# Measuring Nepotism Through Shared Last Names: Response to 

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#### Abstract

In a recent article, I showed that in several academic disciplines in Italy, professors display a paucity of last names that cannot be explained by unbiased, random, hiring processes. I suggested that this scarcity of last names could be related to the prevalence of nepotistic hires, i.e., professors engaging in illegal practices to have their relatives hired as academics. My findings have recently been questioned through repeat analysis to the United Kingdom university system. Ferlazzo \& Sdoia found that several disciplines in this system also display a scarcity of last names, and that a similar scarcity is found when analyzing the first (given) names of Italian professors. Here I show that the scarcity of first names in Italian disciplines is completely explained by uneven male/female representation, while the scarcity of last names in United Kingdom academia is due to discipline-specific immigration. However, these factors cannot explain the scarcity of last names in Italian disciplines. Geographic and demographic considerations - proposed as a possible explanation of my findings - appear to have no significant effect: after correcting for these factors, the scarcity of last names remains highly significant in several disciplines, and there is a marked trend from north to south, with a higher likelihood of nepotism in the south and in Sicily. Moreover, I show that in several Italian disciplines positions tend to be inherited as with last names (i.e., from father to son, but not from mother to daughter). Taken together, these results strenghten the case for nepotism, highlighting that statistical tests cannot be applied to a dataset without carefully considering the characteristics of the data and critically interpreting the results.


## Introduction

Cases of nepotism have been documented in Italian universities [1]. Professors were found to engage in illegal practices to have relatives hired as academics in their institution or within the same discipline at other universities. Because the prevalence of nepotism in Italian academia is largely unknown, I recently proposed a statistical method to estimate rates of nepotism based on the distribution of last names of Italian academics [2]. My results confirmed the findings obtained with more complex techniques [3], namely that a) some disciplines are more likely to display nepotistic tendencies, and b) a latitudinal pattern exists, showing a higher probability of nepotism in the south of the country and in Sicily.

The method is simple and requires minimal data, only a list of the names of all professors in Italy, and their corresponding discipline. For a given discipline, count the number of academics $N$ and the number of unique last names $L$. Then draw a random sample from the list of all Italian professors, taking $N$ professors without repetition. Finally, compute the probability $p$ that a number of unique last names $L^{\prime} \leq L$ is found in a sample. If the probability is very low, i.e., it is difficult to find a sample with a number of last names smaller than that empirically observed for the discipline, then the scarcity of last names in the discipline cannot be explained by unbiased (i.e., random) hiring processes.

Clearly, the method does not measure nepotism per se [2], only whether the scarcity of last names can or cannot be explained by a random process. The reasoning for nepotism comes from the lack of alternative explanations for the scarcity of last names. In my work I examined disciplines, which are quite uniformly represented geographically, and thus geographical considerations are unlikely to account for the scarcity of last name in specific disciplines. Scarcity of last names could be due to "career following", the tendency of offspring to follow their parents' careers, but I argued that this is quite unlikely [2] as even extremely specific fields of research yield a significant scarcity of last names. For example, "Philosophy and theory of languages" has significantly fewer names than expected at random [2]. Although the sons and daughters of professors in this discipline could be attracted towards philosophy or linguistics, the expecta-
tion that they will naturally become professors of "Philosophy and theory of languages" is far fetched.

The study attracted much attention in Italy, receiving praise and criticism in equal measure in the popular media. However, only the study by Ferlazzo \& Sdoia [4] addressed the results from a scientific standpoint. In summary, Ferlazzo \& Sdoia criticized my method and argued that neglecting to consider the regional distribution of last names is likely to bias the conclusions. They also repeated the analysis I proposed on a set of professors in the United Kingdom, finding a scarcity of last names comparable to the Italian case. Finally, they repeated the analysis of Italian professors using first (given) names rather than last names, finding that several disciplines "somewhat surprisingly" display a paucity of first names. They concluded that the method I proposed cannot measure nepotism, and that the results I presented are better explained by "social capital transfer", or by geographic and demographic considerations.

Here I show that social capital transfer, geography and demography do not account for my results or those of Ferlazzo \& Sdoia. In fact, a) the results obtained using Italian academics' last names are not affected by the regional distribution of last names - repeating the analysis on a regional or macro-regional basis yields consistent results, b) the scarcity of first names in some disciplines is completely driven by skewed gender representation and immigration, and c) immigration - not social capital transfer - is key to explaining the United Kingdom result. Having ruled out the effects of immigration and those stemming from the regional distribution of names, the suspicion of nepotism, with a concentration in the south, is strengthened, rather than weakened.

In addition, I show that academic positions in some disciplines tend to be "inherited" as last names are. In Italy, women maintain their maiden name, while sons and daughters only take the last name of their father. As such, if we analyze only women, the potential for discovering nepotism is greatly reduced (we can only find inter-sibling nepotistic hires or those involving distant relatives); on the other hand, when analyzing only men we have a higher potential to discover nepotism, as pairs of fathers and sons included in the set would share the same last
name. Analyzing Italian academics divided by gender I find no significant results with women, but highly significant results with men: academic positions tend to be inherited within families. Note that other geographic and demographic effects would equally impact males and females.

The new analysis no only strengthens my findings, but highlights that the proposed method - as with any statistical procedure - cannot be applied to a dataset without first carefully considering the characteristic of the data, and without critically interpreting the results.

## Results and Discussion

## Italy - Last Names: Regional Analysis Confirms the Initial Findings

In this section, I show that repeating the analysis I perfomed on the whole set of Italian professors [2] using only the professors working in a region or macro-region yields comparable results: the scarcity of last names in some disciplines cannot be explained by unbiased processes, and the likelihood of nepotism is higher in the south and in Sicily.

Using the same data as in Allesina [2], last names have been transformed to upper case, and spaces and apostrophes have been removed. I repeated the same analysis [2] using: a) all academics; b) academics divided into those working in the north, center, and south of Italy, those working in Sardinia and those in Sicily; and c) academics working in each of the 20 Italian regions. I present results obtained using $10^{5}$ simulations for each case. I computed a p-value only for disciplines with more than 50 professors (since for small disciplines even significant differences would be negligible from a practical standpoint). All code and data required for repeating the analysis accompanies this article.

Throughout the article, I call highly significant results yielding a p-value $\leq 0.05$ associated with a $q$-value $\leq 0.05$. That is, the highly significant results have low probability of being obtained at random (low p-value) and low probability of being false positives (low q-value). I computed $q$-values using the R package qualue using the bootstrap method 5 .

In Table 1 I report results for the regional analysis. When considering all academics, 11
disciplines show a highly significant scarcity of last names, with six having extremely small pvalues $\leq 0.01$ (Industrial Engineering, Law, Medicine, Geography, Pedagogy and Agriculture). I then divided the academics into macro-regions and repeated the analysis. Clearly, using smaller samples necessarily reduces the statistical power. Considering only the north (the regions Aosta Valley, Liguria, Lombardy, Piedmont, Emilia-Romagna, Friuli-Venezia Giulia, Trentino-Alto Adige and Veneto) and repeating the analysis using the subset of professors working in this part of the country I find a single discipline yields significant results (Industrial Engineering). In the center (Lazio, Marche, Tuscany and Umbria), Medicine and Chemistry yield a significant scarcity of last names. Note that these three disciplines are included in the total list of 11 that were significant at the national level. The results in the south show a higher number of potentially nepotistic disciplines, with 8 significant results ( 6 included in the list of 11 significant at the national level). In Sicily 7 disciplines produce highly significant results (5 in the list of the 11). In Sardinia, mainly due to the small sample size, no result was highly significant. In summary, disciplines found to be problematic at the national level are among those problematic at the macro-regional level.

Repeating the analysis at the smaller, regional level further confirms these findings. For each of the 20 Italian regions, I computed a p-value for each discipline with more than 50 professors, and counted how many results were $\leq 0.05$. Medicine yields low p-values in 8 regions out of 16 , Industrial Engineering in 6 regions out of 15, Law in 4 out of 17 (Table 1). If we order disciplines according to the proportion of regions in which we find p -values $\leq 0.05$, we find that the four with the highest proportions are included in the list of the six with the lowest p-values at the national level.

The regional and macro-regional analysis of last names confirms the findings of my previous work [2]. Some disciplines have a highly significant scarcity of last names, which can be interpreted as a higher likelihood of nepotism. The scarcity of last names is more marked in the south of the country and in Sicily. Note that the analysis has been conducted using a regional or macro-regional pool of names, and thus is not compatible with the explanation of

Ferlazzo \& Sdoia who conjecture that the results could be explained by "migration [that] might have produced a larger variability of last names in the northern regions and a lower variability (i.e., more shared names) in the southern regions" [4]. These results are not surprising, as they closely match the logistic regression analysis I performed [2] and the study of Durante et al. [3]: even when considering the local distribution of last names, the scarcity of last names in some disciplines cannot be explained.

## Italy - First Names: Gender Drives the Results

In this section, I show that analyzing first names in Italian academia simply highlights that in some disciplines women represent a small minority of the professors.

The analysis of first names yields five disciplines with a highly significant scarcity of first names (Table 2): Physics, Industrial and Electronic Engineering, Economics and Earth Sciences have too few first names compared to what would be expected at random. Linguistics and Psychology, on the other hand, have a significant excess of first names. Ferlazzo \& Sdoia find these results "somewhat surprising". However, there is a well-documented bias in gender representation in the so-called STEM (Science, Technology, Engineering and Mathematics) disciplines, where professors are overwhelmingly male. For example, in Italy more than $55 \%$ of the professors in Psychology are women, while in Electronic Engineering less that $13 \%$ are women. To test whether this observation can account for the results, I divided the professors according to gender and computed the proportion of women in each field. We can model the relationship between gender representation and p -values as a logistic function: a sigmoid describes the p -value as a function of the proportion of women. If the fraction of women were driving the p -values, then plotting logit(p-value) against the proportion of women would produce a straight line. The plot indeed shows a strong linear trend $\left(r^{2}>0.8\right.$, Figure 1), indicating that gender is likely to play a strong role in explaining the results.

To further test this hypothesis, I repeated the first-name analysis dividing the professors according to gender. Among males, only Electronic Engineering produces highly significant
results. Among females (representing about one third of the professors), four disciplines are significant, meaning that gender can explain the results for males but not for females.

In order to understand this new result, we have to recongnize a subtle characteristic of the data. Immigration is unfortunately quite rare in Italian academia, with the exception of a few disciplines. In Linguistics, for example, native speakers are routinely hired to teach languages. In Italy, immigration has little effect on the analysis of last names, as there are very few immigrants and most last names are rare even among the native Italians. Thus, the influx of rare foreign last names has negligible effects. However, the analysis of first names can be greatly impacted by immigration, as most Italian first names are very common. Among all 61,340 professors, we find about 27,000 last names, but only about 7,000 first names. The most common last name, ROSSI, is observed 225 times, while the most common first name, GIUSEPPE, more than 1,400 times. Because immigrants represent a source of unique or very rare first names, they could bias the results by introducing unique first names in some disciplines but not in others. The effect is likely to be larger for women, as there is one distinct first name for every 5 male professors, but only one distinct first name for every 7 women.

How can we remove immigrants from the analysis? Unfortunately, information on the birthplace of Italian professors is not available. To determine which disciplines are most affected by immigration, I compiled a list of the 7,500 most common Italian last names from phone book data (included with this article). I then measured the proportion of common names in each discipline. Common last names represent on average $52 \%$ of the last names in each discipline, with Linguistics (43\%) and Anthropology (42.6\%) being the two disciplines with fewer common last names (bottom $5 \%$ of the distribution), and thus more likely to include many immigrants. Removing the two disciplines (which are among the smallest, representing about $3 \%$ of the professors combined) yields one significant result for each gender (M: Electronic Engineering, F: Chemistry).

The scarcity of first names in some disciplines is therefore largely explained by gender representation and immigration. Social capital transfer, geographic or demographic effects appear
to have no appreciable effect. What is "somewhat surprising", therefore, is not the result itself, but rather that Ferlazzo \& Sdoia failed to consider gender as a potential explanation. In fact, countless studies identified uneven gender representation in science and technology [6,7], and several initiatives have been implemented both in the European Union and in the United States to solve this grave problem. A trivial prediction that arises from these findings is that, when analyzing the distribution of first names in any top institution, one would find - unfortunately - exactly the same result: too few last names are present in the STEM disciplines, because too few women work in these fields.

## United Kingdom - Last Names: Immigration Drives the Results

In this section, I show that the results for the set of United Kingdom professors can be explained by immigration, which affects some disciplines more than others.

The dataset from the Research Assessment Exercise (RAE) 2008 is not as well-suited for analysis as the Italian one. In fact, not all professors are present, and each professor may be present more than once - following transfers between institutions [4]. Given that this latter characteristic could greatly hamper the analysis of last names, I follow Ferlazzo \& Sdoia [4] by removing duplicate records identifiable as professors with the same last name and initials (first names are not available) working in the same discipline. Moreover, in the United Kingdom it is very common for married women to take the last name of the husband. This can be accomplished in a number of ways: the woman can take the husband's last name, the two names could be hyphenated, or the prefix "nee"' could be added in front of the maiden name. Because the dataset contains all types of composite names, I kept only the first name in the case of hyphenated names (e.g., "PORCELLINI-SLAWINSKI"), and removed any name in parenthesis (e.g.,"MCCARTHY (FORMERLY RIBBENS-MCCARTHY)", "NAUGHTON (NEE LESNIEWSKA)"). This is important, as otherwise married women would add unique names to the set, biasing the analysis, although Ferlazzo \& Sdoia did not seem to consider this complication. Note that this is not a problem in the Italian dataset, as women in Italy maintain their maiden name.

In many countries "spousal hires" (i.e., hiring a couple at the same time) are encouraged, and marriage - with consequent change of last name - could happen after both partners have been hired. As such, in these countries we expect the scarcity of last name to over-represent nepotism, rather than greatly under-estimate it as in the Italian case - where spousal hires are explicitly forbidden and women keep their maiden name.

I analyzed the 67 self-reported disciplines of the RAE (Units of Assessment, Table 3). The results clearly signal that something other than social capital transfer is responsible for the results. In fact, 24 out of 67 disciplines show a highly significant scarcity of last names. Interestingly, Physics, Pure and Applied Mathematics, Computer Science and Statistics all show an excess of last names, while Celtic Studies, English Literature and History show a paucity of names. Why would social capital transfer happen in some of the humanities, but not in the mathematical sciences? If anything, we would expect the opposite, as there have even been studies showing the heritability of mathematical talent [8], leading to the expectation that career following should be more likely - rather than less - in quantitative disciplines.

If we were to rule out career following, what else could explain the pattern? To elucidate the results, we can start by listing the most common name in each discipline of the Research Assesment Exercise. We find that CHEN is the most common last name in Statistics, WANG in Electric Engineering, in Mechanical Engineering, and in General Engineering, while ZHANG dominates Asian Studies. These are all common last names in China, while in the United Kingdom the most common names are SMITH, JONES and TAYLOR. The large presence of professors of Chinese descent in United Kingdom universities is due to the fact that these institutions attract some of the best researchers from around the world. However, not all the disciplines are equally impacted by immigration, with foreigners more represented in the technical and scientific fields. In comparison, all the most common names in Italian disciplines sound undoubtedly Italian (with ROSSI, RUSSO and FERRARI dominating, as in the general population).

To test whether immigration, rather than social capital transfer, could explain the significant
results, I took the 7,500 most common last names in the United Kingdom (data included with the article) and repeated the analysis using only the professors whose name is included in the set. The rationale is that by analyzing only common names, the relevance of social capital transfer would remain unchanged (we can assume it is equally likely to happen regardless the last name), but the effect of immigration, i.e., the influx of rare names, would be greatly reduced. Clearly, the use of phone book data is not optimal, as common immigrant last names are present (e.g., GALLO, RICCI and ROSSI, common Italian last names, the common Indian last names NAIR, SHARMA, SINGH, PATEL, and the common Chinese CHANG, CHONG, LING, TANG, WONG, YANG are all present in the 7,500 names). Moreover, we are removing the last names of native professors when rare, reducing statistical power. However, in the absence of data on the immigration status of the academics, this analysis serves as a reasonable first approximation.

Repeating the analysis using only the 7,500 "common" names yield only three highly significant results instead of the 24 obtained when using all names (two included in the original list of 24). Thus, immigration largely accounts for the observed pattern.

## Analysis of Italian Last Names - Effects of Immigration and Gender

In this section, I show that the results obtained for the Italian last names are robust to the removal of rare names, and that academic positions tend to be inherited within families.

To show that the results in the Italian case are robust, I repeated the analysis of last names using only the 7,500 most common Italian last names (Table 4). Of the six disciplines yielding the lowest p-values when analyzing all names, all but Agriculture are still highly significant. Hence, although there has been a reduction in the number of highly significant disciplines, it is much less marked than in the United Kingdom case.

Analyzing the last names by gender provides an interesting test. In fact, because in Italy only the last name of the father is passed on to sons and daughters, the potential for nepotism is greatly reduced when analyzing only women. Among women, only intra-sibling nepotistic hires or those involving distant relatives would be recorded, while among men father-son relationships
would also be counted. Besides this difference, the geographical and demographic distribution of last names should affect men and women equally, providing a strong test for the absence of these effects. I therefore repeated the analysis of last names dividing professors into men and women. The results provide strong support for the "inheritability" of academic positions within families (Table 4). In fact, four disciplines (Medicine, Law, Industrial Engineering and Political Science) yield a significant scarcity of last names when considering only men, while no discipline is significant when considering only women.

## Conclusions

In my previous article [2, I proposed a method to determine whether the scarcity of names in a discipline could be determined by unbiased processes. This is not the case for some disciplines in Italy when analyzing first or last names, and in the United Kingdom analyzing last names. However, the cause for the scarcity of names differs between these cases.

When analyzing Italian first names, I showed that the fraction of women in each discipline strongly correlates with the significance (p-value). Hence, my method - as applied by Ferlazzo \& Sdoia [4] - can be seen as a computationally-intensive technique to measure the obvious gender representation bias in, typically, STEM disciplines. Note that in these disciplines there really are fewer first names than one would expect, but the problem this result is highlighting - the scarcity of women in STEM disciplines - is much more difficult to solve than nepotism, and unfortunately affects academic institutions worldwide.

The analysis of last names is better suited to systems where immigration is negligible, as the Italian case. When applied to a system where immigration is common, and more common in some disciplines than others, the scarcity of last names signals the differential impact of immigration, rather than nepotism.

These findings stress that statistical tests cannot be applied to a dataset without considering the special characteristics of the data and critically interpreting the results. Many of the conjectures in Ferlazzo \& Sdoia [4] could have been tested quite easily, as shown here. And in
fact, testing for the absence of geographical and demographic considerations make the case for nepotism stronger.

In Italian academia, some disciplines, especially Medicine, Law and Industrial Engineering, yield a scarcity of last names that cannot be explained neither by geographic nor demographic considerations, a finding that is also robust to analysis of common names only. When testing only men or women, I showed that positions tend to be "inherited" as with last names, i.e., from father to son. All these considerations lead to the conclusion that nepotism is the most logical explanation for these findings.

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## Figures and Tables



Figure 1. Gender Inequality and Scarcity of First Names. Plot of $\operatorname{logit}\left(p_{i}\right)=\log \left(p_{i} /\left(1-p_{i}\right)\right)\left(\mathrm{y}\right.$-axis), where $p_{i}$ is the p -value for discipline $i$ reported in Table 2 as a function of the fraction of women in the discipline. To avoid numerical problems, values $<10^{-6}$ have been set to $10^{-6}$ and those $>1-10^{-6}$ to $1-10^{-6}$.
Table 1. Analysis of Italian Academia: Last Names

| Discipline | Code | Academics | Last Names | p | North-p | Center-p | South-p | Sardinia-p | Sicily-p | Prop. Regions | Count |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Industrial Eng. | ING-IND | 3180 | 2686 | $\leq 0.001$ | $\underline{0.002}$ | 0.135 | $\leq 0.001$ | 0.175 | 0.038 | 0.4 | 6/15 |
| Law | IUS | 5144 | 4023 | $\leq 0.001$ | 0.523 | 0.043 | $\leq 0.001$ | 0.035 | $\leq 0.001$ | 0.235 | 4/17 |
| Medical Sciences | MED | 10783 | 7461 | $\leq 0.001$ | 0.014 | $\leq 0.001$ | $\leq 0.001$ | 0.013 | 0.075 | 0.5 | 8/16 |
| Geography | M-GGR | 377 | 359 | $\underline{0.005}$ | 0.718 | 0.444 | $\underline{0.008}$ | - | - | - | 0/0 |
| Pedagogy | M-PED | 675 | 634 | 0.005 | 0.285 | 0.08 | 0.06 | - | $\leq 0.001$ | 0.167 | 1/6 |
| Agriculture | AGR | 2345 | 2057 | $\underline{0.008}$ | 0.233 | 0.012 | 0.081 | 0.197 | $\underline{0.003}$ | 0.286 | 4/14 |
| Civil Eng. | ICAR | 3836 | 3204 | $\underline{0.01}$ | 0.606 | 0.066 | $\underline{0.007}$ | 0.388 | 0.099 | 0.25 | 4/16 |
| Mathematics | MAT | 2531 | 2211 | $\underline{0.019}$ | 0.116 | 0.937 | 0.057 | - | $\leq 0.001$ | 0.154 | 2/13 |
| Chemistry | CHIM | 3129 | 2683 | $\underline{0.036}$ | 0.055 | $\underline{0.005}$ | 0.159 | 0.298 | $\leq 0.001$ | 0.188 | 3/16 |
| Earth Sciences | GEO | 1196 | 1105 | $\underline{0.047}$ | 0.134 | 0.482 | 0.402 | - | 0.068 | 0 | 0/9 |
| Philosophy | M-FIL | 1125 | 1043 | $\underline{0.048}$ | 0.29 | 0.792 | $\underline{0.021}$ | - | 0.067 | 0.222 | 2/9 |
| History | M-STO | 1453 | 1329 | 0.061 | 0.537 | 0.268 | 0.677 | - | 0.698 | 0.1 | 1/10 |
| Statistics | SECS-S | 1212 | 1122 | 0.088 | 0.647 | 0.145 | $\underline{0.002}$ | - | 0.032 | 0.5 | 4/8 |
| Veterinary | VET | 847 | 799 | 0.126 | 0.604 | 0.127 | 0.07 | - | $\leq 0.001$ | 0.222 | 2/9 |
| Political Sciences | SPS | 1792 | 1622 | 0.14 | 0.02 | 0.241 | 0.373 | 0.756 | 0.98 | 0.077 | 1/13 |
| Life Sciences | BIO | 5140 | 4172 | 0.153 | 0.058 | 0.569 | 0.368 | 0.135 | 0.527 | 0.125 | $2 / 16$ |
| Informatics | INF | 834 | 789 | 0.192 | 0.136 | 0.07 | 0.472 | - | - | 0.143 | $1 / 7$ |
| Physics | FIS | 2472 | 2186 | 0.245 | 0.475 | 0.272 | 0.476 | - | 0.34 | 0 | 0/13 |
| Philology | L-FIL-LET | 1780 | 1618 | 0.278 | 0.709 | 0.464 | 0.104 | - | 0.813 | 0.083 | 1/12 |
| Economics | SECS-P | 3806 | 3221 | 0.291 | 0.363 | 0.115 | $\underline{0.005}$ | 0.033 | $\underline{0.003}$ | 0.235 | 4/17 |
| Physical Ed. | M-EDF | 138 | 136 | 0.347 | - | - | - | - | - | - | 0/0 |
| Art History | L-ART | 815 | 775 | 0.36 | 0.175 | 0.771 | 0.289 | - | - | 0 | 0/7 |
| Electronic Eng. | ING-INF | 2089 | 1880 | 0.389 | 0.266 | 0.604 | 0.128 | - | 0.439 | 0 | 0/12 |
| Archeology | L-ANT | 704 | 678 | 0.702 | 0.319 | 0.593 | 0.302 | - | 0.664 | 0 | 0/6 |
| Near Eastern | L-OR | 317 | 312 | 0.741 | 0.725 | 1 | 1 | - | - | 0 | 0/2 |
| Psichology | M-PSI | 1252 | 1176 | 0.769 | 0.325 | 0.611 | 0.794 | - | 0.23 | 0 | 0/8 |
| Linguistics | L-LIN | 2173 | 2000 | 1 | 0.983 | 0.998 | 0.909 | 0.61 | 0.215 | 0 | $0 / 15$ |
| Demography | M-DEA | 195 | 195 | 1 | 1 | 1 | - | - | - | - | 0/0 |

[^0]Table 2. Analysis of Italian Academia: First Names

| Code | Academics | First Names | p | F-p | M-p | F-p' | M-p' |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| ING-INF | 2089 | 519 | $\underline{\leq 0.001}$ | $\underline{0.012}$ | $\leq 0.001$ | 0.019 | $\leq 0.001$ |
| ING-IND | 3180 | 762 | $\underline{\leq 0.001}$ | 0.058 | 0.015 | 0.095 | 0.04 |
| FIS | 2472 | 685 | $\underline{\leq 0.001}$ | 0.196 | 0.204 | 0.279 | 0.316 |
| SECS-P | 3806 | 950 | $\underline{0.003}$ | 0.031 | 0.104 | 0.096 | 0.2 |
| GEO | 1196 | 439 | $\underline{0.007}$ | 0.427 | 0.083 | 0.504 | 0.119 |
| ICAR | 3836 | 975 | 0.042 | 0.546 | 0.239 | 0.739 | 0.395 |
| CHIM | 3129 | 853 | 0.053 | $\underline{0.001}$ | 0.403 | $\underline{0.005}$ | 0.542 |
| INF | 834 | 354 | 0.058 | 0.56 | 0.264 | 0.618 | 0.325 |
| IUS | 5144 | 1200 | 0.108 | 0.353 | 0.112 | 0.665 | 0.233 |
| MAT | 2531 | 749 | 0.124 | $\underline{0.013}$ | 0.537 | 0.038 | 0.662 |
| SECS-S | 1212 | 461 | 0.13 | 0.08 | 0.148 | 0.131 | 0.196 |
| MED | 10783 | 2002 | 0.165 | 0.334 | 0.683 | 0.771 | 0.913 |
| M-EDF | 138 | 99 | 0.231 | - | 0.089 | - | 0.095 |
| VET | 847 | 368 | 0.244 | $\underline{0.024}$ | 0.409 | 0.041 | 0.468 |
| AGR | 2345 | 721 | 0.253 | 0.981 | 0.056 | 0.993 | 0.1 |
| M-FIL | 1125 | 446 | 0.281 | 0.375 | 0.646 | 0.456 | 0.72 |
| M-GGR | 377 | 218 | 0.559 | 0.209 | 0.305 | 0.247 | 0.331 |
| BIO | 5140 | 1234 | 0.586 | $\underline{0.004}$ | 0.794 | 0.051 | 0.894 |
| M-STO | 1453 | 551 | 0.839 | 0.414 | 0.809 | 0.547 | 0.864 |
| L-ART | 815 | 379 | 0.851 | 0.526 | 0.425 | 0.624 | 0.48 |
| SPS | 1792 | 640 | 0.941 | 0.333 | 0.982 | 0.474 | 0.991 |
| L-ANT | 704 | 355 | 0.978 | 0.206 | 0.967 | 0.276 | 0.975 |
| M-PED | 675 | 346 | 0.982 | 0.685 | 0.677 | 0.759 | 0.712 |
| L-FIL-LET | 1780 | 646 | 0.982 | 0.658 | 0.834 | 0.804 | 0.887 |
| L-OR | 317 | 208 | 0.983 | 0.788 | 0.8 | 0.816 | 0.821 |
| M-DEA | 195 | 147 | 0.986 | 0.789 | 0.929 | - | - |
| M-PSI | 1252 | 536 | 1 | 0.55 | 0.997 | 0.701 | 0.998 |
| L-LIN | 2173 | 944 | 1 | 1 | 1 | - | - |

For each discipline, I report the number of academics, the number of first names and the p-value obtained considering the first names of all professors. I then computed the p-values for the first names within each discipline when I divide the professors in female ( $\mathrm{F}-\mathrm{p}$ ) and male (M-p). Finally, I compute the p-values when the professors in Linguistics (L-LIN) and Demography and Ethnology (M-DEA) have been removed (F-p', M-p'). These two fields contain the highest proportion of foreigners, providing a source of unique or very rare first names.

Table 3. Analysis of UK Academia: Last Names

| Discipline | Code | Academics | Last Names | p | Common-p |
| :---: | :---: | :---: | :---: | :---: | :---: |
| Chemistry | 18 | 1252 | 987 | $\leq 0.001$ | $\leq 0.001$ |
| Celtic Studies | 56 | 158 | 138 | $<0.001$ | <0.001 |
| English Language and Literature | 57 | 2343 | 1682 | $\leq 0.001$ | 0.034 |
| Sports-Related Studies | 46 | 585 | 501 | <0.001 | 0.037 |
| History | 62 | 2296 | 1721 | $\leq 0.001$ | 0.038 |
| Education | 45 | 2232 | 1639 | <0.001 | 0.054 |
| Geography and Environmental Studies | 32 | 1442 | 1133 | $\leq 0.001$ | 0.074 |
| Nursing and Midwifery | 11 | 816 | 678 | <0.001 | 0.137 |
| Agriculture, Veterinary and Food Science | 16 | 1227 | 991 | $\leq 0.001$ | 0.175 |
| Social Work and Social Policy | 40 | 1616 | 1260 | <0.001 | 0.464 |
| Archaeology | 33 | 668 | 577 | 0.001 | 0.041 |
| Earth and Environmental Sciences | 17 | 1423 | 1153 | 0.001 | 0.184 |
| Dentistry | 10 | 471 | 417 | $\underline{0.003}$ | 0.04 |
| Biological Sciences | 14 | 2785 | 2092 | $\underline{0.003}$ | 0.144 |
| Health Services Research | 7 | 637 | 554 | $\underline{0.003}$ | 0.218 |
| Epidemiology and Public Health | 6 | 711 | 613 | $\underline{0.003}$ | 0.243 |
| Pharmacy | 13 | 550 | 484 | $\underline{0.004}$ | 0.062 |
| Mechanical and Aeronautical Engineering | 28 | 1149 | 956 | 0.005 | 0.326 |
| Town and Country Planning | 31 | 530 | 469 | 0.008 | 0.116 |
| Music | 67 | 777 | 670 | $\underline{0.009}$ | 0.154 |
| Asian Studies | 49 | 185 | 172 | $\underline{0.02}$ | 0.062 |
| Drama, Dance and Performing Arts | 65 | 574 | 508 | $\underline{0.02}$ | 0.12 |
| Other Hospital Based Clinical Subjects | 4 | 1935 | 1535 | $\underline{0.026}$ | 0.48 |
| Iberian and Latin American Languages | 55 | 278 | 256 | 0.029 | 0.023 |
| General Engineering and Mining Engineering | 25 | 1817 | 1458 | 0.055 | 0.175 |
| Allied Health Professions and Studies | 12 | 1803 | 1449 | 0.063 | 0.825 |
| Theology, Divinity and Religious Studies | 61 | 638 | 565 | 0.063 | 0.287 |
| Classics | 59 | 558 | 499 | 0.069 | 0.073 |
| Civil Engineering | 27 | 635 | 563 | 0.07 | 0.367 |
| Chemical Engineering | 26 | 258 | 240 | 0.073 | 0.133 |
| Sociology | 41 | 1232 | 1033 | 0.076 | 0.726 |
| Electrical and Electronic Engineering | 24 | 997 | 854 | 0.088 | 0.118 |
| Psychiatry and Neuroscience | 9 | 956 | 822 | 0.093 | 0.043 |
| Communication, Cultural and Media Studies | 66 | 688 | 608 | 0.099 | 0.567 |
| Art and Design | 63 | 2356 | 1837 | 0.101 | 0.933 |
| Metallurgy and Materials | 29 | 500 | 452 | 0.112 | 0.26 |
| Primary Care | 8 | 197 | 186 | 0.131 | 0.672 |
| French | 52 | 485 | 440 | 0.135 | 0.665 |
| Philosophy | 60 | 742 | 655 | 0.17 | 0.513 |
| German, Dutch and Scandinavian Languages | 53 | 280 | 262 | 0.184 | 0.048 |
| Linguistics | 58 | 407 | 375 | 0.23 | $\underline{0.004}$ |
| Psychology | 44 | 1977 | 1587 | 0.256 | 0.838 |
| Library and Information Management | 37 | 363 | 337 | 0.261 | 0.672 |
| Anthropology | 42 | 464 | 426 | 0.321 | 0.192 |
| Cancer Studies | 2 | 901 | 788 | 0.329 | 0.446 |
| Law | 38 | 1987 | 1601 | 0.396 | 0.319 |
| History of Art, Architecture and Design | 64 | 459 | 423 | 0.401 | 0.579 |
| Infection and Immunology | 3 | 784 | 697 | 0.463 | 0.462 |
| Accounting and Finance | 35 | 212 | 203 | 0.464 | 0.588 |
| Middle Eastern and African Studies | 48 | 201 | 193 | 0.493 | 0.476 |
| Russian, Slavonic and East European Languages | 51 | 172 | 166 | 0.501 | 0.173 |
| Development Studies | 43 | 277 | 263 | 0.512 | 0.383 |
| American Studies and Anglophone Area Studies | 47 | 103 | 101 | 0.624 | 0.706 |
| Politics and International Studies | 39 | 1635 | 1358 | 0.637 | 0.461 |
| Pre-clinical and Human Biological Sciences | 15 | 722 | 650 | 0.641 | 0.484 |
| European Studies | 50 | 576 | 528 | 0.674 | 0.401 |
| Architecture and the Built Environment | 30 | 740 | 667 | 0.726 | 0.596 |
| Italian | 54 | 140 | 137 | 0.732 | 1 |
| Business and Management Studies | 36 | 3999 | 2945 | 0.761 | 0.007 |
| Statistics and Operational Research | 22 | 430 | 404 | 0.81 | 0.857 |
| Cardiovascular Medicine | 1 | 466 | 437 | 0.866 | 0.907 |
| Physics | 19 | 2072 | 1690 | 0.914 | 0.295 |
| Other Laboratory Based Clinical Subjects | 5 | 328 | 317 | 0.977 | 0.989 |
| Pure Mathematics | 20 | 793 | 723 | 0.978 | 0.106 |
| Applied Mathematics | 21 | 984 | 885 | 0.995 | 0.08 |
| Computer Science and Informatics | 23 | 2144 | 1794 | 1 | 0.304 |
| Economics and Econometrics | 34 | 1075 | 982 | 1 | 0.259 |

For each discipline, I report the number of academics, the number of last names and the p -value obtained considering the last names of all professors. I then computed the p -values when only the 7,500 most common last names are considered.

Table 4. Analysis of Italian Academia: Common Last Names and Gender

| Code | p | Common-p | $\mathrm{F}-\mathrm{p}$ | $\mathrm{M}-\mathrm{p}$ |
| ---: | :---: | :---: | :---: | :---: |
| MED | $\underline{\leq 0.001}$ | $\underline{\leq 0.001}$ | 0.044 | $\underline{\leq 0.001}$ |
| ING-IND | $\underline{\leq 0.001}$ | $\underline{0.003}$ | 0.453 | $\underline{0.001}$ |
| IUS | $\underline{\underline{0.001}}$ | $\underline{0.006}$ | 0.022 | $\underline{\leq 0.001}$ |
| M-GGR | $\underline{\underline{0.005}}$ | $\underline{\underline{0.028}}$ | 0.38 | 0.213 |
| M-PED | $\underline{0.005}$ | $\underline{0.036}$ | 0.214 | 0.044 |
| AGR | $\underline{0.008}$ | 0.27 | 0.126 | 0.361 |
| ICAR | $\underline{\underline{0.01}}$ | 0.104 | 0.082 | 0.02 |
| MAT | $\underline{0.019}$ | 0.289 | 0.005 | 0.272 |
| CHIM | $\underline{\underline{0.036}}$ | 0.149 | 0.146 | 0.153 |
| GEO | $\underline{0.047}$ | 0.178 | 0.26 | 0.193 |
| M-FIL | $\underline{0.048}$ | 0.126 | 0.375 | 0.259 |
| M-STO | 0.061 | 0.271 | 0.61 | 0.1 |
| SECS-S | 0.088 | 0.258 | 0.832 | $\leq 0.001$ |
| VET | 0.126 | 0.403 | 0.208 | 0.249 |
| SPS | 0.14 | 0.427 | 0.036 | 0.741 |
| BIO | 0.153 | 0.751 | 0.55 | 0.065 |
| INF | 0.192 | 0.539 | 0.364 | 0.382 |
| FIS | 0.245 | 0.469 | 0.25 | 0.56 |
| L-FIL-LET | 0.278 | 0.447 | 0.045 | 0.848 |
| SECS-P | 0.291 | 0.716 | 0.892 | 0.076 |
| M-EDF | 0.347 | 0.342 | - | 0.399 |
| L-ART | 0.36 | 0.515 | 0.701 | 0.063 |
| ING-INF | 0.389 | 0.529 | 0.306 | 0.502 |
| L-ANT | 0.702 | 0.664 | 0.85 | 0.965 |
| L-OR | 0.741 | 0.667 | 1 | 0.816 |
| M-PSI | 0.769 | 0.61 | 0.794 | 0.463 |
| L-LIN | 1 | 0.335 | 0.98 | 0.978 |
| M-DEA | 1 | 1 | 1 | 1 |
|  |  |  |  |  |

For each discipline, I report the p-value obtained considering the last names of all professors. I then computed the p-values when only the 7,500 most common last names are considered, and when professors are divided according to gender.


[^0]:    For each discipline, I report the number of academics, the number of last names and the p-value obtained considering all
    professors. For each macro-region (North, Center, South, Sardinia, Sicily), I report the p-value obtained repeating the analysis on the subset of professor working in the macro region. I also report the proportion of regions in which a discipline yields a p-value $\leq 0.05$ and the count of regions with low p-values. In fact, I only considered regions in which 50 or more academics are working in a given discipline. Underlined (highly significant) values are those with p-value and $q$-value $\leq 0.05$.

