Gender Outcome Disparities in an Online Community of Designers

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1 Extended Abstract

Research in the social sciences has shown that both individual attributes and social networks matter in individual success across various contexts, like in school, on the job market, in the workplace, and so on. However, the specific mechanisms are highly dependent on the social context: the available channels for social contact, the constraints on social ties, the channels for social influence, group size, and other factors clearly influence individual success.

The recently growing popularity of online platforms both for social interactions (e.g. Twitter, Instagram) and job search (e.g. Linkedin, freelancer.com) changes the social mechanisms that determine individual success. Currently, we know very little about how inequalities emerge in these new types of communities. We do know, however, that the design of the sites matters: some researchers express concerns that the use of algorithms and public feedback might retain or even reinforce inequalities in success based on, especially, race and gender [4, 3]. Empirical work in online freelance communities [5, 6, 2] and on collaboration in teams [7, 1] also highlight the presence of gender inequalities.

Online markets in which individuals both compete and cooperate can provide insight into new mechanisms behind gender inequality. In these markets, team performance is central to success. Beyond the question of how the market reacts to women and men, there is also the question of how small-group dynamics in teams impact the success of males and females, and how the performance of the team as a whole is affected by gender diversity.

In this paper we analyze Dribbble, the most "elite" online community for digital designers. The site allows graphic designers to showcase their work in web design, illustration, and other creative areas, follow artists whose work they appreciate, discuss design ideas, and work on collaborative projects in teams. Dribbble enjoys a high prestige in the worldwide community of graphic designers, as it is invitation-only and provides a good platform for advertising one's work. We crawled the pages of all 994 teams on the site, 6,215 users involved in one of the teams, and finally all 60,406 images created by these teams.

Our questions are *do men and women have different success rates on Dribbble?*, and if yes, *what are the factors contributing to the differences?* We separately analyze the effects of individual user characteristics, activity on the site, production patterns, and social network structure to understand how much each of these factors contributes to success of individuals and where gender differences may be reinforced.

Using the variables extracted from our data set, we define three measures of user success: the average number of views, likes, and responses the works of a user get. We build regression models in which we set our measures of success as the dependent variables. As shown in Table 1a shows that men are more successful according to all measures, even after controlling for basic individual characteristics extracted from the profile information.

Since the observed differences between men and women are not explained by basic user-level characteristics and the models do not have a strong explanatory power ($R^2 =< 0.13$), in the following sections we investigate two possible explanations for the observed gender discrepancies in success: that *men and women are creating different products* and that *men and women have different social network structures*.

Since skills and social background might determine the kind of work people produce, in the next step we attempt to quantify how typically male or female a Dribbble user's work is, and if this can explain observed differences in outcomes. We create a measure for skill and image "genderness" using data mining techniques. Interestingly, even though skills are not strongly divisive, we can predict with 0.72 AUC if an image was created by a man or a women using a combination of features extracted directly from the image, and from the user-generated tags. This suggests that indeed some men and women are creating different art. Once controlling for these variables in our models we find that the relationship between gender and outcome is no longer significant, though the resulting model still has limited predictive power.

Finally, we investigate social behavior and network effects on the social network underlying Dribbble. First, we include variables describing user position in the social network into our models about success. In the models described in Table 1 we see that the number of followers a user has is a very strong predictor of success. We also see that the density of a user's ego network has a positive effect on his or her success. We also find that adding these terms adds significant predictive power to all three models.

Finally, we create Exponential Random Graph Models (ERGM) to better understand the differences in male and female users' social networks. The results suggest that women have more cohesive social networks than men. When we return to our original model of success and control for these network features, we find again that gender no longer has a significant impact on success.

In summary, our results demonstrate that there can be multiple potential sources of gender inequalities in online markets. However, this study only puts forth a few simple mechanisms that may be driving these biases. In reality, individual characteristics and social structures are dynamically interrelated: users may adjust their production and self-representation to be able to reach larger audiences, and social relations constantly evolve as a result of users trying to adapt to an ever changing environment. What seems clear, however, is that "gender" remains one of the key categories around which communities produce their understanding of quality and success.

In addition, the described empirical patterns of success also suggest a few lessons for the design of algorithms to present the work of users. Dribbble incorporates common design elements of today's social and labor market platforms, such as sharing content to social ties, publicly visible feedback/success measures, and content recommendation based on popularity/relevance. For example, if Dribbble's search enginew ranks relevant images using views, it indirectly advantages men. If it were to rank images using likes per view, women would be advantaged. This kind of detail is important, given that feedback loops and rich get richer effects can inflate differences in outcomes over time. It certainly merits further investigation by researchers, designers of online platforms, and regulators.

User Averages (log):	Views	Likes	Responses
Log(Number of Shots)	**0.09*****	**0.11*****	-0.004
Log(Age of Account)	0.03	$-$**0.15*****	**0.04****
Leadership Word in Bio	0.05	0.08	**0.08***
Pro-badge	**0.49*****	**0.44*****	**0.29*****
Log(Team Size)	**0.39*****	**0.21*****	**0.002*****
Is Male	**0.19*****	**0.10***	**0.07****
R^2	**0.13**	**0.12**	**0.06**

(a) OLS regressions on user-level variables to predict impact of gender on success. (*Note:* $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$)

User Averages (log):	Views	Likes	Responses
Log(Number of Shots)	$-$**0.55*****	$-$**0.50*****	$-$**0.41*****
Log(Age of Account)	$-$**0.07****	$-$**0.22*****	-0.01
Leadership Word in Bio	-0.04	0.001	0.03
Pro-badge	0.03	0.01	-0.01
Log(Team Size)	**0.24*****	**0.19*****	**0.11*****
Is Male	0.04	-0.04	-0.03
Log(Follower Count)	**0.72*****	**0.69*****	**0.49*****
Twitter Reciprocity	-0.04	-0.06	-0.07
Twitter Ego Density	**0.26*****	**0.34*****	**0.27*****
R^2	**0.67**	**0.67**	**0.50**

(b) The effects of network structure on success.

Table 1: OLS regressions predicting success. (*Note:* $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$)

2 References

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