Give to Get: A Mechanism to Reduce Bias in Online Reviews

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Executive Summary

• A common problem with online reviews is polarization bias: There are many extremely positive or negative reviews and few moderate opinions. This can give a misleading view of opinion about products, services and companies.

• This study presents new statistical evidence showing how one of Glassdoor’s key incentive policies — known as the “give to get” policy — helps reduce polarization bias and encourages more neutral and balanced company ratings on Glassdoor.

• Based on a large sample of more than 116,000 reviews submitted to Glassdoor between 2013 and 2016, we compare the distribution of star ratings for users who faced the give to get policy with a statistically matched control group that did not face the policy.

• We find statistically significant evidence Glassdoor’s give to get policy reduces polarization bias in online company ratings. It reduces the likelihood of extreme 1-star and 5-star reviews by 3.6 percentage points and 2.1 percentage points, respectively. And it raises the likelihood of more moderate 3-star and 4-star reviews by 2.6 percentage points and 2.9 percentage points, respectively, providing a more balanced view of jobs and companies than would otherwise be the case.

• Although many online review sites suffer from polarization bias, these findings suggest it is possible to create more balanced and representative platforms by providing non-monetary economic incentives that encourage more moderate online users — who are often absent from online platforms — to share their opinions online.
I. Introduction

How do we know that we can trust online reviews? Among the general public, there is widespread concern about the fairness of online opinions about products, services and companies — and the motives behind those leaving online reviews. A common fear is that people writing online reviews are biased, having either extremely positive or extremely negative opinions, leaving those with moderate views underrepresented. Online reviews are often suspected of painting a picture of opinion that is more “polarized” than reality, making it hard to obtain a balanced perspective on the quality of products, services or companies.

These fears are not without some basis. Research shows many online reviews do in fact suffer from polarization bias. Studies of today’s most popular online review platforms — including Yelp business reviews and Amazon product reviews — show that the distribution of opinion is polarized, with many extreme positive and negative reviews, and few moderate opinions. This creates a “bi-modal” or “J-shaped” distribution of online product reviews that has been well-documented in the academic literature, making it hard to learn about the true distribution of quality from online reviews.

What can be done to overcome polarization bias in online reviews? In this study we present new evidence of the impact of an online mechanism used by Glassdoor known as a “give to get” model. Since Glassdoor launched in 2008, access to the service has been free for consumers, however the “cost” requires Glassdoor users to submit some form of content — such as a company review, salary, interview review, or benefits review — before being granted free access to the valuable reviews and salaries shared by others. The goal of this policy is to collect content broadly from all online job seekers visiting Glassdoor — rather than just those who self-select into leaving reviews voluntarily.

Based on a large sample of 116,358 Glassdoor reviews left between 2013 and 2016, we compare the distribution of company reviews submitted via the “give to get” mechanism to a control group of statistically matched reviews that were submitted voluntarily. Using standard statistical tests, we show that Glassdoor’s give to get policy significantly reduces polarization bias in online company reviews, creating a more balanced and representative platform for online opinion about employers than would otherwise be the case.

The remainder of this paper is organized as follows. In Section II, we illustrate the problem of polarization bias in two popular online review platforms and explain how Glassdoor’s give to get policy works. In Section III, we present the results of our statistical analysis, illustrating the impact of the give to get policy on the distribution of company reviews on Glassdoor. In Section IV, we summarize our findings and conclude.
II. Correcting Online Review Bias

In this section we illustrate the problem of polarization bias in online review platforms and explain how Glassdoor’s “give to get” mechanism attempts to address these concerns by soliciting online reviews from a more broad set of users with more balanced opinions.

A. Examples of Polarization Bias

Figure 1 shows two prominent examples of polarization bias in online reviews. On the left, we show the distribution of Yelp local business reviews provided by Yelp as of May 1, 2017.4 On the right, we show the distribution of Amazon online product reviews for electronic products from a 2016 data set shared by the International World Wide Web Conference Committee.

In both cases, the distribution of online reviews is characterized by many positive 5-star reviews and negative 1-star reviews, with many more positive than negative reviews represented. By contrast, comparatively few moderate 2-, 3- and 4-star reviews are represented. In the case of Yelp reviews, 46 percent of business reviews were positive 5-star reviews. Similarly, 56 percent of Amazon reviews for electronic products were 5-star reviews. By contrast, just 10 percent of Yelp reviews gave a more moderate 3-star rating, while just 8 percent of Amazon electronics product reviews were rated as 3 stars.

It’s clear from the figure why researchers often refer to this type of distribution as “J-shaped” or bimodal. But while the distribution of online opinion appears highly polarized, experimental research shows that the true underlying distribution of product opinion is typically not highly polarized.

For example, a 2009 experimental study found that the true distribution of product opinions expressed in a laboratory setting was approximately “bell shaped” or normally distributed, with mostly moderate 2-, 3- and 4-star opinions, and about equal numbers of positive and negative reviews.6 This suggests the “J-shaped” pattern we often observe in practice reflects selection bias in the way reviews are being sampled from the population — rather than actual underlying polarization of consumer opinion.

B. Why Are Online Reviews Polarized?

Basic economic theory explains why most online review platforms suffer from polarization bias. As with any behavior, online users make the decision of whether to leave an online review by comparing the perceived costs and benefits of doing so. There is no out-of-pocket cost to leaving an online review, but it is costly in terms of time and effort to write and submit a review. Users who perceive little offsetting benefit will opt out and not leave reviews. Only users who perceive a benefit that outweighs the time and effort of leaving a review will leave one.

What types of online users are most likely to perceive the most benefit from leaving online reviews? In practice, research shows they tend to be users with the most extreme opinions. Individuals with highly negative or positive opinions often perceive a greater psychological benefit from expressing those opinions online, relative to more moderate users. Moderate users in practice often perceive little benefit from sharing their opinions online, and are deterred from doing so by the time and effort required to submit an online review.

This simple economic behavior leads to polarization bias in online reviews, and has dramatic implications for online review platforms. Review sites that rely exclusively on voluntary contributions will systematically collect reviews from the most polarized users, resulting in the bimodal or “J-shaped” distribution of reviews that has been well-documented in academic research.

C. How Glassdoor’s Give to Get Model Works

Glassdoor’s give to get policy works by soliciting online reviews from a broad sample of users on Glassdoor. It offers a simple incentive: Unlimited access to the valuable content on Glassdoor — which includes tens of millions of salary reports and company reviews and insights — in exchange for a contribution of some type of content back to the Glassdoor community.

In the language of economics, the policy raises the perceived benefit of leaving an online review (free access to Glassdoor content) while leaving the perceived costs of submitting reviews unchanged. This tips the balance in favor of submitting reviews among more neutral users who would otherwise perceive little offsetting benefit from sharing opinions online. Glassdoor’s give to get policy is described as follows:

“Glassdoor’s give to get policy requires that you submit a contribution in order to receive unlimited access to other content on our website. It ensures that we have enough salaries, company reviews, interview reviews, & benefits reviews to share with the community.

It only takes a minute to submit, and your contribution is anonymous. Your contribution will also help others, as their contributions will help you. When you contribute a review, salary, interview, or benefit review you will be granted 12 months of unlimited access to our content. After that period you may be asked to contribute another salary, review, interview or benefit review to extend your unlimited access for another 12 months.

If you are not ready to contribute, you can create a Glassdoor account without posting. You will have full access to salary, review, interview, and benefit content for 10 days.”

By soliciting contributions from a broad sample of Glassdoor users, rather than relying on users who voluntarily self-select into reviewing an employer — the policy aims to encourage a more balanced distribution of online reviews. In the next section we quantify this effect, showing how Glassdoor’s give to get policy reduces polarization in Glassdoor reviews.
III. Impact of “Give to Get” on Reviews

In this section, we show the results of a statistical analysis of how Glassdoor’s give to get policy affects the distribution of online company reviews. The results quantify for the first time how this mechanism can help reduce polarization bias on online review platforms.

A. Our Data

To study the impact of Glassdoor’s give to get policy on polarization bias in online reviews, we used a large sample of 58,179 U.S. company reviews submitted after facing the give to get policy between 2013 and 2016. These reviews represent the “treated” group subject to the policy in our analysis.

To study the impact of the policy, we developed a “control” group of online reviews that were not subject to the give to get policy. There are a variety of ways that users may submit content to Glassdoor without facing the give to get policy. For example, users may visit Glassdoor and contribute immediately before being prompted. Similarly, users may have contributed content in the past and choose to contribute again without prompting. In this study, our control group is made up of users like these who have left Glassdoor reviews without being prompted to do so by the give to get incentive.

To develop our control group, we began with a large sample of 304,989 U.S. company reviews submitted voluntarily to Glassdoor during the same time period as our treatment group of reviews that faced the give to get policy. Using a standard propensity score matching technique, we statistically paired each company review in our “treated” group with its closest matching neighbor in the “control” group.

The resulting data file contains 116,358 matched employer reviews: 58,179 “treated” reviews that faced the give get policy and 58,179 observationally similar “control” reviews that were voluntarily contributed and did not face the give to get policy. This framework provides a plausible counterfactual control group for our analysis, allowing us to estimate the causal impact of the give to get policy on the distribution of company reviews.10

A TECHNICAL NOTE ON PROPENSITY SCORE MATCHING

Propensity score matching was done using a “nearest-neighbor” method as implemented via the MatchIt package in R. This method matches each observation in the “treated” group to its nearest neighbor, based on the estimated “propensity score” or probability of having received treatment. Observations were matched on the following dimensions: age, gender, years of education, current or former job, length of employment, company size, company industry, and U.S. metro location.
Table 1 shows summary statistics for the matched data file. The average company rating in our sample is 3.4 out of 5 stars. Forty-three percent are reviews from current employees, while 57 percent are from former employees. Average tenure on the job is 2.5 years. The sample is 54 percent male and 46 percent female, with an average age of 32 years and 15.9 years of education — the equivalent of a bachelor’s degree. Company sizes range from single-employee companies to large employers with 1.86 million employees.

### Table 1. Summary Statistics for the Data File

<table>
<thead>
<tr>
<th>Variable</th>
<th>Observations</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>Min.</th>
<th>Max.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Overall Employer Rating</td>
<td>116,358</td>
<td>3.4</td>
<td>1.3</td>
<td>1</td>
<td>5</td>
</tr>
<tr>
<td>Rating = 1 Star</td>
<td>116,358</td>
<td>0.11</td>
<td>0.32</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Rating = 2 Star</td>
<td>116,358</td>
<td>0.13</td>
<td>0.34</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Rating = 3 Star</td>
<td>116,358</td>
<td>0.25</td>
<td>0.43</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Rating = 4 Star</td>
<td>116,358</td>
<td>0.28</td>
<td>0.45</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Rating = 5 Star</td>
<td>116,358</td>
<td>0.22</td>
<td>0.42</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Year of Review</td>
<td>116,358</td>
<td>n.a.</td>
<td>n.a.</td>
<td>2013</td>
<td>2016</td>
</tr>
<tr>
<td>Current Job = 1</td>
<td>116,358</td>
<td>0.43</td>
<td>0.49</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Years at the Job</td>
<td>116,358</td>
<td>2.5</td>
<td>3.6</td>
<td>0</td>
<td>20</td>
</tr>
<tr>
<td>Gender (Male = 1)</td>
<td>116,358</td>
<td>0.54</td>
<td>0.5</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Years of Education</td>
<td>116,358</td>
<td>15.9</td>
<td>1.5</td>
<td>12</td>
<td>20</td>
</tr>
<tr>
<td>Age</td>
<td>116,358</td>
<td>32</td>
<td>9.8</td>
<td>17</td>
<td>90</td>
</tr>
<tr>
<td>Company Size (# Employees)</td>
<td>116,358</td>
<td>19,520</td>
<td>56,994</td>
<td>1</td>
<td>1,860,000</td>
</tr>
</tbody>
</table>

Source: Glassdoor Economic Research (Glassdoor.com/research)

### B. Our Results

We use two approaches to analyze whether the give to get policy changes the distribution of company reviews on Glassdoor. First, we perform a high level “yes” or “no” statistical test to see whether the overall shape of the distribution of ratings among “treated” reviews that faced the give to get policy is really any different from “control” reviews that did not. This allows us to carefully assess whether the give to get policy has an impact on the overall distribution of Glassdoor reviews.

Second, we use a more detailed approach to examine how the distribution of online reviews is changed by the give to get policy. We use a regression framework to test which of the 1 to 5 star ratings become more or less likely when faced by the policy. This allows us to go beyond the question of whether the overall distribution of reviews is changed by the policy, to see how the probability of each star rating is affected — either positively or negatively — by the give to get policy.

#### i. Approach One: Are the Distributions Different?

Does facing the give to get policy change the overall distribution of online reviews? In Figure 2, we show the distribution of “treated” give to get reviews, and “control” reviews that were voluntarily submitted to Glassdoor.
The vertical axis shows the number of reviews for each star rating. Reviews prompted by the give to get policy are shown in light green, while voluntarily submitted reviews are shown in blue. Areas of common overlap are shown in dark green.

The first thing to note is that compared to many online review platforms, the distribution of Glassdoor reviews is less polarized to begin with. Neither distribution is strongly J-shaped, and both have a single peak around 4 stars. The main reason for this is that Glassdoor has implemented many institutions over the years that are designed to create a balanced platform for company reviews. The give to get policy we examine in this study is just one of these policies. The combined effect of these institutions is that the overall distribution of Glassdoor reviews is less polarized than might otherwise be expected — even before the application of the give to get policy.

**Figure 2. Company Reviews Prompted by “Give to Get” Are Less Polarized**

<table>
<thead>
<tr>
<th>Overall Employer Rating</th>
<th>Give to Get</th>
<th>Overlap</th>
<th>Voluntary</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

In Figure 2, the two distributions are generally similar, but with visually different shapes. Voluntary reviews appear to have more extreme 1-star and 5-star ratings, while give to get reviews appear to have more moderate 3-star and 4-star ratings. But are the two distributions really different, or is this difference just due to randomness?

To test whether the two distributions are in fact different, we apply a simple statistical test known as the Kolmogorov–Smirnov (K-S) test. This is a non-parametric test of whether the distribution of give to get reviews and voluntarily submitted reviews is really different; that is, it tests the null hypothesis that they both actually come from the same underlying distribution. Rejecting the null hypothesis is equivalent to saying the two distributions are in fact really different, and that the give to get policy thus changes the distribution of online reviews.

The results of this test as applied to Figure 2 strongly reject the null hypothesis that the distribution of give to get and voluntarily submitted reviews are the same. This suggests the give to get policy does in fact leads to a significantly different pattern of online reviews on Glassdoor than would be observed without it.
ii. Approach Two: Which Star Ratings Are More or Less Likely?

The test in the previous section shows that the give to get policy changes the overall distribution of company ratings on Glassdoor. But exactly how does it change the distribution?

To examine this, we use a more detailed approach that looks at how the give to get policy affects the probability of each 1-to-5 star ratings on Glassdoor. Using ordinary least-squares regression, we estimate five “linear probability models” — one for each of the five star ratings — to see how the give to get policy impacts the odds of a typical review giving a high versus a low company rating.

Figure 3 shows the results of regressing a binary indicator for each star rating on an indicator for having faced the give to get policy, along with statistical controls for age, gender, highest education, current or former employee status, years at their employer, company size, industry and U.S. metro location. For each star rating, the results tell us whether facing the give to get policy makes that star rating more or less likely. Statistically significant results are marked with a *.13

![Figure 3. Impact of Give to Get Policy on Moderate and Extreme Glassdoor Reviews](image)

* denotes statistically significant at the 99 percent confidence level.

Note: Linear probability regression of give to get policy and various controls on the probability of leaving each “star” level of employer review on Glassdoor. Coefficients show the conditional effect of the give to get policy on the probability of each rating level. Includes controls for age, gender, highest education, current or former employment, years at employer, company size, industry and metro location. Standard errors in parentheses are heteroskedasticity robust. * denotes statistical significance at the 99 percent level (P < 0.01).
Source: Glassdoor Economic Research (Glassdoor.com/research)
In Figure 3, the give to get policy has a statistically significantly and negative effect on the probability of extreme 1-star and 5-star reviews. The policy reduces the odds of a 1-star review by 3.6 percentage points, and reduces the odds of a 5-star review by 2.1 percentage points. By contrast, the policy has a positive and statistically significantly effect on the probability of moderate 3-star and 4-star reviews, raising the odds of each by 2.6 percentage points and 2.9 percentage points, respectively. The policy does not have a statistically significant impact on 2-star ratings.

These results provide the first statistical evidence of the practical impact of Glassdoor’s give to get policy on the distribution of online employer reviews. The results show the policy significantly changes the distribution of company ratings on Glassdoor, and does so in a way that reduces polarization bias — providing a more balanced assessment of company culture than would otherwise be the case.

IV. Conclusion

Many online review platforms suffer from polarization bias, with many extreme opinions and few moderate points of view. In this study, we present the first-ever statistical analysis of an online mechanism used by Glassdoor to counter this form of polarization bias: the give to get policy. By asking online users to submit content in exchange for free access to valuable information on Glassdoor, the policy effectively draws a sample of company reviews from a much broader — and less polarized — base of users than would otherwise be the case.

Our statistical analysis shows Glassdoor’s give to get policy significantly changes the distribution of online reviews, and does so in a way that reduces polarization bias. It reduces the likelihood of extreme 1-star and 5-star reviews by a statistically significant 3.6 percent and 2.1 percent, respectively. In addition, it raises the odds of more moderate 3-star and 4-star reviews by 2.6 percent and 2.9 percent, respectively. Taken together, this helps create a more balanced and neutral platform for online opinion about jobs and companies.

These findings suggest that polarization bias is not inevitable in online reviews platforms. By providing basic economic incentives that encourage those with more neutral opinions to submit reviews, online platforms can significantly reduce polarization bias, providing a more balanced and representative picture of the distribution of online opinions about products, services and companies.
Appendix

Table A1 presents the full results of our linear probability model regression of the odds of observing each of the five Glassdoor star rating on an indicator of having faced the give to get policy, along with controls for various user and employer characteristics. These estimates correspond to Figure 3 in the body of the study.

Table A1. Complete Linear Probability Model Results (Regression of the Probability of Each Star Rating on an Indicator for the Give to Get Policy Plus Controls)

<table>
<thead>
<tr>
<th>Variable</th>
<th>1 Star</th>
<th>2 Star</th>
<th>3 Star</th>
<th>4 Star</th>
<th>5 Star</th>
</tr>
</thead>
<tbody>
<tr>
<td>Give to Get Policy = 1</td>
<td>-0.036***</td>
<td>0.001</td>
<td>0.026***</td>
<td>0.029***</td>
<td>-0.021***</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.002)</td>
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<tr>
<td>Controls:</td>
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<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>Age</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Gender</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Highest Education</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Current or Former Employee</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Years at Employer</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Company Size</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Industry</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Metro Location</td>
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<td>X</td>
<td>X</td>
<td>X</td>
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</tr>
<tr>
<td>Observations</td>
<td>116,358</td>
<td>116,358</td>
<td>116,358</td>
<td>116,358</td>
<td>116,358</td>
</tr>
<tr>
<td>Adjusted R-squared</td>
<td>0.043</td>
<td>0.017</td>
<td>0.013</td>
<td>0.018</td>
<td>0.05</td>
</tr>
</tbody>
</table>

Note: Linear probability regression of give to get policy and various controls on the probability of leaving each “star” level of employer review on Glassdoor. Coefficients show the conditional effect of the give to get policy on the probability of each rating level. Includes controls for age, gender, highest education, current or former employment, years at employer, company size, industry and metro location. Standard errors in parentheses are heteroskedasticity robust. *** denotes statistical significance at the 99 percent level (P < 0.01).

Source: Glassdoor Economic Research (Glassdoor.com/research)
Notes


3. Note that job search is always free on Glassdoor; only access to company reviews and salaries is subject to the give to get policy.


7. For an overview of “polarization effects” and other factors that influence the decision of whether to leave online reviews, see Wendy W. Moe, David A. Schweidel and Michael Trusov (Fall 2011), “What Influences Customers’ Online Comments,” MIT Sloan Management Review. Available at http://sloanreview.mit.edu/article/what-influences-customers-online-comments/.


11. The Kolmogorov-Smirnov test is considered “distribution free” and provides a flexible way to compare samples from unknown underlying distributions, such as the data used in this analysis. More information about the test as implemented by the ks.test() command in R is available at https://stat.ethz.ch/R-manual/R-devel/library/stats/html/ks.test.html.

12. The K-S test returns a very small p-value of 0.00000000000000022.

13. A full table of regression results is provided in the Appendix.