International Gender Differences and Gaps in Online Social Networks*

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Abstract. Article 1 of the United Nations Charter claims "human rights" and "fundamental freedoms" "without distinction as to [...] sex". Yet in 1995 the Human Development Report came to the sobering conclusion that "in no society do women enjoy the same opportunities as men"[1]. Today, gender disparities remain a global issue and addressing them is a top priority for organizations such as the United Nations Population Fund. To track progress in this matter and to observe the effect of new policies, the World Economic Forum annually publishes its Global Gender Gap Report. This report is based on a number of offline variables such as the ratio of female-to-male earned income or the percentage of women in executive office over the last 50 years.

In this paper, we use large amounts of network data from Google+ to study gender differences in 73 countries and to link online indicators of inequality to established offline indicators. We observe consistent global gender differences such as women having a higher fraction of reciprocated social links. Concerning the link to offline variables, we find that online inequality is strongly correlated to offline inequality, but that the directionality can be counter-intuitive. In particular, we observe women to have a higher online status, as defined by a variety of measures, compared to men in countries such as Pakistan or Egypt, which have one of the highest measured gender inequalities. Also surprisingly we find that countries with a larger fraction of within-gender social links, rather than across-gender, are countries with *less* gender inequality offline, going against an expectation of online gender segregation. On the other hand, looking at "differential assortativity", we find that in countries with more offline gender inequality women have a stronger tendency for withing-gender linkage than men.

We believe our findings contribute to ongoing research on using online data for development and prove the feasibility of developing an automated system to keep track of changing gender inequality around the globe. Having access to the social network information also opens up possibilities of studying the connection between online gender segregration and quantified offline gender inequality.

* This work was done while the first author was at Qatar Computing Research Institute.

[1] http://hdr.undp.org/en/content/human-development-report-1995

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1 Introduction

Gender equality and full empowerment of women remains elusive in most countries around the world. Women are often at a significant disadvantage in fields such as economic opportunities, educational attainment, political empowerment and in terms of health. Reducing and ultimately erasing the "Gender Gap" in these fields is both an intrinsic, moral obligation but also a crucial ingredient for economic development. By limiting women's access to education and economic opportunities an immeasurable amount of human resource is lost and huge parts of the population are not able to develop their full potential.

To quantify gender inequality around the globe and to track changes over time, for example in response to policies put in place, the World Economic Forum annually publishes "The Global Gender Gap Report" in collaboration with the Center for International Development at Harvard University and the Haas School of Business at the University of California, Berkeley. This report ranks countries according to a numerical gender gap score. These scores can be interpreted as the percentage of the inequality between women and men that has been closed and so a large gap score is desirable. In 2013 the leading country Iceland had an aggregate score of 0.87, whereas Yemen scored lowest with 0.51. Scores are based on publicly available "hard data", rather than cultural perceptions, and variables contributing include the ratio of female-to-male earned income and the ratio of women to men in terms of years in executive office (prime minister or president) for the last 50 years. The emphasis of the report is on the relative gender difference for the variables considered rather than the absolute level achieved by women.

This paper contributes to this line of work by quantifying gender differences around the globe using existing methodology and applying it to *online* data, concretely data derived from Google+ for tens of millions of users. We start our analysis by describing the absolute differences along dimensions such as the number of male vs. female users or their virtual, social ranking in terms of number of followers. Our main emphasis is on studying correlations between online indicators of inequality and existing offline indicators. We do this both for the purpose of validation, to be sure that what we measure is linked to phenomena in "the real world", and for the purpose of devising new indicators, where a seemingly important online measure does not seem to be in good agreement with existing indicators.

Our current study is deliberately done *without* doing analysis of the content shared by men and women in different countries, and we are only relying on network structure data. One reason for this choice was one of global coverage: doing any type of content analysis for languages spanning all continents and having results comparable across languages and countries remains a fundamental challenge. Doing something only for English would have beaten the purpose of measuring gender inequality online in virtually all developing countries. A second reason for our choice was the fact that current indices are based on "hard data". Whereas the number of followers is well-defined, things such as the sentiment or mood of a user are hard to measure in an objective manner and are difficult to compare across cultures.

Analyzing gender differences for 73 countries we find both expected and surprising trends. Our main findings are:

- Countries with more men than women online are countries with more pronounced gender inequality.
- Women are more tightly cliqued and their links are more reciprocated.
- In countries with higher offline inequality women are, suprisingly, followed more than men. This result holds both using the mean and the median, and it holds for other "status" metrics such as PageRank.
- Countries with a larger fraction of within-gender social links, rather than across-gender, are countries with *smaller* offline gender inequalities.
- Countries with larger offline gender inequalities have a larger "differential assortativity" where women have a stronger preference for within-gender links than men.
- Applying existing gap-based methodology to online data yields a strong negative correlation, up to $r = -0.76$, with existing offline measures.

Generally our analysis is more quantitative and descriptive rather than qualitative and diagnostic. Though we describe the gender differences we find and comment on whether they agree with (at least our) expectations, we do not attempt to give explanations. We hope that experts in domains such as gender studies or social psychology will find our analysis useful and that it can save as a starting point for more in-depth studies focused at the root causes of what we observe.

As more and more economic activity becomes digital and moves online, as more and more education happens online through MOOCs and other initiatives, and as more and more of political engagement happens online we are convinced that, ultimately, quantifying gender inequality also has to crucially take into account online activity.

2 Related Work

As far as we are aware, this is the first study that links online gender differences in dozens of countries to existing quantitative offline indicators. However, lots of valuable research has been done looking at gender differences and gender inequality offline and online separately and such work has considered various psychological, sociological and economical differences. It is not within this paper's scope to serve as a complete review of literature in gender studies but, rather, it should give the reader a good overview of aspects than have been investigated.

2.1 Offline

Feingold conducted a meta-analysis to investigate differences in personal traits between genders as reported in literature [13]. For some traits such as extroversion, anxiety and tender-mindedness, women were higher, while for others such as assertiveness and self-esteem, men had higher scores. And, as one might hope, there are also traits with no observed gender differences such as social anxiety and impulsiveness.

Pratto et al. studied gender differences in political attitudes [30]. By analyzing a sample of US college students, they found that men tend to support more conservative ideology, military programs, and punitive policies, while women tend to support more equal rights and social programmes. They also show that males were in general more social dominance oriented than females.

Costa et al. [10] aggregated results of psychological tests from different countries for the so-called "Big Five" basic factors of personality: Neuroticism, Extroversion, Openness to Experience, Agreeableness, and Conscientiousness [29]. They observed that, contrary to predictions from the social role model, gender differences concerning personality were most pronounced in western cultures, in which traditional sex roles are comparatively weak compared to more traditional cultures. In a similar line of work, Schmitt et al. [34] conceived the General Sex Difference Index and observed that sex differences appear to diminish as one moves from Western to non-Western cultures.

Hyde performed a meta-analysis on psychological gender differences to show that, according to the gender similarities hypothesis, males and females are alike on most psychological variables, contrasting the differences model that states that men and women are vastly different psychologically [19].

2.2 Online

Gender Gap. Bimber analyzed data from surveys in the United States, in which people were asked about Internet access and frequency of utilization [4]. His analysis showed that there is a gap in access regarding the gender, but that this gap is not related to the gender itself, but rather to socioeconomic factors, such as education and income. Collier and Bear investigated the low participation of women in terms of contributions to Wikipedia [9]. They found strong support that the gender gap is due to the high levels of conflict in discussions, and also due to a lack of self-confidence in editing others' work. Iosub et al. investigated the communication between editors in Wikipedia and observed that female editors communicate in a way that develop social affiliation [20]. In terms of online social network usage in the US in 2013, women had higher rates of users for Facebook, Pinterest or Instagram, whereas usage was similar for both genders for Twitter and Tumblr [8]. In our data for the US, we have more male users. A possible explanation for this is an increased concern for privacy with a corresponding choice to reveal less information about themselves. See related work further down on this subject.

Privacy and Interests. Researchers investigated whether there is a difference between genders regarding the kind and amount of information shared online. Thelwall conducted a demographic study of MySpace members, and observed that male users are more interested in dating, while female users are more interested in friendship, and also tend to have more friends [36]. When analyzing the privacy behavior, women were found to be more likely to have a private profile. Joinson analyzed reports on motivation to utilize Facebook [21]. He found that female users are more likely to use Facebook for social connections, status updates and photographs than male users. Also, female users are more prone to make an effort to make their profile private. Bond conducted a survey among undergraduate students regarding their utilization in OSNs and found that female participants disclose more images and information on OSN profiles than male participants [7]. They also observed that the kind of content shared between genders are different. For instance, female users tend to share more content about friends, family, significant others, and holidays, while male users are more likely to post content related to sports. Other works also investigated the vocabulary used by users in OSNs, and found that there is differences regarding the semantic category of words between women and men [28,12]. Quercia et al. studied the relationship between information disclosure and personality by using information from personality tests done by Facebook users, and found out that women are less likely than men to publicly share privacy-sensitive fields [32].

Network. Szell and Thurner analyzed the interactions between players of a massive multiplayer online game [35]. They constructed the interactions graphs and observed that there are differences between male players and female players for all kinds of connections. For instance, females have higher degrees, clustering coefficient and reciprocity values, while males tend to connect to players with higher degree values. Ottoni et al. also investigated the friendship connections of the users in Pinterest and observed that females are more reciprocal than males [28]. In our analysis, we also found women to have a higher clustering coefficient and a larger fraction of reciprocated friendship links on Google+. Heil et al. analyzed Twitter data from 300 thousand users, and found that males have 15% more followers than women. When looking at homophily, they found that on average men are almost twice as likely to follow other men than women, and, surprisingly, women are also more likely to follow men [18,26]. In our analysis, we observed homophily for both genders in Google+, i.e. females tend to follow more females and males to follow more males. Recent work has also looked at generalizing concepts from the "Bechdel Test"[2] to Twitter [14]. The authors look at tweets from the US for users sharing movie trailers, which are then linked to Bechdel Test scores, and they find larger gender independence for urban users in comparison to rural ones, as well as other relations with socio-economic indicators.

Socio-Economic Indicators from Online Data. Putting aside the concrete issue of gender inequality, we are essentially interested in using online data as a socio-economic indicator. This idea in itself is not new and previous research has attempted to estimate things such as unemployment rates [1], consumer confidence [27], migration rates [37,17], values of stock market and asset values [6,5,38] and measures of social deprivation [33]. Work in [31] is also related as it looked at search behavior, in this case "forward looking searches" and links such queries to estimates of economic productivity around the globe.

[2] `http://en.wikipedia.org/wiki/Bechdel_test`

3 Data Set

Our dataset was created by collecting public information available in user profiles in the Google+ network. We inspected the *robots.txt* file and followed the sitemap to retrieve the URLs of Google+ profiles. Since we retrieved the complete list of profiles provided by Google+, we believe our data set covers almost all users with public profiles in Google+ by the time of the data collection. The data collection ran from March 23rd of 2012 until June 1st of 2012. When inspecting the sitemap we found 193,661,503 user IDs. In total we were able to retrieve information from 160,304,954 profiles. Some IDs were deleted or we were not able to parse their information. With the social links of the users, we have constructed a directed graph that has 61,165,224 user nodes and 1,074,088,940 directed friendship edges.

Country Identification. To identify a user's country in Google+, we extracted the geographic coordinates of the last location present on the *Places lived* field and identified the corresponding country. We were able to identify the country of 22,578,898 users.

Gender. Google+ provides a self-declared gender field where the user can choose between three categories: *female*, *male* and *other*. As any other profile field in Google+ (except for the name), it is possible to put this information as private, so we do not have this information for all users. Of the 160 millions users, 78.9% provided the gender field publicly, from which 34.4% are female, 63.8% are male and 1.8% selected "other".

Details of the Google+ platform and a data characterization of an early version of the dataset are discussed in a previous work [25]. A summary of the number of users for each country can be found in Table A.1 (appendix). We only selected countries with at least 5,000 users for each gender.

3.1 Online Variables

As doing any type of content analysis for dozens of languages and cultures is extremely challenging, we decided to study how *network* metrics could be indicators for gender gaps. At the country-level, we looked at the following metric which we hypothesized could be an indication of online gender segregation.

- The *assortativity*[3] is the fraction of links to the same gender rather than across genders. A large value can be indicative of either strong same-gender linkage preference, or simply a highly imbalanced gender distribution of the users, which trivially makes cross-gender links less likely.

We also computed the following metrics for each user from one of the 73 countries in our data set.

[3] We use "assortativity" rather than "homophily" to emphasize the correlation rather than necessary a causal link.

- The *in-degree*, also referred to as the number of followers, counts the number of "circles" a user is in. A large in-degree can be seen as an indicator of popularity or status.
- The *out-degree*, also referred to as the number of followees or friends, counts the number of users a user has in their circles.
- The *reciprocity* is the fraction of reciprocal links in relation to the out-degree, i.e. the fraction of times where the act of following is reciprocated by the receiving user.
- The *clustering coefficient* for a particular node is the probability of any two of its neighbors being neighbors themselves. It is calculated by the fraction of the number of triangles that contain the node divided by the maximum number of triangles possible (when all the neighbors are connected), which for a directed graph is equal to $n(n-1)$, where n is the number of neighbors that reciprocate the connection. A large value typically indicates a large degree of "cliqueness" and more tightly connected social groups.
- The *PageRank* measures the relative importance of a user in the network and, unlike the mere in-degree, is influenced by the "global" social graph structure. A damping factor $d = 0.85$ was used for the iterations of the algorithm. A large PageRank value is often thought of as an indicator of "centrality" or "importance" in the social graph.
- The *differential assortativity* is the "lift" of the fraction of users of the same gender followed by a particular user. It is calculated by dividing the fraction of links to the same gender by the share of that gender for the country of the user. A large value means that users are more likely than by random chance to follow other users of their same gender. The comparison against random chance corrects for the fact that in an online population of, say, 80% males are trivially more likely to follow other males even without any same-gender homophily.

These per-user metrics are then aggregated into a per-country score as described in the next paragraph. Though we group the results by country, connections across countries are included in our analysis. So a reciprocal link between two users in Brazil and Qatar would contribute to the statistics of both countries.

Gender Gap. One of the goals of our study was to devise an "Online Gender Gap" score and to see how this relates to the existing offline Gender Gap scores. We therefore followed the same methodology of computing a "gap" score: First, we group the users by country and gender, and calculate the average of the variable for each country-gender group. After having the aggregated value for each country-gender group, we calculate the gender ratio by dividing the female value by the male value, for each country. Differently from the Global Gender Gap score methodology, we do not truncate the ratio at 1, since we want to analyze the trend even when the value is higher for female users, especially as some of our variables, such as the number of followers, exhibited a counter-intuitive trend. Furthermore, for some of our variables such as the Differential Assortativity, it is also not intuitively obvious if a high or a low gender-specific value is desirable and, correspondingly, it is unclear if high or low values should be truncated.

Note that, in line with the Global Gender Gap report, a large "gap value" is actually *desirable* in the sense that it typically indicates gender equality or female dominance for the variable considered, whereas a very low gap value is undesirable as it indicates that the variable considered is lower for women than for men.

3.2 Offline Variables

The Global Gender Gap Index [4] is a benchmark score that captures the gender disparities in each country. It takes into account social variables from four categories (economy, politics, education and health), such as life expectancy, estimated income, literacy rate and number of seats in political roles. The index is built by (1) calculating the female by male ratio of the variables, (2) truncating the ratios at a certain level (1.0 for most variables), (3) calculating subindexes for each one of the four categories (weighted average in relation to the standard deviation) and (4) calculating the un-weighted average of the four subindexes to create the overall index. The scores range from 0 (total inequality) to 1.0 (total equality). For this study we use the 2013 Global Gender Gap report [16].

We also use additional economic variables and demographic information to see if these are linked to online gender gaps. For population and internet penetration information we use information from the Internet World Stats website[5] on internet usage for 2012. The GDP per capita information was collected from the World Bank website[6] and is for 2011. Information for more recent years was missing for some countries which is why we selected data from 2011.

4 Gender Differences Online

Before we link online variables to offline indicators of gender gaps, we first describe how men and women in 73 countries differ in their usage of Google+. Figure 1 shows the gender ratio of the variables for each country. We observe that for some variables there is a female predominance (such as for "Reciprocity" and "Clustering Coefficient"), while for others there's a male predominance (such as "Number of followees"). In most cases, the gender predominance is the same across countries, but for some variables ("Number of followers") there are divergences.

5 Online and Offline Gender Gaps

To test the significance of the difference between female and male values of the variables we conducted a permutation test that does not make assumptions

[4] `http://www.weforum.org/issues/global-gender-gap`
[5] `http://www.internetworldstats.com`
[6] `http://www.worldbank.org`

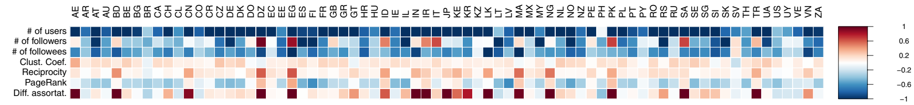

Fig. 1. A color plot of the logarithm, base 2, of the (female value)/(male value) gender ratio (GR), i.e. $\log_2(\mathrm{GR})$, for the variables in each country. The scale is truncated at -1.0 and 1.0. A value higher than 0 (blue) indicates male predominance, and lower than 0 (red) means female predominance.

about the distribution of the variables.[7] First, for each country we compute the average of a variable across all female users and compare the value with the one obtained for the male users. Let δ be the observed difference. Then we use the same set of users, but now randomly permute the gender label. The basic idea is to see if the observed difference could have arisen due to random variance or whether it is more systematically linked to the gender of the users. We now calculate the average of the two groups derived from the permutation, and calculate the difference δ_p. We repeat this process 1,000 times to estimate the level of variability of δ_p. Finally, we mark the δ as significant if it was in the bottom/top 0.5% (or 2.5%) of the percentiles of the δ_p. In Table 1 we present the significance test result for some variables for a fraction of the countries. In Table B.2 (appendix) we present the values for all the countries. For most countries and most variables the difference between female and male is significant.

6 Linking Online and Offline Gender Gaps

Whereas the previous section looked exclusively at online gender differences, here we focus on linking online and offline gender gaps across 73 countries.

Figure 2 shows the linear regression between online variables and the Global Gender Gap scores. GR stands for Gender Ratio (female divided by male value). We observe that the gap score for the number of users is positively correlated with the gender gap score. Countries with a roughly equal number of male and female users online tend to score better (= higher) for the offline gap scores. Surprisingly, at least to us, we also find that the number of followers and other measures of "status" are negatively correlated for both networks. For example, Pakistan has an offline Gender Gap score of 0.546 (with 1.0 indicating equality) but, at the same time, women who are online in Pakistan have on average (and in median) more followers than their male counterparts. . We discuss potential reasons later in the paper.

The two plots in the right column of Figure 2 show the linear regression plots of the assortativity variables in Google+. When we analyze the Differential

[7] See `http://en.wikipedia.org/wiki/Resampling_%28statistics%29#Permutation_tests` for background information on permutation tests in statistics.

Table 1. Significance test results for variables in Google+ for a subset of our 73 countries, ranked in descending order of the number of users. The value on the left is the average female value and the value on the right is the average male value, followed by the significance result ('*' is 95% significant, '**' is 99% significant). The full list of results can be found in Table B.2 (appendix).

Country	In-degree ♀/♂	Out-degree ♀/♂	Recipr. ♀/♂	Clust. Coeff. ♀/♂	PageRank ♀/♂
United States	34.8/47.1**	20.6/30.3**	0.49/0.50**	0.31/0.28**	2.0e-08/2.6e-08**
Russian Federation	17.7/20.8**	31.0/36.1**	0.45/0.41**	0.38/0.32**	1.5e-08/1.8e-08**
Italy	34.7/22.0	22.7/33.3**	0.51/0.48**	0.33/0.29**	1.8e-08/2.0e-08**
Viet Nam	36.9/57.4**	41.7/78.3**	0.41/0.34**	0.29/0.29	1.8e-08/2.0e-08**
Philippines	11.6/16.6**	28.8/38.5**	0.42/0.41	0.40/0.36**	1.4e-08/1.6e-08**
Pakistan	25.4/15.8**	35.3/49.1**	0.40/0.31**	0.32/0.29**	1.6e-08/1.3e-08**
Saudi Arabia	39.3/24.6**	30.2/47.4**	0.37/0.33**	0.29/0.26**	1.7e-08/1.6e-08
Bangladesh	17.4/15.2	30.4/54.1**	0.41/0.30**	0.32/0.30**	1.4e-08/1.3e-08
United Arab Emirates	19.6/18.4	21.4/33.6**	0.46/0.42**	0.28/0.22**	1.7e-08/1.7e-08
Greece	19.0/22.1	26.5/40.3**	0.47/0.44**	0.34/0.30**	1.5e-08/1.8e-08**
Norway	16.8/40.3**	17.6/30.8**	0.57/0.56**	0.35/0.31**	1.7e-08/2.5e-08**
Sri Lanka	20.9/21.1	23.7/50.7**	0.47/0.36**	0.31/0.30*	1.6e-08/1.6e-08
El Salvador	12.8/11.5	31.7/28.7	0.38/0.39	0.21/0.24**	1.4e-08/1.5e-08*
Guatemala	10.1/12.1	21.2/26.2**	0.46/0.40**	0.27/0.29*	1.5e-08/1.5e-08
Slovenia	10.0/18.2**	16.8/30.2**	0.56/0.53**	0.27/0.28	1.6e-08/2.1e-08**

assortativity we observe that most countries, clustered together on the dashed line, have similar values for female and male, meaning that the level of gender assortativity is the same for women and men. On the other hand, in countries with a low Gender Gap score there's a female predominance, meaning that women in these countries connect much more among themselves than expected when compared to men. This could be seen as an indication of women "shying away" from cross-gender linkage in such countries. When we analyze not the gap but the actual assortativity of a country we observe a positive correlation with the gap score, meaning that in countries with higher Gender Gap score (= little inequality), there is higher assortativity (= more within-gender linkage). We discuss potential hypotheses explaining this arguably surprising finding in Section 7.

Figure 3 presents the matrix of correlation between the online and offline variables, essentially summarizing the linear regression fits from Figure 2 and adding more variables. As in Figure 2, the Gender Gap Score is positively correlated with the gender gap of the number of users in Google+, and, surprisingly, negatively correlated with the gap of the number of followers, reciprocity and PageRank. In terms of assortativity, there is a negative correlation for differential assortativity, meaning that female users connect more among themselves in countries with a low Gap score, while the actual assortativity of the network is positively correlated, implying more segregation in countries with high Gender Gap score.

Fig. 2. Linear regression and correlation between online social network metrics and the Global Gender Gap score. GR stands for Gender Ratio (female by male value). See Table A.1 (appendix) for a list of 2-letter country codes. The p-values for the correlation were all lower than 0.01.

7 Discussion

One of our main motivation for this work was to see if online data could be used to derive global indicators of gender inequality and whether these indicators were in some sense "grounded" in that they are linked to existing indicators. Our findings indicate that this indeed the case.

Surprisingly, the directionality of important indicators was *opposite* from what we had expected. Concretely, we found that all indicators of gaps in online social status such as the average number of followers, or the Pagerank on Google+ all had noticeable *negative* correlations (.65 and -.76 correspondingly) with the aggregated offline gender gap score. For example in Pakistan, with a gender gap score of 0.55, indicating a large inequality, we found that women have on average 50% more followers on Google+ than men. Note that the number of followers is typically heavy-tailed [22] and for such distributions it is known that the observed average will increase as the sample size increases[8]. As we have fewer women and men for countries where we observe these effects, the actual effect might hence be even stronger. We also mention that we observed the same effect by looking at medians, rather than averages, indicating a robust result not caused by outliers.

[8] See, e.g., `http://en.wikipedia.org/wiki/Pareto_distribution` which has an infinite mean when $\alpha \leq 1$.

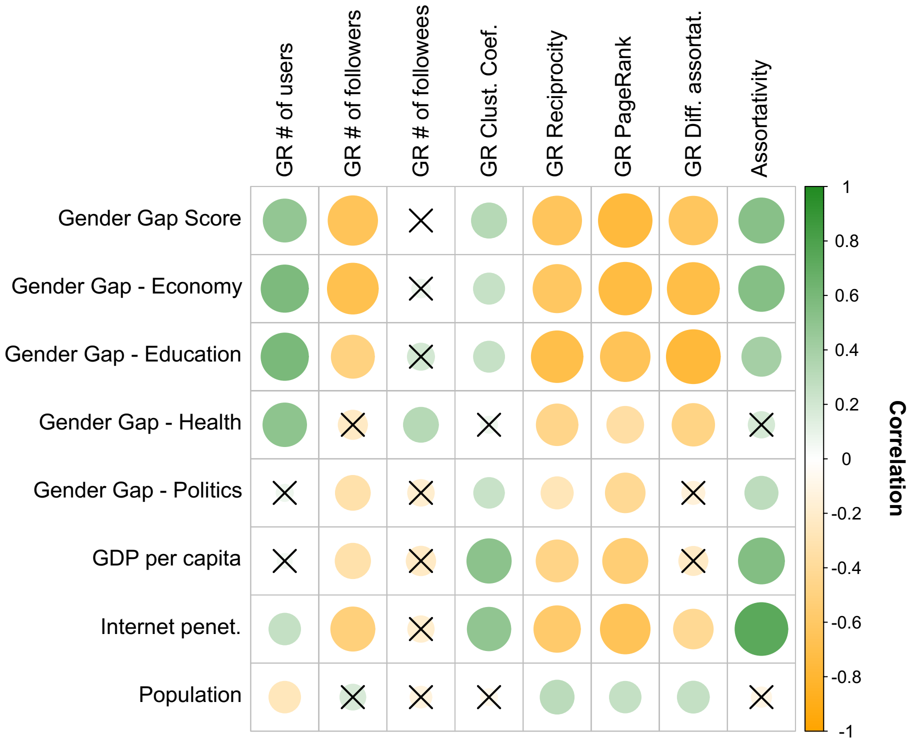

Fig. 3. Correlation between offline variables and the ratio of online variables of the countries. GR stands for Gender Ratio (female by male value). The relation is marked with an X when the p-value of the correlation is lowen than 0.05.

Our current hypothesis is that this unexpected result might be due to the so-called "Jackie Robinson Effect"[9]. Jackie Robinson was a baseball player who who became the first African-American to play in Major League Baseball in the modern era. If he had been only good, rather than great, it is unlikely that he would have been given a chance to play rather than a slightly less talented white alternative. Similarly, one might imagine that women that are online in countries where women have more limited online access compared to men must be extraordinary to begin with. In a similar vein it was found that female politicians perform better than their male counter-parts as doing just as well would not suffice to "make it" [2].

The effect above might also be linked to our observation of more within-gender linkage for countries such as Finnland or Norway, compared to Egypt or Pakistan. Other potential explanations for this observation could be acts of online "stalking" or "staring" where women attract follow links from men, causing more cross-gender linkage. This latter hypothesis is also consistent with

[9] `http://en.wikipedia.org/wiki/Jackie_Robinson`

our observation that in countries with more offline gender inequality women have a stronger tendency for withing-gender linkage than men, potentially indicative of shying away from cross-gender linkage.

Of course, our current data set and methodology are by no means perfect. Clearly, our user set is by no means representative of the overall population. Generally, we expect people over a higher social status to be overrepresented in our data. But even the fact that for Pakistan we find about 8 times as many male Google+ users as female ones is in itself a signal. Also note that for certain applications the selection bias might be irrelevant. If, for example, the main purpose of using online data is to have a low-cost and real-time alternative to compute the offline gender gap index then as long as it works, despite the selection bias, the selection bias itself becomes irrelevant. As a comparison, if it is possible to accurately predict current levels of flu activity from social media data then there is no reason to question this approach, assuming that the prediction remains valid as the online population continues to change [3,23,11].

The example of monitoring flu activity also points to another limitation of our study: the use of only one data source. For flu monitoring using online data, Google Flu Trends [15] is the de-facto standard and baseline to beat. Recently, its use as a figurehead has however been questioned [24]. Still, it seems promising to look at, say, the relative search volume of topics associated with gender roles to see if their search volume could be indicative of gender gaps. Additionally, gender differences on comments on national, political sites could be indicators for political engagement.

Another big limitation is our decision to ignore the content/topics that are discussed. The main reasons for this are (i) technical difficulties when dealing with content analysis for dozens of different languages and character sets, in particular if the results need to be comparable across countries, and (ii) the emphasis of existing offline indices on "hard data" rather than sentiments or more qualitative analysis. Still, it seems valuable to look at the topics discussed by, say, men and women in Mali to get better insights into their lived online experiences. In future work we plan to focus on a limited set of countries and languages and study topical differences in depth. Integrating content could also lead to an improvement of the already decent fit between a combination of online indicators and the offline gender gap scores. Finally, it could provide hypotheses for the root causes of the differences we observe.

Our current analysis is based on a static snapshot of time. However, our declared goal is to design a system that frequently calculates the latest online indicators of gender gaps and makes these publicly available. This is done with initiatives such as the United Nations Global Pulse in mind. "The Global Pulse initiative is exploring how new, digital data sources and real-time analytics technologies can help policymakers understand human well-being and emerging vulnerabilities in real-time."[10] Similarly, the United Nations Population Fund supports use of Data for Development and "women's roles and status, spatial mobility of populations and differentials in morbidity and mortality within

[10] http://www.unglobalpulse.org/

population subgroups were singled out as pressing concerns"[11]. At a broader level, more and more non-profit organizations are advocating the use of data mining "for good" and, as an example, the US Center for Disease Control and Prevention is organizing a competition to encourage the use of social media to predict flu activity[12].

Ultimately, of course, the goal is not just to describe and quantify gender gaps but to close these gaps. Here, a large amount of responsibility undoubtedly lies with politicians and people in positions of power. As good policy making needs to be linked to quantifying the progress made, and there is a necessity to observe the impact of new policies, measurement efforts are a valid objective in their own right. However, it is well worthwhile thinking about how social media and online social networks could in itself be used as a tool to facilitate the process of closing the gap, rather than as a mere data source. It might for example be possible to automatically strengthen the social capital of underprivileged women or, if nothing else, it could be used as communication channel to support the cause of gender equality.

8 Conclusion

We presented a large-scale study of gender differences and gender gaps around the world in Google+. Our analysis is based on 17,831,006 users from 73 countries with an identified gender and, to the best of our knowledge, is the first study that links online indicators of gender inequality to existing offline indicators.

Our main contribution is two-fold. First, we describe gender differences along a number of dimensions. Such insights are valuable both as a starting point for in-depth studies on identifying the root causes of these differences, but also when it comes to designing gender-aware systems. Second, we show how applying existing offline methodology for quantifying gender gaps can be applied to online data and that there is a respectable match in form of a 0.8 correlation across 73 countries.

Looking at individual variables we also find surprising patterns such as a tendency for women in less developed countries with larger gender differences to have a *higher* social status online as measured in terms of number of followers or Pagerank. We hypothesize the existence of an underlying "Jackie Robinson Effect" where women who decided to go online in a country such a Pakistan are likely to be more self-confident and tech-savvy than random male counterparts. Such an effect might also be linked to the fact that we observe a *higher* within-gender link assortativity for countries with *less* offline gender inequality, though alternative explanations include men "stalking" women online.

As more and more economic activity, education, and political engagement happens online we are convinced that, ultimately, quantifying gender inequality has to crucially take into account online activity.

[11] http://www.unfpa.org/public/datafordevelopment

[12] http://www.cdc.gov/flu/news/predict-flu-challenge.htm

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Appendix

A List of Countries

Table A.1. List of countries with their respective 2-letter country codes and the total number of female and male users. We select only countries with at least 5,000 females and males.

Country		# users			Country		# users		
Code	Name	Female	Male	Total	Code	Name	Female	Male	Total
US	United States	2,186,509	2,910,470	5,096,979	KR	South Korea	16,570	60,696	77,266
IN	India	363,956	1,964,070	2,328,026	SE	Sweden	22,342	54,815	77,157
BR	Brazil	563,173	716,455	1,279,628	BE	Belgium	21,755	55,223	76,978
GB	United Kingdom	210,801	445,343	656,144	AE	United Arab Emirates	12,250	57,399	69,649
ID	Indonesia	136,013	396,028	532,041	DK	Denmark	20,219	47,470	67,689
RU	Russian Federation	140,024	326,464	466,488	CZ	Czech Republic	19,409	46,548	65,957
CA	Canada	147,247	255,750	402,997	SG	Singapore	20,798	43,515	64,313
MX	Mexico	129,566	261,958	391,524	FI	Finland	21,831	41,072	62,903
DE	Germany	98,500	275,813	374,313	GR	Greece	17,578	41,393	58,971
ES	Spain	116,997	221,343	338,340	IE	Ireland	21,277	35,959	57,236
IT	Italy	87,028	226,777	313,805	RS	Serbia	16,458	40,241	56,699
FR	France	98,628	211,602	310,230	CH	Switzerland	14,255	42,085	56,340
JP	Japan	57,234	221,049	278,283	AT	Austria	15,487	37,185	52,672
CN	China	45,551	199,300	244,851	NO	Norway	15,246	35,795	51,041
AU	Australia	87,605	156,493	244,098	IL	Israel	15,101	33,752	48,853
VN	Viet Nam	64,539	152,459	216,998	EC	Ecuador	15,611	31,654	47,265
TH	Thailand	80,655	117,904	198,559	NZ	New Zealand	17,462	29,547	47,009
AR	Argentina	68,877	116,617	185,494	SK	Slovakia	16,061	27,749	43,810
TR	Turkey	25,974	147,023	172,997	LK	Sri Lanka	7,186	35,540	42,726
CO	Colombia	62,590	110,004	172,594	BG	Bulgaria	13,136	25,260	38,396
PH	Philippines	78,760	81,601	160,361	HR	Croatia	13,612	23,944	37,556
MY	Malaysia	60,607	95,842	156,449	MA	Morocco	7,170	29,434	36,604
UA	Ukraine	46,132	105,582	151,714	DO	Dominican Republic	10,750	23,303	34,053
PL	Poland	48,381	102,802	151,183	SV	El Salvador	11,891	19,049	30,940
NL	Netherlands	40,074	104,336	144,410	DZ	Algeria	5,176	24,887	30,063
PK	Pakistan	15,420	128,150	143,570	CR	Costa Rica	9,632	20,186	29,818
IR	Iran	27,153	112,444	139,597	KE	Kenya	6,868	22,522	29,390
CL	Chile	53,286	81,165	134,451	NG	Nigeria	5,050	23,523	28,573
EG	Egypt	19,414	113,495	132,909	GT	Guatemala	7,342	20,189	27,531
ZA	South Africa	34,153	66,871	101,024	UY	Uruguay	9,966	14,552	24,518
SA	Saudi Arabia	15,173	85,416	100,589	LT	Lithuania	10,416	13,801	24,217
PE	Peru	32,296	66,141	98,437	KZ	Kazakhstan	5,727	12,555	18,282
RO	Romania	28,907	63,982	92,889	PY	Paraguay	6,273	10,730	17,003
PT	Portugal	32,218	59,238	91,456	SI	Slovenia	5,644	11,269	16,913
VE	Venezuela	32,623	56,556	89,179	LV	Latvia	5,722	9,979	15,701
BD	Bangladesh	7,029	74,221	81,250	EE	Estonia	5,337	8,337	13,674
HU	Hungary	30,525	48,858	79,383					

B Significance Test Results

Table B.2. Significance test results for variables in Google+ for our 73 countries, ranked in descending order of the number of users. The value on the left is the average female value and the value on the right is the average male value, followed by the significance result ('*' is 95% significant, '**' is 99% significant).

Country	In-degree ♀/♂	Out-degree ♀/♂	Recipr. ♀/♂	Clust. Coeff. ♀/♂	PageRank ♀/♂
United States	34.8/47.1**	20.6/30.3**	0.49/0.50**	0.31/0.28**	2.0e-08/2.6e-08**
India	25.5/23.2	20.3/38.2**	0.52/0.41**	0.25/0.23**	2.0e-08/2.0e-08
Brazil	20.4/28.7**	38.0/48.0**	0.37/0.39**	0.16/0.17**	1.7e-08/2.2e-08**
United Kingdom	30.9/26.8	20.5/28.9**	0.47/0.46**	0.33/0.29**	1.8e-08/2.1e-08**
Indonesia	25.0/17.7**	39.5/53.4**	0.43/0.33**	0.36/0.34**	1.9e-08/1.6e-08**
Russian Federation	17.7/20.8**	31.0/36.1**	0.45/0.41**	0.38/0.32**	1.5e-08/1.8e-08**
Canada	33.9/38.9	19.6/29.1**	0.48/0.48	0.31/0.28**	1.8e-08/2.2e-08**
Mexico	10.5/12.6**	22.8/28.0**	0.45/0.41**	0.28/0.27*	1.5e-08/1.6e-08**
Germany	21.5/42.2**	21.9/31.6**	0.49/0.47**	0.35/0.31**	1.6e-08/2.1e-08**
Spain	13.7/29.2**	20.4/29.1**	0.50/0.47**	0.32/0.29**	1.6e-08/2.2e-08**
Italy	34.7/22.0	22.7/33.3**	0.51/0.48**	0.33/0.29**	1.8e-08/2.0e-08**
France	15.6/24.7**	19.8/30.5**	0.49/0.46**	0.33/0.29**	1.6e-08/2.1e-08**
Japan	32.0/35.0	30.8/49.1**	0.44/0.37**	0.34/0.32**	1.9e-08/1.9e-08
China	45.1/46.3	48.0/76.5**	0.41/0.31**	0.27/0.25**	1.9e-08/1.8e-08
Australia	14.8/21.5**	18.5/27.2**	0.48/0.48	0.33/0.29**	1.5e-08/2.0e-08**
Viet Nam	36.9/57.4**	41.7/78.3**	0.41/0.34**	0.29/0.29	1.8e-08/2.0e-08**
Thailand	19.4/29.1**	34.0/48.2**	0.41/0.39**	0.34/0.31**	1.6e-08/2.2e-08**
Argentina	13.4/17.8**	22.7/29.7**	0.43/0.43*	0.29/0.27**	1.6e-08/1.9e-08**
Turkey	18.8/15.1**	29.0/45.7**	0.46/0.36**	0.32/0.28**	1.5e-08/1.4e-08
Colombia	9.6/10.9**	24.8/31.0**	0.44/0.40**	0.28/0.27**	1.4e-08/1.6e-08**
Philippines	11.6/16.6**	28.8/38.5**	0.42/0.41	0.40/0.36**	1.4e-08/1.6e-08**
Malaysia	11.8/32.7**	26.5/38.1**	0.45/0.40**	0.33/0.30**	1.4e-08/1.8e-08**
Ukraine	20.1/37.9**	31.8/43.0**	0.48/0.45**	0.37/0.31**	1.6e-08/1.9e-08**
Poland	8.1/13.6**	17.0/23.9**	0.53/0.50**	0.37/0.32**	1.5e-08/1.8e-08**
Netherlands	15.7/22.3**	18.6/27.5**	0.51/0.50**	0.33/0.28**	1.6e-08/2.1e-08**
Pakistan	25.4/15.8**	35.3/49.1**	0.40/0.31**	0.32/0.29**	1.6e-08/1.3e-08**
Iran	50.2/35.6	34.9/49.0**	0.46/0.39**	0.30/0.29**	1.9e-08/1.7e-08
Chile	9.7/13.5**	17.7/23.4**	0.50/0.50*	0.27/0.26**	1.6e-08/2.0e-08**
Egypt	34.2/18.9**	30.3/62.4**	0.38/0.25**	0.31/0.28**	1.7e-08/1.3e-08**
South Africa	10.5/17.9**	19.4/31.0**	0.45/0.42**	0.29/0.26**	1.4e-08/1.8e-08**
Saudi Arabia	39.3/24.6**	30.2/47.4**	0.37/0.33**	0.29/0.26**	1.7e-08/1.6e-08
Peru	12.2/11.3	27.7/34.9**	0.41/0.36**	0.28/0.28	1.5e-08/1.5e-08
Romania	22.8/24.0	34.4/52.7**	0.43/0.38**	0.35/0.31**	1.5e-08/1.7e-08**
Portugal	13.3/20.4**	22.6/35.9**	0.47/0.46**	0.27/0.26**	1.5e-08/1.9e-08**
Venezuela	13.5/14.4	28.6/34.9**	0.42/0.39**	0.28/0.26**	1.5e-08/1.7e-08**
Bangladesh	17.4/15.2	30.4/54.1**	0.41/0.30**	0.32/0.30**	1.4e-08/1.3e-08
Hungary	10.0/12.4**	17.9/22.5**	0.55/0.53**	0.34/0.31**	1.5e-08/1.8e-08**
South Korea	17.7/26.8**	26.8/42.1**	0.48/0.42**	0.33/0.31**	1.6e-08/2.0e-08**
Sweden	16.8/23.6**	17.6/28.2**	0.58/0.57*	0.37/0.31**	1.7e-08/2.3e-08**
Belgium	13.8/17.6*	17.9/26.4**	0.50/0.49**	0.34/0.29**	1.6e-08/1.9e-08**
United Arab Emirates	19.6/18.4	21.4/33.6**	0.46/0.42**	0.28/0.22**	1.7e-08/1.7e-08
Denmark	12.7/18.4**	14.8/23.5**	0.57/0.57	0.34/0.29**	1.7e-08/2.2e-08**
Czech Republic	12.2/20.2**	17.0/27.1**	0.56/0.52**	0.38/0.31**	1.6e-08/2.1e-08**
Singapore	14.8/20.6**	19.5/30.0**	0.51/0.49**	0.27/0.24**	1.7e-08/2.1e-08**
Finland	13.4/47.0**	13.7/23.5**	0.60/0.59*	0.37/0.35**	1.6e-08/2.5e-08**
Greece	19.0/22.1	26.5/40.3**	0.47/0.44**	0.34/0.30**	1.5e-08/1.8e-08**
Ireland	13.9/22.2**	17.3/27.4**	0.49/0.48	0.35/0.31**	1.6e-08/2.1e-08**
Serbia	13.9/46.9*	19.8/31.8**	0.53/0.47**	0.31/0.30	1.5e-08/2.0e-08**
Switzerland	22.4/29.2	20.6/33.3**	0.50/0.48**	0.31/0.28**	1.7e-08/2.2e-08**
Austria	14.2/27.9**	17.9/31.4**	0.52/0.49**	0.37/0.33**	1.5e-08/1.9e-08**
Norway	16.8/40.3**	17.6/30.8**	0.57/0.56**	0.35/0.31**	1.7e-08/2.5e-08**
Israel	23.2/61.5	24.5/37.4**	0.50/0.49	0.26/0.23**	1.8e-08/2.5e-08**
Ecuador	8.5/8.5	27.6/31.4**	0.40/0.36**	0.32/0.31**	1.4e-08/1.3e-08
New Zealand	14.3/22.4**	16.7/27.8**	0.51/0.50**	0.33/0.29**	1.6e-08/2.0e-08**
Slovakia	6.4/12.8**	13.1/21.1**	0.61/0.58**	0.32/0.30**	1.6e-08/2.0e-08**
Sri Lanka	20.9/21.1	23.7/50.7**	0.47/0.36**	0.31/0.30*	1.6e-08/1.6e-08
Bulgaria	14.9/19.1**	25.2/36.2**	0.48/0.46**	0.34/0.31**	1.5e-08/1.8e-08**
Croatia	8.9/14.5**	15.0/26.4**	0.54/0.50**	0.32/0.30**	1.4e-08/1.7e-08**
Morocco	20.7/18.3	27.1/57.9**	0.44/0.30**	0.25/0.26	1.7e-08/1.4e-08**
Dominican Republic	16.7/16.0	27.5/39.3**	0.43/0.38**	0.27/0.27	1.6e-08/1.7e-08
El Salvador	12.8/11.5	31.7/28.7	0.38/0.39	0.21/0.24**	1.4e-08/1.5e-08*
Algeria	20.7/10.6**	27.6/51.4**	0.34/0.22**	0.25/0.27	1.3e-08/1.0e-08**
Costa Rica	14.6/15.1	20.3/27.6**	0.50/0.46**	0.27/0.27	1.7e-08/1.8e-08
Kenya	13.1/14.8	28.6/42.0**	0.42/0.34**	0.27/0.26	1.6e-08/1.5e-08
Nigeria	8.7/8.4	31.9/47.7**	0.31/0.21**	0.26/0.27	1.2e-08/1.1e-08*
Guatemala	10.1/12.1	21.2/26.2**	0.46/0.40**	0.27/0.29*	1.5e-08/1.5e-08
Uruguay	13.2/13.9	23.9/28.6*	0.46/0.46	0.27/0.27	1.5e-08/1.7e-08**
Lithuania	7.9/19.3**	19.3/34.5**	0.51/0.49**	0.30/0.28**	1.5e-08/2.0e-08**
Kazakhstan	16.5/16.8	33.6/35.6	0.38/0.37	0.33/0.32	1.4e-08/1.5e-08
Paraguay	16.8/18.2	28.1/34.0**	0.45/0.42**	0.23/0.23	1.8e-08/1.8e-08
Slovenia	10.0/18.2**	16.8/30.2**	0.56/0.53**	0.27/0.28	1.6e-08/2.1e-08**
Latvia	11.8/19.7**	26.2/35.3*	0.51/0.48**	0.34/0.31**	1.5e-08/2.3e-08**
Estonia	8.9/15.0**	15.0/25.7**	0.54/0.51**	0.26/0.25	1.6e-08/1.9e-08**