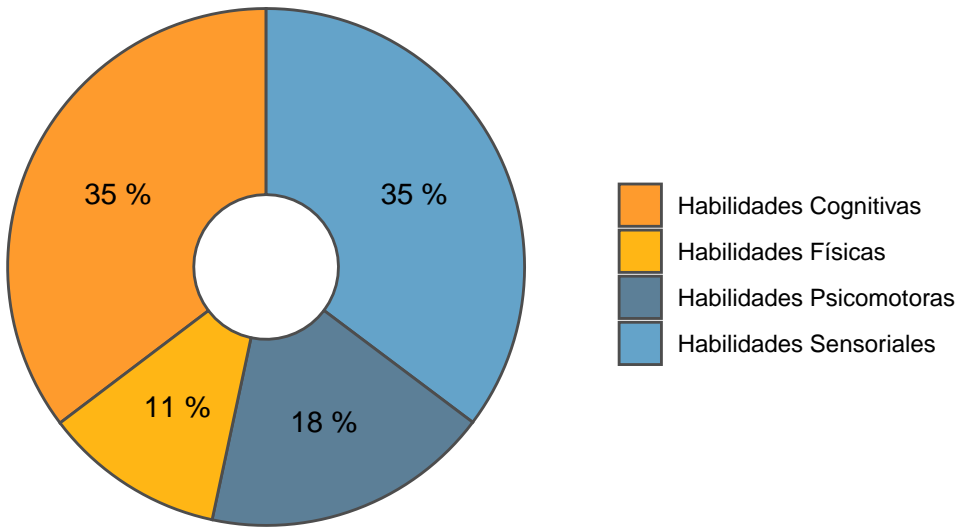


Figure 63: ?(caption)

Porcentaje de vacantes que requiere cada habilidad con probabilidad mayor a cero.

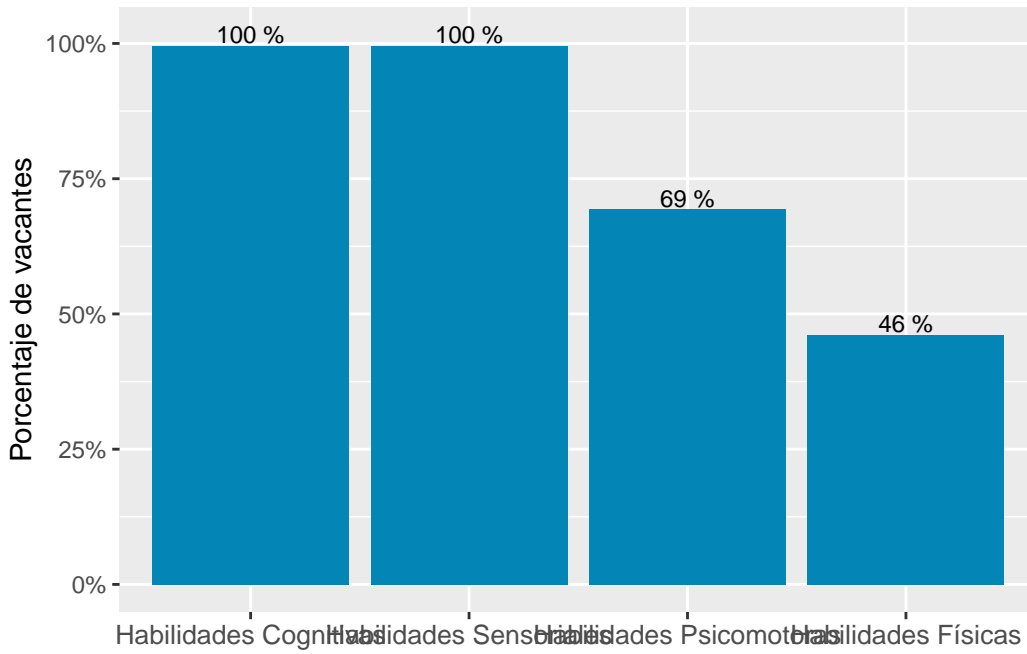


Figure 64: ?(caption)

Subhabilidades

Top 5 subhabilidades dentro de cada país

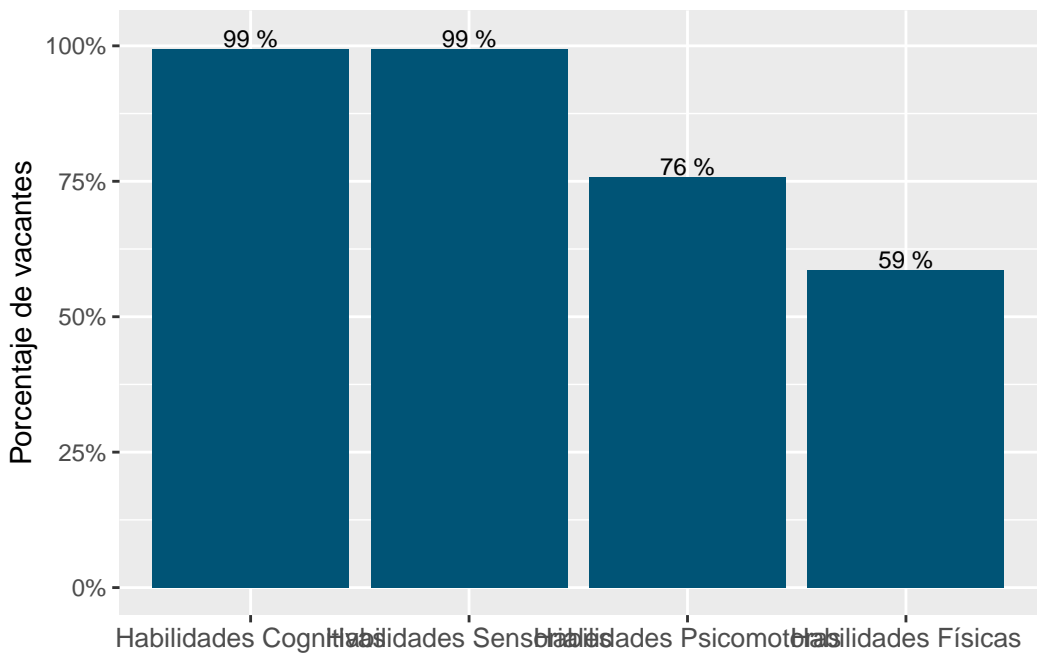


Figure 65: ?(caption)

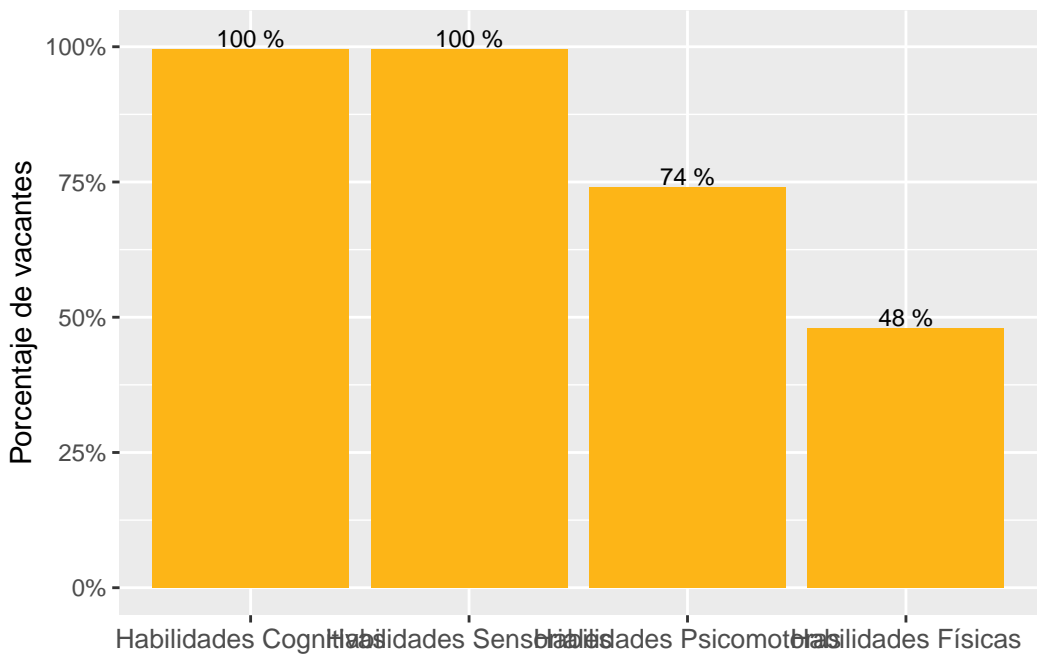
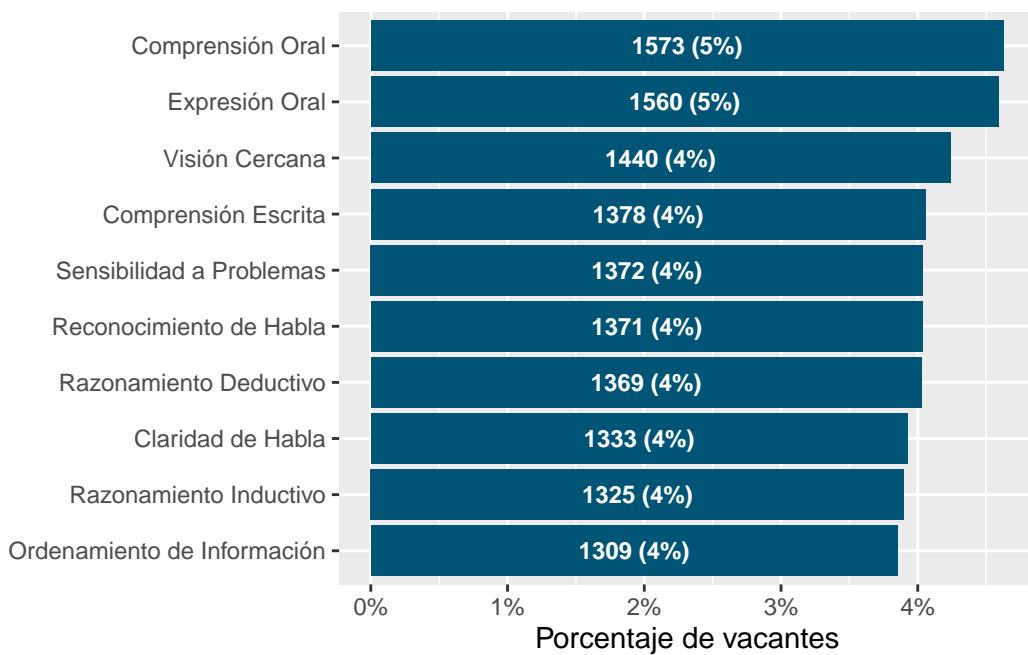
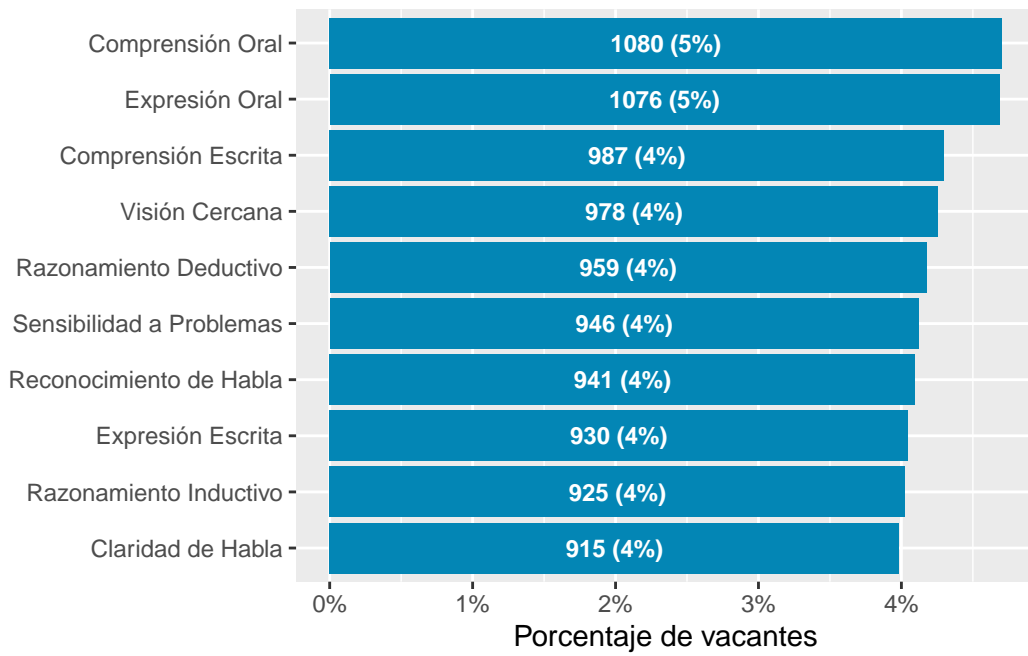
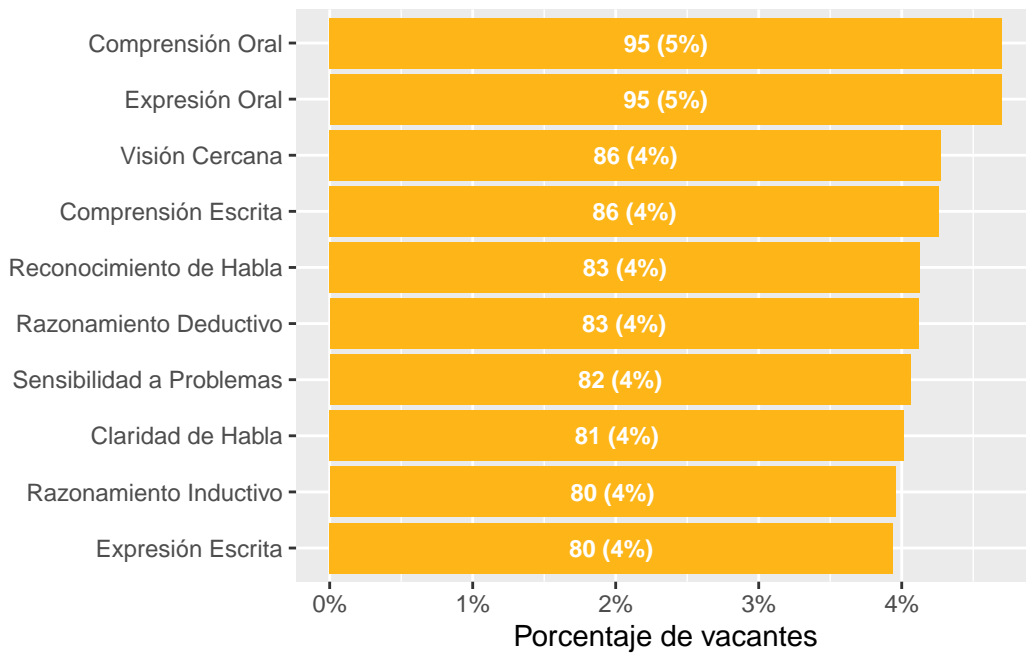


Figure 66: ?(caption)





Top 5 Subhabilidades dentro de cada grupo de habilidades

[[1]]

[[2]]

[[3]]

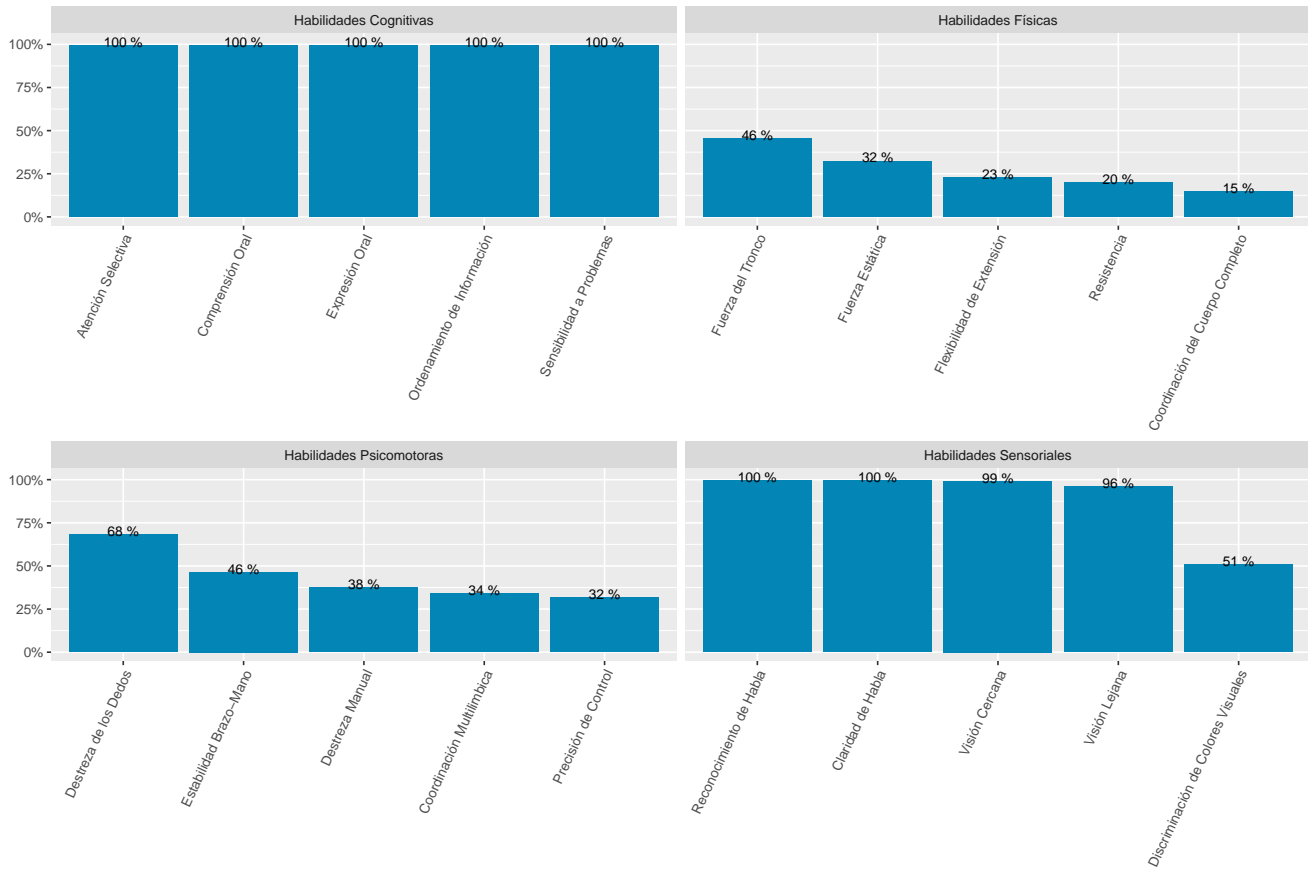


Figure 67: ?(caption)

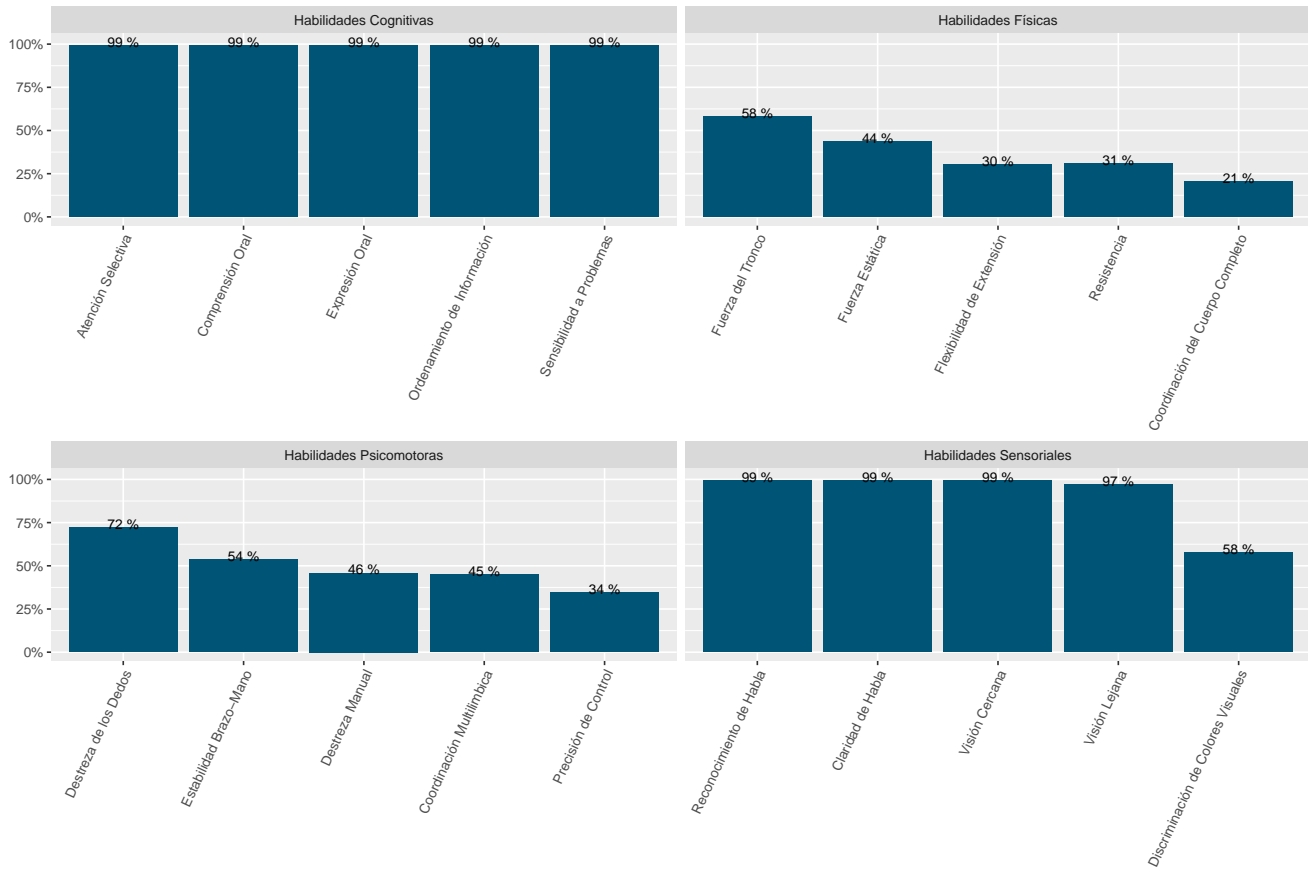


Figure 68: ?(caption)

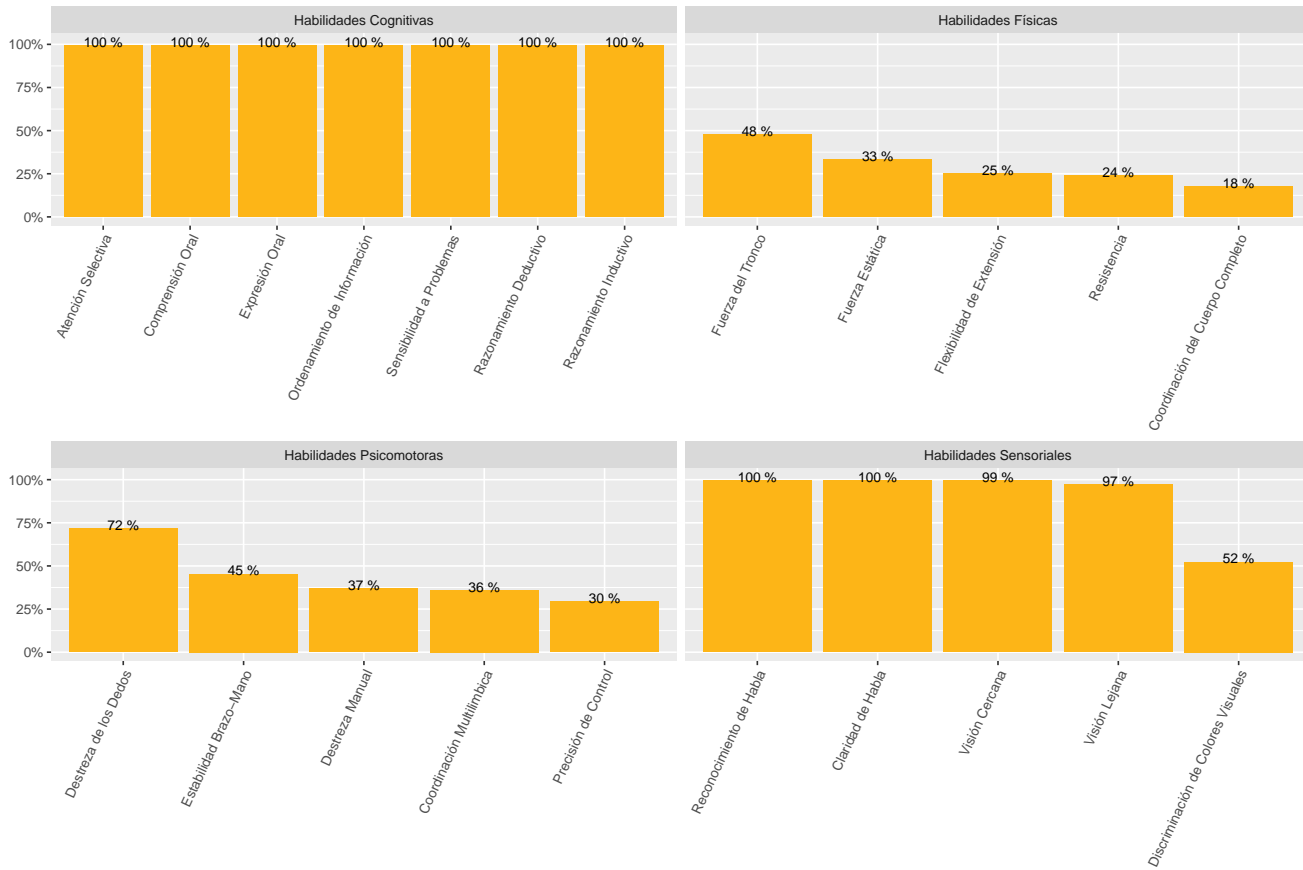
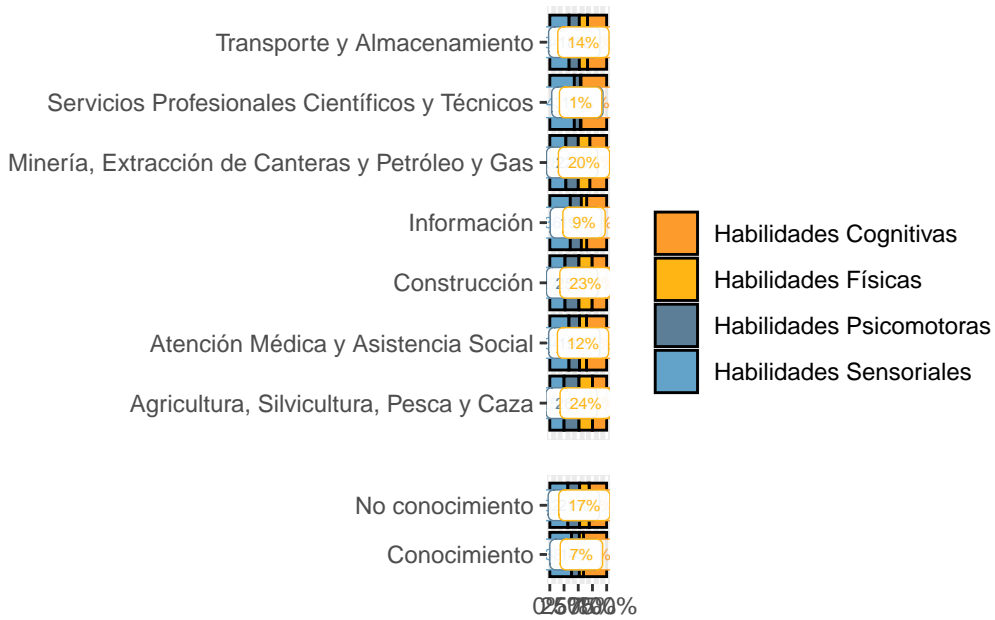
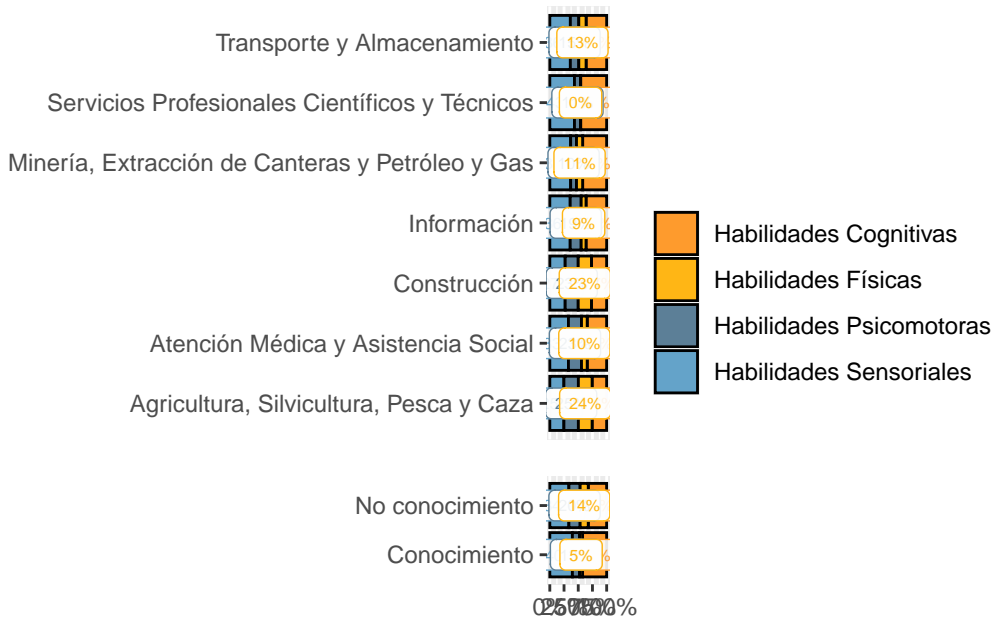
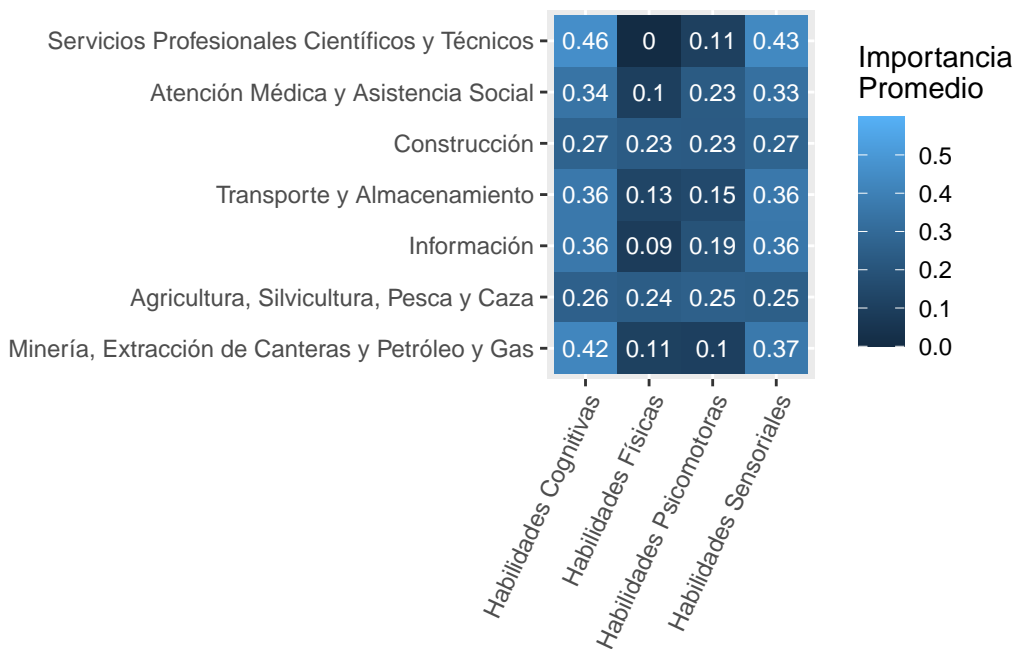
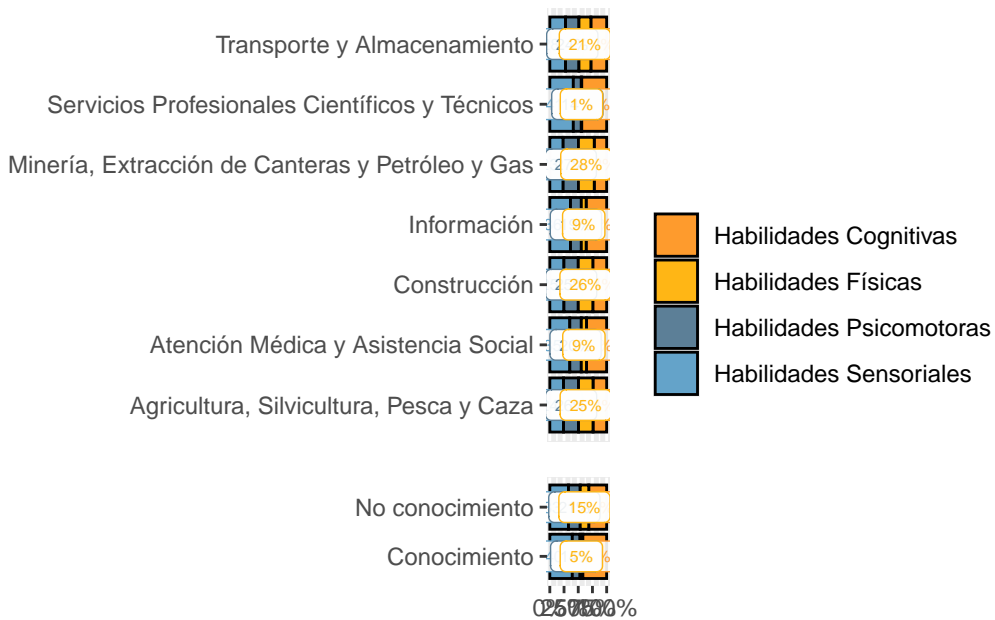
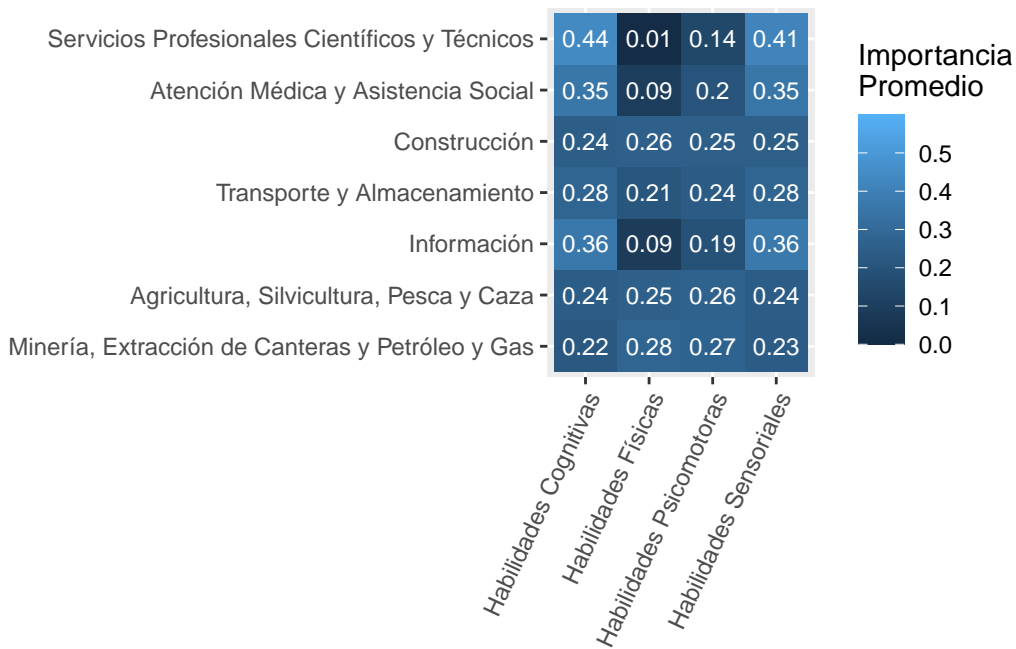
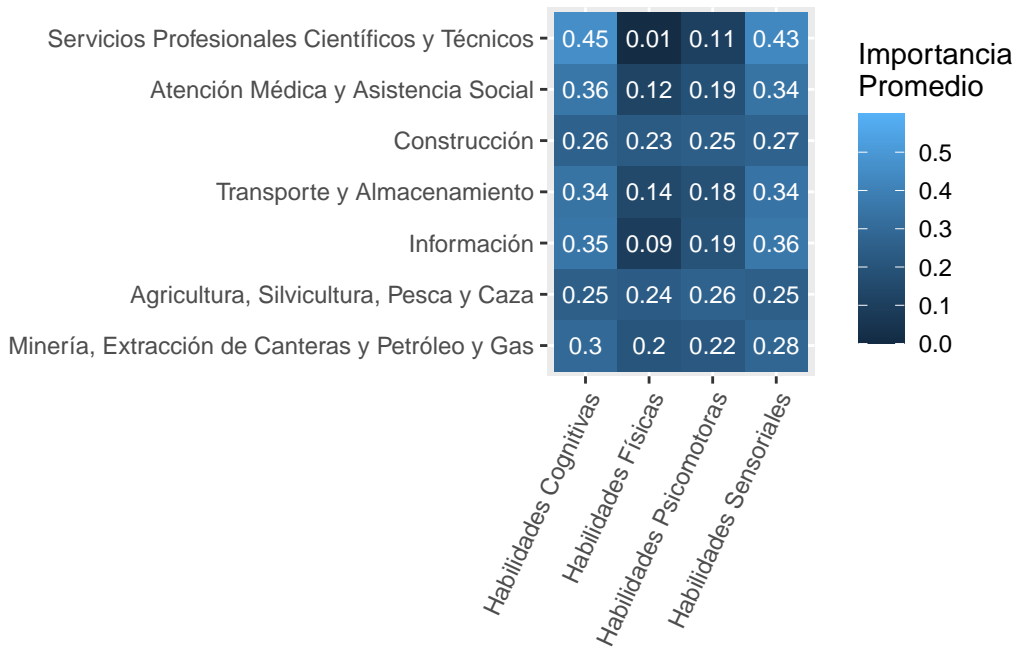


Figure 69: ?(caption)

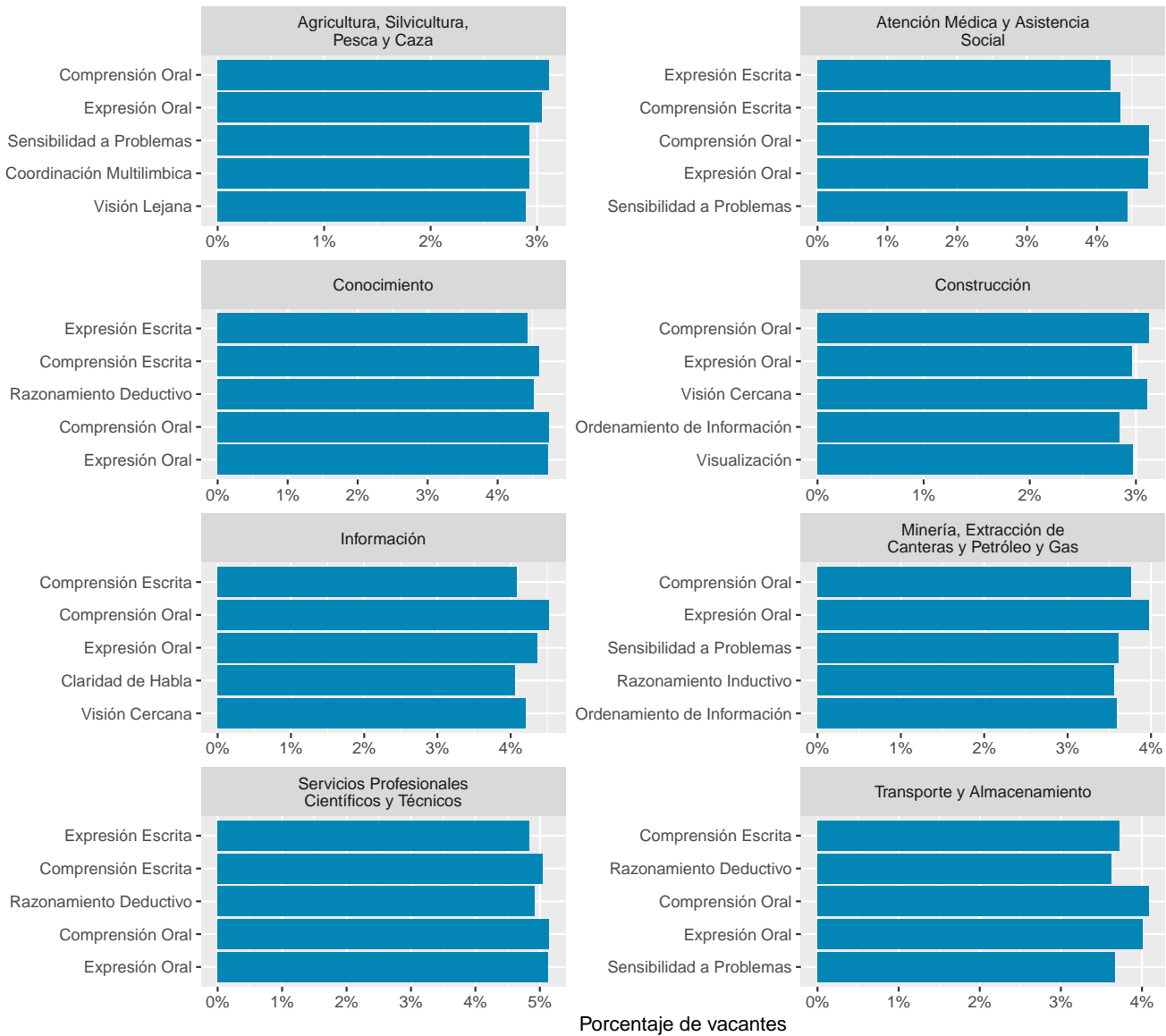
Habilidades demandadas por sector por país

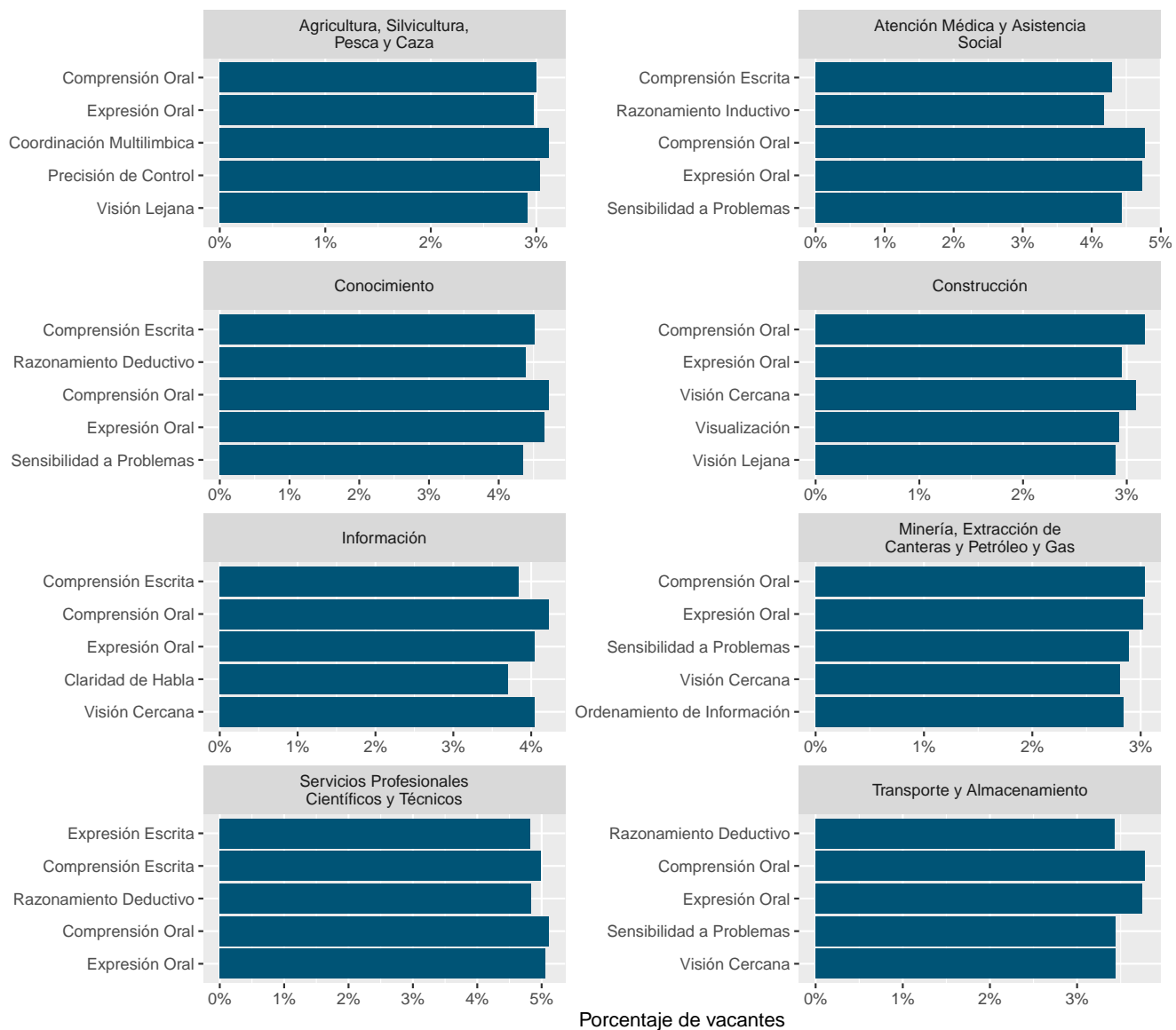


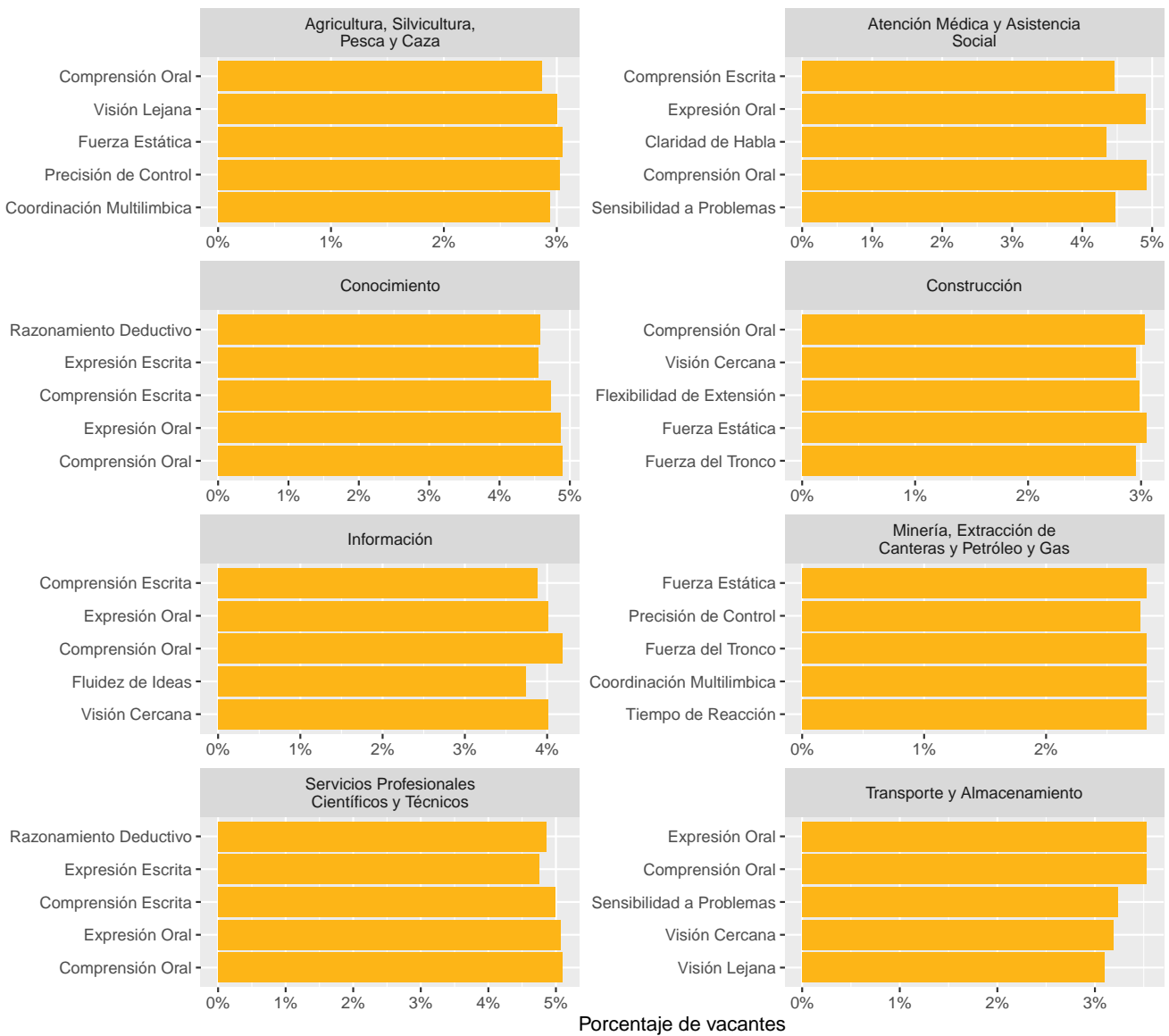




Top 5 Sub habilidades por sector por país







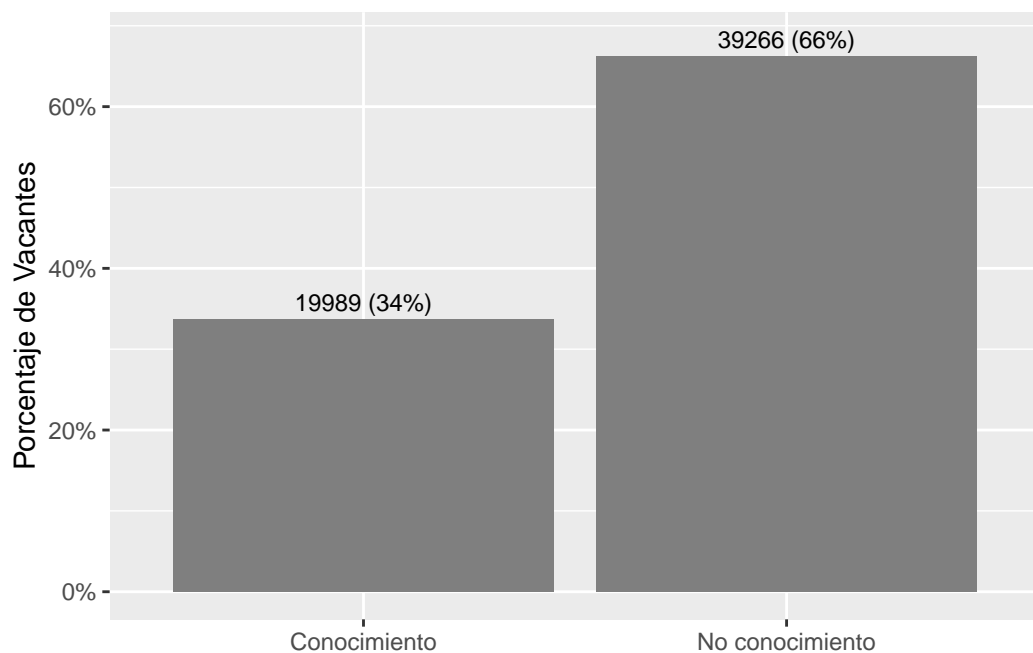
Top occupations of most focus sectors

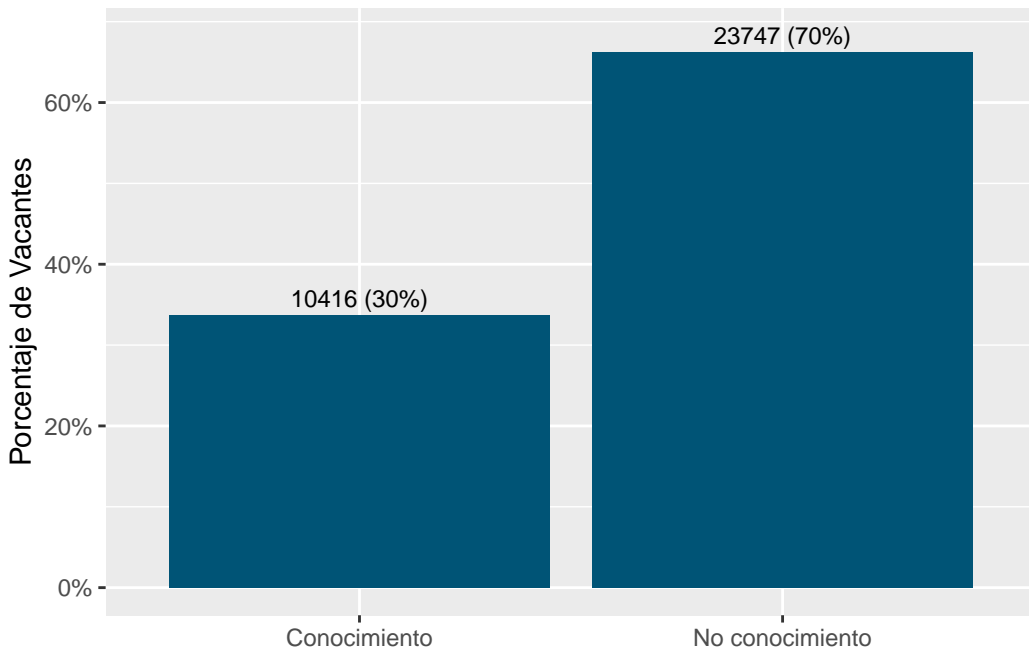
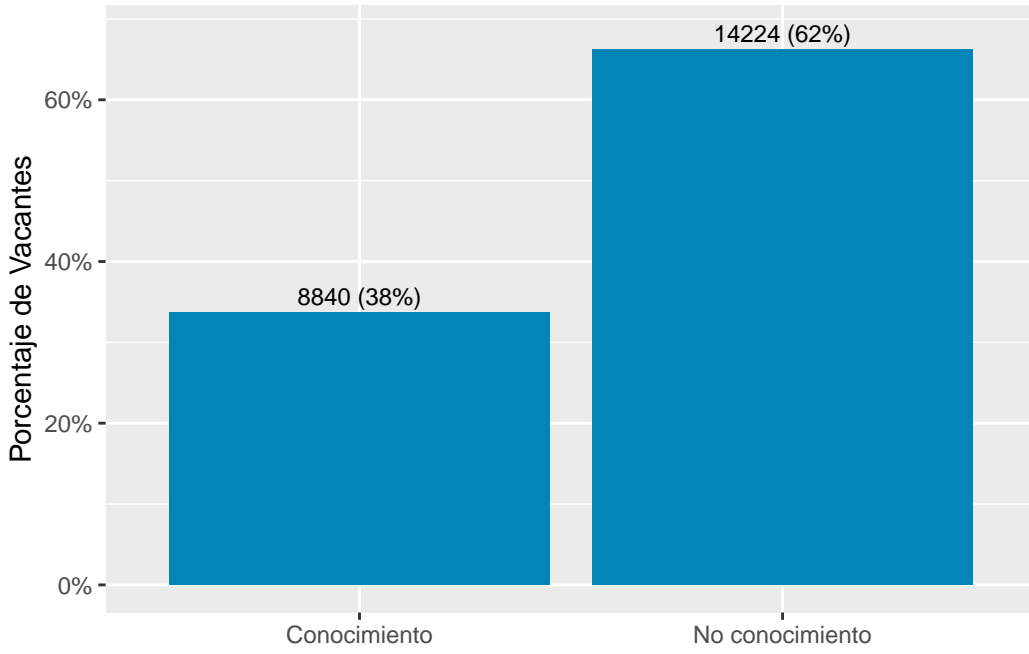
Table 31: ?(caption)

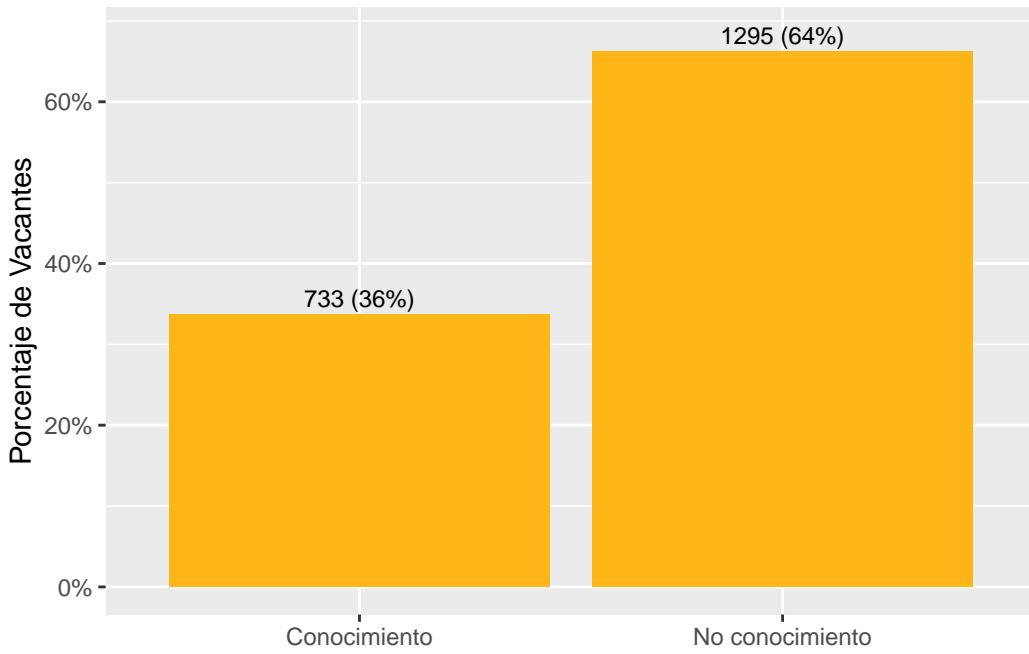
(a)

rank	Agriculture Forestry Fishing And Hunting
1	Trabajadores de Pesca y Caza, 46 (26.6%)
2	Supervisores Directos de Trabajadores de Ocupaciones Relacionadas con la Agricultura, la Pesca, y la Silvicultura,
3	Operadores de Equipo de Tala Forestal, 41 (23.7%)
4	Operadores de Equipo Agrícola, 23 (13.3%)
5	Trabajadores y Jornaleros Agrícolas, de Cultivos, de Viveros y de Invernaderos, 18 (10.4%)

Actividades del conocimiento





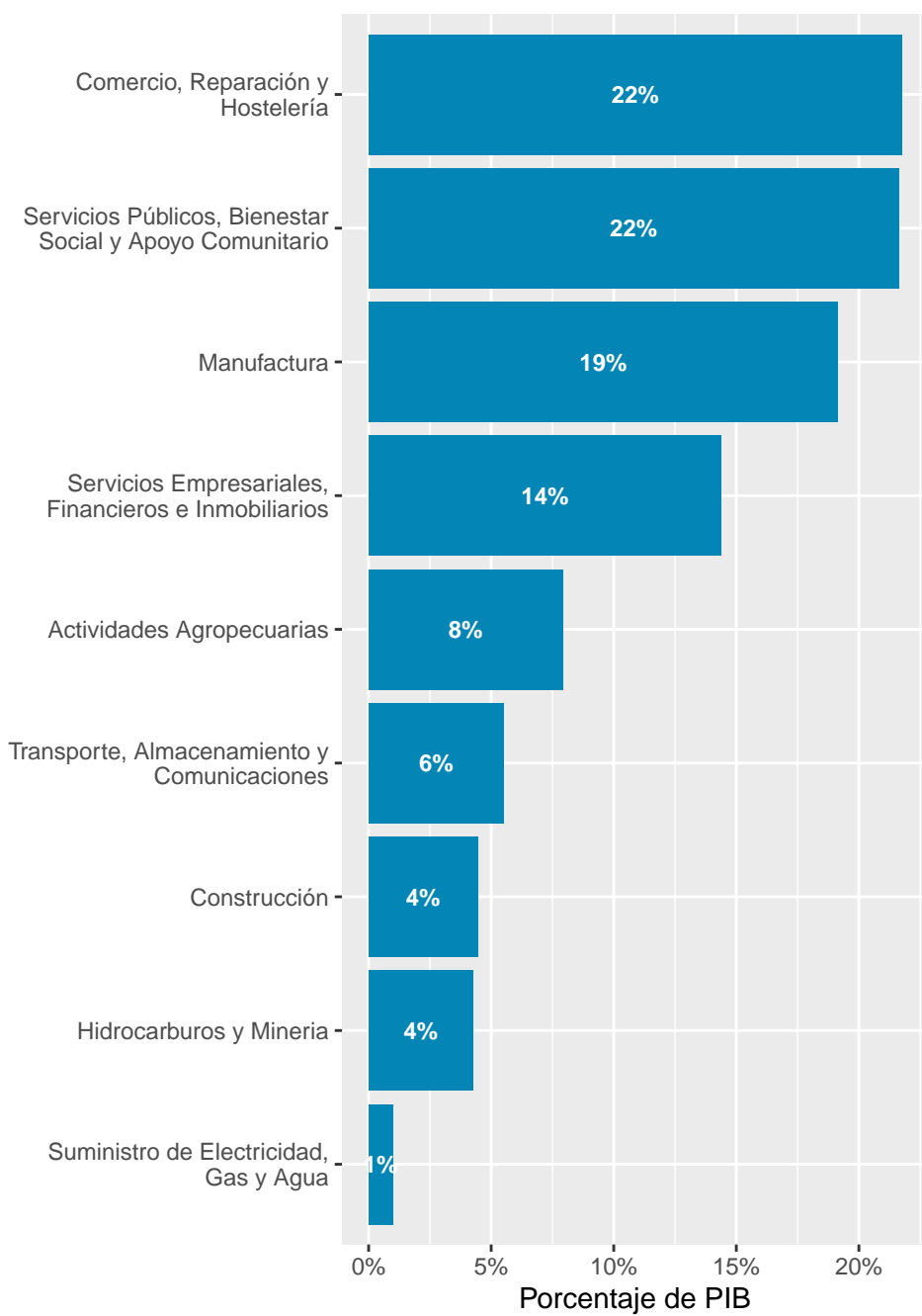


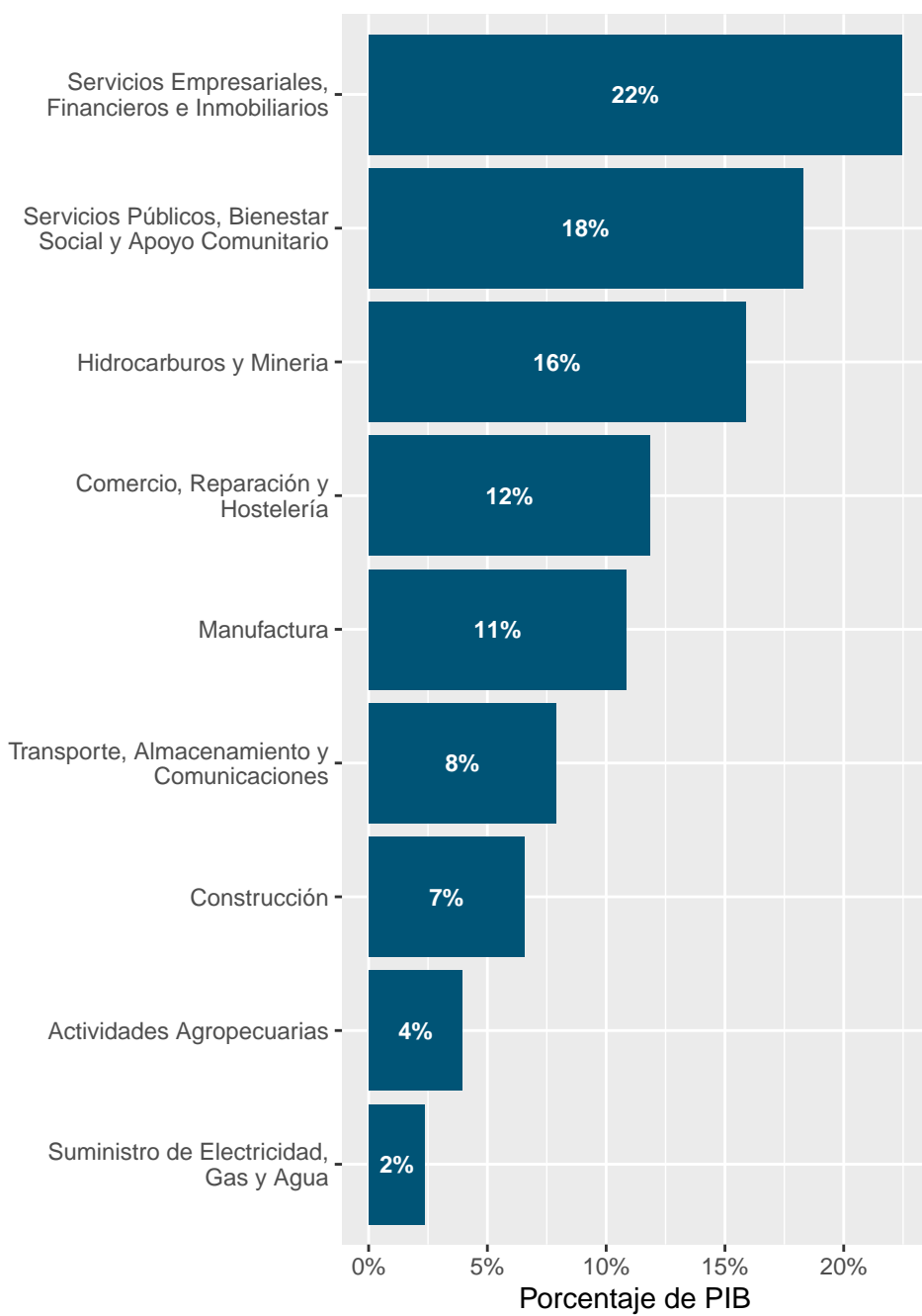
PIB y Empleo por Sector

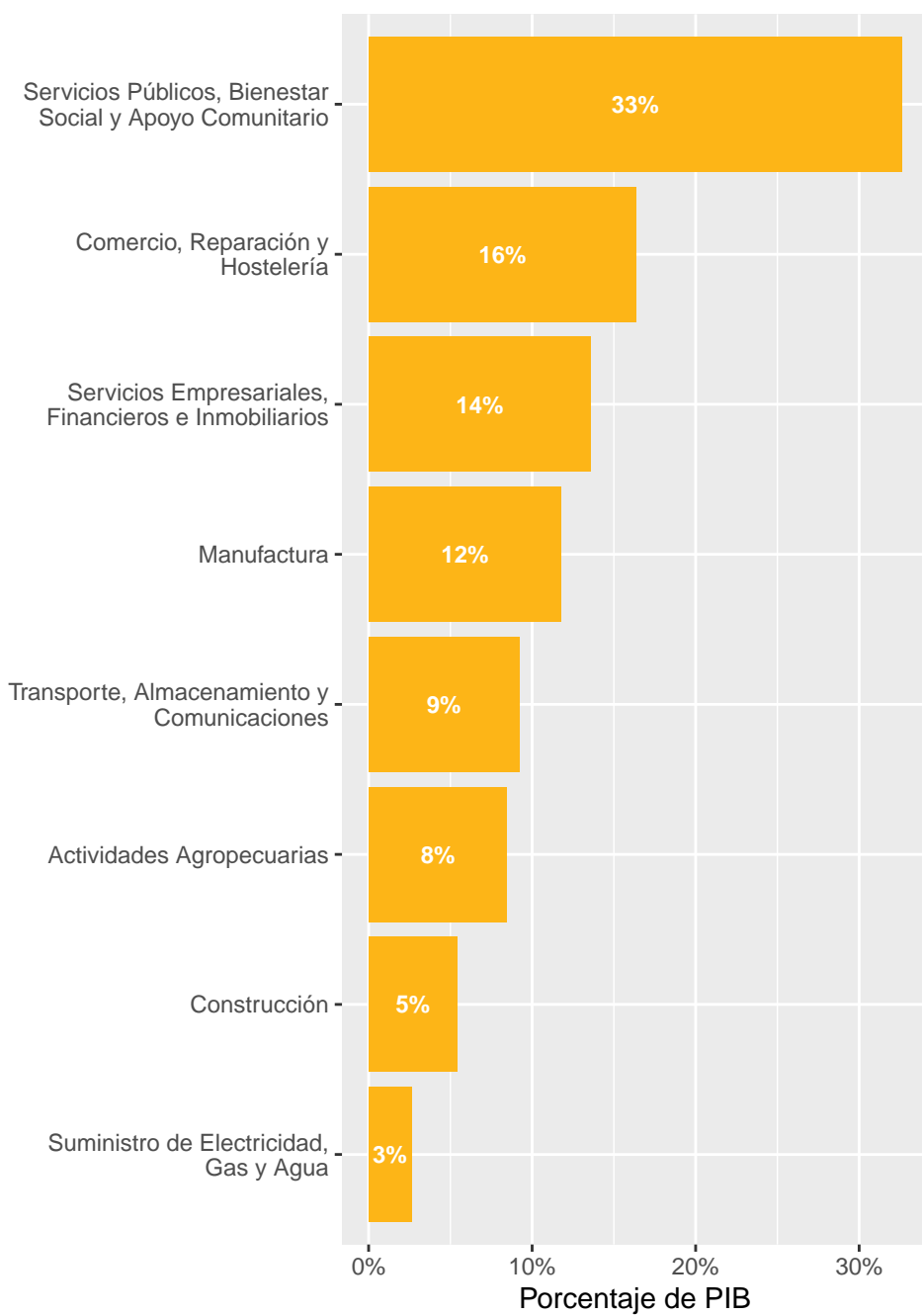
PIB

[1] "Uruguay tiene un sector menos: explotacion de minas y canteras (incluye extraccion de petroleo cru

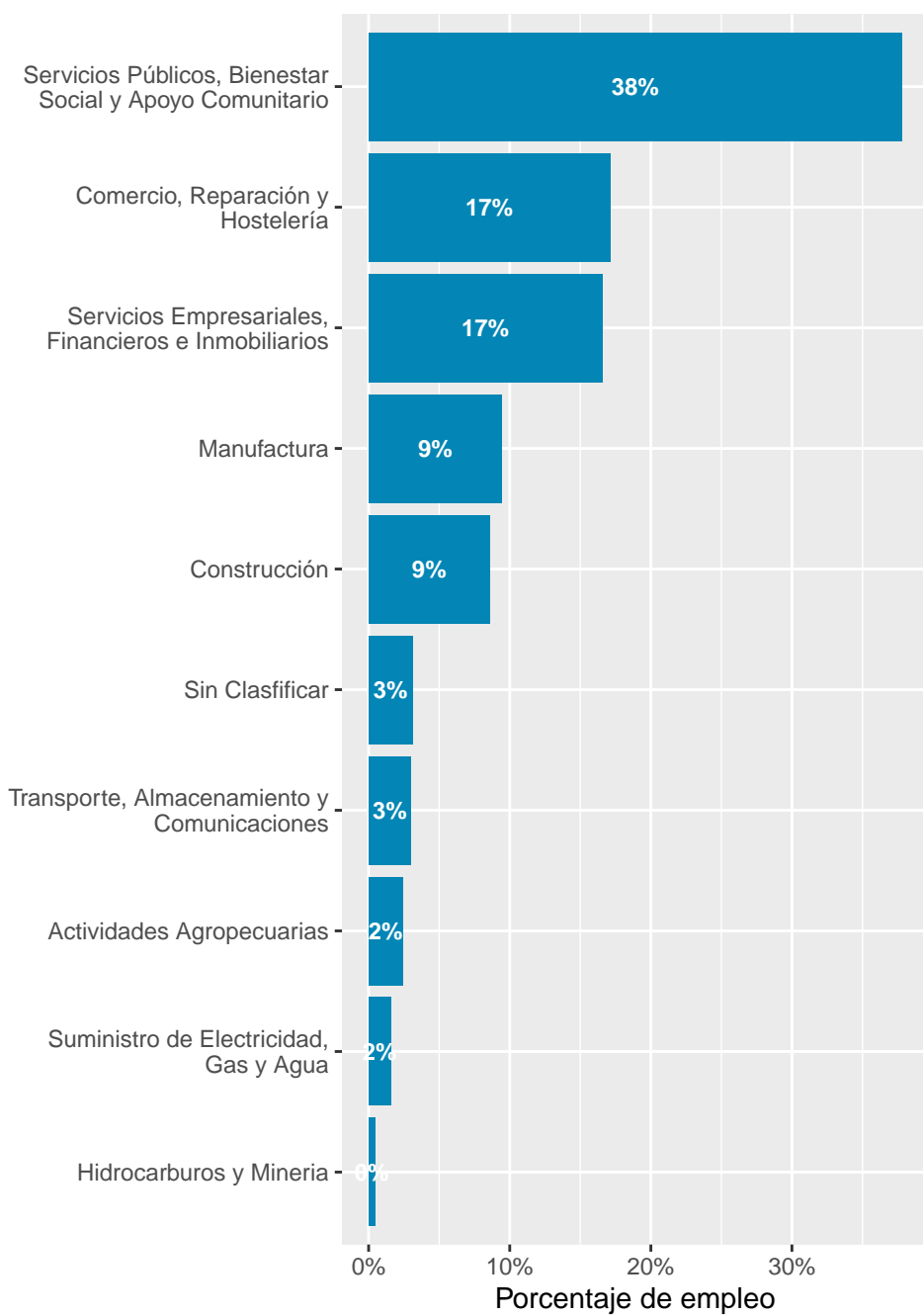
```
# A tibble: 3 x 2
# Groups:   pais_estandar [3]
  pais_estandar     n
  <chr>           <int>
1 Argentina         10
2 Chile              10
3 Uruguay            9
```

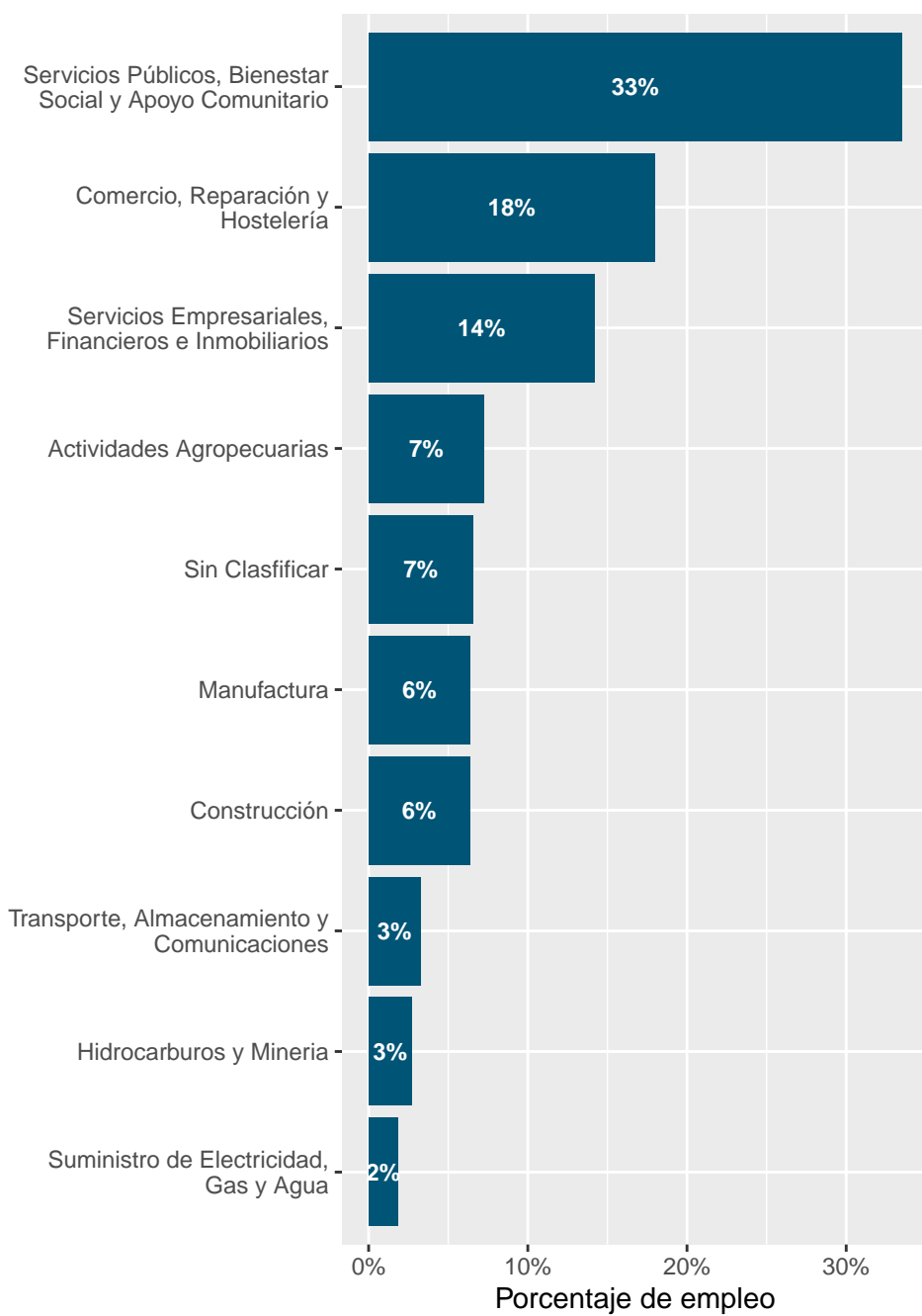


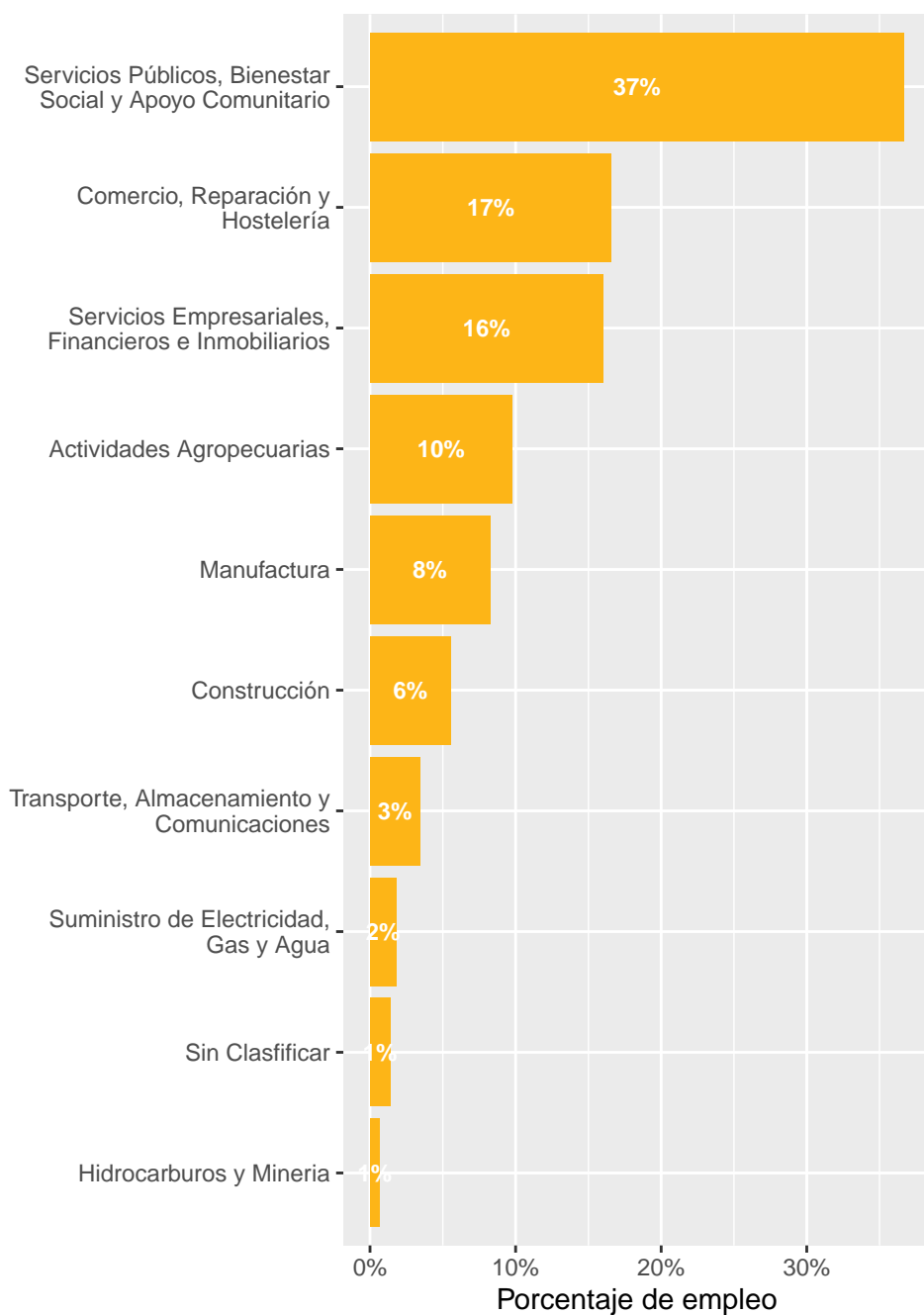




EMPLEO



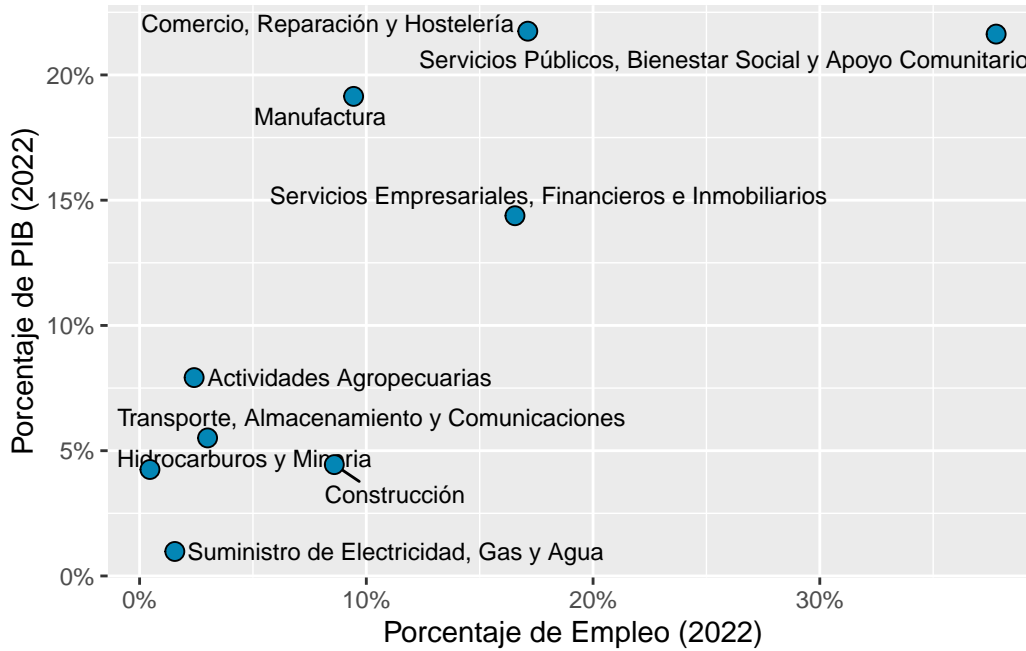




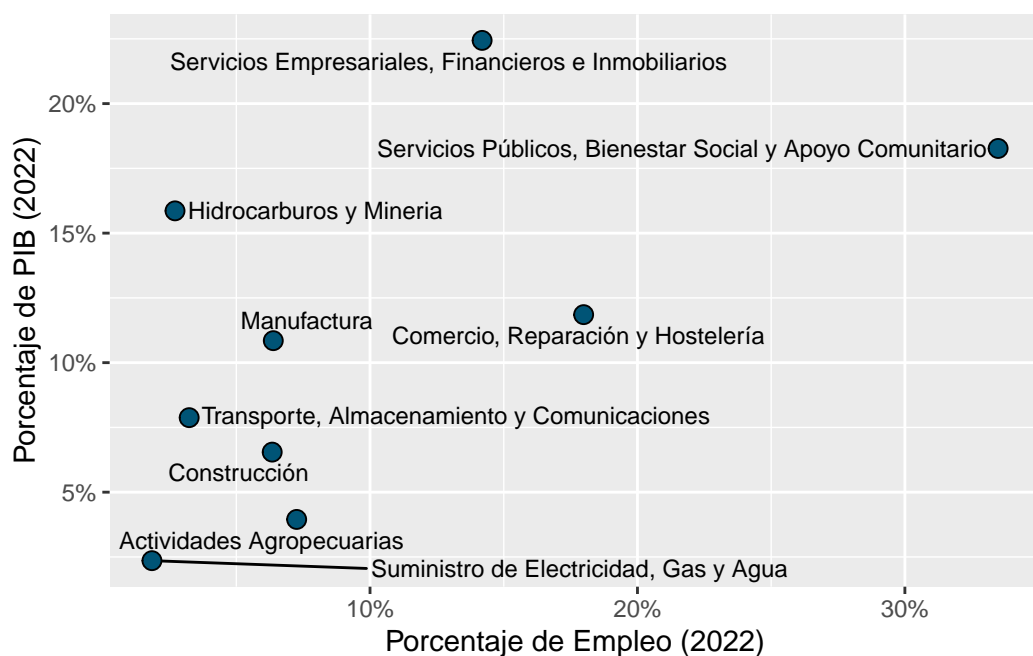
PIB y Empleo

Rubro	Porcentaje de Empleo	Porcentaje de PIB
Comercio, Reparación y Hostelería	17.12%	21.75%
Servicios Públicos, Bienestar Social y Apoyo Comunitario	37.78%	21.63%
Manufactura	9.44%	19.14%

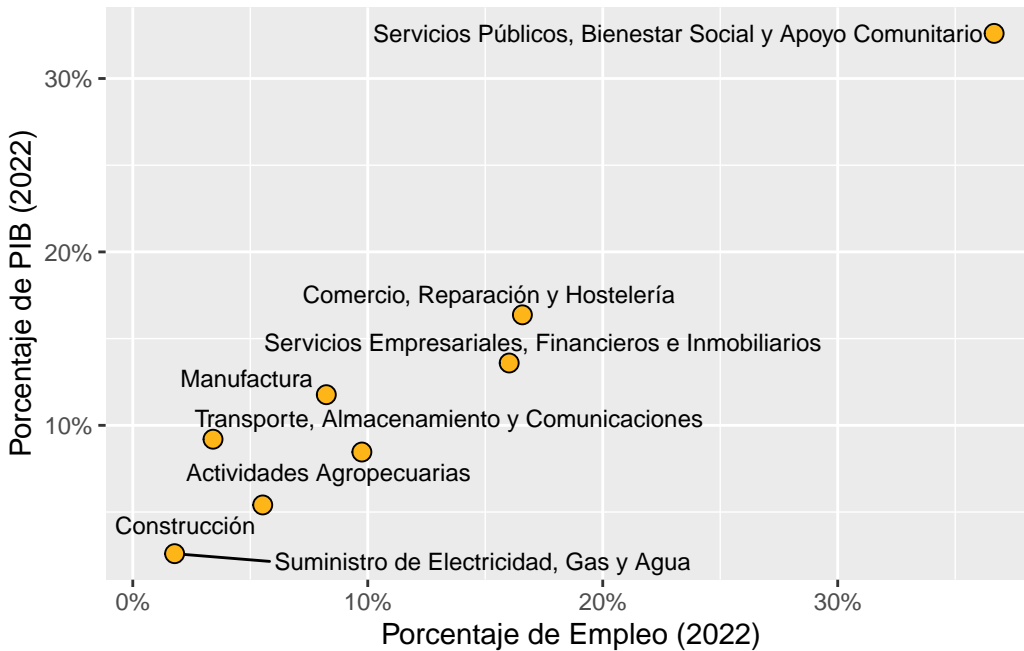
Servicios Empresariales, Financieros e Inmobiliarios	16.56%	14.38%
Actividades Agropecuarias	2.41%	7.92%
Transporte, Almacenamiento y Comunicaciones	3.00%	5.51%
Construcción	8.59%	4.44%
Hidrocarburos y Minería	0.46%	4.25%
Suministro de Electricidad, Gas y Agua	1.55%	0.98%
Sin Clasificar	3.10%	NA



Rubro	Porcentaje de Empleo	Porcentaje de PIB
Servicios Empresariales, Financieros e Inmobiliarios	14.19%	22.44%
Servicios Públicos, Bienestar Social y Apoyo Comunitario	33.49%	18.27%
Hidrocarburos y Minería	2.71%	15.86%
Comercio, Reparación y Hostelería	17.99%	11.85%
Manufactura	6.38%	10.85%
Transporte, Almacenamiento y Comunicaciones	3.24%	7.88%
Construcción	6.34%	6.55%
Actividades Agropecuarias	7.26%	3.95%
Suministro de Electricidad, Gas y Agua	1.85%	2.36%
Sin Clasificar	6.56%	NA



Rubro	Porcentaje de Empleo	Porcentaje de PIB
Servicios Públicos, Bienestar Social y Apoyo Comunitario	36.66%	32.60%
Comercio, Reparación y Hostelería	16.58%	16.37%
Servicios Empresariales, Financieros e Inmobiliarios	16.02%	13.59%
Manufactura	8.24%	11.77%
Transporte, Almacenamiento y Comunicaciones	3.41%	9.20%
Actividades Agropecuarias	9.75%	8.46%
Construcción	5.53%	5.41%
Suministro de Electricidad, Gas y Agua	1.78%	2.60%
Hidrocarburos y Minería	0.64%	NA
Sin Clasificar	1.39%	NA



Discussing occupational codes in online job postings data [DONE]

- The occupation classification system is O*NET SOC 19.
- O*NET SOC 19 is compatible with SOC 18.
- SOC 18 allows us to classify jobs into occupational major and minor groups, as well as to use wage estimates of the US to categorize them into high, medium, and low wage occupations.
- More importantly, SOC 18 groups are compatible with SOC 10 groups, and SOC 10 groups are compatible with [IDB occupational groups](#)
- There are 9 occupations without the proper occupational title in English. That must be due to an error in the ETL process. **Will notify Eric.**
- The Uruguay file doesn't have the Dynamic Flexibility sub ability.
- There are vacancies with null sector weights (don't belong to any sector.) **Will notify Eric.**

**How we made sure O*NET SOC 19 was used to name the occupations?*

We load the list of occupational titles in Argentina, Uruguay and Chile vacancies' samples and compare it with the official O*NET SOC 19 catalog.

We find a perfect match.

```
[1] "There are 758 occupations in the arg, ury and chl data"
```

[1] "757 of these occupations were found in SOC O*NET 19 catalog"

```
# A tibble: 1 x 1
  occupation
  <chr>
1 <NA>
```

Some examples of the ONET SOC 19 codes found are

```
# A tibble: 15 x 3
  occupation          onet_soc_code_19 onet_soc_desc_19
  <chr>              <chr>            <chr>
1 Labor Relations Specialists 13-1075.00      Resolve dispute~
2 Foreign Language and Literature Teachers, ~ 25-1124.00      Teach languages~
3 Construction and Building Inspectors 47-4011.00      Inspect structu~
4 Accountants and Auditors 13-2011.00      Examine, analyz~
5 Retail Salespersons 41-2031.00      Sell merchandis~
6 Cooks, Restaurant 35-2014.00      Prepare, season~
7 Cashiers 41-2011.00      Receive and dis~
8 Chefs and Head Cooks 35-1011.00      Direct and may ~
9 Executive Secretaries and Executive Admini~ 43-6011.00      Provide high-le~
10 Industrial Engineering Technologists and T~ 17-3026.00      Apply engineeri~
11 First-Line Supervisors of Production and O~ 51-1011.00      Directly superv~
12 Waiters and Waitresses 35-3031.00      Take orders and~
13 Potters, Manufacturing 51-9195.05      Operate product~
14 Aircraft Mechanics and Service Technicians 49-3011.00      Diagnose, adjus~
15 Multiple Machine Tool Setters, Operators, ~ 51-4081.00      Set up, operate~
```

Every occupation in spanish should have its' english counterpart. Some doesn't

[1] "There are occupation titles in spanish (onet_job) with no occupation title in english (occupation)"

```
# A tibble: 27 x 2
  occupation onet_job
  <chr>      <chr>
1 <NA>      Conductores de Vehículos de Servicios de Transporte y Choferes
2 <NA>      Analistas Financieros y de Inversiones
3 <NA>      Diseñadores de Programas Software
4 <NA>      Auxiliares Docentes de Educación Especial
5 <NA>      Técnicos de Emergencias Médicas
6 <NA>      Científico de Datos
7 <NA>      Maestros de Educación Especial de Jardín de Infantes
8 <NA>      Gerentes de Instalaciones
```

```

9 <NA>      Analistas Forenses Digitales
10 <NA>     Administradores de Seguridad
# i 17 more rows

```

We are able to map these O*NET SOC 19 to SOC 18 detailed, and major occupations

```

# A tibble: 6 x 10
  o_net_soc_2019_code o_net_soc_2019_title      x2018_soc_code x2018_soc_title
  <chr>              <chr>                <chr>          <chr>
1 11-1011.00         Chief Executives      11-1011        Chief Executiv~
2 11-1011.03         Chief Sustainability Offic~ 11-1011        Chief Executiv~
3 11-1021.00         General and Operations Man~ 11-1021        General and Op~
4 11-1031.00         Legislators           11-1031        Legislators
5 11-2011.00         Advertising and Promotions~ 11-2011        Advertising an~
6 11-2021.00         Marketing Managers    11-2021        Marketing Mana~
# i 6 more variables: broad_group <chr>, broad_group_title <chr>,
#   minor_group <chr>, minor_group_title <chr>, major_group <chr>,
#   major_group_title <chr>

```

```

# A tibble: 2 x 4
  o_net_soc_2019_code o_net_soc_2019_title      x2018_soc_code x2018_soc_title
  <chr>              <chr>                <chr>          <chr>
1 33-3051.00         Police and Sheriff's Patro~ 33-3051        Police and She~
2 33-3051.04         Customs and Border Protect~ 33-3051        Police and She~

```

Understanding Uruguay demand by occupation

There is demand for personal service, but not so much for healthcare highly technical services. However, sample size is so small one needs to be cautious when drawing conclusions about these sectors. Specially for Uruguay, it's best to focus on larger sample occupational groups like "Sales and Related", "Office and Administrative Support" etc.

major_group_title	occupation	postings	me
Healthcare Practitioners and Technical Occupations	Acupuncturists	3	
Healthcare Practitioners and Technical Occupations	Dentists, General	3	
Healthcare Practitioners and Technical Occupations	Ophthalmologists, Except Pediatric	6	
Healthcare Practitioners and Technical Occupations	Orthodontists	3	
Healthcare Practitioners and Technical Occupations	Pharmacists	5	
Healthcare Practitioners and Technical Occupations	Registered Nurses	3	
Healthcare Support Occupations	Home Health Aides	1	
Healthcare Support Occupations	Nursing Assistants	4	
Healthcare Support Occupations	Personal Care Aides	7	

Healthcare Support Occupations	Pharmacy Aides	2
Personal Care and Service Occupations	Childcare Workers	6
Personal Care and Service Occupations	Costume Attendants	3
Personal Care and Service Occupations	First-Line Supervisors of Personal Service Workers	15
Personal Care and Service Occupations	Manicurists and Pedicurists	3
Personal Care and Service Occupations	Nannies	13

Google jobs abilities compared to O*NET's

The prevalence of subabilities in online job vacancies can be grouped by occupation and contrasted with the *level* and *importance* scores O*NET Analysts assigned to each subability in each occupation profile.

If we find that online vacancies in the South Cone require different skills than what O*NET experts said is important to perform at a job we'll have an interesting discussion about what the Vacancies Mining algorithm is doing and how different are the same occupations across different countries.

There is a strong correlation between IDB abilities scores and O*NET's
Each dot is an occupation–ability combination

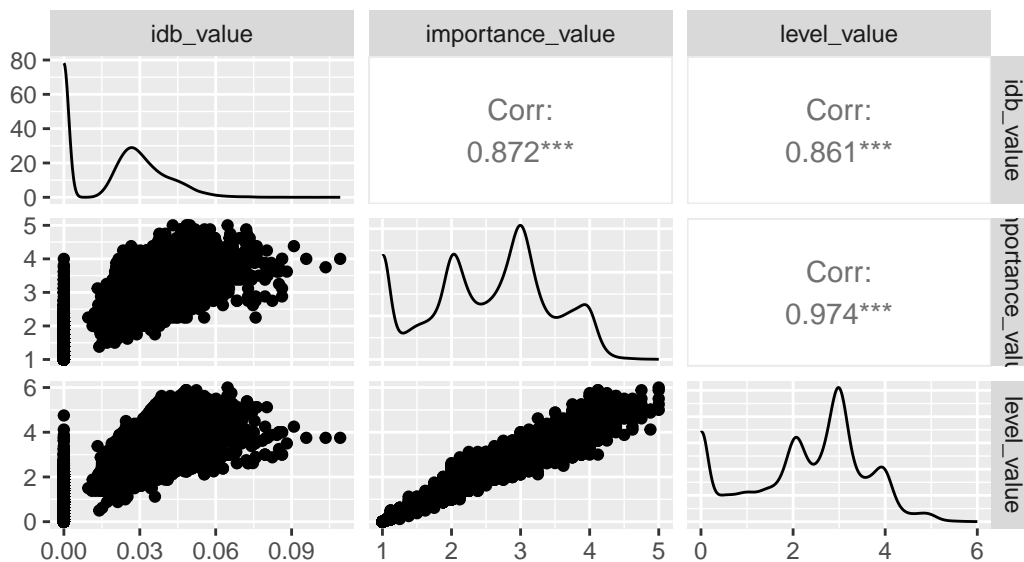


Figure 70: ?(caption)

Discussing the sector (rama) information available in online job postings data (DONE)

The names of the 20 presented ramas coincide with NAICS 2-digits classifications. Most LAC data sources show employment estimates by industry in ISIC or ISIC-related codes.

Interestingly, the sector or “Rama” is across multiple columns and each doc_id can have multiple values. There isn’t a categorical classification of the rama each firm belongs to, but rather a continuous one, where there are weights representing the chances a firm belongs to each sector.

They don’t assign a category, but rather a 20 positions vector that gives probabilities from 0 to 1 to each vacancy.

I found a couple of puzzling things in the data.:

- There are doc_ids with no prediction. They don’t belong to any sector.
- There are (ties) doc_ids with the same positive prediction. This turns makes any attempt to assign only one sector to each posting a little polemic.

```
# A tibble: 2 x 2
  is_zero mean_casos
  <chr>      <dbl>
1 Is zero      17.8
2 Not zero      2.24
```

```
# A tibble: 6 x 5
  doc_id                sector                value total    n
  <chr>                 <chr>                 <dbl> <dbl> <int>
1 IcBB0juXZT8BiD2XAAAAAA== other_services_except_public_admin~ 79 79 1
2 ct1JrwQ54xivPQpxAAAAAA== educational_services                99 99 1
3 bo7X77th8vwAAAAAA== government                            43 78 1
4 72DNO-KNkrEAAAAAA== government                            43 78 1
5 kqPOGYOTJTYAAAAAA== professional_scientific_and_techni~ 31 31 1
6 If6uaYoqh6CHO4dpAAAAAA== other_services_except_public_admin~ 79 79 1
```

```
[1] "Total documents: 23435"
```

```
[1] "Documents with a prediction 23069"
```

```
[1] "Documents without a prediction 366"
```

```
[1] "Documents with more than 1 prediction (excluding those with no prediction) 2260"
```

```
# A tibble: 2,260 x 5
  doc_id                sector                value total    n
  <chr>                 <chr>                 <dbl> <dbl> <int>
1 vubaCpc3QxIAAAAAAA== other_services_except_public_admin~ 21 66 2
2 vubaCpc3QxIAAAAAAA== professional_scientific_and_techni~ 21 66 2
3 FAVNbJ4eY_wLOcg4AAAAAA== professional_scientific_and_techni~ 12 24 2
4 FAVNbJ4eY_wLOcg4AAAAAA== retail_trade                    12 24 2
```

5	EzJVBKu6nSupL41kAAAAAA==	professional_scientific_and_techn~	12	24	2
6	EzJVBKu6nSupL41kAAAAAA==	retail_trade	12	24	2
7	Af-RP22V5xoAAAAAA	professional_scientific_and_techn~	12	24	2
8	Af-RP22V5xoAAAAAA	retail_trade	12	24	2
9	SXIXuzy1_1UAAAAAA	professional_scientific_and_techn~	12	24	2
10	SXIXuzy1_1UAAAAAA	retail_trade	12	24	2

i 2,250 more rows

[1] "Documents with 100% certainty on 1 prediction 167"