Working papers series

WP ECON 21.03

Gendered cities: Studying urban gender bias through street names

Dolores Gutiérrez-Mora
Universidad de Sevilla

Daniel Oto-Peralías
Universidad Pablo de Olavide

Keywords: Street names, toponyms, cities, quantitative analysis, gender inequality, women.

JEL Classification: J16, R19, Z13

Department of Economics

Gendered cities: Studying urban gender bias through street names

Dolores Gutiérrez-Mora and **Daniel Oto-Peralías**

March 2021

Abstract

This paper uses text analysis to measure gender bias in cities through the use of street names. Focusing on the case of Spain, we collect data on 15 million street names to analyze gender inequality in urban toponyms. We calculate for each Spanish municipality and each year from 2001 to 2020 a variable measuring the percentage of streets with female names over the total number of streets with male and female names. Our results reveal a strong gender imbalance in Spanish cities: the percentage of streets named after women is only 12% in 2020. We also observe substantial differences across Spanish regions, and concerning new streets, gender bias is lower but still far from parity. The second part of the paper analyzes the correlation of our indicator of gender bias in street names with the cultural factor it is supposed to capture, with the results suggesting that it constitutes a useful cultural measure of gender equality at the city level. This research has policy implications since it helps to measure a relevant phenomenon, given the strong symbolic power attributed to street names, which has been elusive to quantify so far.

Keywords: Street names, toponyms, cities, quantitative analysis, gender inequality, women

Dolores Gutiérrez-Mora, Universidad de Sevilla, Departamento de Historia, Teoría y Composición Arquitectónicas, Escuela Técnica Superior de Arquitectura. Av. Reina Mercedes, 2, Seville, 41012, Spain.

Daniel Oto-Peralías, Universidad Pablo de Olavide, Departamento de Economía, Métodos Cuantitativos e Historia Económica. Carretera de Utrera, Km. 1, Seville, 41013, Spain. E-mail: dotoper@upo.es

Acknowledgements: We thank conference participants at the European Regional Science Association Conference (Lyon, 2019), IX Jornadas Arte y Ciudad: Visiones Urbanas (Madrid, 2020), and seminar participants at the Universidad Pablo de Olavide, University of St Andrews, Universidad Pública de Navarra, and Joint Research Center of the European Commission in Seville for valuable comments and suggestions. Financial support by the Spanish Ministry of Science, Innovation and Universities through grant ECO2017-86780-R (AEI/FEDER, UE) is gratefully acknowledged.

1 Introduction

Streets named after men vastly outnumber those named after women. How large is this gender bias in our cities? To what extent does it vary across time and space? Are our cities becoming more egalitarian in this sphere? Does this bias reflect the view of the population towards gender roles? The aim of this article is to develop a methodology to quantify gender bias in street names through computational tools of text analysis. By doing so, we construct a geographic-specific and time-variant indicator of female share in street names that helps us answer these questions, and consequently, study the geographic variability of the phenomenon, its evolution over time, and its explanatory factors.

Street names carry a strong symbolic power and are very present in our everyday life. In addition to their physical presence on street signs, they are constantly used in ordinary situations. An apparently mundane facet of urban management, "street naming systems also make up the very foundations of urban spatial imaginaries" (Rose-Redwood et al., 2017, p. 309). Although not commonly noticed, they exert a subtle but constant influence, naturalizing the social and cultural meanings inscribed on them (Azaryahu, 1996; Rose-Redwood et al., 2010). Gender bias in street names should therefore not be overlooked, and there are indeed numerous social initiatives across countries pursuing a more egalitarian presence of women in the cityscape (Bigon and Zuvalinyenga, 2020).

We collect data on 15 million street names in Spain to analyze gender inequality in urban toponyms. We calculate for each Spanish municipality and each year from 2001 to 2020 a variable measuring the percentage of streets with female names over the total number of streets with male and female names, which we call "female share". A crucial feature of our methodology is the development of a classifier algorithm to be able to compute such an indicator for a large sample of spatial units (i.e., towns, cities, etc.), on a large territorial scale (a whole country, or potentially several of them), and at a yearly basis, which represents a major progress regarding what has been done so far. This allows comparative studies across cities, as well as tracking them over time.

Our results reveal a strong gender imbalance in Spanish cities: the female share in streets named after a person goes from 9.6% in 2001 to 12.1% in 2020. These aggregate values hide a lot of spatial variation, with provincial average values ranging from 8.4 to 16.9%. Focusing on cities larger than 200k inhabitants and provincial capitals, the indicator ranges from 5.6% (Elche) to 20.6% (Jaén). Concerning new and renamed streets, gender bias is lower but still very far from parity as the female share is 18.4% for the whole period, and again with a wide geographic variation.

The second part of the paper analyzes the correlation of our indicator of gender bias in street names with the cultural factor it is supposed to capture. We find that municipalities with a higher female share in street names tend to have larger, better educated and younger populations, larger service sectors, more separations and divorces, and lower gender gaps in labor force activity rate, education and housework. In addition, people living in towns with a higher female share have on average more egalitarian gender views. Interestingly, we further show that provinces with a higher female share have also historically had more prominent women, as measured by the percentage of female entries in the Spanish Biographic Dictionary.

The low proportion of women in the streetscape constitutes further evidence of their underrepresentation in the public sphere. This exclusion not only reflects a historical and cultural fact, but also contributes to its perpetuation by making the presence of male names more 'natural' in daily life. In addition, their symbolic marginalization through a gendered street map leads to feelings of exclusion, revealed through interviews and by the existence of social movements (Bigon and Zuvalinyenga, 2020). The female share indicator can be a useful tool for a more just urban management policy in order to monitor progress towards a more inclusive urban toponymy. Such a policy contributes to the UN Millennium Development Goals of gender equality, empowerment of women, and more inclusive and safer cities.

From a research perspective, the female share indicator constitutes a useful measure for the analysis of factors favoring women-friendly policies at the local level. Moreover, it can also be used as a proxy for cultural attitudes towards gender roles, expanding the possibilities of analysis with this novel measure. While this article focuses on the Spanish street map, the proposed methodology of measuring gender bias in street names on a large scale is applicable elsewhere.

The remainder of the paper is organized as follows. Section 2 provides some background and a brief overview of the related literature. Section 3 discusses the methodology for the construction of the female share indicator and tests its validity. Section 4 presents the main results of the indicator as well as its correlation with other variables related to gender inequality and the role of women in society. Finally, Section 5 puts forward some implications and concludes.

2 Background and related literature

This study uses a research methodology that applies text analysis to urban toponyms in order to measure sociocultural phenomena at the local level (Oto-Peralías, 2017, 2018). Street names are not random; they represent cultural markers of a city and its history. Street names reflect the commemorative decisions of municipalities over time and, as such, can be understood as a "manifesto" about its cultural, social and political values (Rose-Redwood et al., 2010, 2017). Building on these insights, Oto-Peralías (2018) proposes the use of the information contained in street names to measure cultural variables at the city level, which is very convenient given the growing interest in studying the causes and consequences of cultural factors, and the scarcity of data at the local level.

Focusing on religiosity, the most prominent cultural factor in Spanish street names, Oto-Peralías (2018) shows that the population in provinces with a higher percentage of religious streets tends to have stronger religious beliefs, as reflected by church attendance. Moreover, municipalities with more religious streets have on average a lower incidence of separation and divorce and fewer *de facto* couples. Thus, these results support the existence of a relationship between street names and the cultural values of the population. These findings appear to apply to other countries as well. In applying this to the case of Scotland, people living in areas with street names commemorating Great Britain are less likely to identify themselves as Scottish only (Oto-Peralías, 2017).[1]

In addition to the usefulness of urban toponyms to measure certain cultural values, the critical geographic literature attributes a strong symbolic power to them. This branch of the literature focuses on the process of naming and its implications. That process, according to Rose-Redwood et al. (2010), "sheds light on power relations—how some social groups have the authority to name while others do not—and the selective way in which such relations reproduce the dominance of certain ideologies and identities over others" (p. 462). Street names introduce a version of history and cultural values into the common space of everyday life and, therefore, can contribute to the reproduction of this narrative, becoming powerful instruments for legitimizing the status quo (Azaryahu, 1996). This symbolic power is reflected in the frequent modification of street names that accompanies important political changes, by which political regimes seek to "naturalize" their authority (Palonen, 2008; Rose-Redwood et al., 2010, 2017; Drozdzewski, 2014).

Given the emphasis of the critical geographic literature on the symbolic power of street names, the representation of all sectors of the population has a crucial role for their social inclusion (Lombardo and Meier 2018), and the lack of symbolic representation gives rise to an unfriendly environment for the exercise of representative activities. Ethnicity, class, gender, sexuality, etc., have been and are reasons for exclusion at the symbolic representative level (Berg and Kearns, 1996; Tretter, 2011; Forrest, 2018). However, women are not comparable to the rest of the groups, as they are not a minority but half of the population, also contained in the other groups.[2]

Women have historically been excluded from public life, towards the private sphere (Madanipour, 1999). As a result, their work has been less known and recognized, making it more difficult to be present in the public realm. Within this context, the overrepresentation of male names in the cityscape not only reflects a historical and cultural fact; it can also contribute to its perpetuation by making the presence of male names to be more "natural" in

[1] From a methodological point of view, this line of work is related to articles that study regional identity through traces such as town and business names (Ambinakudige, 2009; Cooper et al., 2010; Fuchs, 2015; Liesch et al., 2015; Weaver and Holtkamp, 2016). See also Graham and De Sabbata (2015) for an interesting quantitative analysis of toponyms at the worldwide level.

[2] The official narratives that follow armed conflicts seek to reinforce a certain feeling of national identity, which is reflected in the commemorations that perpetuate a particular version of history, notably in street names. In these cases, female identities tend to be considered of secondary importance and consequently, women protagonists are generally forgotten (McDowell, 2008; Mamvura et al., 2018). The persistence of these names over time makes it difficult for women to access these urban representative spaces.

the public sphere.[3] This male predominance can aggravate a certain feeling of exclusion from the urban space, affecting "the urban political experience and emotional well-being of women" (Bigon and Zuvalinyenga, 2020, p. 2). Understandably, there is a reaction to this unfair situation: the desire of (symbolic) empowerment and reclaiming of the public space, channeled through social movements that promote a greater presence of women in street names.[4]

Finally, concerning studies focusing on gender inequality in toponyms, most of them are case studies of specific cities that reveal a large gender bias in street names. For Spain, case studies of Madrid, Seville and Santiago de Compostela break down the profile of commemorated women, finding a high percentage of them belonging to the religious sphere (Fernández, 2004; Núñez, 2019; Novas, 2018). For other countries, studies of cultures as different as Buenos Aires (Argentina) and Anping (Taiwan) conclude that gendered street names contribute to the persistence and reinforcement of gender stereotypes, that is, the traditional perception of the female role in society (Cavalo, 2019; Yu, 2014). Bigon and Zuvalinyenga (2020) show that the exclusion of women from urban place names is salient in Sub-Saharan Africa. Moreover, these works show that women are not only quantitatively under-represented, but also qualitatively in the hierarchy of the urban network (with female names being relatively more frequent in secondary streets and the periphery). It is worth emphasizing that the attempts so far to measure gender bias in urban toponyms are referred to a single city or a small number of cities. Our work is the first to do it at a large scale, for all towns and cities in a country.

3 Measuring gender bias through street names

3.1 Data

Our main dataset is the *Electoral Census Street Map* provided by the Spanish Statistics Office (INE, 2020). This dataset contains the list of Spanish streets and roads, indicating their name, type (avenue, street, square, etc.), and municipality code. An important advantage of this dataset is that it provides data from 2001 to 2020 (except 2002 and 2003), thereby allowing

[3] Beyond street names, linguists consider that our language itself may influence and constraint our thinking (Ginsburgh and Weber, 2020). Regarding the symbolic power of language, Mavisakalyan (2015) finds that countries with gender-intensive languages have lower female labor force participation, and that speakers of these languages have a higher prevalence of gender-discriminatory attitudes. Relatedly, Galor et al. (2020) show that the presence of grammatical distinction based on gender, and its association with gender bias, has an adverse impact on the educational results of women.

[4] Some examples include "Toponomastica femminile" (Italy), "Las calles de las mujeres" [The street of women] (international), "Mapping female versus male street names" (international), "A tu nombre" [To your name] (Uruguay), "Merezco una calle" [I deserve a street] (Spain), and "Rehov MiShela" [a street of her own] (Israel). As the French group "Osez le Féminisme!" put it in a performance in which they symbolically rename 60 streets in Paris, "street names attest to our history: they belong to a political choice, revealing the values that the city wishes to embody" (The Independent, August 27, 2015).

temporal analysis. Other sources, such as *Open Street Map*, provides data for all countries but focusing on the present day. We also use a geographic layer containing all the streets and roads of the country in 2017 (IGN, 2020) to be able to measure not only the number of streets of each gender, but also their length.

The full dataset (2001-2020) contains almost 15 million streets, which divided by 18 years renders an average of 830,000 per year. Before using it to construct indicators, the data needs to be cleaned and processed: (i) repeated street names in a municipality, with the same road type, are removed, (ii) the text is converted to lowercase, and accent marks, special characters and common *stopwords* are removed to streamline the text search process; (iii) a blank space is added at the beginning and end of each street name, which reduces potential confusions when identifying names, and (iv) street names shorter than three characters are removed. The resulting number of streets for the whole period is 14,840,202.

The *Electoral Census Street Map* includes a unique code for each road. This number allows us to identify new streets and streets that have been renamed. When a road with a new identifier number appears in a given year within a municipality, we code this street as a new street. Relatedly, when a street with the same identifier changes its name, it is coded as a rename. According to this, during the period 2001-2020 there have been 174,022 new streets and 38,430 renames. These numbers correspond to the 24.2% and 5.3% of the total number of streets in 2001, respectively. The total variation in streets between 2001 and 2020 is 154,636, which does not match the number of new streets because some streets disappear from the dataset when there are no electors living there anymore. This latter figure (the net growth of streets) amounts to the 21.5% of the number of streets in 2001. For comparison purposes, Spain's population growth during the same period was somewhat smaller, 15.4%.

3.2 Construction of the indicator

The street-name indicator of female share is defined as:

$$FS_{m,y} = \frac{F_{m,y}}{M_{m,y}+F_{m,y}} \times 100 \qquad (1)$$

where the numerator $-F_{m,y}-$ captures the number of streets in municipality m and year y containing a female name (i.e., referred to women), and the denominator $-M_{m,y}+F_{m,y}-$ measures the total number of streets referred to both men and women.

The most challenging task is to identify whether a street has a male or female name. For this purpose, we develop an algorithm to classify streets according to their gender, if any.[5] Our

[5] This task is significantly different to detecting the gender of a given forename, for which there are already some commercial Apps available (Santamaría and Mihaljević, 2018). The difference lies in that only a fraction of streets is named after a person. In addition, not all streets with forenames actually refer to men or women ("false positives"), and many male and female streets do not actually contain names but nicknames or last names. Therefore, available gender guessers are not appropriate here.

text-analysis algorithm is based on a “dictionary-based method”, which uses pre-specified dictionaries (or lists) of terms to obtain an estimate of the result of interest (Gentzkow et al., 2019). The classifier algorithm is constructed following five steps (Figure 1):[6]

i) We create a street-level binary variable denoted by *stname_male* measuring whether streets contain any of the 1,000 most frequent male forenames in Spain (INE, 2016). Analogously, we create a variable *stname_female* to capture the presence of female forenames.

ii) To avoid “false positives”, we need to tackle ambiguous names. This is important because many names in the aforementioned lists can refer to both a person and something else. Examples are “Israel” (male) and “Rosa” (female), which may also refer to a country or a flower (or color). We proceed as follows: first, we revise the previous lists of the 1,000 most frequent male and female forenames and detect the ambiguous ones; and second, we recode *stname_male* and *stname_female* as 0 when a street has an ambiguous forename *and does not* contain a surname *nor* a compound forename. That is, we consider that ambiguous names that are not accompanied by a surname nor another forename (ie. compound name) do not refer to a person.

iii) We correct those cases in which a street name contains both a male and a female forename. This happens in two cases: a) a same forename is used for both men and women (e.g., “Andrea”); and b) compound forenames formed by a male and a female name (e.g., “José María”). In the first case, streets are excluded and consequently *stname_male* and *stname_female* are coded as 0. In the second case, the gender of the street depends on the position of each forename (if the male forename is placed before the female one, it is considered a male name, and vice versa).

iv) To address “false negatives”, we create lists of male and female words such that if a street name contains one of these terms, it will be coded as male or female, respectively. For the construction of these lists, we gather data from several sources, involving a substantial data collection effort. First, we use the lists of words collected in Oto-Peralías (2018, Table 1), which categorizes the 200 most frequent words in the street names of each Spanish region. Second, we use the dataset of famous people *Pantheon 2.0* (Yu et al, 2016) and select entries for which the place of birth or death is Spain, which renders 2,130 names (14,7% of them female). Third, we create a training dataset made up of 10,000 manually-classified streets, from which we also collect male and female words. The resulting lists of terms contain keywords such as “don”/“doña” [Sir, Madam], “doctor”/“doctora” [male/female doctor], and “duque”/“duquesa” [duke, duchess], as well as nicknames and last names of famous figures such as “Goya”, “Cervantes” and “Ramón y Cajal”.

v) Religious streets related to God, Christ, Virgin Mary (and her apparitions), apostles, and saints are not taken into account and consequently removed. These names are relatively more frequent among female streets and could bias the relevant female share as streets named -for

[6] A more detailed description of the classifier algorithm is provided in Supplementary Material I.

instance- after Virgin Mary (very common in Spain) are not really commemorating relevant figures to the modern concept of gender equality. Nonetheless, as an alternative measure of the female share, we also keep religious streets.

[*Insert Figure 1 here*]

We use the training dataset mentioned above to develop the algorithm, which helps us create the dictionaries of terms that feed the classifier. As expected, our classifier performs very well with the training dataset. Regarding male streets, the coefficients of precision, sensitivity, specificity, and accuracy are all above 99%. With respect to female streets, the coefficients are 95.8, 97.7, 99.9 and 99.8, respectively. These are not 100% as we do not want to overfit the model to the data.

Once street names are classified, we compute for each municipality M_m and F_m as $\sum_1^N stname\_male_i$ and $\sum_1^N stname\_female_i$, respectively. Figure 1 represents the steps of the classifier algorithm using the year 2001 as an example. It can be seen that the steps of removing false positives, adding false negatives, and removing religious streets are crucial for the final outcome.

3.3 Validity of the indicator

This section assesses the validity of the indicator, that is, whether its measurement is close to the real value. For this purpose, we construct a test dataset, made up of 5,000 streets selected randomly, which we classify manually. Table 1 shows the performance of the classifier algorithm against the test dataset. The accuracy is very high for both male and female streets (97.3 and 99.2%, respectively). Regarding the other coefficients, the weakest results are for sensitivity due to the presence of false negatives, which are more common than false positives. This is hardly surprising given the local nature of the data, where many streets are named after local people using their nicknames or surnames. The last column reports a coefficient that we call "deviation rate", which is calculated as cases identified as positives divided by real positives minus one. This is an important coefficient because if it is similar for male and female streets, then the female share will also be similar to its "true" value. This is actually the case here, as the difference between the deviation rates is about one percentage point (pp.). Consequently, the female share based on the classifier is very similar to the one based on human-made classification (12.32 vs 12.48%). Thus, the classifier algorithm is not error-free, but to the extent that errors identifying female streets are similar in relative magnitude to errors identifying male streets, errors offset one another and do not bias the female share.

[*Insert Table 1 here*]

The probability of a small difference in the deviation rate between male and female streets is positively related to the sample size. Intuitively, when the sample is small, counting one female street more can have a large impact on the deviation rate and -hence- on the female share. Figure 2 presents the results of a simulation exercise with sample sizes ranging from 10 to 500. Panel A shows that the larger the sample size, the smaller the difference in the deviation rate between male and female streets. Consistently, Panel B depicts a similar negative relationship with the mean absolute error of the female share. Interestingly, this graph gives us a measure of the expected error depending on the number of streets. For instance, for a sample of 10 streets, the expected difference with the "true" female share lies between 1.5 and 7 pps. For a sample of 100 streets, this declines to the interval between 2.5 and 3.5 pps. Finally, Panel C reports the mean error, which shows whether, on average, the female share from our algorithm is higher or lower than the "true" value. As the trend line is just below zero, the classifier tends to slightly underestimate the female share.

[*Insert Figure 2 here*]

To further assess the validity of the classifier algorithm, we compare our estimates with results of case studies conducted for specific cities in Spain. We collect data on 26 estimates of the female share for a variety of cities and years from several sources. They largely correspond to Spain's most important cities such as Barcelona, Madrid, Valencia and Sevilla, although there are also smaller cities such as Huesca, Cáceres and Girona. Figure 3 represents the relationship between the estimates of our classifier algorithm and those of case studies.[7] Remarkably, the correlation between both measures is very strong (0.94). In addition, the classifier does not systematically over nor underestimate the female share, as errors are both above and below the 45-degree line.[8]

[*Insert Figure 3 here*]

4 Female share: results

4.1 National level results

This section presents the results of the female share indicator for Spanish street names. To begin with, we report the results for the whole country. Panel A of Figure 4 shows the evolution of the female share from 2001 to 2020 for all existing streets. The baseline indicator (solid line) goes from 9.6% in 2001 to 12.1% in 2020, thereby indicating a strong gender imbalance in the

[7] The list of sources, cities and years are provided in Supplementary Material II. Some cities are included more than once when coming from different sources or referring to different years. Religious names are included when case studies do so. Most observations refer to the standard definition of female share (circular marker), but there are two cases in which the female share refers to new streets named during a particular period (crosses), and two cases measuring the fraction of female streets over the total number of streets (squares).

[8] It is worth noting that it is virtually impossible to calculate the "true" value of the female share, even in carefully done case studies. This is because some streets have ambiguous names, and it is almost impossible to know whether the name is intended to refer to a person. One would need to know the very origin of the street name (the meaning given by the local community). As explained above, ambiguous names are not considered in our classifier, but the criterion applied by case studies may differ. Consequently, some differences between our estimates and those of case studies are expected.

street map and a slow progress towards parity. When we take a more flexible approach regarding religious streets and include streets named after saints, the female share increases roughly 1 pp.; and when considering all religious streets, the female share increases about 4 pps. Panel B focuses on new and renamed streets. The female share is significantly higher and more volatile, ranging between 13.6% in 2015 and 24.5% in 2020. While these values are higher, they are still far from 50% that would imply parity.

Panel C depicts the frequency distributions of male and female streets, focusing on the 100 most common street names of each gender. Interestingly, the concentration in female names is higher: the relative frequency of the most common female name (the politician and women's rights advocate Clara Campoamor) is 2.3%, while that of the most common male name (Cervantes) is approx. 1%. Considering the cumulative distributions, the top-10 female street names concentrate 12.8% of all female streets, while the top-10 male ones concentrate 6% of male streets. This fact reveals that local authorities tend to resort to famous nationwide figures to a larger extent for female names than for male names.

[*Insert Figure 4 here*]

Streets are heterogeneous, particularly in length, so the female share could be different when considering street length. To shed light on this, we combine our main dataset with a geographic layer containing every street and road in the country in 2017 (IGN, 2020). We manage to match 78.5% of all streets with male and female names in 2017. For these streets, the baseline measure of the female share is 10.58%, while it slightly declines to 10.24% when taking into account street length. The picture is very similar for both metrics because the average length of male streets is only slightly longer than that of female streets (236.07 and 227.67 meters, respectively). Finally, we further calculate a related measure in which we weight each street by its category (street, avenue, square, etc.), where weights are given according to the average length of streets of each category for similar municipalities.[9] This measure can be calculated for more than 99.5% of streets and renders a female share of 12.43% in 2020, slightly higher than the baseline indicator. Therefore, the results are fairly similar no matter the way the female share is calculated. Indeed, the correlation among these three measures is very high for the analyzed period (above 0.995).[10] Given this evidence, the rest of the article focuses on the simpler baseline indicator.

4.2 Regional and city level results

[9] More specifically, for each province, we create 5 quantiles of municipalities by their number of streets. Next, within each quantile (within each province), we calculate the average length of streets of each category. Then, this average length is used as a weight.

[10] The cross-section correlation at the municipality level of the baseline female share with the measure in meters is 0.945, and with the weighted measured by street category is 0.976.

The main advantage of street names to measure social phenomena is its spatial granularity. It allows the study of the phenomenon of interest at the regional and local levels. Figure 5 represents the female share at the provincial level, which is the second-tier administrative division in Spain. Panel A shows the female share in 2020, while Panel B does so for new and renamed streets during the period 2001-2020. There is substantial spatial variation, with values ranging from 8.4% (Soria) to 16.9% (Granada) in the former, and from 10.1% (Teruel) to 29.3% (Córdoba) in the latter. Panel C shows the distribution of values of the female share indicator. We can notice that the distribution slowly shifts to the right from 2001 to 2020, and that the distribution for new and renamed streets is wider and with higher values. Panel D depicts a positive correlation between the female share in 2001 and that for new and renamed streets (p=0.49). Thus, provinces with a higher percentage of female streets in 2001 have on average named more streets after women during the next 20 years, reflecting some persistence or inertia over time.

[*Insert Figure 5 here*]

Figure 6 represents the data at the city level. We focus on towns equal to or larger than 10,000 inhabitants for visualization purposes. Panel A shows the female share in 2020 and reveals a significant spatial variation. It is common to find neighboring cities with different female shares. Panel B is analogous to the previous one but for new and renamed streets. The map is populated with more black dots as the female share is higher for new streets. Panels C, D and E depict binned scatter plots looking at the relationship between different versions of the female share indicator. The first scatterplot compares the baseline female share (on the x axis) with this measure when including religious streets (y axis). The former is generally lower than the latter, and this is because religious streets are relatively more frequent among female streets. Panels D and E show that the baseline indicator of female share is highly correlated with alternative measures weighted by street length and street category. This latter result suggests that the main driver of gender inequality in the streetscape is the much higher frequency of male names rather than differences in street length or their category.[11]

[*Insert Figure 6 here*]

The granularity of the data enables us to zoom in on cities and visualize the gender composition of the street map, and even to calculate the female share at the city district level. Figure 7 draws the gendered street maps of Spain's largest cities. These visualizations, fed with the output of our classifier, are valuable tools to communicate and make visible the research question addressed, clearly showing relevant patterns and trends (Sword and Liu, 2015). Thus, by measuring gender bias in street names it is possible to analyze and visualize this, thereby favoring a public reflection.

[*Insert Figure 7 here*]

[11] Another not explored dimension in which streets may differ is in their position within the urban network, with some case studies finding a higher frequency of female streets away from the city center.

4.3 Correlations of the female share

This section analyzes the correlations of the female share indicator at the municipality level. This exercise is interesting to know what factors are related to (gender) egalitarian naming policies. In addition, to the extent that the commemorative decisions of the local community reflect its cultural values, this exercise gives us clues about the determinants of the population attitudes towards gender roles.

Figure 8 focuses on variables related to a greater or lesser extent to gender equality at the local level. To begin with, one would expect more egalitarian attitudes towards gender roles in bigger towns, with a young and educated population. This is exactly what Panels A to C show. Considering average age (Panel B), the fitted line implies that an increase of 10 years in average age is associated with a decrease of 2 pps. in the female share. This is a sizeable variation given an average female share of just 8.2% for the whole sample of municipalities.[12]

The next row (Panels D to F) analyzes the correlations with: i) the service sector share in employment, ii) the percentage of separated and divorced people, and iii) the percentage of residents born in the municipality. Regarding the first variable, the service sector has been (and still is) the most feminized sector, implying more chances for women to work outside and play relevant public roles. The second variable, the percentage of separated and divorced people, is also expected to be higher in areas where women are more independent. Concerning the last variable, a lower percentage of residents born in the municipality implies a more dynamic place, with weaker ties with older generations and possibly less traditional attitudes towards gender roles. Interestingly, the female share is positively correlated with the first two variables, while the correlation is not clear in the latter case.

The bottom part of the figure (Panels G to I) includes indicators that explicitly aim to capture gender (in)equality in several dimensions for which data is available at the local level. These are the gender gaps in: i) labor force activity rate, ii) percentage of population with secondary or higher education, and iii) percentage of population doing housework. Remarkably, there is a clear negative relationship between the female share in street names and these measures of gender gap. Considering the gender gap in housework (Panel I), an increase of 25 pps. (moving from percentile 20th to 80th) is associated with a decrease of 1 pp. in the female share.[13]

[*Insert Figure 8 here*]

[12] All variables are measured in 2001. The female share is censored at the 95th percentile to mitigate the influence of abnormally high values. Variable definitions, sources, and descriptive statistics are provided in Supplementary Material III.

[13] Figure 8 reports simple bivariate correlations, but we show in Supplementary Material IV that they are robust when controlling for a set of 17 region binary variables. On top of this, we additionally include the log of town population, which does not alter the results either. Moreover, if we focus on towns with more than 100 streets (where measurement errors are lower), the correlations remain largely unchanged.

To further assess the link between the female share indicator and the population attitudes towards gender roles, we collect survey data from the *ISSP Family and Changing Gender Roles* modules, corresponding to the years 1994, 2002, and 2012 (CIS, 2020). These three surveys have six questions that can be combined to create a composite indicator of attitudes towards gender roles.[14] There are 2,732 individuals distributed across 70 cities for which we know the municipality code. This enables us to analyze whether the female share of the respondent's municipality is related to her gender views. We use the following hierarchical linear model estimated via Ordinary Least Squares (OLS):

$$Y_{i,c,r} = \alpha + \beta \cdot Ind_{i,c,r} + \delta \cdot C_{c,r} + \gamma \cdot FS_{c,r} + \eta \cdot R_r + \varepsilon_{i,c,r} \qquad (2)$$

where $Y_{i,c,r}$ is the composite indicator of gender views of individual i living in city c located in region r. $Ind_{i,c,r}$ is a vector of control variables at the individual level (sex, age, marital status, educational level, socioeconomic status, and interview year); $C_{c,r}$ is a vector of control variables at the city level (log population in 2001 and number of streets); $FS_{c,r}$ stands for the female share in street names; R_r refers either to a set of 17 binary variables, one for each Spanish region, or a set of 50 binary variables, one for each province; and $\varepsilon_{i,c,r}$ is the error term. The coefficient of interest is γ, which captures the effect of 1 pp. increase in the female share.

Table 2 reports the results. Column 1 shows a positive correlation between the female share indicator and gender views, which is statistically significant at 10%. Columns 2 and 3 add individual-level and municipality-level control variables, respectively, with little impact on the coefficient of interest. Column 4 further includes a set of 17 binary indicators, one for each region, which makes up our baseline model. This model only exploits variation in interview responses within regions but not across regions. The coefficient is now larger and more precisely estimated. Moving from the town in the sample with the lowest female share (1.3%) to the one with the largest (38.46) is associated with an increase of 0.49 in gender views, a non-negligible magnitude (given a standard deviation of 1.5). Column 5 includes a set of 50 binary indicators, one for each province, which does not alter the previous results. All in all, these results suggest that people living in towns with a higher female share tend to have more egalitarian gender views. Arguably, more egalitarian communities name more streets after women than less egalitarian ones.

[*Insert Table 2 here*]

Finally, we explore whether places where women have historically played more prominent roles are more likely to commemorate them in their streets. To measure the historical prominence of women in society, we use the Spanish Biographical Dictionary (Real Academia de la Historia, 2018), a monumental work containing more than 50,000 historical figures. We calculate the percentage of dictionary entries in each province referring to women. Figure 9 shows that there is indeed a clear positive (province-level) correlation between the female share

[14] See Supplementary Material V for details on the construction of the indicator.

indicator and the percentage of female entries. This correlation is robust to the inclusion of control variables such as per capita GDP and total population.[15]

[*Insert Figure 9 here*]

5 Discussion and conclusions

This article develops a methodology to quantify gender bias in street names through the use of computational tools of text analysis. This allows to measure gender bias in urban toponyms on a massive scale. We apply the methodology to 15 million roads that make up the Spanish street map for the period 2001-2020. The female share (i.e., the percentage of female streets over the total number of male and female streets) goes from 9.6% in 2001 to 12.1% in 2020. Considering new and renamed streets, the female share is higher, laying in the range 14-24%, but still far from 50% that would imply parity.

The female share indicator has an intrinsic value as a measure of the symbolic relevance given to women in the cityscape, allowing its comparison across space and time. Beyond this, our analysis shows that the female share is correlated with the cultural value it is supposed to capture. Municipalities with a higher female share tend to have larger, more educated and younger populations, larger service sectors, more separations and divorces, and lower gender gaps in labor force activity rate, education and housework. In addition, people living in towns with a higher female share tend to have more egalitarian gender views. We further show that provinces with a higher female share in street names also had relatively more prominent women historically, as measured by the number of female entries in the Spanish Biographic Dictionary.

Before concluding, three points are worth discussing. The first one has to do with the precision of the indicator. As mentioned above (Section 3), the larger the size (number of streets) of the town, the more precise the indicator. From 200 streets onwards, the absolute error is expected to be below 2.5 pps. Testing our results against a test dataset and case studies of specific cities provides reassurance to our methodology, but the algorithm is not error-free, and errors might be large for particular cases. Therefore, caution is needed when interpreting the results in an individual manner, in particular for small towns. In contrast, the analysis of the relationship of the indicator with other factors is safer since the main implication of measurement errors would be a downward bias in the coefficient of interest.

The second point is related to the applicability of this methodology to other countries and world regions. The classifier algorithm is based on dictionaries of terms with Spanish names and famous figures. When applying it to other countries, one needs to collect data to feed these dictionaries with the most common male and female names, as well as keywords denoting gender. Given the nature of the task, the methodology is more easily applicable to languages

[15] These results are provided in Supplementary Material VI.

with a strong gender system (with grammatical distinctions based on gender) like Spanish than to gender-neutral ones like Finnish.

Finally, although this article's main purpose is positive rather than normative, a more balanced representation of men and women in the cityscape seems to be a desirable outcome for societies that aspire to become more egalitarian. Our methodology can be a useful tool for urban management to monitor progress towards this goal. Increasing the female share in new streets is the easiest way forward in this regard, to avoid the opposition that may accompany renaming processes. From a research perspective, the female share indicator can be used as a useful measure for the analysis of factors favoring women-friendly policies at the local level. Moreover, it can also be used as a proxy for cultural attitudes towards gender roles, expanding the possibilities of analysis with this novel measure.

References

Ambinakudige S (2009) Revisiting ''the South'' and ''Dixie'' delineating vernacular regions using GIS. *Southeastern Geographer* 49: 240–250.

Azaryahu M (1996) The power of commemorative street names. *Environment and Planning D: Society and Space* 14(3): 311-330.

Berg LD and Robin AK (1996) Naming as norming: 'race', gender, and the identity politics of naming places in Aotearoa/New Zealand. *Environment and Planning D: Society and Space* 14(1): 99-122.

Bigon L and Zuvalinyenga D (2020) Urban Pulse-Gendered urban toponyms in the global South: a time for de-colonization? *Urban Geography*, forthcoming.

Cavalo LE (2019) Androcentrismo y espacio público: análisis exploratorio sobre la subrepresentación femenina en la nomenclatura urbana de la Ciudad Autónoma de Buenos Aires. *Feminismo/s* 33: 249-271.

CIS (2020) Estudios 2113, 2529 and 2942. Centro de Investigaciones Sociológicas. Available at: http://www.cis.es/

Cooper CA and Knotts HG (2010) Declining Dixie: regional identification in the modern American South. *Social Forces* 88: 1083-1101.

Drozdzewski D (2014) Using history in the streetscape to affirm geopolitics of memory. *Political Geography* 42: 66-78.

Fernández V (2004) *Memoria de mujeres en el callejero de Madrid.* Madrid: Concejalía de Gobierno de Empleo y Servicios al Ciudadano.

Forrest C (2018) What's in a name? A feminist reflection on street name changes in Durban. *Agenda* 32(2): 53-61.

Fuchs S (2015) An integrated approach to Germanic place names in the American Midwest. *The Professional Geographer* 67: 330-341.

Galor O, Özak Ö and Sarid A (2020) Linguistic traits and human capital formation. *AEA Papers and Proceedings* 110: 309-13.

Gentzkow M, Kelly B and Taddy M (2019) Text as data. *Journal of Economic Literature* 57(3): 535-574.

Ginsburgh V and Weber S (2020) The economics of language. *Journal of Economic Literature* 58(2): 348-404.
Graham M and De Sabbata S (2015) Mapping information wealth and poverty: the geography of gazetteers. *Environment and Planning A: Economy and Space* 47(6): 1254-1264.
IGN (2017) Redes de Transporte. Instituto Geográfico Nacional. Available at: www.ign.es.
INE (2016) Apellidos y nombres más frecuentes. Instituto Nacional de Estadística. Data referred to January 2015. Available at: www.ine.es
INE (2020) Callejero de Censo Electoral. Instituto Nacional de Estadística. Available at: www.ine.es.
Liesch M, Dunklee LM, Legg RJ, Feig AD and Krause AJ (2015) Use of business-naming practices to delineate vernacular regions: a Michigan example. *Journal of Geography* 114: 188-196.
Lombardo E and Meier P (2018) Good symbolic representation: the relevance of inclusion. *PS: Political Science & Politics* 51(2): 327-330.
Mcdowell S (2008) Commemorating dead 'men': gendering the past and present in post-conflict Northern Ireland. *Gender, Place and Culture* 15(4): 335-354.
Madanipour A (1999) Why are the design and development of public spaces significant for cities? *Environment and Planning B: Planning and Design* 26(6): 879-891.
Mamvura Z, Muwati I and Mutasa DE (2018) 'Toponymic commemoration is not for one sex': the gender politics of place renaming in Harare. *African Identities* 16(4), 429-443.
Mavisakalyan A (2015) Gender in language and gender in employment. *Oxford Development Studies* 43(4): 403-424.
Novas M (2018) Commemorative urban practices and gender equality: the case of Santiago de Compostela city's urban toponymy. *Hábitat y Sociedad* (11).
Núñez T, Cantero FJ, León JM, León JM and Troyano Y (2019) *Nombres de Mujer en las Calles de Sevilla*. Sevilla: Ayuntamiento de Sevilla
Oto-Peralías D (2017) What do street names tell us? An application to Great Britain's streets. Available at SSRN: https://ssrn.com/abstract=3063381.
Oto-Peralías D (2018) What do street names tell us? The "city-text" as socio-cultural data. *Journal of Economic Geography* 18(1): 187–211.
Palonen E (2008) The city-text in post-communist Budapest: street names, memorials, and the politics of commemoration. *GeoJournal* 73: 219–230.
Real Academia de la Historia (2018) Diccionario Biográfico Español. Available at: http://dbe.rah.es/
Rose-Redwood R, Alderman D and Azaryahu M (2010) Geographies of toponymic inscription: new directions in critical place-name studies. *Progress in Human Geography* 34: 453-470.
Rose-Redwood R, Alderman D and Azaryahu M (2017) Contemporary issues and future horizons of critical urban toponymy. In: Rose-Redwood R, Alderman D and Azaryahu M (eds) *The political life of urban streetscapes: Naming, politics, and place.* Taylor & Francis Group, pp. 309-319.
Santamaría L and Mihaljević H (2018) Comparison and benchmark of name-to-gender inference services. *PeerJ Computer Science* 4: e156.
Swords J and Liu X (2015) Visualizing urban and regional worlds: power, politics, and practices. *Environment and Planning A: Economy and Space* 47: 1235–1240.

Tretter E (2011) The power of naming: the toponymic geographies of commemorated African-Americans. *The Professional Geographer* 63(1): 34-54.

Weaver R and Holtkamp C (2016) Determinants of Appalachian identity: using vernacular traces to study cultural geographies of an American region. *Annals of the American Association of Geographers* 106: 203-221.

Yu SL (2014) The production of a gendered space: reading women's landmarks in Anping, Taiwan." *Asian Women* 30(4): 53-74.

Yu AZ, Ronen S, Hu K, Lu T and Hidalgo CA (2016) Pantheon 1.0, A Manually Verified Dataset of Globally Famous Biographies. *Scientific Data* 2:150075. [Version 2.0 used]

FIGURES AND TABLES

Figure 1. Diagram of the classifier algorithm. Spanish streets in 2001

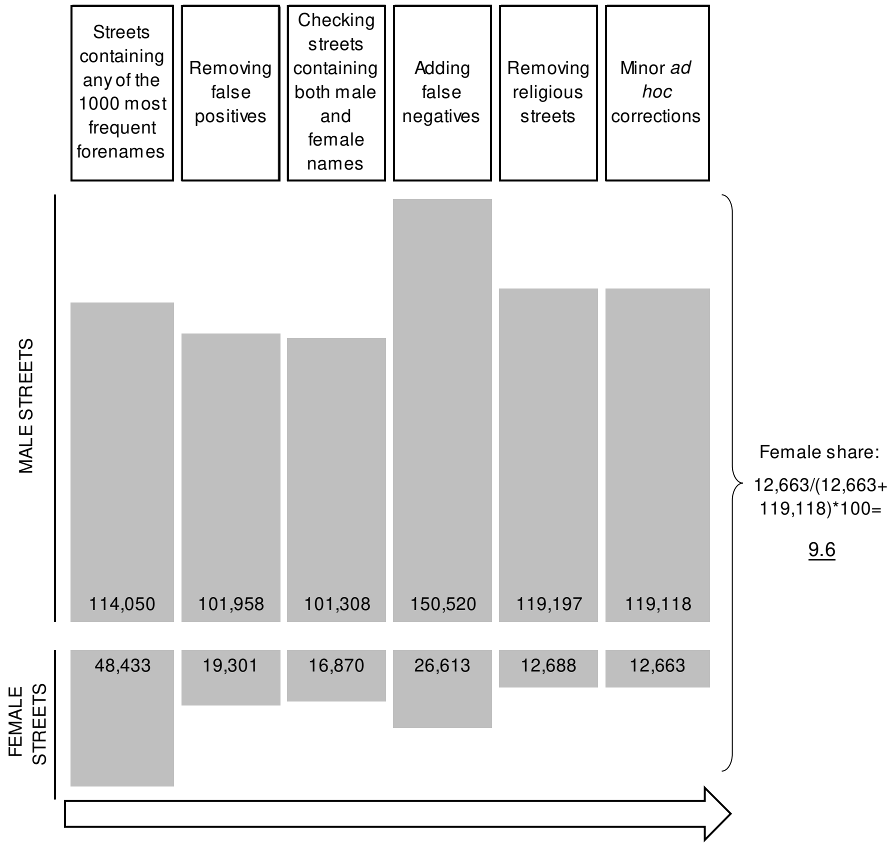
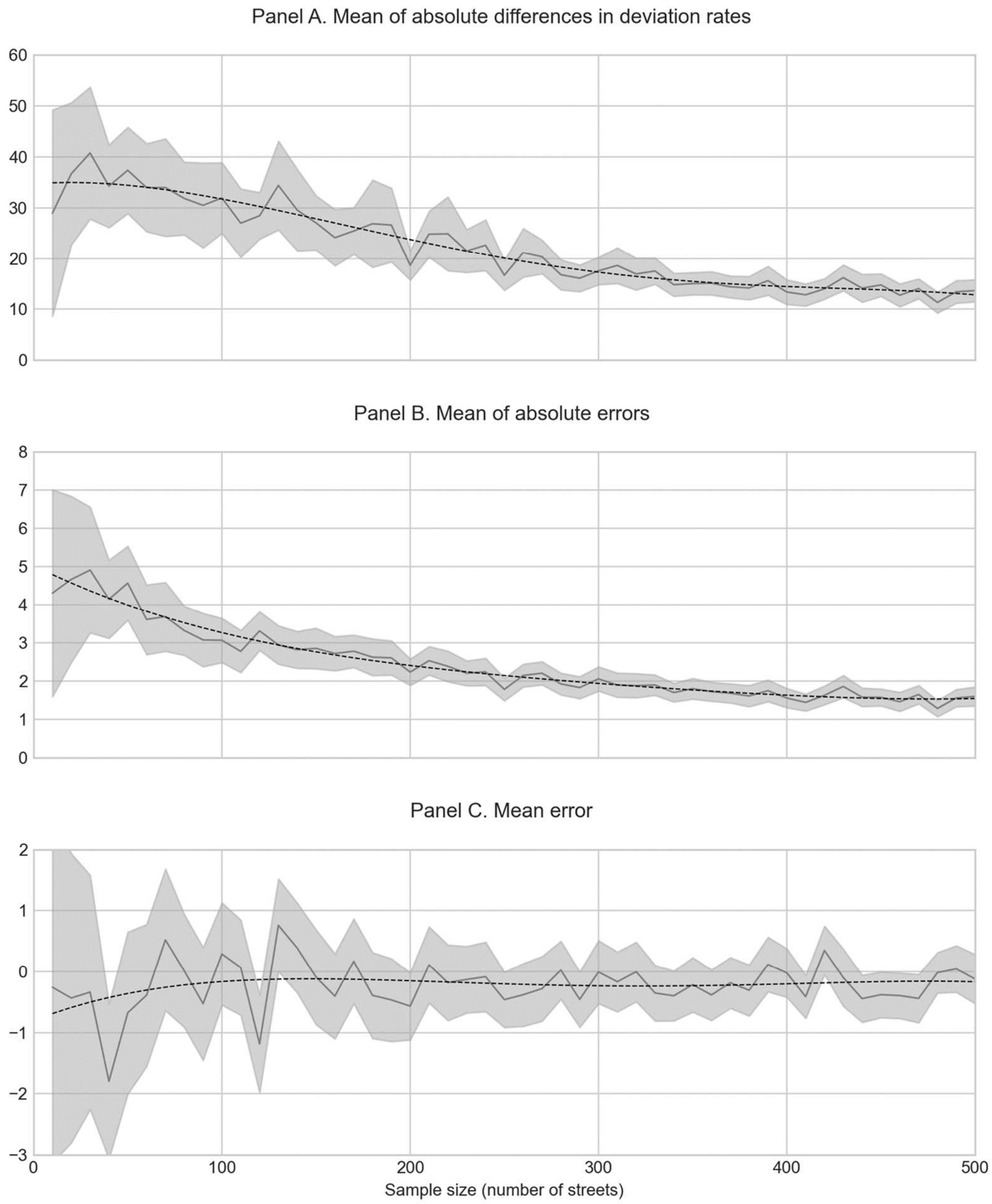
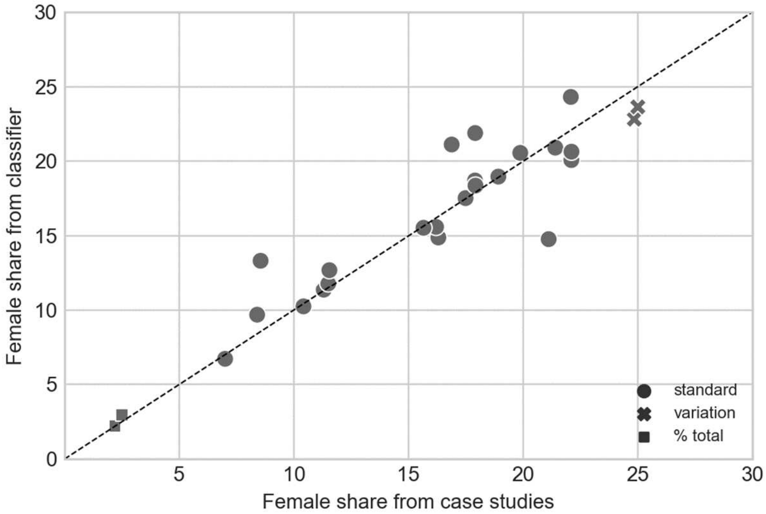


Figure 2. Accuracy of the classifier by sample size



Notes: Simulation exercise based on 100 random samples for each sample size. Panel A reports the mean of the absolute differences in deviation rates between male and female streets (see notes to Table 1 for a definition of deviation rate). Panel B reports the mean absolute error between the female share calculated through our algorithm and that calculated manually, while Panel C reports the mean error. 95% confidence intervals depicted in grey. The plots also contain the fourth-order polynomial trend lines.

Figure 3. Accuracy of the classifier against case studies



Notes: This plot represents the relationship between the female share from our classifier algorithm and that from case studies conducted for specific cities and years. Most of the points refer to the standard definition of female share for specific years (circular marker), but there are two cases in which the female share refers to new streets named during a particular period of years (crosses), and two cases that refer to the fraction of female streets over the total number of streets (squares).

Figure 4. Main results at the national level

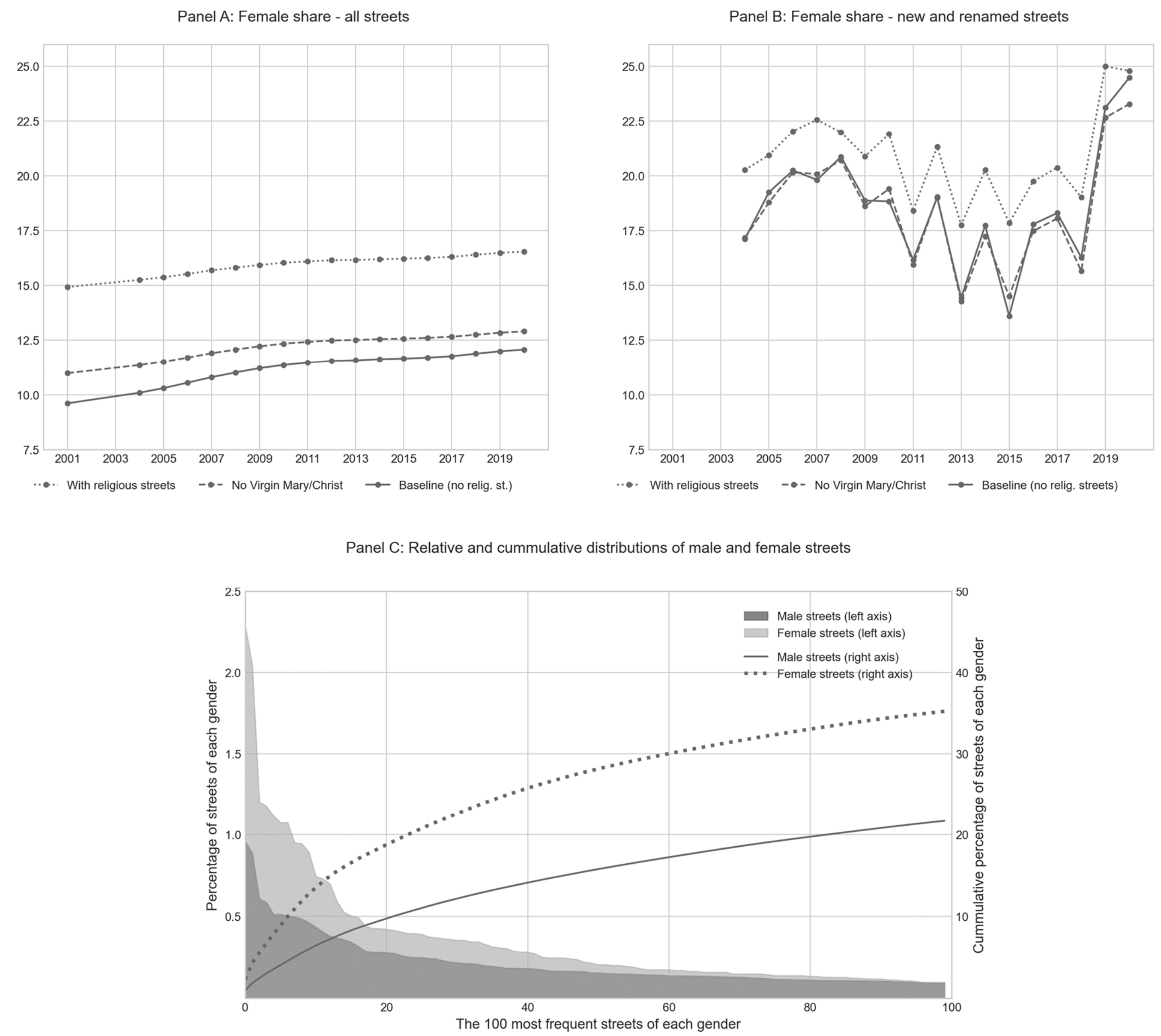


Figure 5. Female share at the provincial level

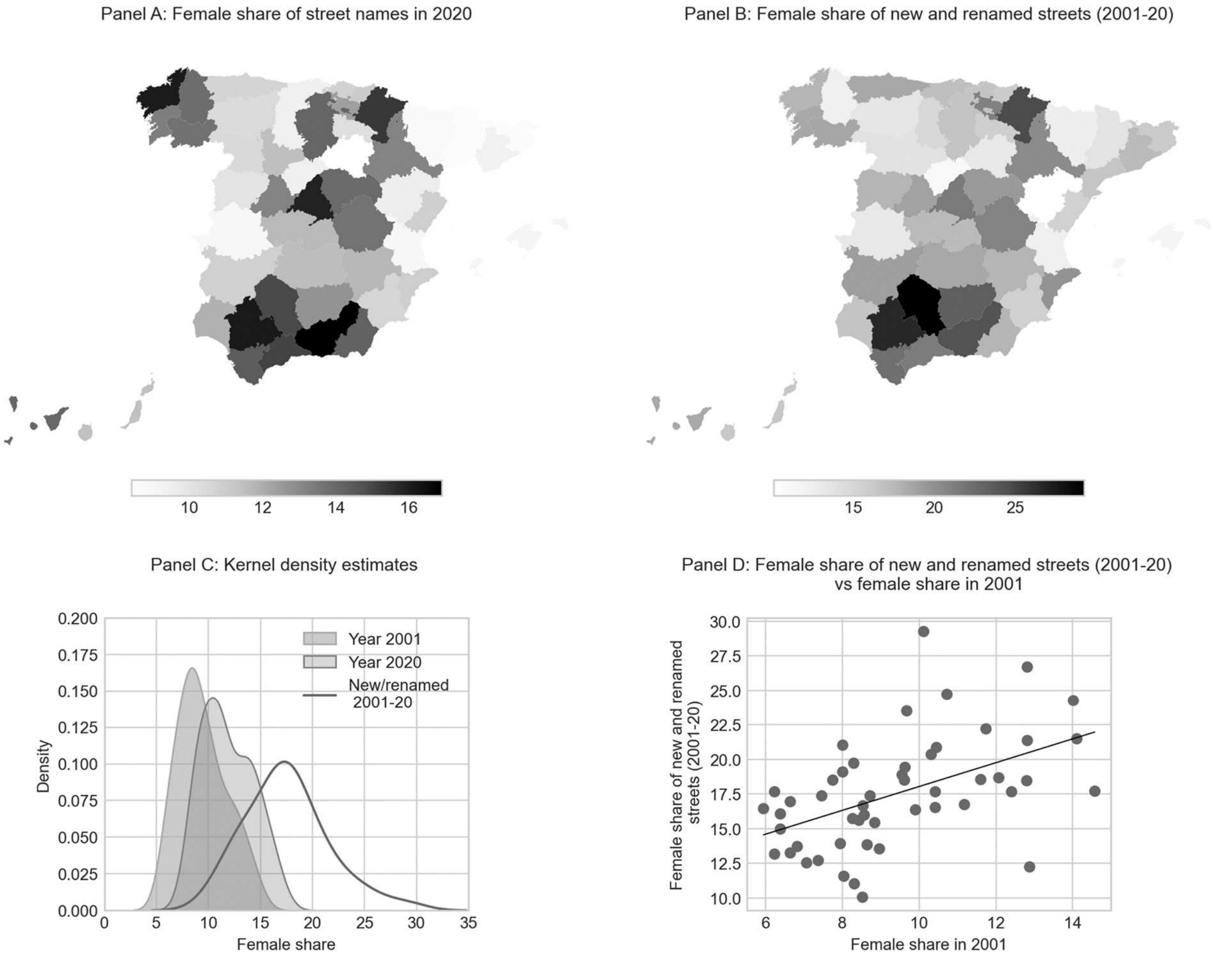
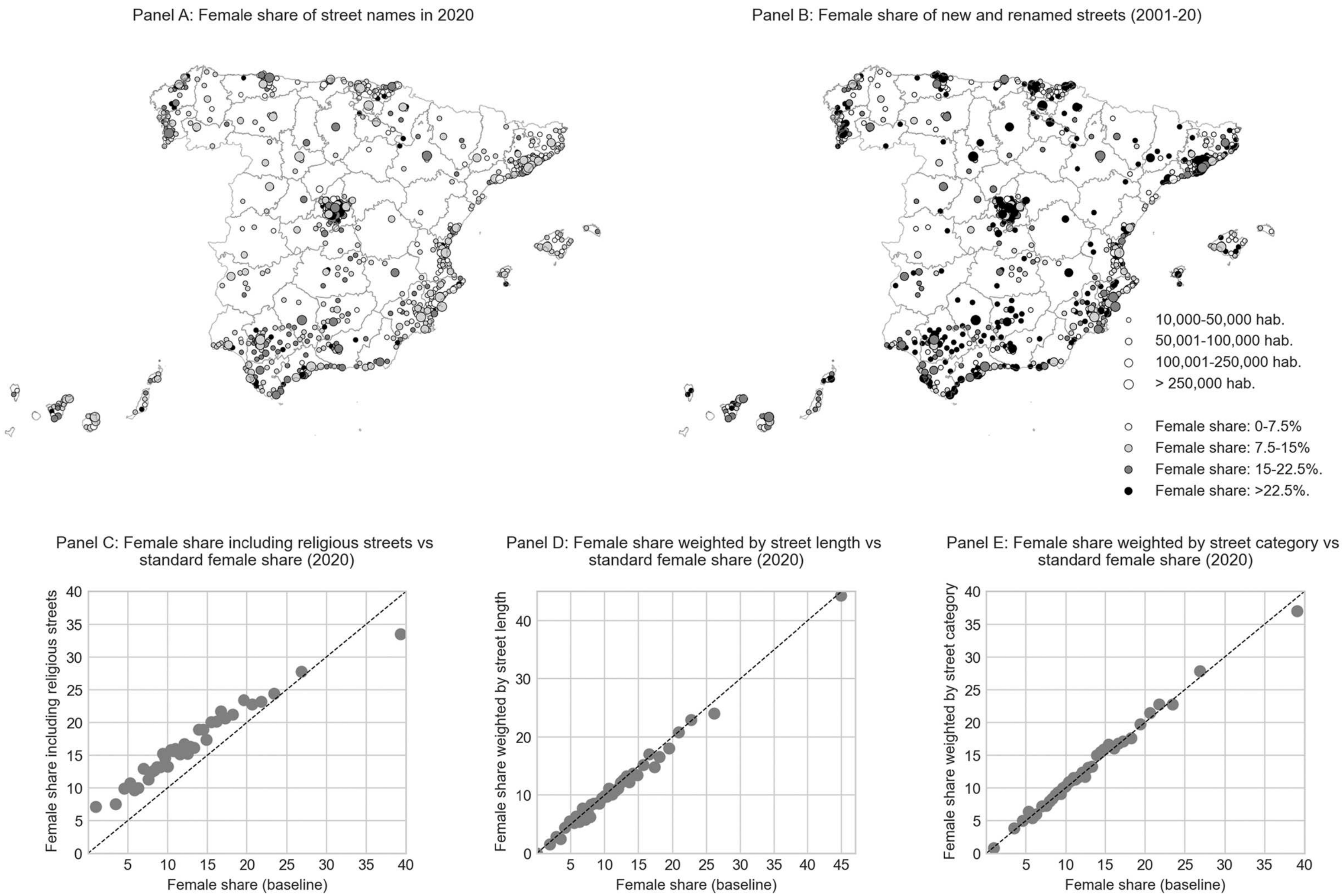
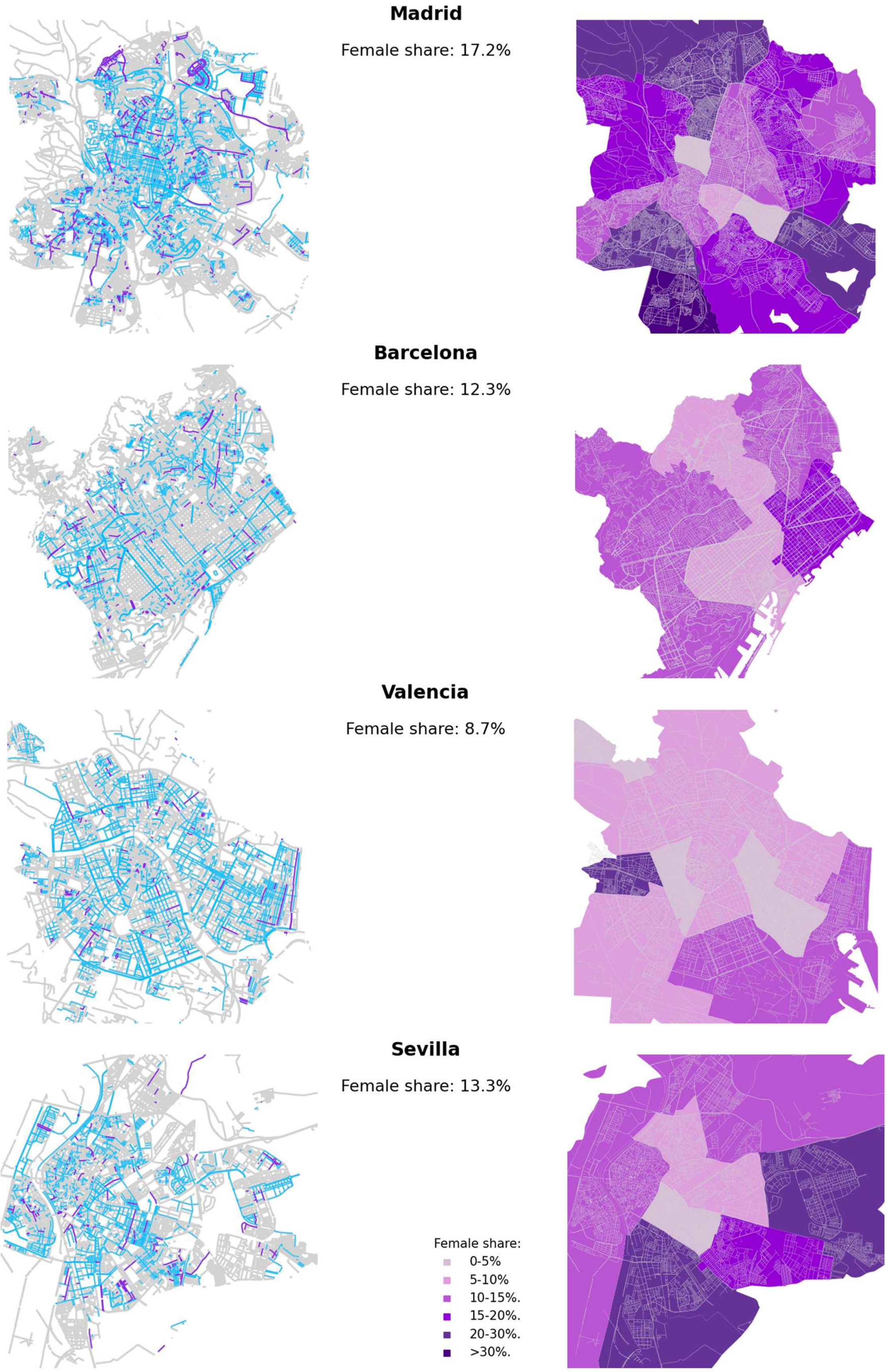


Figure 6. Female share at the municipality level



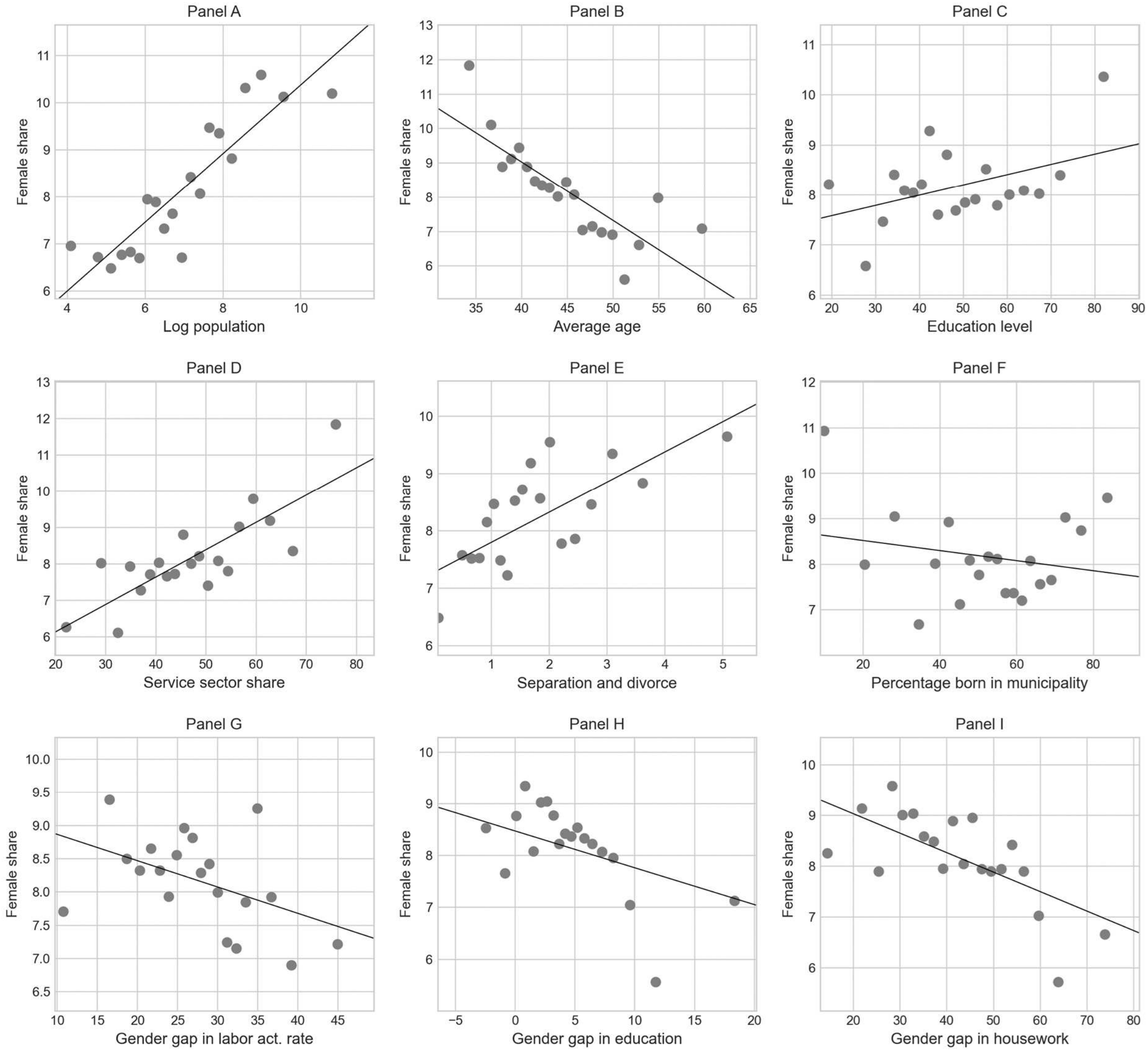
Notes: For visualization purposes, the figure excludes towns smaller than 10,000 inhabitants in 2020. Panels C, D and E depict binned scatter plots.

Figure 7. Female share in Spain's largest cities



Notes: Data used in the figure: Open Street Map.

Figure 8. Correlations of the female share at the municipality level



Notes: The figure shows binned scatter plots along with the best fitted line. All data correspond to 2001. The female share is winsorized at the 95th percentile.

Figure 9: Female share in street names and historically prominent women

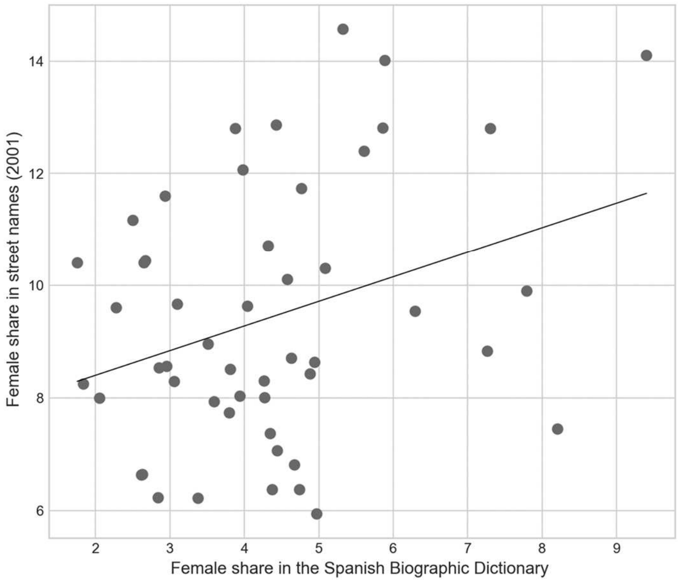


Table 1. The performance of the classifier algorithm against the test dataset

	Precision	Sensitivity	Specificity	Accuracy	Deviation rate
Male streets	96.49	87.69	99.32	97.28	-9.12
Females streets	87.50	78.40	99.71	99.18	-10.40

Female share	
Classifier algorithm →	12.32
Human-made classification →	12.48

Notes: Precison equals TP/(TP+FP), sensitivity TP/(TP+FN), specificity TN/(TN+FP), accuracy (TP+TN)/(TP+TN+FP+FN), and deviation rate (TP+FP)/(TP+FN)-1, all expressed in percentage points and where TP, TN, FP, and FN stand for true positive, true negative, false positive, and false negative, respectively.

Table 2. The female share in street names and attitudes towards gender roles

	(1)	(2)	(3)	(4)	(5)
Female share in 2001	0.0102*	0.0075*	0.0072*	0.0132***	0.0115***
	(0.0055)	(0.0045)	(0.0043)	(0.0045)	(0.0035)
Individual level controls		Yes	Yes	Yes	Yes
City level controls			Yes	Yes	Yes
17 region dummies				Yes	
50 province dummies					Yes
Number of observations	2850	2660	2660	2660	2660
Number of clusters	70	70	70	70	70
R-squared	0.001	0.200	0.200	0.215	0.235

Notes: Individual level controls include sex, age, marital status, educational level, socio-economic status, and interview year. City level controls include log population in 2001 and number of streets. All variables referred to year 2001. Variable definitions are provided in Table A1 (Suppl. Material II). Standard errors clustered at the municipality level in parentheses. * p<0.1, ** p<0.05, *** p<0.01.