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MPIfG Discussion Paper 26/1

A Practical Guide to LinkedIn Advertising Reach Data for Social Science

Methods, Challenges, and Five Applications

Saila Stausholm and Javier Garcia-Bernardo

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MPIfG Discussion Paper 26/1
Max-Planck-Institut für Gesellschaftsforschung, Köln
Max Planck Institute for the Study of Societies, Cologne
May 2026
DOI: 10.17617/2.3706150

MPIfG Discussion Paper
ISSN 0944-2073 (Print)
ISSN 1864-4325 (Internet)

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Abstract

LinkedIn data offers a unique way to study how professional groups and organizations underpin economic and political life. This paper shows how LinkedIn's advertising reach data, which provides anonymized counts of users by job title, skills, employer, and location, can be used to study organizational and professional dynamics relevant to a wide range of issues in political economy and economic sociology. We showcase the potential through five illustrative cases: 1) the revolving doors between Wall Street and US financial regulators; 2) the geography of professionals such as accountants and bankers; 3) the professional composition of interdisciplinary firms such as antitrust consulting firms; 4) recruitment by different industries and specifically big professional services firms in the face of new regulatory demands for sustainability reporting; and 5) the emergence of a profession of cyber security professionals over time. Alongside these examples, we provide a step-by-step guide for implementing the method in practice and discuss how linking professional attributes with geographical or organizational characteristics can provide new answers to various research questions. We hope this paper serves as a helpful practical guide as well as inspiration for new research questions.

Keywords: computational social science, LinkedIn, organizational behavior, professionals, social media

Zusammenfassung

LinkedIn-Daten bieten eine besonders geeignete Basis, die Einflussnahme von Berufsgruppen und Organisationen auf das wirtschaftliche und politische Leben zu untersuchen. Die Werbezielgruppen-Daten der Plattform beinhalten anonymisierte Zahlen zu Nutzern nach Berufsbezeichnung, Fähigkeiten, Arbeitgeber und Standort. In unserem Artikel zeigen wir, wie diese Daten für die Analyse organisationaler und beruflicher Dynamiken genutzt werden können, die für eine Vielzahl von Themen in der politischen Ökonomie und der Wirtschaftssoziologie relevant sind. Wir veranschaulichen ihr Potenzial anhand der folgenden fünf Beispielfälle: 1) des Drehtür-Effekts zwischen Wall Street und US-Finanzaufsichtsbehörden; 2) der geografischen Verteilung von Fachpersonal für Wirtschaftsprüfung und Bankwesen; 3) der Kombination von Berufen in Unternehmen mit gemischten Berufsprofilen (zum Beispiel in der Kartellrechtsberatung); 4) der Rekrutierung durch verschiedene Branchen und insbesondere durch große Professional-Services-Unternehmen angesichts neuer regulatorischer Anforderungen an die Nachhaltigkeitsberichterstattung; und 5) der Entstehung einer Berufsgruppe von Expertinnen und Experten für Cybersicherheit. Ergänzend zu diesen Beispielen bieten wir eine Schritt-für-Schritt-Anleitung zur Anwendung der Methode und zeigen, wie die Verknüpfung beruflicher Attribute mit geografischen oder organisationalen Merkmalen neue Antworten auf verschiedene Forschungsfragen liefern kann. Wir hoffen, dass dieser Beitrag als hilfreicher praktischer Leitfaden und als Inspiration für neue Forschungsfragen dienen wird.

Schlagwörter: computergestützte Sozialwissenschaft, Fachpersonal, LinkedIn, Organisationsverhalten, Social Media

Contents

A Practical Guide to LinkedIn Advertising Reach Data for Social Science: Methods, Challenges, and Five Applications

1 Introduction

With the rise of computational social science, data from social media is becoming an increasingly popular research methodology within the social sciences, including the study of social groups such as professions (Henriksen and Seabrooke 2016; Suddaby, Saxton, and Gunz 2015) and organizations (Tonidandel, King, and Cortina 2018; Wenzel and Van Quaquebeke 2018; George et al. 2016; Bail 2017; Luciano et al. 2018). In this paper, we showcase how the online professional networking site LinkedIn can be used to investigate research questions in the social sciences.

Previous studies across the social sciences have primarily studied individual LinkedIn profiles. See, for example, cases in political science (Coen and Vannoni 2016; Ennser-Jedenastik 2015; Lall 2017; Pérez-Durán 2019), organisation studies (Henriksen and Seabrooke 2016), management studies (Stewart and Kuenzi 2018; Xu et al. 2020), and sociology (Childress and Nault 2019). Here, we showcase how LinkedIn's ad reach data can be used for quantitative analysis across organizations, geographical areas, or professional groups.

Through the LinkedIn Campaign Manager, researchers can sort LinkedIn users into different targeted ad audiences based on a host of characteristics. By counting the number of targeted users under different chosen attributes, we can infer the size of different attribute combinations within the LinkedIn audience. Being able to estimate the distribution of skills across firms, or the distribution of a profession across industries, or even the distribution of firms across cities, is useful for a host of research questions within organizational, sociological as well as management and economic geography studies. For example, looking at links between organizations can help understand "revolving door" dynamics or knowledge flows and career patterns (Kipping, Bühlmann, and David 2019) and understanding organizational dominance (Kirkpatrick et al. 2023). Mapping job titles geographically is useful for understanding the "global reach" of a profession or its role in economic globalization and global value chains (Boussebaa and Faulconbridge 2019; Harrington 2015). Mapping the educational composition of interdisciplinary niches reveals how "epistemic arbitrage" is practiced (Seabrooke 2014). Mapping skills and interests shows how emerging skills are being sought after by different firms. Mapping the industries employing new professional profiles reveals boundary work (Nicklich, Braun, and Fortwengel 2020).

Our paper provides a condensed user-friendly guide to using LinkedIn's ad reach data, which has so far been used only rarely in social science research. We hope this guide serves as a platform to enable more researchers to use this novel type of data. To this end, we also provide five illustrative examples that serve to showcase the type of research design it is possible to conduct with this method.

Our five cases all tie into many different agendas and literatures and should be treated as illustrative for the data's potential. All five cases could, and deserve to, be treated more in depth, including combining with mixed-methods triangulation and a deeper theorization. This is however outside the scope of this paper. While we find the cases interesting individually, we have chosen to include them as five mini case studies to show the very different ways this data can be used and analyzed. We provide a useful guide to how to use this method for data generation alongside critical considerations on what LinkedIn data might be useful for. We hope this serves as inspiration for further studies, along with our practical guidance on how to create research designs using this data.

The paper continues with a short description of how LinkedIn and other social media have been used for social science research. We then go on to outline our proposed method and data source, and the steps involved in designing, collecting, and verifying the research. We show five short examples of different uses of this data, including geographical mapping, longitudinal research, comparative designs, and relational/network designs.

2 LinkedIn as a source of social and organizational research

Utilizing internet-based data is an emerging research methodology, with the field of computational social science utilizing a wide variety of new data sources to study both old and new questions in the social sciences (George et al. 2016; Murthy 2012). For example, Facebook has been used for survey respondent collection (Brickman Bhutta 2012; Schneider and Harknett 2022) and to study organizations (Bail 2017) and social mobility (Chetty et al. 2022). The online micro-blogging platform Twitter (now X) has been used to understand political and economic sentiments (Caton, Hall, and Weinhardt 2015; Enli and Skogerbø 2013; Vicente 2023); to study the demographics and social status of users (He and Tsvetkova 2023; McCormick et al. 2017); and to understand polarization (Bail et al. 2018). Other research has used other forms of internet-based Big Data to explore questions related to migration (Guardabascio, Brogi, and Benassi 2023; Leysen and Verhaeghe 2023; Wanner 2021), how transnational communities connect (Alinejad et al. 2019), and the diffusion of cryptocurrencies (Park and Park 2020).

The choice of online medium is important given the differentiated content on different sites. While particularly Facebook and Twitter (X) have been prevalent sources of social research, the user bases and content do not represent professional and organizational dynamics well. Even if professionals are on those media, they may share updates about political views alongside family event photos and sports commentary. To study professional or organizational phenomena, it is therefore preferable to use specialized social media for professional networking and résumé sharing, chief amongst which is LinkedIn (Chiang and Suen 2015). The use of social media data for studying various social phenomena holds a vast potential but should also be approached with the caveat that the usefulness varies with the specific research question and the group of interest (Murthy 2008). While social media platforms provide unprecedented data on social dynamics, it is also shaped by self-selection, which varies widely across platforms (van Dijck 2013). This paper explores the specific use cases in which LinkedIn, an online professional networking site, can provide data helpful to scholars of certain professions and organizations.

LinkedIn provides by far the richest and most encompassing resource for gathering information on a range of organizations and professions. Professionals are likely to use LinkedIn as a platform for communication about their professional interests, to signal prestige, and to network with peers. Likewise, organizations are likely to use it to promote their organization to potential employees. Due to basic data structures to which users must conform in filling out their profiles, the systematism of LinkedIn data is relatively high, even though the data is self-reported. For instance, in filling out their career experience, a user is prompted to fill out basic information on the position/role, the organization, the year of employment, etc. Some employers actively encourage their employees to self-report on LinkedIn and use LinkedIn to promote the organization and their employers, and some even provide training and templates in how to fill out the data consistently and usefully.

LinkedIn profiles and communities have often been studied qualitatively. For example, netnography studying online communities can use LinkedIn groups to study the debates and dynamics within professional networks (Jeacle 2021). Alternatively, a more in-depth analysis of LinkedIn profiles can use various methods such as sequence analysis to study how careers are shaped across and within organizations (Biemann and Datta 2014; Seabrooke and Nilsson 2015; Seabrooke and Tsingou 2021). These studies have mostly focused on the analysis of CVs.

Previous research using LinkedIn ad data is sparse but has demonstrated potential to study labor market migration and mobility patterns (Bertè, Paolotti, and Kalimeri 2023; Perrotta et al. 2022; State et al. 2014; Vieira et al. 2022) and labor gender gaps (Al Tamime, Strohmaier, and Weber 2024; Jacobs et al. 2025; Kashyap and Verkroost 2021). While the potential for LinkedIn ad data has been noted in the broader field of computational social science, we are unaware of applications within political economy and economic sociology except our previous work (Stausholm and Garcia-Bernardo 2024). This paper illustrates how LinkedIn ad data can be used within these fields and showcases examples to encourage engagement with the data source for a diverse set of questions.

3 A step-by-step guide to LinkedIn ad data

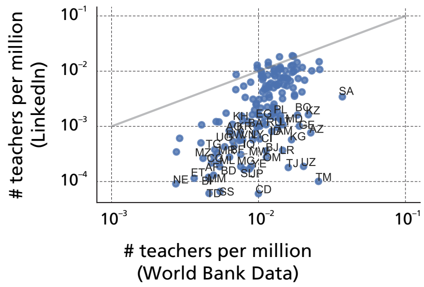
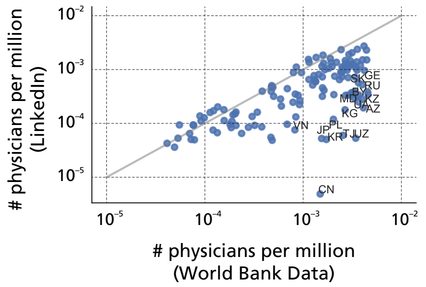
There are two main ways to search for information on LinkedIn. The search box from the home page yields varying results depending on who is searching. We therefore do not recommend using this search. Instead we recommend using the "LinkedIn Campaign Manager." The LinkedIn Campaign Manager allows you to create ads targeted to a specific audience (by adding inclusion and exclusion criteria) in a specific location. The location is the only required filter and can be any geographical area such as a city, a country, or a region. Before the ad is completed and the payment processed, the page shows the estimated size of the audience. This means researchers cannot identify individuals, but only the aggregate number of people who share specific characteristics. This treatment differs from CV analysis in not having a temporal/sequential component, as there is no granularity in terms of data on individuals. What is gathered is a rounded number of how many LinkedIn profiles exist that have a given number of characteristics/parameters.

Here, we detail how LinkedIn ad data can be used to track the *size* of these professional groups and the *distribution* of them across countries, cities, and firms. Mapping where professionals are located and their characteristics – and where they are absent – reveals how expertise underpins markets, regulation, and organizational power. For example, looking at the distribution of tax professionals shows that professionals are not located in small island tax havens but in OECD countries (Stausholm and Garcia-Bernardo 2024).

To make such findings meaningful, it is crucial to consider the representativeness of LinkedIn data. Coverage depends heavily on both geography and profession (Zide, Elman, and Shahani-Denning 2014). Therefore the representativeness has to be considered for every individual case and research question. Market penetration varies substantially across countries, where LinkedIn is a niche social media in some countries and a very commonly used one in others. For some professions there is high coverage even in countries where LinkedIn is not very popular in the general population. Table 1 illustrates the types of professions it is likely more useful for: those that depend on online presentation and are not overly secretive.

Table 1 outlines some critical dimensions important to consider before embarking on research based on LinkedIn. This method should be used to study groups that are likely to be online. Whether this is the case could be explored by comparing with proxy data or testing on a subsample, though it requires some judgement calls on what types of alternative data can be used to justify the reliability. In Table 1 we used World Bank statistics for the professions that are relatively well-known and documented. For Deloitte employees we have compared LinkedIn results with what we could find on the Deloitte official web page. This is cumbersome but useful if it can be used as a proxy for studying a broader population that might resemble Deloitte employees with respect to likelihood of being on LinkedIn but where official data on them is lacking. We recommend finding benchmark data for verification or proxy as an important part of using LinkedIn data to verify the use cases.

Table 1 Differentiating between professions online

<table>
<tr><th></th><th>Profession does not depend on online presentation</th><th>Profession depends upon online presentation</th></tr>
<tr><td>Profession is easily accessed for study</td><td>No, other methods are better.
Example: Nurses, teachers.

Comparison between the number of teachers (primary and secondary) in LinkedIn and according to official World Bank statistics.</td><td>Yes, but other methods are available too.
Example: Politicians, physicians.

Comparison between the number of physicians in LinkedIn and according to official World Bank statistics.</td></tr>
<tr><td>Profession is not easily accessed for study</td><td>No, these professions depend upon anonymity.
Example: Spies, drug lords, hackers, pirates.

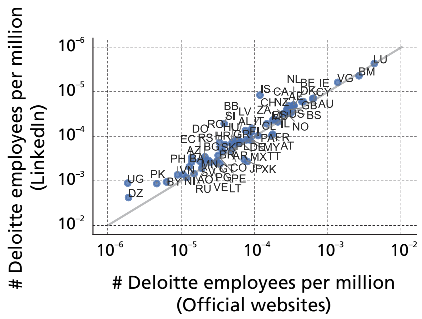
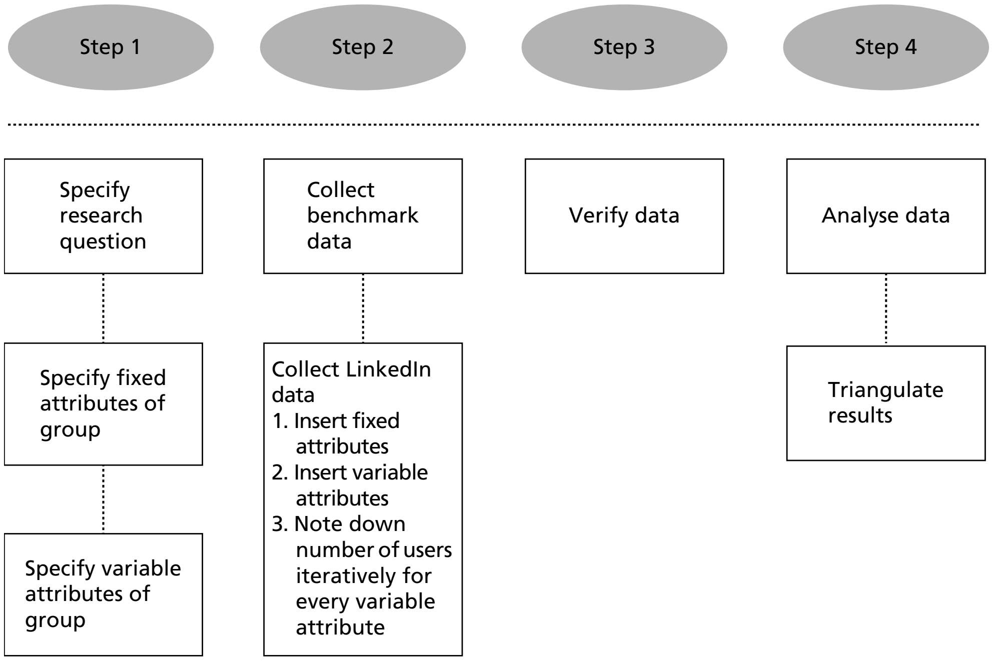
Search yields few or no results.</td><td>Yes, online identities can be studied and will provide new aspects.
Example: Tax advisors, consultants, finance professionals.

Comparison between the number of Deloitte employees on LinkedIn and according to the Deloitte website.</td></tr>
</table>

Figure 1 outlines the steps involved in using the LinkedIn methodology. The specification of the fixed and variable attributes of the group is crucial and determines how fine-grained the data will be, as there will be one data point for each of the variable attributes. The second step consists of data collection, with the third and fourth steps being concerned with post-collection handling of the data, including triangulation. We explain all steps further in the following.

Figure 1 Steps in the methodology



Source: Authors.

Step 1: Research design and query specification

The first step in our research design is to define the group of professionals whose size we would like to quantify. This group of people typically represents an established profession, but can also represent all employees in a sector, people working for a specific organization, or having attended the same educational institution. We call these the fixed attributes of the group. Next, we operationalize the attributes of such a group using the available search filters of LinkedIn. LinkedIn enables finding users through many criteria, such as location, job title, company, industry, gender, age, or educational characteristics. The vast number of search criteria provides opportunities to narrowly match a group of professionals, but also challenges in finding the most appropriate search options, since the same people can be targeted using different search filters – e.g., you can match bankers using the "financial" sector or using specific job titles. In choosing the fixed attributes it is important to consider different search options. Open search is not possible, but job titles provide a very high degree of granularity. Job titles are also the most precise for most instances, as many can claim a skill on their profile without working directly with it. Researchers should familiarize themselves with the most recently updated guidance from LinkedIn on how their targeting works, as policies can be updated frequently (LinkedIn 2020).

The search criteria can also be used as exclusion criteria. This is helpful to increase the validity of the data by excluding job titles that are similar but irrelevant – for example we may want to exclude tax partners working for the government if looking at the tax services profession. In some cases it might also be relevant to exclude self-employed people. For each query some judgement calls need to be made, and it is therefore best to start out with some knowledge of the industry or group and a plan to verify the data, as we discuss further in steps 2 and 3.

Once the fixed characteristics of our group of people have been operationalized, we must define a "variable attribute." This is a search filter that we change while keeping the other filters fixed, enabling the building of a dataset through iterative searches. An example of such an attribute is location, which we would use if we were interested in the geographical distribution of a group of professionals. However, each of the attributes used in the first step can in principle be used as a variable attribute. As a result, the researcher iterates over the different values of the variable attribute, in the process collecting the aggregated number of LinkedIn profiles with the characteristics searched for, which can be used as a measure of the size and scope of the group of people being analyzed. In choosing the variable attributes it is important to consider risks of double-counting, as one profile can have more than one of the variable attributes. For example, while an individual cannot be located in two countries, it is possible to have more than one educational background, and researchers should design the query with that caution in mind, for example by using exclusion criteria. The last part of the research design is gaining ethical approval by your institutional review board.

Step 2: Collecting data

The LinkedIn Campaign Manager allows potential advertisers to define their target audience based on factors such as location, job title, and company size. The web page then displays the count of profiles meeting those criteria. It is worth noting that this count reflects the number of profiles and is not simply an algorithmic prediction of potential ad engagement (this would likely be lower as not all users are active frequently).[1] As the data is just an aggregated number, it is anonymous. This data is openly accessible to all LinkedIn users.

The collection of quantitative data on the size of professional groups through LinkedIn is done simply by searching for specific criteria and then noting down the number of search results in an iterative way, each time varying, for example, the location criteria.

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1 "The Forecasted Results pane provides an estimate of: **Target audience size**. The target audience size estimates the number of unique member accounts that fit your targeting criteria. As your campaign serves ads, the number of member accounts that you reach will be lower than the target audience size." LinkedIn March 2024.

If your interest is limited to a few firms, a few industries, or a few locations, your search can be done manually by selecting and deselecting locations one by one. For smaller datasets, including the majority of examples in this paper, no coding skills are required. However, if you are, for example, interested in many firms and/or data on a country-by-country level, it may be worth going through the Marketing Developer Program, which provides direct access to the API (an application programming interface is a set of instructions about how to communicate with the server). While APIs are typically the fastest, most consistent, and more ethical way to retrieve information, access to the LinkedIn API requires explicit approval by LinkedIn, and therefore comes with potential data restrictions as well as financial costs.[2] If you are based in the European Union, scraping lawfully accessed data (e.g., accessed through your personal LinkedIn account) for research is allowed under the text and data mining exception in Directive (EU) 2019/790.

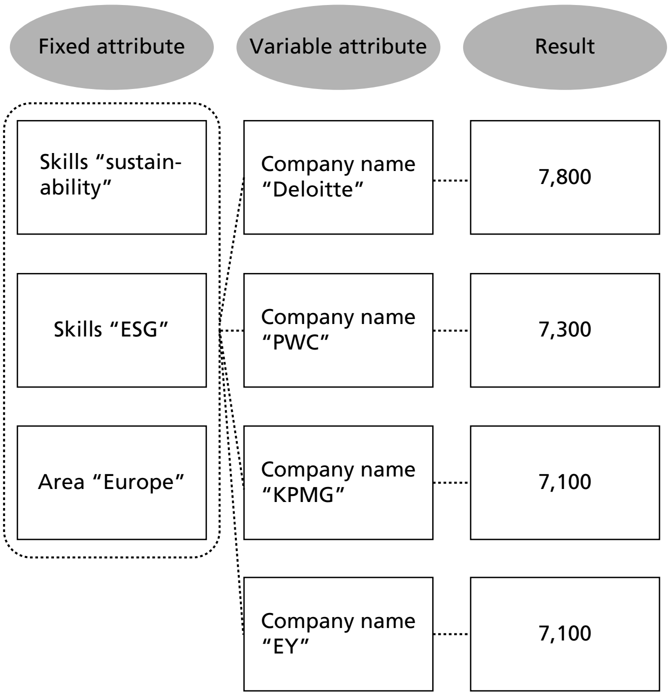
The search process works by selecting specific values within a variable attribute. This can be straightforward with location, as locations are mutually exclusive, but it becomes virtually impossible when it comes to member skills, where there can be substantial overlap as members may have more than one skill listed. This also means researchers should be aware of the risks of double-counting before aggregating search results.

The advertisement search will present results rounded up/down and will not show results that are smaller than 300. This can be remedied by adding together one location with an audience above 300 and the location with the unknown audience and subtracting the known audience from the aggregated audience. While the resulting number is still rounded and most likely anonymous, researchers should also consider privacy implications with respect to reidentification. An alternative approach would be to group small countries into regions, or group together other characteristics until a sufficient sample size is reached.

In Figure 2 we provide a visualization of the data retrieval process in a very simple search, from the fourth case below. First we identify everyone who lives in Europe and has skills related to environmental, social, and governance (ESG) and sustainability in their résumé. Then we limit the group to people who are employed by the company Deloitte and note down the number listed of how many users these criteria respond to. We then take out Deloitte and search for the next firm, PwC, take down the number – and so on. For each variable attribute there is a corresponding result, so mapping a job category across countries in the EU, for example, would provide twenty-seven data points.

2 https://business.linkedin.com/marketing-solutions/marketing-partners/become-a-partner/marketing-developer-program#get-started

Figure 2 Search specification and result example



Source: Authors and LinkedIn Campaign Manager.

Step 3: Verifying data

While being a popular platform, LinkedIn is not a neutral and all-knowing central repository for information on all professions. Using quantitative data from LinkedIn will never be free of some degree of sampling bias. Particularly when doing comparisons across countries, it is worth noting that the use of competing platforms, or outright bans of the service, biases results downwards in these countries. Results in countries with more established internet access and where the job market is more digitized have higher coverage. There are also some countries that are simply not available on LinkedIn's ad manager, since they are affected by sanctions.[3] However, this problem depends on the profession that is being studied. Professions that cater to a domestic clientele (e.g., teachers) will be particularly affected by the biases, whereas professions that cater to an international clientele would likely be present on LinkedIn even if the platform is not popular in their home country (Table 1). In general, the researcher should pay attention to the issues of coverage (how complete the data is) and accuracy (how precise the data is).

Using the described methodology requires careful consideration of the object of study and presents some verification steps. Crucially, each specific study should always verify the coverage of the data and whether there are certain biases. The best way to do so is to

3 https://www.linkedin.com/help/linkedin/answer/42246/prohibited-countries-policy?lang=en

compare the findings with known distributions of the profession studied. This can, for example, be if the number is known for a portion of countries. Another strategy, if this is not available, is to compare the findings of a similar profession where a known benchmark does exist. For example, Deloitte employees (for which we have information on their geographical distribution) may be a good benchmark for accountants. Some of the employees are accountants themselves, and the employees in general have similar attributes in terms of education, salary, international orientation, and prestige. Comparing the number of Deloitte employees found on LinkedIn and the number reported on their websites can help assess the accuracy of accountant data for each country.

Normalizing the data can help compare across countries. If LinkedIn is considered to have full coverage, we could of course normalize by taking the ratio to the general population. If there is not full coverage for the profession, it is tempting to normalize using the total number of LinkedIn users in each country, but this only works if the use of LinkedIn generally correlates perfectly with the use of LinkedIn by the group studied. We therefore do not recommend this, as the relative usage of LinkedIn also depends on the specific profession being researched.[4] For one group it might follow proportionally to the general population's use of LinkedIn, while for another group there is almost full presence on the platform in every country, as shown in Table 1. Comparing the ratio of tax lawyers to LinkedIn audience in Korea and the United States would lead to a higher proportion of tax lawyers in Korea, but only because other professions in Korea do not use LinkedIn, and as such the denominator of the fraction becomes artificially small. In fact, we argue that the propensity to be on LinkedIn can depend more on profession than on geography.

When searching for firms, it is important to be aware that firms may set up separate LinkedIn entities for different geographical units – including large multinational corporations. Therefore it is important to make sure the search for all relevant entities is thorough. When filtering a profession by company, we suggest searching by each possible separate entity, for example by searching for "Deloitte A" (which may lead to adding Deloitte Argentina, Deloitte Armenia), then "Deloitte B," "Deloitte C," etc. Furthermore, the researcher should always inspect the data for outliers and check if this could be the issue, if there are countries that fall far below the trend line.

A final consideration regarding coverage when scraping LinkedIn data across countries is language differences. We test whether it makes a difference to search for teachers with a profile in Spanish or English (this is one of the filtering options) in a range of countries. In the English-speaking countries, the use of a Spanish profile yields fewer results. However, in the Spanish-speaking countries, the use of an English profile yields equivalent results, which suggests English profiles capture all translations of the job title. The researcher should therefore refrain from querying using local languages – unless the study is interested in foreign languages (e.g., Spanish in the United States).

4 We however recommend adding both the population of the country and the total number of LinkedIn users as control variables in regression analysis.

The LinkedIn Campaign Manager makes it impossible to verify individual profiles. This implies that counting a small number of fraudulent or duplicate profiles is unavoidable. This may depend on the type of profession being investigated. For example, there are likely more fake profiles that use HR or recruitment as their occupation. If these are the types of professions you want to investigate, you need to consider how to limit your counting of fake profiles. Unfortunately, it is not possible to limit the audience to profiles that have been active for a minimum amount of time. Similarly, the number of people with job titles with high desirability may be biased upwards. For example, according to LinkedIn there are 1.5 million chief executives in the United States. However, the occupational employment statistics (https://www.bls.gov/oes/current/oes111011.htm) indicate that there are only 195,530 in May 2018. Of those, we may be interested in weeding out self-employed or non-established firms. This can be achieved by filtering by company size. Filtering companies with information on size reduces the number of chief officers to 700,000, which further reduces to 200,000 if only companies with at least 200 employees are included. Companies with no information on company size correspond to companies that are not registered on LinkedIn, which indicates that they are small entities. Therefore including only the ones where we have data for company size will decrease the title bias when analyzing attractive job titles. Alternatively, using different types of executives (such as chief technology or financial officer, CTO or CFO) can provide a less biased association of the number of executives within a region.

Finally, it is important to note that the data from this source will never be completely unbiased, even if the trend toward expansion of the network continues. Governments are imposing bans and restrictions on the service, and competing networks arise. The direction and geography of the biases, however, will vary depending on the group studied. We therefore encourage researchers to take all possible steps toward verifying the data and to consider the plausibility of results through triangulation (Turner, Cardinal, and Burton 2017). Table 2 summarizes the main sources of error in LinkedIn ad data, mapped onto the total survey error (TSE) framework. We follow the TSE framework (Groves et al. 2011), widely used to assess data quality in survey research, and apply it here to LinkedIn data, along with our recommendations for addressing these issues.

Step 4: Applications and analysis

The high number of potential professional groups, along with the many potential variable characteristics on organizations, traits, or geographies, means the potential research to be done with this data type is very large. Our goal here is to showcase the potential of LinkedIn ad data for research on professions and organizations by outlining five examples (Table 3). These are not exhaustive cases but rather examples meant to illustrate what can be done with this data source.

Table 2 Sources of error in LinkedIn ad data mapped to the total survey error framework

Potential errors	Recommendation
Representation side Always check unexpected data; may indicate issues with search or sampling bias.	
Coverage error: Undercoverage Data penetration varies across countries and across professions. Competing platforms, bans, culture, and internet access affect representation. Language filters can exclude users.	Researchers must assess both how complete and accurate the LinkedIn data is for their profession. Compare findings with known profession distributions or use benchmarks. Using English as default includes all profiles. Use local language only if language is relevant to search.
Coverage error: Overcoverage Fake profiles are counted in the search.	Avoid title sets prone to fraud (e.g., "CEO"); filter by verified company size.
Nonresponse error: Small groups Small subgroups (<300) are hidden in the LinkedIn Campaign Manager.	Aggregate groups or include in the search a small group with known size.
Adjustment error: Normalization LinkedIn usage varies across both professional groups and geography, so total LinkedIn use can not be used to normalize a professional group	Use general population ratios if coverage is assumed high for professional group. Otherwise avoid normalizing.
Measurement side Always think carefully about your fixed and variable attributes.	
Specification error: Ambiguous operationalization of professions (e.g., "banker" as title vs. "finance" industry). Misalignment between LinkedIn categories and theoretical constructs.	Pilot multiple operationalizations.
Measurement error: Overlapping member skills (risk of double-counting).	Do not sum overlapping skill queries, estimate unions using exclusion criteria
Processing error: Geographical variation for multinationals Firms may have multiple LinkedIn pages by country, which need to be aggregated.	Search thoroughly using patterns like "Deloitte A," "Deloitte B," and combine them in your query.

Table 3 Description of the five case examples

Research topic	*Group (fixed attribute)*	*Variable attribute*	*Data structure*[a]
Connections between organizations	Currently employed at FED or SEC	Former employment at list of private financial institutions A, B, and C	X with former employment in A, B, or C
Geography of professionals	Job title "accountant"	Location (country or city)	X in country A X in country B X in country C
Professional composition of interdisciplinary organizations	Currently employed in list of firms	Degrees of study, Field of study, Member skills	X with degree A X with degree B X with study field A X with study field B X with skill A X with skill B
Skill profiles among competing industries and firms	Member skill: sustainability and ESG	Current employment at list of professional service firms	X in firm A X in firm B X in firm C
Industries forming emerging profession	Job title includes "cyber security"	Company industries	X in industry A X in industry B

a "X" is the number of LinkedIn users.

4 Case 1: The revolving doors between Wall Street and financial regulators

LinkedIn provides relational data, enabling researchers to understand "linked ecologies" and revolving doors (Abbott 2005; Seabrooke and Tsingou 2015; 2021; Stone 2013). By choosing the filter "Company Connections," researchers can extract information on the links between firms. For example, employees at Coca-Cola have 1,400 1st-degree connections to employees working at Deloitte, 1,600 with employees at KPMG, 1,500 with EY, and 1,300 with PwC. Network analyses can be carried out in such relational data, such as centrality analysis to understand the importance of each firm, community detection to find clusters of cohesive companies, and diffusion models to understand how information spreads across the network of firms.

One classic case for concern when it comes to company connections is the revolving door between regulators and the financial sector (Seabrooke and Tsingou 2021). As an illustrative case, we identify 30,000 LinkedIn users who currently work at the SEC or the Federal Reserve (including the twelve local branches). Out of these 30,000, 13,000 have company connections with the fifteen largest US banks.[5] This indicates that over a third of the regulators have at least one connection on LinkedIn to current employees of the banks they regulate. The revolving door argument is, however, more concerned with overlaps in employment histories. This can be reached by limiting the audience to those with current employment at any of the FED branches or SEC who do not have a past employment at any of the fifteen largest banks. Of the 30,000 current employees at the SEC and FED, 2,000 have previously worked at one or more of the fifteen largest banks. These data can be further investigated through filtering, for example by experience.

It is worth noting that LinkedIn is particularly useful for identifying employment patterns among people who have *previously* worked at specific institutions, as in this case of the financial regulators. To understand the background of current employees, other methods could also be used, as these are easily identifiable. But as companies rarely keep records on their former employees, this method is good at easily identifying patterns in where employees go on to. Of the 47,000 LinkedIn users who have previously worked at the FED or SEC, 2,000 are now in one of the fifteen largest banks.

These numbers illustrate a relationship between regulators and the financial sector in which there is a perhaps unsurprising overlap in both connections and employment histories. This serves merely as an illustration of the potential from this data, but it should be noted that the analysis can be extended significantly. For example, iterative searches could be employed to analyze the differences between different branches of the regulators. More banks could of course also be added to the search, and iterative

5 JPMorgan Chase, Bank of America, Wells Fargo, Citigroup, U.S. Bancorp, PNC Financial Services, Truist Bank, Goldman Sachs, Capital One Financial, TD Group US Holdings, Bank of New York Mellon, State Street, BMO, Citizens Financial, First Citizens Bank. Source: Goldberg 2024. https://www.bankrate.com/banking/biggest-banks-in-america/

searches could again reveal differences between financial institutions' overlap with regulators. A comparison could also be done with other sectors such as accounting firms or law firms to map the background of financial regulators. Finally, the same method can of course be used to understand revolving door dynamics in other sectors – for example between climate change policy agencies and fossil fuel industries – or revolving doors between competing firms.

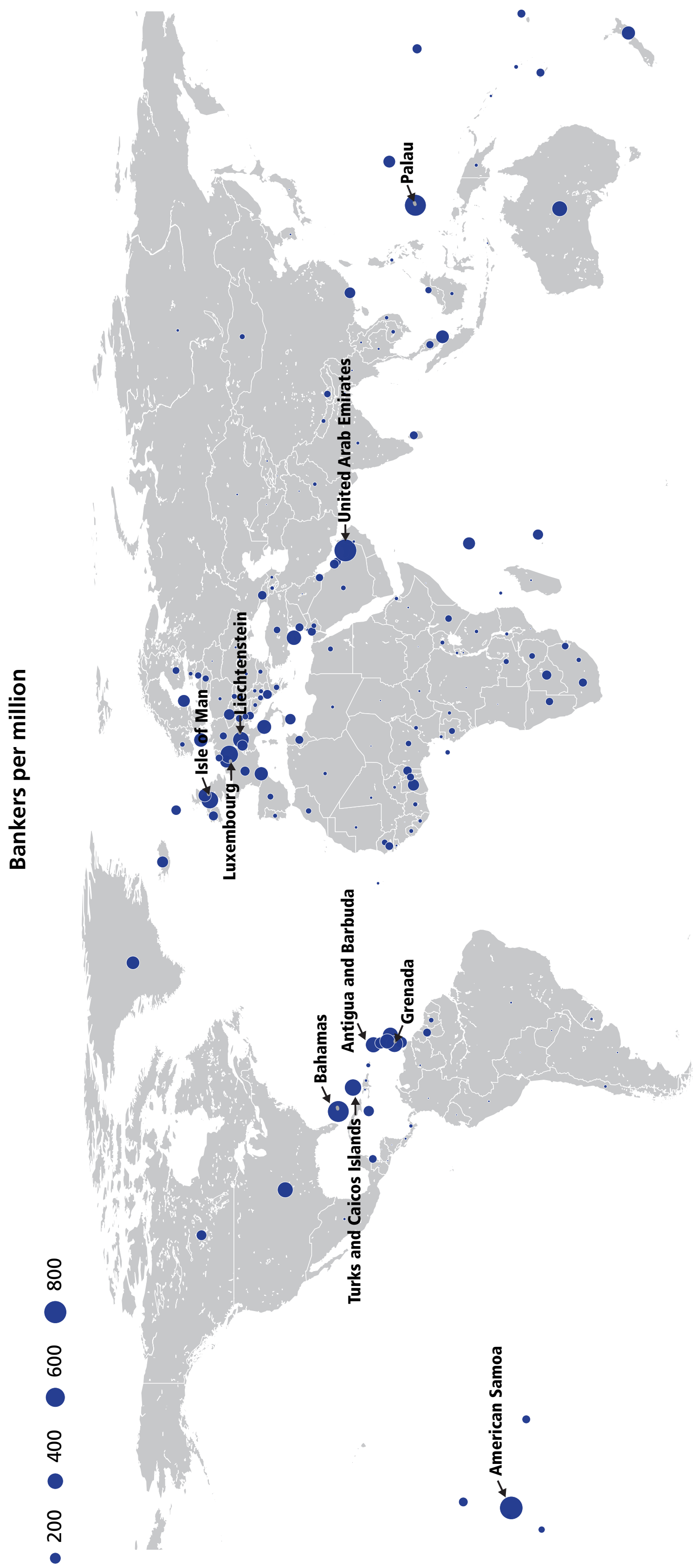
5 Case 2: The geography of professionals: The case of accountants and bankers

From the data we have gathered using this methodology of scraping the results from the LinkedIn ad builder, we can analyze the geographical distribution on a map. Figures 3 and 4 show the size of the profession relative to population. The examples below show a world map of profiles with the title "Banker" (Figure 3) and a European map of profiles with the title "Accountant" (Figure 4).

Obtaining an overview of the distribution of job titles and skills within a field has tremendous potential for entrepreneurial and innovation research in particular. The distribution of certain skills, as reflected in the skills section or in job titles, might be used to better understand the difference between the success of entrepreneurial and innovative hubs. Creating a quantitative measure of the presence of particular skills in an economy can be tested as a predictor of various economic and organizational outcomes.

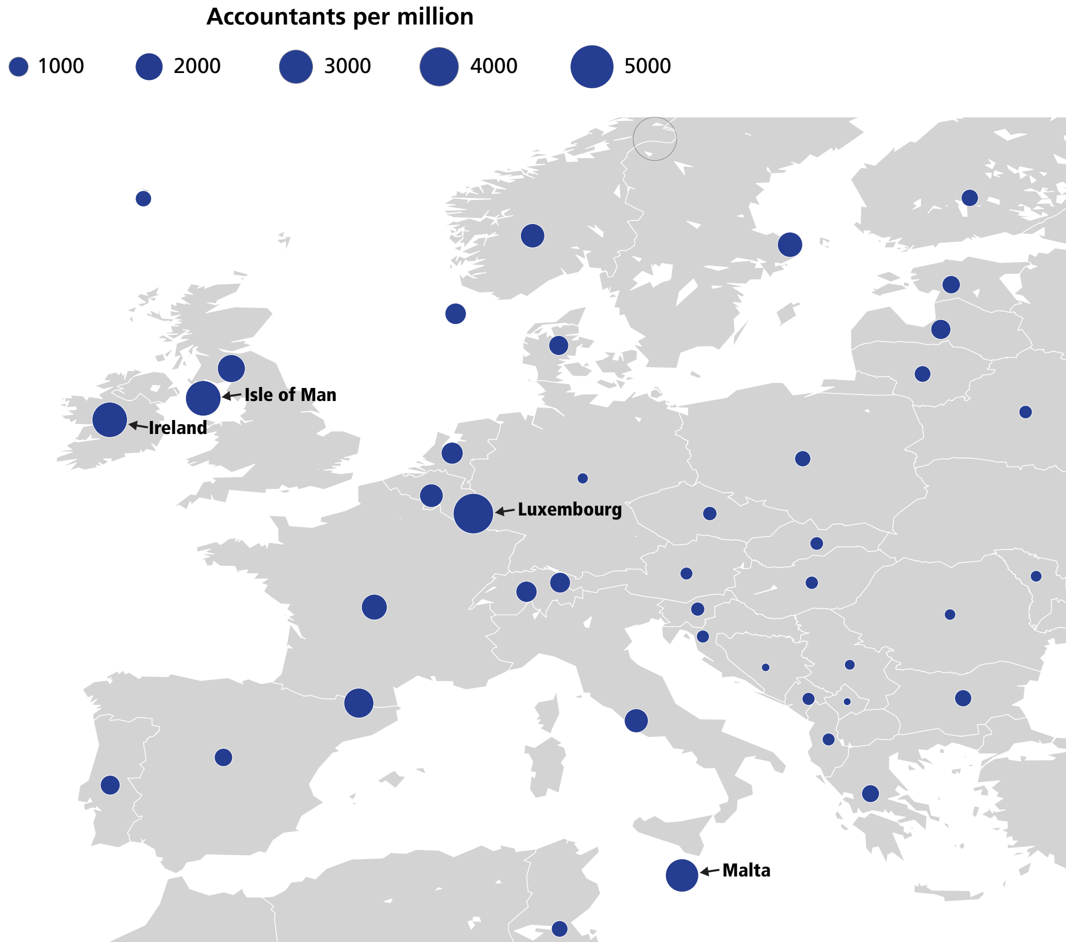
The concentration and distribution of professional skills can also be used as an explanatory variable, explaining the features of the environment. The relationship between organizations and their environment is a fundamental issue for organization studies, and measuring the environment and particularly operationalizing the concept of environmental complexity remains a core challenge for the field (Cannon and John 2007). Dess and Beard (1984) suggest geographical concentration of employment to be a target measure for computing the complexity of the environment. Likewise, Sharfman and Dean (1991) use percentage of scientists in the workforce. For certain groups, LinkedIn data enables this measure to be even more fine-grained and attuned to the specific sector studied because it will provide a more detailed picture on the level of both geography and specific titles or skills.

Figure 3 Geographical distribution of job titles with "Banker"



Source: LinkedIn Campaign Manager, collected by authors. Blue dots denote numbers relative to population.

Figure 4 Geographical distribution of job titles with "Accountant"



Source: LinkedIn Campaign Manager, collected by authors. Blue dots denote numbers relative to population.

6 Case 3: Institutionalizing epistemic arbitrage: Antitrust consulting as a hybrid legal-economic profession

Competition cases such as antitrust or mergers and acquisitions are traditionally handled by lawyers. However, competition law consulting by economists is an emerging niche of consulting services. They work on behalf of clients in mergers and acquisitions to provide evidence for market concentration through econometric modeling. This unique mix of legal and economic expertise provides an interesting setting to understand how these two professions interact and the practice of epistemic arbitrage (Seabrooke 2014). We use LinkedIn ad reach data to identify this sector and explore the educational background prevalent in these firms, relevant to questions of which type of professional – lawyer or economist – is dominant.

We define the fixed attribute as anyone currently employed by the main consulting firms specialized in antitrust and competition law, as identified by the firm ranking in GRC100.[6] We verified the data by comparing the ad reach for one of the firms (Compass Lexecon) with their web page. The web page states they have "825+" employees, whereas LinkedIn finds 850 profiles, which indicates a good match with high coverage. Searching for the full list of firms, we find 12,000 LinkedIn users worldwide. 4,400 are economists (having marked economics as their field of study). Only 530 have a law degree, defined as either an LLM, LLB, or JD in law, or having marked law or legal studies as their field of study. 3,700 have marked "business, management, marketing and related support services" as their field of study. 2,000 have an MBA. 670 studied political science or public administration. 1,300 have studied finance or financial management services. 910 have studied accounting, including the categories "accounting and finance" and "accounting and business/management accounting" and "accounting and related services." 2,200 have degrees unrelated to competition and markets, as they come from a STEM background, with fields of study such as physics, math, or engineering[7] that are unrelated to the subject matter but potentially useful for modeling large data. While the categories are not mutually exclusive – a LinkedIn user could have studied physics and later gone on to have a degree in law, for example – these descriptives paint a picture of the general distribution of professional types within this niche.

Other than degrees, we can also use the field "member skills" to analyze the skills that this audience has reported. This is self-reported data that is not necessarily verified in the same way as educational degrees would be in a hiring process, but nevertheless a good descriptive of how the group present themselves online. 5,700 mark "economics" as their skills. 2,000 mark "competition law" or "EU competition law" among their skills, while 6,500 have the more general areas of "law," "corporate law," "international law," and "contract law" among their skills. 4,100 mark "data science" and 4,600 have marked the programming languages R, VBA, and Python.

The high number of economists and STEM backgrounds relative to lawyers in this niche of consulting services suggests a "quantification" of legal processes regarding antitrust and competition cases. The very large number who marked data and coding expertise as skills suggests this sector is subject to the rise of a "coding elite" (Burrell and Fourcade 2021).

6 AlixPartners, Bates White Economic Consulting, Berkeley Research Group, Case Associates, CEG | Competition Economists Group, Charles River Associates, Compass Lexecon, Copenhagen Economics, Cornerstone Research, E.CA Economics, Economists Incorporated, Edgeworth Economics, Frontier Economics, Lear – Economic Consultancy, NERA, Oslo Economics, Oxera Consulting LLP, RBB Economics, Tendências Consultoria Integrada, Tendencias Consultoria Integrada, The Brattle Group, The Brattle Group, Inc, THE BRATTLE GROUP LIMITED, THE BRATTLE GROUP LIMITED SUCURSAL EN ESPAÑA

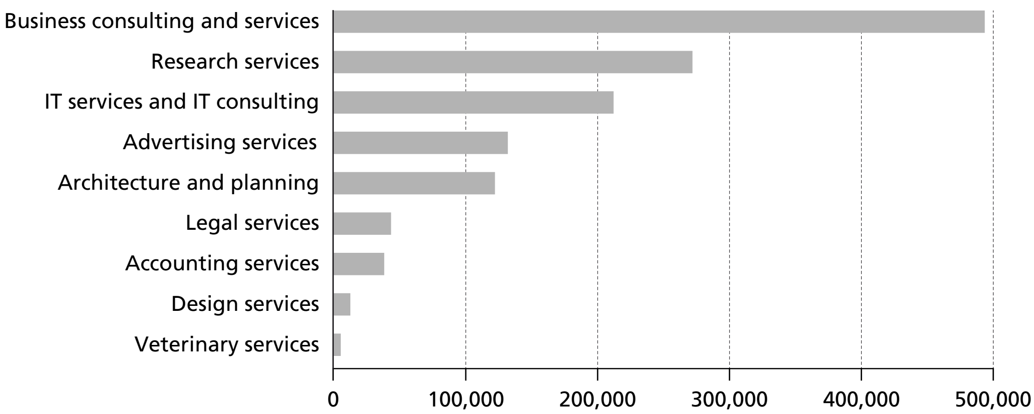
7 Full list of STEM fields of study used: Physics, Theoretical and Mathematical Physics. Engineering Physics/Applied Physics, Engineering Physics, Physical Chemistry, Statistics, Mathematics and Statistics, Mathematics, Physical Sciences, Engineering, Biology, General Biology/Biological Sciences, General Physical Sciences. Other categories such as "Chemistry" were added but dropped when the number of users did not increase.

7 Case 4: New skills in demand: The case of sustainability reporting

The European Union introduced the Corporate Sustainability Reporting Directive in 2023, a new reporting standard in which companies need to publish more information about sustainability and environmental impact. This has increased demand for professionals with expertise in sustainability reporting, not only in-house but also externally. This has led to a new and growing type of consulting, offered both by traditional accounting and consulting firms such as EY, PwC, KPMG, and Deloitte, as well as by new specialized consulting firms that focus only on sustainability reporting.

In the EU, 3.6 million LinkedIn users list themselves as having the following member skills: environmental, social, and governance (ESG), sustainability, sustainability reporting, sustainable business, or sustainability consulting. However, LinkedIn has the data on their company industry for only a third of these. Figure 5 presents the company industries of users with these skills listed in their profile, with the main sectors being professional and business services. 37,000 of these work in accounting, but the emerging reporting scheme is intricately linked to stakeholder management and not just reporting – as evidenced by the 130,000 who work in advertising services.

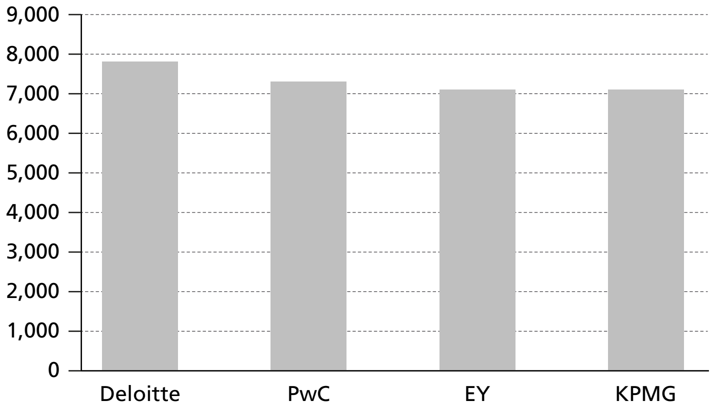
Figure 5 Company industries for sustainability skills



Source: LinkedIn Campaign Manager, collected by authors.

The member skills can also be compared across firms. For illustration, we focus on the leading accounting and consulting firms PwC, Deloitte, EY, and KPMG, who offer support for their clients to comply with these new reporting requirements. These four firms have hired remarkably similar numbers of people who mark these skills on their profile (Figure 6).

Figure 6 LinkedIn users employed with sustainability skills



Source: LinkedIn Campaign Manager, collected by authors.

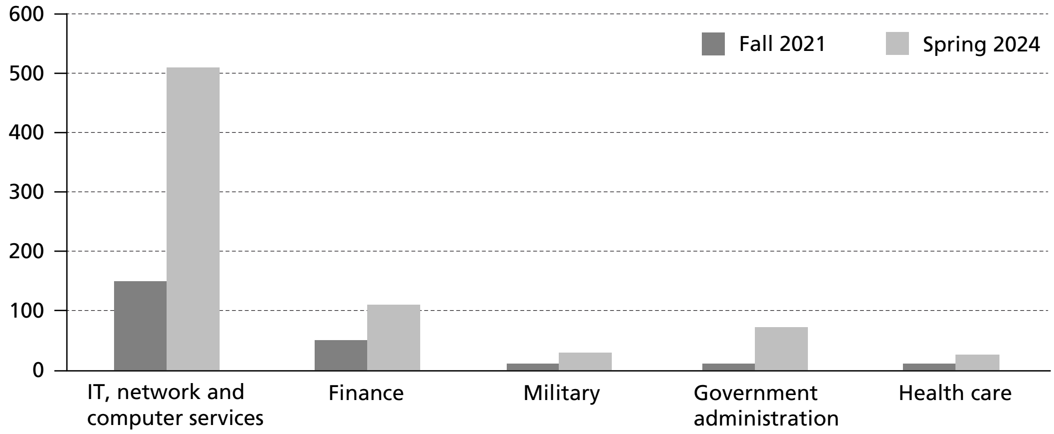
This type of application of the LinkedIn ad reach data could be useful for understanding how specific skills are distributed across industries. It is more limited in reliability than other applications, as member skills are self-reported and less verifiable relative to employment or education. There is also less uniformity in whether people report any skills in their profile.

8 Case 5: Emerging professions: The case of cyber security

When a new profession is emerging, it might be interesting to understand where and through what organizations and sectors this profession is shaped. Given the formation of a new industry, here it might make sense to employ longitudinal methods. LinkedIn does not provide longitudinal data but only shows a snapshot of what an audience size would be on the day of the search. Therefore longitudinal data requires repeating the same search over time.

An example of an emerging profession is cyber security professionals. These are not formed through a formal degree qualification and have various backgrounds, but are a recent but rapidly growing phenomenon across many sectors (Willers 2022). We searched for all users with job titles that include “cyber security” across all locations in the fall of 2021 and again in the spring of 2024. In this short amount of time, the number of profiles with these job titles has increased from 380,000 to 880,000. A search was done in both March and April of 2024, and in only just over a month the number grew by 20,000. For such a rapidly growing profession, many years of iterative searching may not be needed, as change is already visible within a manageable time period.

Figure 7 Sectors of cybersecurity professionals



Source: LinkedIn Campaign Manager, collected by authors.

For an emerging profession, it might be interesting to understand what sectors are shaping and supplying this phenomenon. Of the 380,000 profiles on LinkedIn who work with cyber security in 2021, we can detect that around 150,000 of them work in IT and internet services, computer and network security, or computer networking, and computer software. 50,000 work in finance. Only around 10,000 work in the military; however it is possible that military personnel have different career patterns which make them less likely to join LinkedIn (as they advance internally in an organization rather than across organizations). The rest work in the private sector in manufacturing, retail, logistics, or corporate services. 6,100 work for one of the tech firms Apple, Google, Amazon (including Amazon Web Services), and Microsoft.

In 2024, while the overall number of profiles with these job titles has increased immensely (Figure 7), the largest increase comes from IT, network and computer services. Government administration has increased rapidly from 3 percent to 8 percent of the total work force – potentially given the geopolitical changes which occurred during this time.

A longitudinal study using the LinkedIn ad reach data necessarily comes with some uncertainty. First, it requires a bit of planning of when data should be collected and with what intervals. Secondly, there are some threats to consistency, if LinkedIn changes its categories or otherwise alters access to the page. There might also be threats to consistency if countries come under US sanctions as LinkedIn ad data can only be used to target users in non-sanctioned countries. Therefore in the case of the cyber security job titles, while we searched globally, Russia is part of the 2021 data but not the 2024 data. If in 2021 we had noted the data on a country-by-country basis, this would not be an issue as we could simply remove Russia in the older data, but this is not possible from the global figures and cannot be amended after the fact. We encourage longitudinal studies to take these risk factors into consideration when planning a study and, as with all other use cases, verify and triangulate findings. We further encourage researchers to evaluate critically whether the assumption is likely to hold that this group is likely to update their LinkedIn profile within the interval used.

9 Conclusion

The data strategies that we have outlined hold both significant potential and important challenges. LinkedIn ad reach data offers a unique chance to build large-scale evidence on professions and organizations that are often hard to study. It allows researchers to map where different groups are located, track emerging skills, examine gender and age patterns, and explore how professionals and organizations are connected across sectors and countries. At the same time, the presence and presentation of professional groups on LinkedIn varies over geographical regions and professions, and studies must be designed with careful attention to context. We suggest triangulation of findings with qualitative information, for example by interviewing people in the industry or organization, by using findings in the relevant scientific literature, or through other qualitative information such as reading company or industry reports (see, e.g., Turner, Cardinal and Burton 2017).

Beyond descriptive mapping, LinkedIn ad data can support traditional quantitative regression designs. For example, it might be of interest to analyze what factors determine the presence of specific professional groups, such as the tech industry, the concentration of lobbyists, or the number of wealth managers. It can also be used to study how inequalities in gender, location, and professional characteristics are created and sustained across different contexts.

Legal and ethical considerations are also critical. Rules on data protection and text and data mining are evolving and are highly country-specific. We encourage researchers to confer with the legal unit of the university to ensure they follow the current local rules at all times. While this is particularly relevant when named persons appear, using the data in the aggregated form should also be done in ways that are mindful of legal and ethical considerations.

In this paper, we provide a step-by-step guide to implementing LinkedIn ad reach data collection, illustrated through five diverse applications. Together, the workflow and examples demonstrate how this source can enrich the study of professions, organizations, and regulatory dynamics. At the same time, our discussion of coverage and bias underscores that LinkedIn data are never neutral and must be benchmarked carefully against external sources. Used critically, researchers can transform this platform from a commercial advertising tool into a scientific instrument for understanding how professions and organizations structure contemporary societies.

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