CESifo WORKING PAPERS

6750
2017

November 2017

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Apostolos Filippas, John J. Horton, Joseph M. Golden

CESifo

Impressum:

CESifo Working Papers
ISSN 2364-1428 (electronic version)
Publisher and distributor: Munich Society for the Promotion of Economic Research - CESifo GmbH
The international platform of Ludwigs-Maximilians University's Center for Economic Studies and the ifo Institute
Poschingerstr. 5, 81679 Munich, Germany
Telephone +49 (0)89 2180-2740, Telefax +49 (0)89 2180-17845, email office@cesifo.de
Editors: Clemens Fuest, Oliver Falck, Jasmin Gröschl
www.cesifo-group.org/wp

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CESifo *Working Paper No. 6750*
Category 14: Economics of Digitization

Reputation in the Long-Run

Abstract

Feedback scores in an online marketplace have risen sharply over time, leading to substantial top-censoring. Some of the increase is explained by more satisfied raters, but at least 35-45% is attributable to raters applying lower standards. We show that this "reputation inflation" is the equilibrium outcome of a model in which (a) inferences made by future trading partners determine what constitutes "bad" feedback and (b) giving "bad" feedback is costly to raters. The introduction of a new feedback system confirms our model predictions: raters were candid when feedback was private, but when feedback suddenly became public, reputations began inflating.

Apostolos Filippas
NYU Stern School of Business
USA - 10012 New York NY
apostolosfilippas@gmail.com

*John J. Horton**
NYU Stern School of Business
USA - 10012 New York NY
john.horton@stern.nyu.edu

Joseph M. Golden
Collage.com, Inc.
Mountain View / California / USA
jgolden9@gmail.com

*corresponding author

November 13, 2017
Author contact information and code are currently or will be available at http://www.john-joseph-horton.com/. Thanks to Richard Zeckhauser, Andrey Fradkin, David Holtz, Ramesh Johari, Nico Lacetra, Xiao Ma, and Aaron Sojourner for very helpful comments and suggestions. Helpful feedback was received at the Crowdsourcing Seminar at Carnegie Mellon University at the School of Computer Science, the NBER Summer Institute on the Economics of Digitization, and the MIT Conference on Digital Experimentation.

1 Introduction

Scores of various kinds—credit scores, school grades, restaurant and film "star" reviews, restaurant hygiene scores, Better Business Bureau ratings—have long been important sources of information for market participants. A large literature documents the economic importance of such scores (Resnick et al., 2000; Jin and Leslie, 2003; Resnick et al., 2006; Mayzlin et al., 2014; Ghose et al., 2014; Luca, 2016; Luca and Zervas, 2016). As more of economic and social life has become computer-mediated, opportunities to generate and apply new kinds of scores—particularly in marketplace contexts—have proliferated (Dellarocas, 2003), as has the number of individuals and businesses subject to these "reputation systems" (Farrell and Greig, 2016; Hall and Krueger, Forthcoming; Katz and Krueger, 2016).[1]

In online marketplaces, "reputations" are typically calculated from the numerical feedback scores left by past trading partners. As many have noted, the distribution of feedback scores in various online marketplaces seems implausibly rosy.[2] For example, the median seller on eBay has a score of 100% positive feedback ratings, and the tenth percentile is 98.21% positive feedback ratings (Nosko and Tadelis, 2015). On Uber and Lyft, it is widely known that anything less than 5 stars is considered "bad" feedback. Of course, there is no ground truth that tells us what the distribution of scores in some market "should" look like. However, a high degree of top-censoring suggests a lost opportunity with respect to how much information the reputation system provides.

In this paper we examine the reputation system of a large online labor market.

[1] These kinds of online marketplaces are becoming increasingly consequential as they grow rapidly, making their shortcomings consequential as well. Katz and Krueger (2016) find that the share of workers whose main job is an alternative work arrangement—defined to include independent contractors and freelancers—has increased from 10.7 percent in 2005, to almost 16 percent in 2015. A large part of this increase can be attributed to employment in online platforms; Farrell and Greig (2016) show that participation in the online platform economy amongst adults has risen from less than 0.2 percent in 2012, to 4.3 percent in 2016. The same authors also find that the annual growth rate of workers receiving income from online platforms exceeds 100 percent. Hall and Krueger (Forthcoming) report that more than 460,000 drivers were actively participating on the Uber platform by the end of 2015.

[2] A survey conducted by the PEW research center finds that while more than 80% of U.S. adults read online reviews before purchasing an item, almost 50% believe that it is hard to assess the truthfulness of these reviews (see http://www.pewinternet.org/2016/12/19/online-reviews).

We find that the distribution of recent employer feedback for workers is highly top-censored, with an overwhelming majority receiving perfect feedback.[3] However, the distribution has not always been this skewed—the fraction of workers receiving the highest possible rating of 5 stars went from 32% to 85% in just 6 years. We show that this top-censoring has been consequential, in that feedback scores have become less informative about worker quality over time.

Our main focus is understanding the cause of the rise in feedback scores. There are two distinct—but not mutually exclusive—reasons feedback scores could be rising: (1) raters are becoming more satisfied, or (2) raters are lowering their standards. This second possibility—giving higher scores despite not being more satisfied— can be thought of as a kind of inflation.[4] Disentangling these two reasons requires longitudinal data that include both the feedback scores and an alternative measure of rater satisfaction.

As an alternative measure of rater satisfaction, we use the sentiment raters express in the written feedback that accompanies numerical scores. To capture this sentiment, we fit a model that predicts numerical feedback from the text of written feedback. Critically, the model is fit using feedback from a narrow window of time early in our data set. With our method, we can learn the relationship that prevailed between written sentiment and score when the training feedback was created. Using the predictions, we can then decompose the growth in average feedback score into a component due to improvements in market "fundamentals" (e.g., improved marketplace features, better cohorts of workers, less picky employers, and so on) that increased rater satisfaction (as reflected in feedback text), and the residual component that cannot be explained by changes in fundamentals.

We find that although predicted feedback scores have increased over time, they have not increased nearly as much as the actual, numerical feedback scores. Our estimates suggest that about 35-45% of the increase in scores during a 6 year period was due to inflation, i.e., raters lowering their standards. Further, to the extent that written feedback is also subject to inflation, our approach *understates*

[3]We use the terms "employer" and "worker" for consistency with the literature, and not as a comment on the legal relationship of the transacting parties.

[4]This kind of inflation is similar to the conjecture about college grade inflation (Babcock, 2010; Butcher et al., 2014).

the role of lower standards in explaining the rise in average feedback.

As a less model-dependent approach to quantify inflation, we also compare the numerical feedback scores associated with the same common sentences appearing in written feedback in two different time periods. We show that the same sentences systematically have higher associated numerical feedback scores in the latter period. To the extent that the meaning of the same sentences has not changed between these time periods, reputation inflation is the culprit.

We next turn to understanding the cause of reputation inflation, or why raters lower standards over time. A starting point is noting the asymmetry in costs to giving different kinds of feedback. Anecdotal evidence from raters suggests that many give "good" feedback despite being unsatisfied. Some report they fear retaliation, while others claim to not want to harm the rated individual, as feedback is highly consequential. Although rated workers can not retaliate by giving the employer bad feedback (given the design of the system (Bolton et al., 2013)), they can still complain, bad-mouth the rater, withhold future cooperation, and so on. These "reflected" costs make giving "bad" feedback costlier to the rater than giving "good" feedback.

The cost of giving bad feedback could provide an explanation for why feedback scores are higher than they would be if more employers reported truthfully. However, it cannot by itself explain the dynamics of ever-higher scores we observe: inflation would require the cost of leaving a given "bad" score to increase over time. We hypothesize this is precisely what happens; the same nominal feedback score (e.g., 3 "stars") can become costlier to the rated worker over time, and hence costlier for the rater to give. In other words, the cause of inflation is that what constitutes "bad" feedback—feedback that causes worse market outcome for raters receiving that score—is endogenous, depending on the current distribution of feedback scores, and what inferences future employers make from a score.

To formally illustrate how reputations can inflate, we present a simple model of a marketplace with a reputation system. We show that there exists a stable equilibrium in which sellers only report "good" feedback, regardless of actual performance, and reputations are universally inflated, even when raters derive

some benefit from telling the truth.[5] While our observed data is consistent with this theory, we will report evidence from a platform intervention that allows us to test this hypothesis.

The platform intervention was the introduction of a new, parallel reputation system that, at first, asked employers to rate workers "privately." The private feedback was not conveyed to the rated workers, nor made public to future would-be employers. At the same time, raters were still asked to give the status quo "public" feedback, both written and numerical. The conjecture motivating the private feedback feature was that raters would be more candid in private, willing to give "bad" feedback if not exposed to the reflected cost from angry workers.

Eventually, the platform began releasing batched *aggregates* of this private feedback score to would-be employers. With this aggregation, the worker would not know ex post which particular rating employer gave which feedback, unless every rater in the batch gave the same rating. However, with this private feedback now being reported, it became consequential to workers, who now had incentives to try to encourage good private feedback. To the extent that employers care about the fate of workers and do not want to harm them with bad feedback, or believe that it could get "back" to them, giving bad feedback suddenly had a cost.

This private feedback quasi-experiment is useful for our purposes because it allows us to test our model's predictions, and assess its assumptions about the causes of reputation inflation, namely that (1) the rater's choice of what score to give is "strategic"—in the sense that employers consider the likely costs and benefits to what they report—and as such, are more candid in private because there are no reflected costs, and (2) when costs are introduced by the switch to public revelation, inflation occurs.

Using only data before the switch to public revelation, we first document that raters are far more candid about "bad" performance when their opinions will not be shared publicly. We find that 28.4% of the employers that privately reported

[5]In our model, the degree of reputation inflation depends on how much cost the rated entity can impose on the rater for bad feedback. This could explain why in less personal settings—such as consumers rating products on Amazon or restaurants on Yelp—ratings are more spread out. In contrast, inflation is likely more acute in highly "personal" settings, such as on peer-to-peer platforms (Sundararajan, 2013; Horton and Zeckhauser, 2017).

that they would definitely not hire the same worker in the future, publicly gave at least a 4-star feedback score for that worker. We also find that employers giving bad private feedback are far more likely to forgo giving public feedback of any kind, and hence directly verify an important conjecture in the marketplace reputation literature (Dellarocas and Wood, 2008; Nosko and Tadelis, 2015). Together, the differences in how often and what kind of feedback employers are willing to give publicly versus privately, are consistent with the hypothesis that giving bad feedback publicly is costlier than giving it in private. This means that the switch to public revelation was a positive cost shock.

When the platform suddenly made private feedback scores public, private feedback scores began increasing immediately but there was no corresponding change in the sentiment of written feedback—the no-longer-private feedback became inflated, mirroring what we observed with public feedback, albeit in a much shorter time window. Importantly, the fact that the sentiment of written feedback remained more or less constant provides us with direct evidence that written feedback sentiment is an estimate of satisfaction that is less prone to inflation that numerical feedback. Further, this change implicates the role of the reflected cost of bad feedback: when getting bad feedback became costly to workers, it also became costly to give, and there was less "bad" feedback. As bad feedback became scarce, what was mildly negative before became very negative, starting the inflation process we describe in our model.

A natural question is whether the problem of reputation inflation is commonplace in markets. We suspect the reputation inflation problem is widespread, given that many marketplaces share the same features as the one we study, and nearly all have those features that we show lead to inflation. As some evidence of generality, using data from another online labor market we show that average numerical feedback ratings have also increased strongly over time.

Our key contribution is documenting the extent and practical importance of reputation inflation in a large online marketplace with a state-of-the-art reputation system. We also elucidate the root cause of that inflation, and our analysis reveals the dynamics that lead to this outcome. Our long-run, whole-system perspective is possible because we use a data set spanning over a decade of the operations of the marketplace. While our paper is not the first to explain how

reputations can be biased (Dellarocas and Wood, 2008; Li and Hitt, 2008; Hu et al., 2017), we believe it is the first to show how individually rational choices about what feedback to leave can push the market towards a less informative equilibrium, and hence put the reputation system on an inexorable path towards uselessness. Whether reputation systems can be designed that are less prone to inflation is an open research question.

The rest of the paper is organized as follows. Section 2 describes our empirical setting, and documents that average feedback scores increase over time. Section 3 conducts a textual analysis to show that the increase in scores is not solely due to positive changes in fundamentals, and examines the negative informational implications of reputation inflation. A model for reputation inflation is presented in Section 4, and its predictions are tested by employing private feedback data in Section 5. We conclude in Section 6.

2 Empirical context

The setting for our study is a large online labor market. In online labor markets, firms and individuals hire workers to perform tasks that can be done remotely, such as computer programming, graphic design, data entry, and writing. Markets differ in their scope and focus, but common services provided by the platform include maintaining job listings, hosting user profile pages, arbitrating disputes, certifying worker skills and, importantly, maintaining reputation systems (Horton, 2010).

Online labor markets have offered a convenient setting for research, due to the excellent measurement afforded in an online setting, and the ease with which field experiments can be conducted (Horton et al., 2011). Much of the research has focused on the role of information in employer decision-making (Pallais, 2013; Stanton and Thomas, 2015; Agrawal et al., 2016; Chan and Wang, Forthcoming; Horton, 2017). There is also a growing literature on online labor markets as a phenomenon and as a domain to study online marketplaces more generally. This literature explores topics such as the nature of economic relationship created (Chen and Horton, 2016), the role of preference signaling (Horton and Johari, 2015; Horton, Forthcoming), and the bidding process (Zheng et al., 2016).

One particular focus of the literature has been reputation systems. Moreno and Terwiesch (2014) show how employers use reputation information—and subsequently how workers adjust their bidding strategies in light of this employer conditioning. Cabral and Hortacsu (2010) also find that eBay sellers condition their behavior on their current reputations. Moreno and Terwiesch (2014) also use written feedback as an alternative measure of rater satisfaction, though they extract the sentiment using unsupervised learning techniques, in contrast to our supervised learning where the label is the associated numerical feedback score. Dimoka et al. (2012) show that reputation is more important in labor than in product markets, as a "bad" seller may by chance offer a great product, but a "bad" worker almost certainly produces bad work. Reputation matters when hiring workers for fixed-price contracts, while its role is diminished for contracts with hourly payments (Lin et al., Forthcoming). Kokkodis and Ipeirotis (2015) explore the "transferability" of reputations, showing that reputation scores can become more predictive of future performance when job category information is incorporated.

2.1 Status quo reputation system

On the platform used in our study, when one party ends a contract—typically the employer—both parties are prompted to give feedback.[6] Employers are asked to give both written feedback, e.g., "Paul did excellent work—I'd work with him again" or "Ada is a great person to work for—her instructions were always very clear," and numerical feedback. The numerical feedback is given on several weighted dimensions: "Skills" (20%), "Quality of Work" (20%), "Availability" (15%), "Adherence to Schedule" (15%), "Communication" (15%) and "Cooperation" (15%). On each dimension, the rater gives a score on a 1-5 scale. The scores are aggregated according to the dimension weights. A worker's reputation at a moment in time is the average of her scores on completed projects, weighted by the dollar value of each project. On the worker profile, a lifetime score is shown as well as a "last 6 months" score. Showing recent feedback is presumably the

[6] We use the present tense here to describe the reputation system before the introduction of private feedback.

platform's response to the opportunism that becomes possible once a employer or worker has obtained a high, hard-to-lower reputation (Aperjis and Johari, 2010; Liu, 2011). Despite the aggregation of individual scores into a reputation, the entire feedback "history" is available for inspection to interested parties. Workers can view the feedback given to previous workers rated by that employer and the feedback received by an employer from that same worker.

The reputation system could be characterized as state-of-the-art for a bilateral system, in the sense that direct tit-for-tat conditioning is not possible (Dellarocas, 2005; Bolton et al., 2013; Fradkin et al., 2015). Both the employer and the worker have an initial 14 day "feedback period" in which to leave feedback. The platform does not reveal public feedback immediately. Rather, the platform uses a "double-blind" process. If both parties leave feedback during the feedback period, then the platform reveals both sets of feedback simultaneously. If, instead, only one party leaves feedback, then the platform reveals it at the end of the feedback period. Thus, neither party learns its own rating before leaving a rating for the other party.

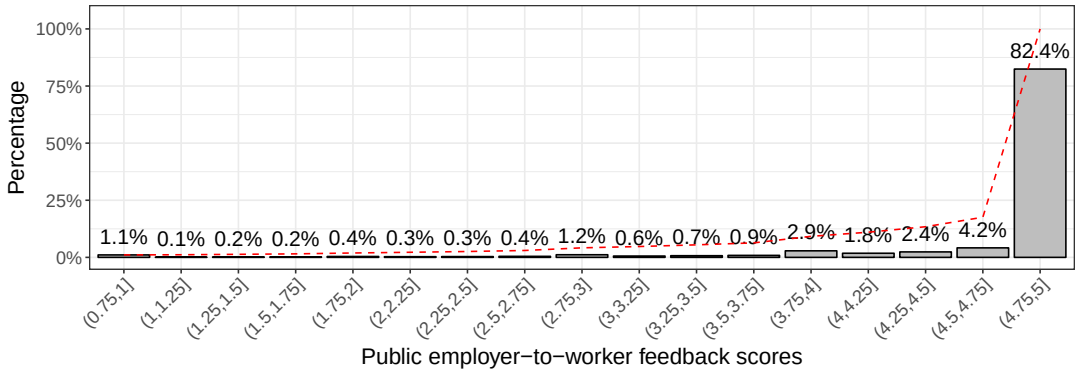
Despite the reputation system features designed to prevent tit-for-tat feedback, there is nothing to stop parties from engaging in "pre-play" communication about their intentions. We have some evidence that feedback manipulation occurs, from forum and blog postings, communication between employers and workers, and complaints directly to the platform. It is generally difficult to directly assess the severity of this problem, partially because communication about manipulation between the two parties may occur entirely in private, such as via email. However, a survey of platform employers found that 20% had felt pressure to leave more positive public feedback. Leaving feedback is not compulsory, though it is strongly encouraged. These encouragements seem effective, in that over the history of the platform, 68% of employers eligible to leave feedback have chosen to do so.

2.2 Feedback now and over time

The distribution of employer-on-worker feedback scores in the market is highly right-skewed. Figure 1 depicts the histogram of completed assignments that re-

ceived a feedback score from the employer, from January 1, 2014 to May 11, 2016. Public feedback scores are between 1 and 5 stars, inclusive, and with increments of 0.25 stars. Each bar is labeled with the percentage of total observations falling in that bin, and the red dashed line shows the cumulative number of assignments with feedback less than or equal to the right limit of the bin it is above. We observe that more than 80% of the evaluations fall in the 4.75 to 5.00 star bin (1,339,071 observations). The ratings distribution is *slightly* J-shaped (Hu et al., 2009), with some weight in the lowest bin of observations rated with exactly 1 star.

Figure 1: Distribution of employer numerical feedback to workers for the period January 1, 2014 to May 11, 2016.

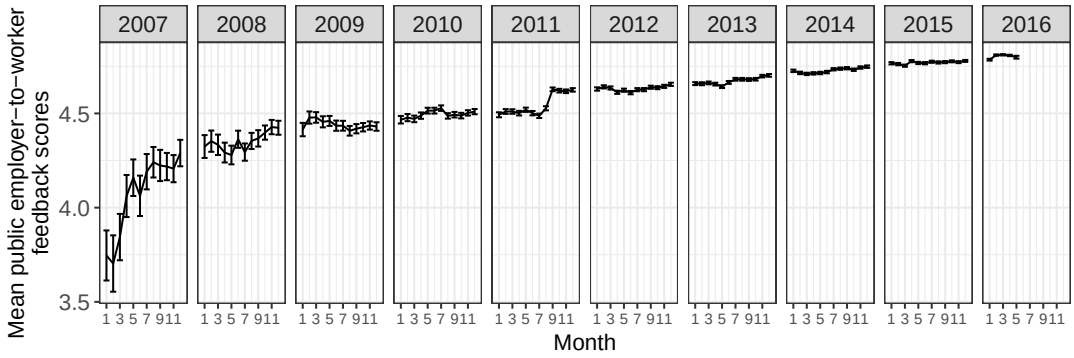


Notes: The histogram of public numerical ratings assigned by employers to workers, discretized by 0.25 star interval bins is shown. The value of each bin is shown above it, and the red line depicts the empirical cumulative density function. The sample we use consists of all completed contracts from January 1, 2014 to May 11, 2016, for which the employer provided feedback. This sample corresponds to the last three panels from Figure 2.

The average feedback pooled over the whole sample shown in Figure 1 is 4.76. In Figure 2 we plot the average monthly feedback over time. This measure is for contracts ending within that month, and hence approximately the month when that feedback was given. There is a clear increase in the feedback scores awarded on the platform: the numerical feedback score average has increased by more than one star over the ten years of operation of the platform, from 3.74 in the beginning of 2007, to 4.79 in May 2016. The strongest period of increase was 2007, when average feedback scores increased by about 0.75 stars.

The increase in average feedback shown in Figure 2 could be the outcome of

Figure 2: Monthly average public feedback scores assigned to workers by employers on completed projects.

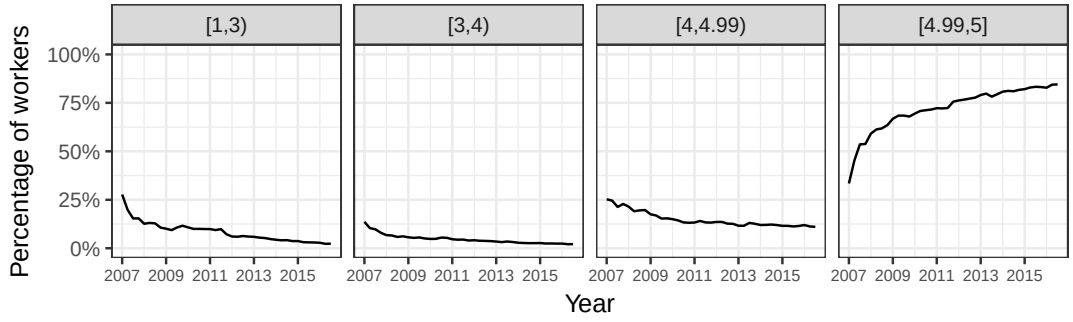


Notes: This figure plots the average public feedback scores assigned by employers to workers on completed contracts by month. The average scores are computed for every month, and a 95% interval is depicted for every point estimate. The scale for feedback is 1 to 5 stars. The histogram for all feedback for the last three panels is shown in Figure 1.

raters giving less "bad" feedback, more "good" feedback, or some combination thereof. For example, we could see a decrease in the proportion of workers that receive 1-star ratings, and an increase in the percentage of workers receiving 3 stars. Figure 3 shows the fraction of contracts having a rating within different ranges, over time. We can see in the leftmost panel of Figure 3 that completed contracts regularly received ratings in the $(0, 3]$ range in the early days of the platform. Further, early on the ratings assignments were reasonably dispersed, with every bin containing at least 15% of the employers' ratings. Near the end of our data, completed contracts essentially never receive a rating in the $(0, 3]$ star bin, despite nearly 30% of such contracts getting this rating originally. Instead, there has been a dramatic increase in the fraction of contracts getting exactly 5 stars: 32% of contracts received a 5-star rating at the start of sample, compared to 85% at the end of the sample.

We also have evidence that the kind of feedback increase we observe is not unique to our marketplace. We obtained contemporaneous feedback data from another large online labor market. The average monthly feedback given by employers to providers on the second marketplace is plotted in Figure 4. Although the average feedback on this marketplace starts from a higher point—likely reflecting the greater age of this platform (launched in 1999)—an increase is also

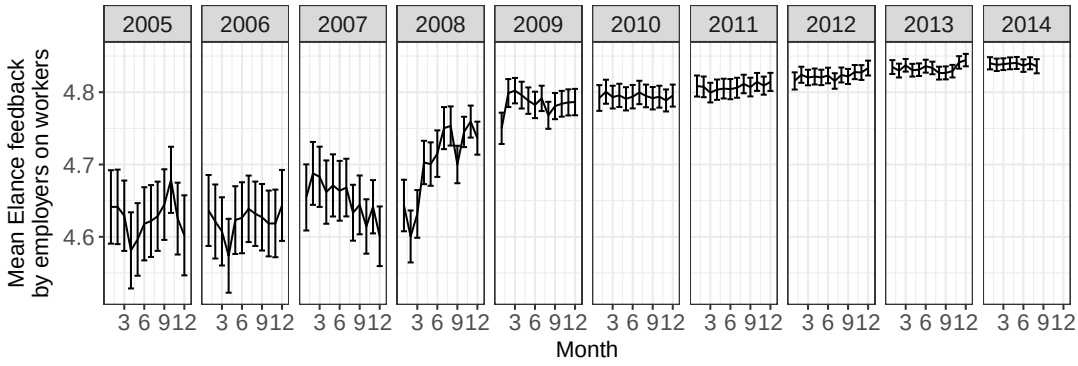
Figure 3: Percentage of completed projects receiving different star ratings over time.



Notes: This figure plots the fraction of public feedback scores assigned in a given month into four bins, $[1, 3)$, $[3, 4)$, $[4, 4.99)$, and 5 stars, over time.

present over time.

Figure 4: Monthly average public feedback scores on a competing marketplace assigned to workers by employers.



Notes: This figure plots the average public feedback scores assigned by employers to workers on completed contracts on a competing platform. The average scores are computed for every month, and the 95% interval is depicted for every point estimate. The scale for feedback is 1 to 5 stars.

3 Reasons for the increase in feedback scores

The previous section documents the increase in feedback scores over time. However, there are two potential reasons for this increase: (1) rater satisfaction has

increased, and (2) raters are lowering their standards. We cannot disentangle these two reasons by only using the numerical feedback score, as it reflects potential changes in both rater satisfaction and standards. As an alternative measure of rater satisfaction, we use the public written feedback that employers generate. We will argue that written feedback is an attractive alternative measure because changes in sentiment are more likely to reflect changes in rater satisfaction, rather than a change in standards.

3.1 Written feedback as an alternative measure of performance

To make the two kinds of feedback comparable, we fit a predictive model that predicts numerical feedback scores from the feedback text. The predictive model is fit on a narrow time window, and the fitted model is then used to estimate out-of-sample feedback scores of the written feedback for the entire sample.

Words used in written feedback can certainly become "inflated," with work that would have elicited a "good" now garnering a "great."[7] However, some words found in written feedback, such as "unresponsive," are less subjective and are likely to retain the same meaning, more or less, over time. We also suspect that written feedback is inherently less subject to inflationary pressures. The reason is that the nature of written feedback and how it is used on the platform makes it less costly for raters to be candid, and these costs are central to explaining reputation inflation (which we discuss later in the paper).

The reason that the costs to the rater for giving "negative" written feedback are lower than for numerical feedback is that it is harder for workers to complain about textual "tone" than it is to complain about a non-perfect star rating. Workers also likely care less about bad written feedback because of how it is presented, and are thus less likely to try to compel better feedback: written feedback is not aggregated or put on a scale, and hence cannot as easily be used for cross-worker comparisons. These comparisons are precisely what makes the feedback consequential for workers. Relatedly, many would-be employers would

[7]For example, an employer's written feedback in our dataset reads: "This is the most impressive piece of coding in the history of software development!"

likely not bother to read the often voluminous collection of written feedback, making any particular written feedback less consequential.

To the extent that written feedback offers a a more or less unchanging measure of rater satisfaction, it is useful for disentangling changes in rater satisfaction from changes in rater standards. Importantly, to the extent that written feedback is also subject to inflation, our approach will underestimate the magnitude of the inflation in scores.

3.2 Predicting numerical feedback from written feedback

To extract the sentiment of the written feedback, we employ a standard machine learning approach. We use a sample of our written feedback corpus as the training set, with the associated numerical scores as the set of labels. We fit a model that predicts the public feedback score, given the text of the written feedback. We use a standard natural language preprocessing pipeline: our data is stripped of accents and special characters, is lowercased, stopwords are removed, a matrix of token counts (up to 3-grams) is created, and is weighed using the TFIDF method. We then perform an extensive grid search over a set of different learning algorithms and their correspnding hyperparameters, evaluating each configuration using a 5-fold cross validation.[8] We keep the best performing model in terms of average squared error.[9] An important step in our method is deciding the time period where the training corpus for our model will come from.

The average quarterly feedback over time, for both the numerical public feedback, and the feedback predicted from the written feedback, are plotted in Figure 5. For this figure, the predictive model is trained with a written feedback corpus from the earliest quarter in our data (indicated with a dashed red line), and consists of 1,492 feedback samples. As expected, the predicted and actual scores match up during the training period. Going forward, both scores increase, but the predicted feedback score increases at a much slower rate. On average,

[8]The algorithms we use are linear regression, lasso regression, ridge regression, gradient boosting regression, and random forest regression.

[9]Our analysis is performed using the Python scikit-learn package implementation. The package's webpage provides a detailed description of the implementations of each model (see http://www.scikit-learn.org/stable/user_guide.html).

numerical feedback goes from 3.75 in the beginning of 2006 to 4.84 stars at the beginning of 2016. In contrast, the average score predicted from the written feedback only goes to 4.45 stars.

In Figure 6 we again plot the average quarterly feedback over time, for both the numerical public feedback and the feedback predicted from the written feedback. However, our training sample now comes from a longer time period indicated by the two vertical red lines, and is larger, consisting of 10,555 feedback samples. As expected, the predicted and actual scores closely match up during the training period. However, in the period before, the predicted score is higher than the numerical score, and vice versa post the training period. We adjust the second score by a constant, so that the predicted score matches the actual feedback score in the beginning of our dataset. With this adjustment, the average predicted feedback score at the end of the data set "should" have only been 4.32 stars.

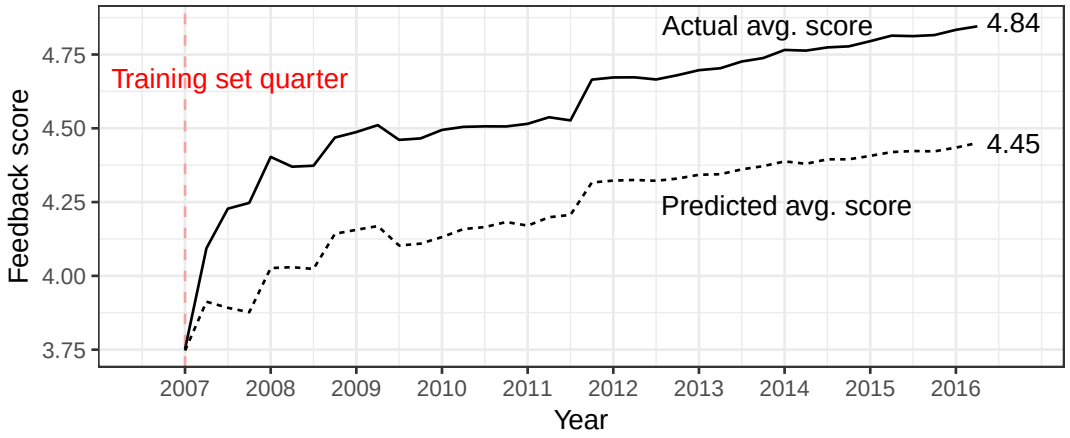
The divergence between written sentiment and numerical feedback implies that a substantial amount of the increase in numerical feedback scores is due to lower rater standards. Our approach also allows us to quantify the contribution of lower rater standards to the increase. Using the first quarter sample, the point estimate is that 36% of the increase in feedback scores is due to inflation, whereas the larger sample from the middle of the data implies 48% of the increase is due to inflation.

It is essential to note that to the extent written feedback is also subject to inflation ("good" work now garners a "great"), our method understates the extent of reputation inflation taking place on the platform, and so we view our approach as providing a lower bound estimate.

3.3 Average feedback scores of lexically similar sentences

A potential shortcoming with the approach of Section 3.2 is that the lexical composition of reviews could presumably change over time. While we have no evidence that supports this hypothesis, in what follows we take an alternative approach: as a more direct measure of inflation, we examine whether the same sentences found in written feedback correspond to different feedback scores at

Figure 5: Numerical public feedback and predicted score from textual feedback using the first quarter as the training period.

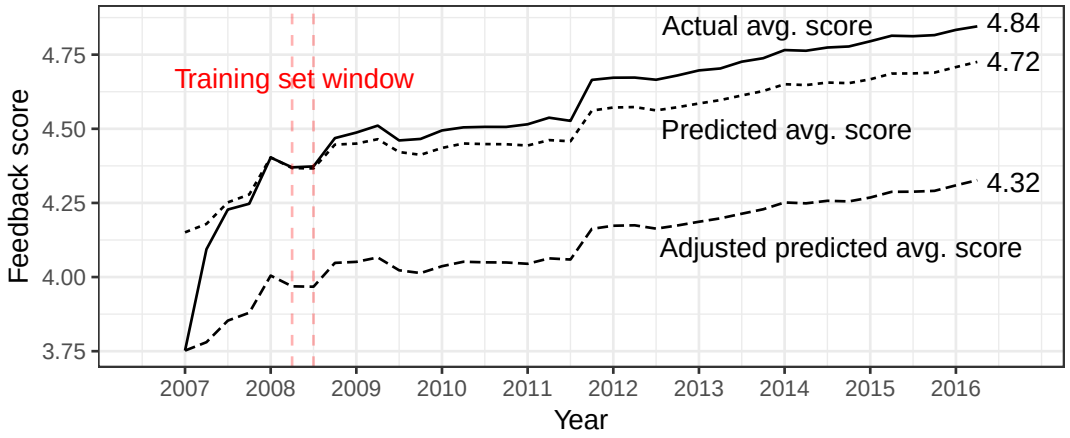


Notes: This figure plots the evolution of average public feedback scores (solid line) versus the average predicted score of textual feedback (dotted line) assigned by employers to workers. The red line indicates the quarter from which training data was obtained for the predictive model. The training set consists of 1,492 samples taken from the earliest quarter in our data.

different points in time. We select written feedback from 2008 and 2015. We scan through the written feedback generated in these periods for lexically similar sentences, and then compare average feedback by phrase, across the two periods. To find similar sentences, we use the Levenshtein distance of the sentences as our measure of textual similarity (Yujian and Bo, 2007), defined as the minimum number of single-character edits required to change one sentence to the other, and keep only those sentences whose lexical similarity is higher than 95%. Our procedure allows us to extract 5,952 pairs of lexically similar sentences from the two periods.

To illustrate our approach, Figure 7 shows the average numerical feedback scores for a set of example short sentences that are commonly used on employer written feedback, by period. We selected sentences spanning both "good" and "bad" feedback, and which most frequently occurred in the corresponding written feedback in our data, such as "great to work with," "would hire again," "terrible," and "would not recommend." We can see across terms that the numerical feedback scores associated with identical sentences have increased considerably over time, and this increase has affected both positive and negative sentences.

Figure 6: Numerical public feedback, predicted score from textual feedback using the second and third quarters of 2008, and predicted score adjusted for inflation.



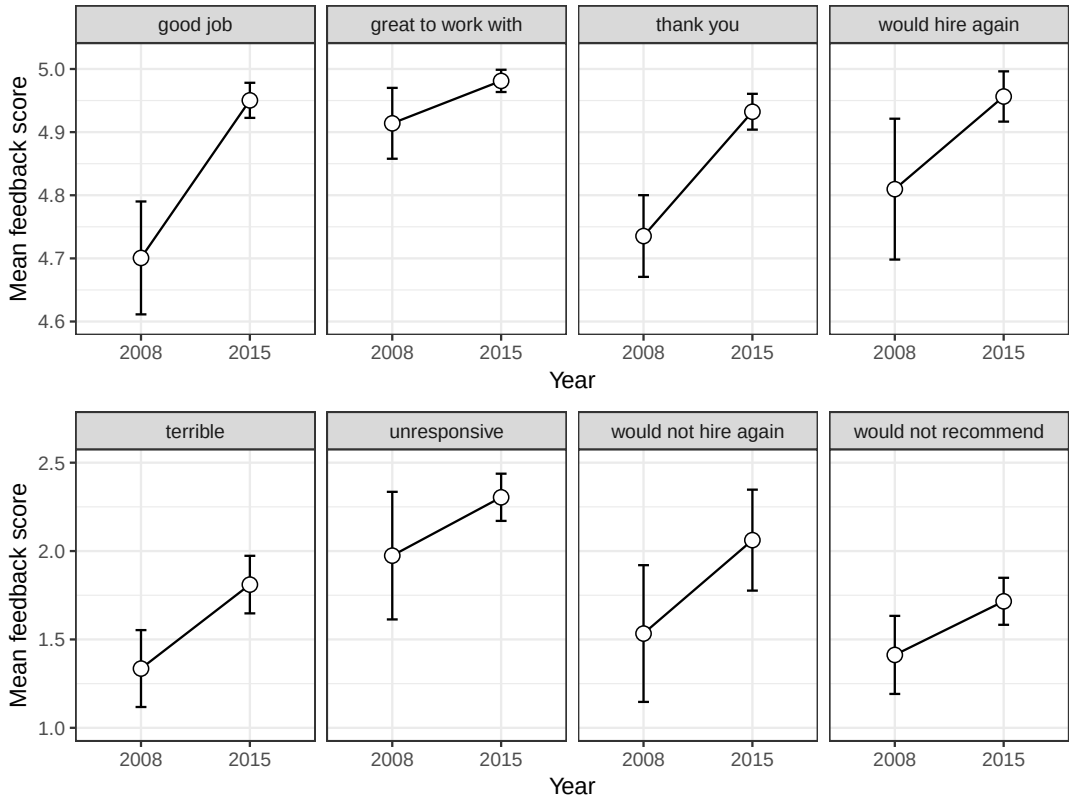
Notes: This figure plots the evolution of average public feedback scores (solid line) versus the average predicted score of textual feedback (dotted line) assigned by employers to workers, and the adjusted average textual score (dashed line). The red lines indicate the quarters from which training data was obtained for the predictive model. The training set consists of 10,555 samples. Adjusted predicted scores are calculated by subtracting the constant from the predicted scores that allows the left endpoints of the adjusted and actual score lines to coincide.

Using the whole collection of identified sentences, we find that the average difference in numerical feedback scores is 0.10 stars, with a 95% confidence interval of $[0.086, 0.114]$. As the increase in average numerical feedback scores between the 2008 and 2015 period is 0.35 stars, a back-of-the-envelope calculation suggests about 30% of the overall increase is due to inflation, which is close to our lower bound estimate from our predictive modeling approach. Note that we are excluding data from year 2007 when the majority of the overall increase occurred.

3.4 Informational implications of reputation inflation

The impact of reputation inflation could be minimal if market participants "know" about the rate of inflation and adjust accordingly; even if individuals are not well-informed, the platform could implement statistical adjustments in its design of the reputation system to uncover the "true" (non-inflated) scores. However, if the pooling in the highest feedback "bin" becomes acute, statistical corrections

Figure 7: Difference over time in the average employer feedback score associated with a set of example sentences.



Notes: This figure shows the average numerical feedback associated with exact sentences found in the text of numerical reviews, in 2008 and 2015. A 95% confidence interval is shown for each mean.

cannot recover the lost information. This is partially due to the fact that, by design, numerical scale systems are prone to top-censoring; for the question "rate on a scale from 1 to X," the value of X must be pre-specified.[10] Changes in the reputation system, such as adding a higher ceiling in the feedback scores or additional dimensions of reputation, may temporarily mitigate—but do not solve—the problem.[11]

To see the problem created by top-censoring, consider the information con-

[10]This is why reputation inflation differs from monetary inflation; a sandwich that used to cost $0.50 and may now cost $12. However, this could not happen if price was mechanically restricted to be below $1.

[11]See also https://www.youtube.com/watch?v=KOO5S4vxi0o.

veyed by observing a binary variable X, as it is captured by the information-theoretic entropy $H(X) = p\log(p) + (1-p)\log(1-p)$, where p is the probability of one outcome. As p goes to either 1 or 0, the information conveyed by the variable—in our case, the observed feedback score—goes to zero. However, this binary characterization of the reputation system is a simplification that could elide an important way in which rising—and even more compressed scores—could convey just as much (or even more) information. Consider increasing all nominal scores by some fixed amount and then "shrinking" all scores toward some new higher mean. This transformation would have no informational implications. To assess informativeness, we need to take an empirical approach.

To assess the informativeness of the feedback scores about worker quality over time, we conduct a variance decomposition, showing how the fraction of unexplained variance in feedback scores changes over time. Suppose that the data generating process of a worker's feedback is

$$\text{SCORE}_{it} = a_{it} + c_t + \epsilon_{it}, \tag{1}$$

where a_{it} is the worker's true quality, c_t is a baseline time effect, and ϵ_{it} is some noise term such that $E[\epsilon_{it}] = 0$.[12] If, over time, more of the variation in feedback scores can be explained by the variation in the noise term rather than by variation in the quality of individuals, then a feedback score is becoming less informative of the worker's true quality.

Consider a Bayesian employer trying to infer the quality of a worker from a score: the more the feedback score is attributable to noise, the lesser its impact on the employer's posterior belief of worker's quality after observing this score. To wit, let $\Pr(a) \sim N(a_0, \sigma_0^2)$ be the employer's prior distribution for worker quality, and let $\epsilon \sim N(0, \sigma^2)$ be the noise term with known variance σ^2, and a be the worker's true quality, which the employer forms a posterior about after observing a feedback score. After observing the worker's feedback score SCORE,

[12] For simplicity, we are treating the feedback score as continuous. The logic is identical in the dichotomous case.

the employer's posterior is

$$\Pr(a|\text{SCORE}) = N\left(\frac{\frac{1}{\sigma^2}\text{SCORE} + \frac{1}{\sigma_0^2}a_0}{\frac{1}{\sigma^2} + \frac{1}{\sigma_0^2}}, \frac{1}{\frac{1}{\sigma^2} + \frac{1}{\sigma_0^2}}\right).$$

From the above equation, as $\sigma^2 \to \infty$, $\Pr(a|\text{SCORE}) \to \Pr(a)$, or in words, as the noise component of the score explains more of the variance, the observed feedback becomes less informative, and at the limit, has no effect on the employer's beliefs.[13]

To explore the informativeness of feedback scores empirically, we make two assumptions. First, for a suitably small window of time (i.e., a quarter), we assume that the baseline time effect, c_t, is fixed. Second, we assume that the population distribution of a_{it} can have a changing mean, reflecting shifts in worker quality, but its variance is constant; workers could be getting systematically better or worse, but their abilities are not getting more or less spread out.

The fraction of variance due to noise is the quantity

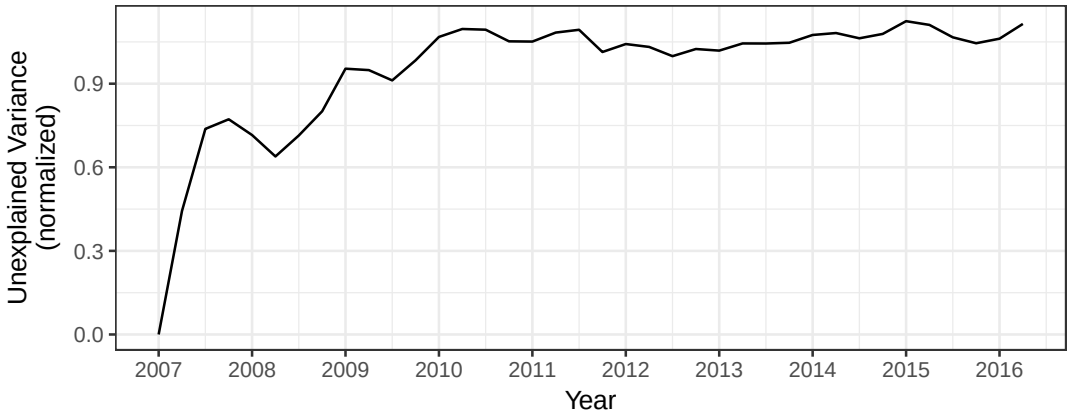
$$\frac{Var(\epsilon)}{Var(\text{SCORE})} = 1 - \frac{Var(a)}{Var(\text{SCORE})}. \tag{2}$$

If this ratio increases over time, feedback scores are becoming less informative. We can easily compute this fraction for a time period t by performing the regression implied by Equation 1—the quantity of Equation 2 is $1 - R_t^2$, where R_t^2 is the coefficient of determination from the period t regression.

We fit the regression described in Equation 1 on the feedback scores generated in every quarter of our data separately. On each of these regressions, we are using fixed worker effects to estimate a_{it}, thereby allowing worker quality to evolve in time, even "within" a worker. Figure 8 plots the percentage difference of $1 - R_t^2$ from the minimum unexplained variance, which is found at the first period in our data. The increase in unexplained variance from 2007 to 2016 is about 118% (from 0.32 to 0.70). This strong positive trend in the explained variance implies that the relative importance of noise in explaining feedback grows over time, which in turn implies that the informativeness of feedback about worker quality

[13] Gelman et al. (2014) provide a derivation of this result, which can also be found in most standard Bayesian analysis textbooks.

Figure 8: Feedback score variance not explained by worker quality over time. Scores are reported as percentage differences with respect to the minimum unexplained variance.



Notes: Unexplained variance is reported the percentage difference with respect to the minimum unexplained variance of the time series, which is attained at the first period of this figure. The data of each quarter consists of workers with at least 2 jobs in that quarter, as otherwise the fixed effect a_{it} would perfectly predict their feedback score. Utilizing different cutoffs does not quantitatively change our results.

has deteriorated.

4 A model of reputation dynamics

To help explain the implications of our empirical findings and understand why inflation occurs, we develop a model of employers leaving public feedback to workers in a competitive online labor market. Though our framing here is a labor market, the same framework can be applied to the more general case of buyers and sellers giving public feedback.

4.1 Setup

Consider an online labor market composed of workers and employers. Workers are matched at random with employers, after which workers produce output $y \in \{0, 1\}$. The worker produces output $y = 1$ with probability $\Pr(y = 1|q) = q$, from which the employer obtains utility equal to 1, by selling the output on some

product market. The employer obtains zero utility in the case that output $y = 0$ is produced.

Workers are characterized by their quality $q \in \{q_L, q_H\}$, with $q_L < q_H$. Employers know the fraction of high quality workers in the marketplace, which we denote by θ. After the employer observes the worker's realized output y, she generates a signal to the marketplace in the form of feedback $s \in \{0, 1\}$, where $s = 1$ denotes "good" feedback, and $s = 0$ "bad" feedback. In the next "round," employers observe the most recent feedback assigned to the worker, and form Bayesian beliefs about the worker's quality. We assume that both sides are price-takers, and hence workers are paid their expected marginal product, which is

$$w_s = \Pr(q = q_H|s)q_H + (1 - \Pr(q = q_H|s))q_L.$$

The worker's cost of bad feedback, realized in the next round, is the difference in compensation between receiving good feedback, $w_{s=1}$, and bad feedback, $w_{s=0}$, that is

$$\Delta w = w_{s=1} - w_{s=0}.$$

Whenever the employer tells the truth, that is when $s = y$, she obtains a benefit $b > 0$.[14] If the worker's output is good ($y = 1$), then the employer has no incentive to lie and always assigns good feedback ($s = 1$) to the worker. However, in the case that the worker produces no output ($y = 0$) and the employer truthfully reports $s = 0$, the worker incurs a cost Δw, which is the wage penalty in the next round. We assume that some fraction of this cost is "reflected" back on the employer.[15] Employers differ in how much of this cost is reflected: let c_i be the employer-specific fraction of this cost that is reflected back on the rating employer. The employer thus incurs a cost of $c_i \Delta w$, where c_i is drawn from some distribution $F : [\underline{c}, \bar{c}] \to [0, 1]$, with $\underline{c} \geq 0$.

In light of these reflected costs, some employers might give positive feedback

[14] This benefit includes idiosyncratic reasons to report truthfully as well as platform-specific benefits, such as awards by other users for being an accurate reviewer (e.g. user review ratings on Yelp).

[15] These costs include the cost of harming the worker's future prospects, the cost of the worker complaining or withholding future cooperation, and even the cost from other workers being unwilling to work for the employer in the future if the employer has a reputation as a "strict" rater.

even if the worker's output was bad, thereby avoiding the cost of giving bad feedback. This decision will depend on c_i, and so employer i will not report truthful feedback if

$$b \leq c_i \Delta w. \tag{3}$$

Let p denote the fraction of employers that generate truthful feedback in the most recent round, and assume that p is common knowledge. When considering a particular worker that received bad feedback in the previous round, i.e., $s = 0$, the Bayesian employer infers that

$$\begin{aligned}\Pr(q = q_H | s = 0; p) &= \frac{\Pr(s = 0 | q = q_H; p)\Pr(q = q_H)}{\Pr(s = 0; p)} \\ &= \frac{(1 - q_H)\theta}{(1 - q_H)\theta + (1 - q_L)(1 - \theta)}.\end{aligned}$$

Note that the p term divides out as $s = 0$ always implies truthful reporting. In contrast, if the worker received good feedback, i.e., $s = 1$, the Bayesian employer infers that

$$\begin{aligned}\Pr(q = q_H | s = 1; p) &= \frac{\Pr(s = 1 | q = q_H; p)\Pr(q = q_H)}{\Pr(s = 1; p)} \\ &= \frac{\big(q_H + (1 - q_H)(1 - p)\big)\theta}{\big(q_H + (1 - q_H)(1 - p)\big)\theta + \big(q_L + (1 - q_L)(1 - p)\big)(1 - \theta)}.\end{aligned}$$

The cost of bad feedback to a worker is then

$$\Delta w(p) = w_{s=1;p} - w_{s=0;p} = \frac{\theta(1 - \theta)(q_H - q_L)^2}{k - pk^2}, \tag{4}$$

where $k = \theta(1 - q_H) + (1 - \theta)(1 - q_L)$, which is the probability that a randomly chosen worker will produce bad output.

We see from Equation 4 that $\Delta w(p) > 0$ for all p, implying that as long as $c_i > 0$, there is always a cost to the employer of giving bad feedback, which they must compare to their benefit b from telling the truth. Further, when p is large, i.e., when most of the employers truthfully report, feedback is a more accurate measure of quality, and hence the value of positive feedback increases, along with the wage penalty $\Delta w(p)$. In contrast, when the majority of firms lie, the signal

from good feedback is less informative, and the wage penalty narrows. We note that this makes which feedback is "good" and "bad" endogenous in our model: the market effect of a feedback score depends on what is considered "good" and "bad," which in turn depends on the choices of all other employers.

We now consider what an equilibrium of this market would be. Let p_E denote the fraction of firms that truthfully assign negative feedback when the market equilibrium has been attained. The equilibrium fraction is found by solving the equation

$$p_E = F\left(\frac{b}{\Delta w(p_E)}\right), \tag{5}$$

to which a unique solution always exists for any continuous distribution function. Importantly, the two extreme cases where

$$p_E = \begin{cases} 1, & \text{if} \quad b \geq \bar{c}\Delta w(1) \\ 0, & \text{if} \quad b \leq \underline{c}\Delta w(0) \end{cases}$$

correspond to an all-truthful and an all-lying equilibrium. If the benefit to assigning truthful feedback is higher than the cost for every employer, then no employer has incentive to lie ($p_E = 1$), while if the costs are too high, all employers lie ($p_E = 0$).[16] To the extent that we think of employers as both strategic and narrowly self-interested, the all-lying equilibrium is the likely equilibrium, as the benefit b is likely small or sometimes even zero, while the employer-specific costs c_i could be substantial.

4.2 Convergence and the evolution of average feedback

We now consider the marketplace's convergence to the equilibrium prediction. Consider a marketplace where every employer starts off truthfully reporting feedback, that is, $p_0 = 1$. To avoid cases where the convergence process is trivial, we also assume that the equilibrium truth-telling fraction is not the all-truthful equilibrium.

In every period, employers randomly match with workers, workers produce

[16] In the case where all employers have the same cost, p_E can be interpreted as the probability of truthfully generating public negative feedback in the resulting mixed strategy equilibrium.

outputs, and employers subsequently report feedback. Among the employers, a fraction $\theta_B = (1-\theta)(1-q_L) + \theta(1-q_H)$ receives a bad output, i.e., $y = 0$. These employers then compare their benefit from truth-telling with the cost of truthfully reporting bad feedback. Employers whose cost from truth-telling is lower than the benefit give bad feedback to the workers. Therefore, a fraction $l_0 = \theta_B[1 - F(\frac{b}{\Delta w(p_0)})]$ begins to lie after the first period, and hence $p_1 = p_0 - l_0$.

We now examine the convergence of this process. Let $T(x) = F(b/x)$ be the proportion of sellers that are better off truthfully reporting if the cost of bad feedback is x. From Equation 5 we obtain $T(p_E) = p_E$. Since F is a cumulative distribution function, and Δw is convex and decreasing in its argument, T is a decreasing but non-negative function. As a result, $p_2 < p_1$, but $l_1 < l_0$, and hence $p_1 - p_2 < p_0 - p_1$. Following the same argument, we can inductively show that the dynamics of the marketplace result in convergence to the equilibrium truth-telling fraction p_E, and that the rate of convergence decreases as the market approaches the equilibrium point. This is precisely the pattern we observed empirically in Figure 2: reputation initially inflates fast, but then flattens out as the equilibrium fraction is approached.

4.3 Model discussion and implications

In online labor markets and other peer-to-peer markets, it seems likely that both wage penalties for workers and employers' reflected cost coefficients are high. Reasons for the high worker cost of bad feedback include that workers are often highly substitutable, but each worker has few transactions, and hence each rating is more consequential. Further, feedback scores are often the only signal of quality. On the employer side, as transactions are more personal, the reflected costs are likely higher. In contrast, when individuals assign feedback to products (e.g. movie reviews) there is likely no reflected cost, and our model predicts that there will be no inflation. Indeed, numerical scores on such platforms exhibit no inflation, but are rather characterized by lower averages, a much higher spread, and, in some cases, a decreasing temporal pattern (Li and Hitt, 2008; Moe and Schweidel, 2012; Godes and Silva, 2012; Hu et al., 2017).

However, the underlying importance of rater costs seems to hold even when

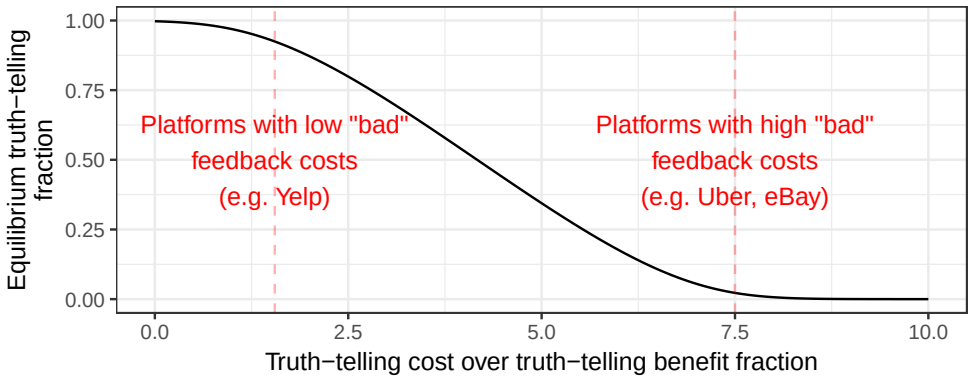
reviews are much more impersonal. In a recent study, Proserpio and Zervas (Forthcoming) find that after hotels started replying to bad reviews on a travel review website, the number of users who leave bad feedback decreases, despite no change in hotel quality. It seems probable that raters might find the hotel's response embarrassing, and/or it becomes clear that an actual person is "harmed" by the negative review.

To provide a graphical depiction of this intuition, we plot in Figure 9 the equilibrium truth-telling percentage for different truth-telling cost to truth-telling benefit ratios. To increase truth-telling costs, we increase the mean of the distribution of "reflected" cost coefficients, keeping everything else constant. When the cost-to-benefit ratio is low, we see that most of the employers truthfully report their feedback in equilibrium. This is the case for platforms such as Yelp or movie rating websites, where the raters are giving feedback to businesses, and transactions are less personal. Furthermore, reviewers in these platforms likely view themselves as performing a service for fellow consumers, and being known for good, honest reviews is at least part of the incentive people have for participating. In the language of our model, these sites have a higher b. As the cost-to-benefit ratio increases, the equilibrium truth-telling percentage approaches zero, and the average feedback scores are hence inflated: this is the case for platforms such as Uber or eBay, where the "reflected" costs are high.

The employers' cost of assigning bad feedback is proportional to the workers' cost from receiving bad feedback in our model. This assumption is made because workers are more likely to retaliate when the cost of negative public feedback is higher, thereby reflecting a higher cost back on the employer. Modern reputation systems attempt to decrease the probability and the cost of retaliation.

To increase truthful feedback, the platform could increase employers' benefit from reporting it. For example, the platform could provide monetary incentives for users who generate feedback, as dissatisfied users often choose not to leave any feedback (Dellarocas and Wood, 2008; Nosko and Tadelis, 2015). Such types of interventions generally have two problems. First, it is not clear how the platform can measure the truthfulness of feedback. Second, this solution is expensive, and hence not likely to be scalable (Fradkin et al., 2015). This implies that platforms are more likely to find success through decreasing reflected costs. We

Figure 9: Truth-telling equilibrium fraction as a function of the ratio of the mean cost over the benefit of generating truthful feedback.



Notes: For this figure, the parameters used in computing the equilibrium truth-telling fractions are $q_H = 0.8, q_L = 0.2, \theta = 0.5, b = 1, F \sim N(\mu_C, 1)$. Alternative distribution and parameter choices of parameters yield qualitatively similar results.

study one such intervention that decreased the costs of assigning bad feedback in the following section.

5 Using private feedback to measure the cost of publicly assigning negative feedback

Our model in Section 4 proposes a process by which reputation inflates in online marketplaces. A key feature of our model is Equation 3, which posits that an employer lies if $b \leq c_i \Delta w$. If the cost of bad feedback to the workers is zero, then employers should be truthful for any positive value of b, and thus would generate more "bad" feedback. To test this model feature empirically, we would need a setting where the workers' costs of bad feedback—and hence the employers' reflected costs—are exogenously changed. Fortunately, the platform provided such a change.

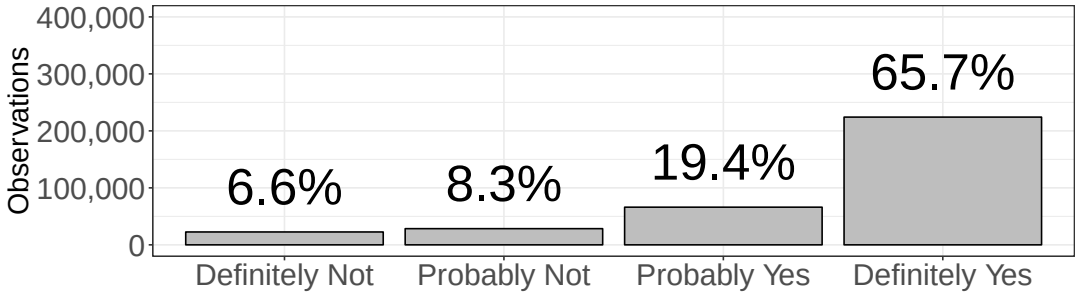
In response to the inflating public feedback, the platform introduced a new experimental "private feedback" feature in April, 2013. On the completion of a contract, employers were asked to generate private feedback in addition to public feedback. Critically, the platform let the employers know that private feedback

would not be shared with the rated worker or future would-be employer, and would only be collected by the platform. Employers were initially asked the private feedback question, "Would you hire this freelancer [worker] again, if you had a similar project?" There were four response options: "Definitely yes," "Probably yes," "Probably not," and "Definitely not." At the beginning of 2014, the employers were instead asked to rate the worker on a scale of 0 to 10.

5.1 Comparing private and public feedback

The distribution of the responses to the private feedback question are shown in Figure 10. Although the most common response was "Definitely Yes," about 15% of the employers gave unambiguously bad private feedback ("Definitely Not" and "Probably Not"). In contrast, during the same period less than 4% of the employers gave a numerical score of 3 stars or less. Given this gap, we might suspect that some employers expressing a negative private sentiment are less than candid in public.

Figure 10: Distribution of answers to the private feedback question, "Would you hire this freelancer [worker] again, if you had a similar project?"

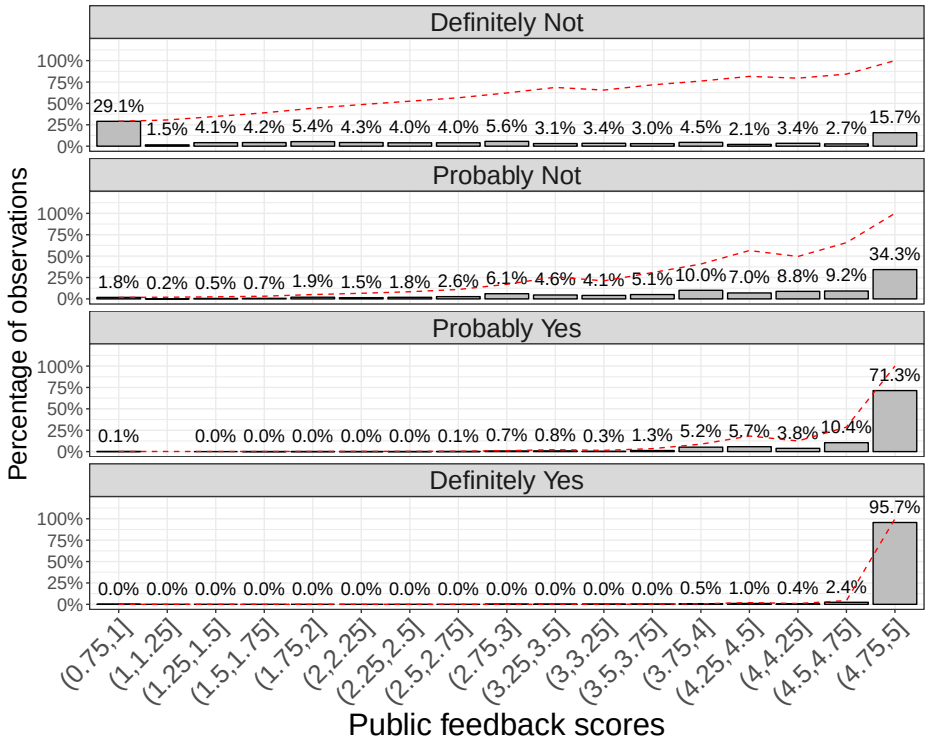


Notes: This figure shows the count of employers choosing each of the four private feedback options following the completion of a contract. The question the employer was asked was the first version of the private feedback question, "Would you work with this freelancer [worker] again, if you had a similar project?" For each bar, the percentage of responses is also shown.

As employers assigned both public and private feedback for the same contract, we can compare the two scores assigned by the same employer on the same contract. Figure 11 shows the distribution of public feedback, by each of the four private feedback categories. The employers that selected "Definitely yes," also left

very positive public feedback, with more than 95% of these observations falling into the highest bin. As the private feedback became increasingly more negative, a higher mass of the distribution of public ratings moved towards lower scores. Among those employers that selected the "Definitely No" answer, 29.1% assigned a 1-star rating. Surprisingly, the second most common choice for these employers at 15.7% was in the 4.75 to 5.00 bin, while 28.4% publicly assigned more than 4 stars. In short, many privately dissatisfied employers publicly claimed to be satisfied.

Figure 11: Distribution of publicly given feedback to workers, by private feedback.

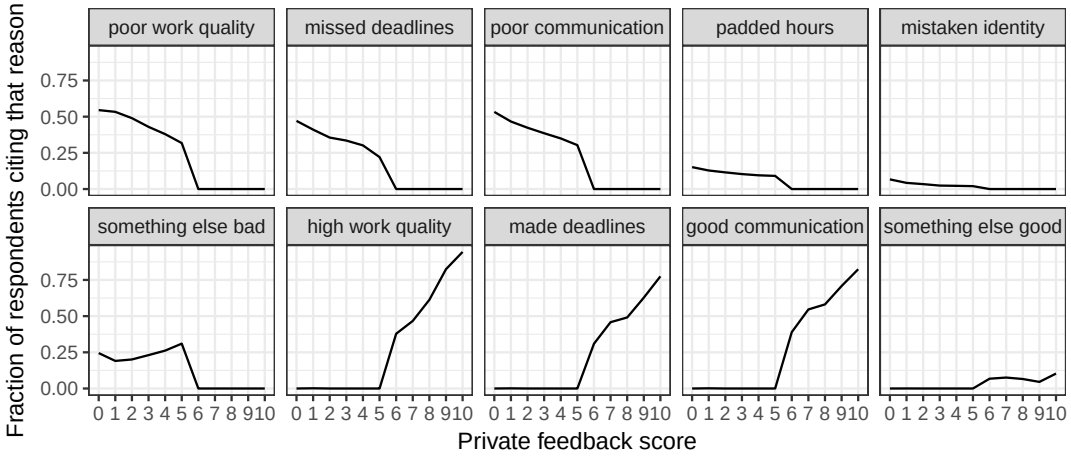


Notes: This figure plots the distribution of public feedback scores, computed separately for every set of users that gave the same answer to the private feedback question. The red dotted line plots the cumulative distribution function.

One concern with any new feedback feature is that raters might simply not understand the new ratings, particularly the 0 to 10 scale. However, we have evidence that employers, at least collectively, understood quite well what the

scale meant. When asked for private feedback, the platform also displayed a set of reasons that the employer could optionally select to indicate the reason for their score. Positive reasons were shown when the assigned feedback was above 5, while negative reasons were shown otherwise (during the 0 to 10 scale period). We use this "reason" information to verify that employers did not misrepresent the private feedback question. The fractions of private feedback reports citing these different reasons against the assigned private feedback score (0 to 10 scale) are plotted in Figure 12. We can see that there is a clear trend in the "correct" direction for both scores, indicating that private feedback scores were correctly assigned, at least on average.

Figure 12: Fraction of users citing a given reason when giving private feedback, by score.

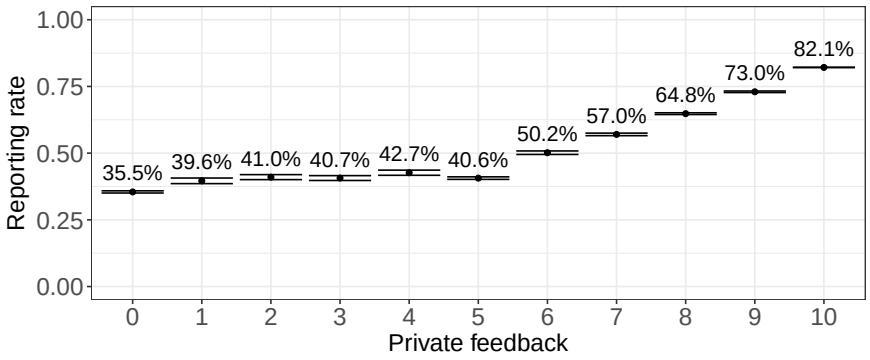


Notes: This figure plots the fraction of feedback reports that cited each reason as the basis of the feedback being positive or negative, against the private feedback score given. Across every case, we notice that employers that assigned more extreme feedback scores tend to cite reasons of the same sentiment more frequently.

In our model, employers have to choose $s = 1$ or $s = 0$, though in actual reputation systems raters have the option to say nothing, perhaps avoiding some of the cost, and instead getting some benefit. A commonly made assertion in the literature is that negative feedback is likely to be under-provided compared to positive feedback. Dellarocas and Wood (2008) conjecture that the high percentage of positive reputation measures on eBay reflect the inclination of unsatisfied

buyers to leave no feedback, which Nosko and Tadelis (2015) confirm indirectly. We find the same result, in that the public feedback reporting rate decreases as the private feedback worsens, even when accounting for user dropout. Figure 13 plots the public feedback reporting rates for those contracts that received private feedback, conditional on the private feedback score. It is important to note that these employers deliberately *chose* not to give public feedback—they gave the private feedback on the same interface as the public feedback.

Figure 13: Public feedback reporting rate, public feedback given for contracts with private feedback by private feedback score.



Notes: This figure shows the reporting rate of public feedback scores for those contracts that received private feedback. The reporting rate is computed separately for every assigned private feedback score, before average private feedback scores were made public.

Recall from Equation 3 our assumption that in the absence of reflected costs, employers will give more "bad" feedback. As private feedback was not utilized by the platform, the cost to worker $\Delta w = 0$, and hence employers are more likely to truthfully report $s = 0$ privately, while either saying nothing publicly or giving a (false) positive report. Of course, when $y = 1$ the employers are satisfied, and the employers truthfully report $s = 1$. Our findings from the initial period in which private feedback was collected provide us with indirect evidence that there are costs of giving "bad" public feedback and as such, it is undersupplied.

5.2 Increasing the cost of negative private feedback

Our interpretation of private versus public feedback is that for bad public feedback, the cost to the worker, Δw, was positive, whereas for bad private feedback the same cost was zero. As a result, private feedback was more candid, i.e., more employers were more likely to report $s = 0$ when $y = 0$, as the employers' costs were increasing in the workers' cost of negative feedback. We now consider what happened when the platform made a change that raised the cost Δw from zero to some positive amount, by changing how that private feedback was used on the platform.

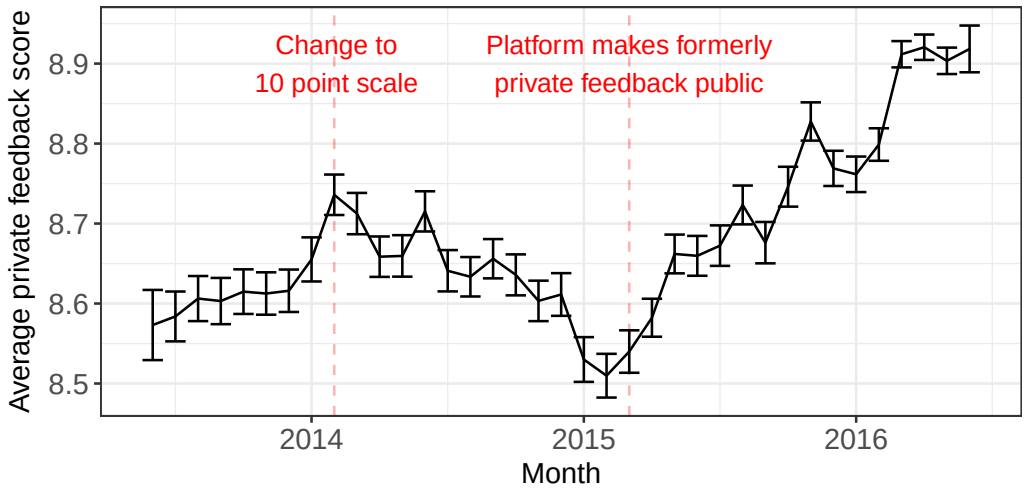
The change was the platform's announcement in March 2015 that the private feedback ratings would be used to compute a new aggregate feedback score for workers. The aggregate score on a worker's profile was only updated after the worker received five new feedback scores, to prevent workers from identifying which employer gave them which feedback. This score would be publicly available, and shown on the profile of each worker.

To the extent that employers used this new score in their hiring decisions, the workers' cost of private feedback went from zero to some positive number. In the logic of our model, the platform's hope was that by not allowing workers to know which employer gave feedback, the distribution of c was pushed towards 0. However, if many employers do not want to hurt the worker or fear some other kind of generalized ex post retaliation, the private feedback measure could start to inflate after the policy change.

To see how the revelation of private feedback affected the private feedback scores, the time series of average scores by month are shown in Figure 14. Unlike public feedback, private feedback was initially relatively stable, exhibiting little fluctuation and no clear trend. The date of the platform's private feedback policy change is indicated by the vertical red line. We can see that, immediately after the revelation, the formerly flat series started exhibiting an increasing trend in the average private feedback scores. In terms of our model, when the cost Δw went up, the cost of truth-telling went up and employers started lying.

Of course, this increase could be due to increases in fundamentals. However, we can use the same "text as alternative measure of satisfaction" approach by

Figure 14: Monthly average "private" feedback given by employers to workers.

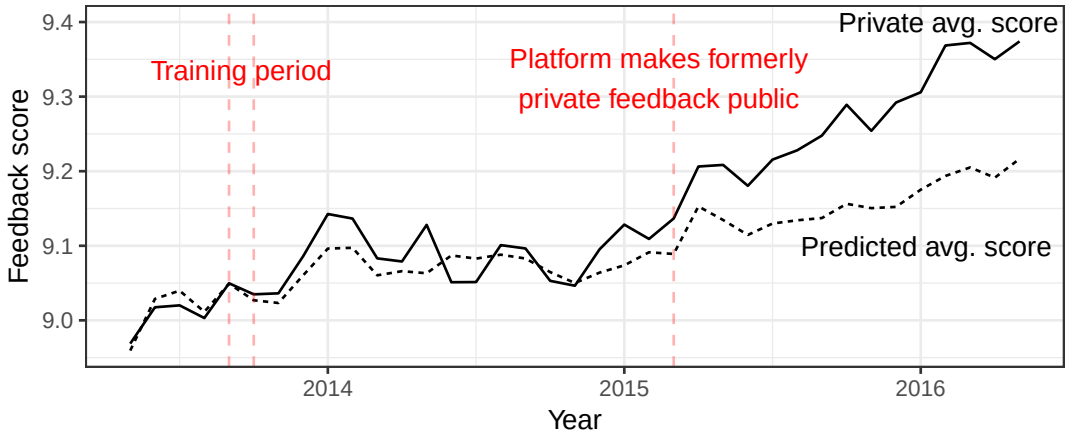


Notes: This figure shows the average monthly private feedback (on a 1 - 10 point scale) given by employers to workers. The left red dashed vertical line indicates the point in time when the platform switched from the private feedback question to eliciting private feedback on the 0-10 scale. The right red dashed vertical line indicates the point in time in which employer private feedback scores were aggregated and added to worker profiles. These aggregate scores were changed after the worker received five new feedback scores, to prevent workers from identifying which employer gave them which feedback. Prior to this point, scores were only collected by the platform and not used publicly in any way.

using the written feedback given by employers. We fit a model that predicts private feedback scores from public written feedback, using data obtained from employers that left both public written feedback and private feedback scores during a short time window. In Figure 15 we plot the average private feedback of contracts that also received textual feedback (solid line), versus the predicted private feedback from the corresponding textual feedback (dashed line). The predicted and actual private feedback scores closely match up until the time that the platform makes the private feedback information publicly available.

After the private feedback revelation change, both scores increase, but the actual private feedback scores clearly overstate that trend. After the private feedback revelation, the average private feedback score increased by 0.24 points, while the average predicted scores only increased by 0.12 points, indicating that at least 50% of the increase is due to inflation.

Figure 15: Private feedback score and predicted private score from textual feedback using the second and third quarters of 2013 as the training period.



Notes: This figure plots the evolution of average private feedback scores (solid line) versus the average private score predicted from textual feedback (dashed line) assigned by employers to workers. The left solid red lines indicate the period from which training data was obtained for the predictive model. The training set consists of 61,316 samples. The right red dashed vertical line indicates the point in time in which employer private feedback scores were aggregated and added to worker profiles. We also note that the average private feedback score for contracts for which employers also left written feedback is higher (compare the y-axis scale to that in Figure 14); this indicates that when employers have had a bad experience, they avoid publicly stating their opinion via text.

Increasing employer costs to leaving negative feedback results in inflation—which is our central claim. Further, this increase in scores does not happen instantly, leading to a one-off step change in feedback, but rather occurred over time, consistent with our modeling of the inflation process.

6 Conclusion

This paper documents that the reputation system in an online marketplace was subject to inflation—we observe systematically higher scores over time, which cannot be fully explained by overall improvements in fundamentals. This inflation was consequential for market actors as the information the system conveyed decreased over time. A theoretical model is developed which hypothesizes that the root of inflation is the costs that raters incur when leaving negative feedback.

A market intervention where the costs to negative feedback were increased—namely by making previously private feedback public—yielded data consistent with the predictions of our model.

Though our findings have direct implications for online platforms that are affected by this inflation, reputation inflation is likely not an online phenomenon, but is seemingly also present in the non-digital world. For example, there is widespread concern about grade inflation, and some schools have taken steps to counter it (Butcher et al., 2014). The debate found in this literature stream mirrors many of the issues we examine in this paper, namely whether the increase in grades is due to fundamentals, such as better student cohorts, or due to different standards, and whether information is lost. Babcock (2010) finds evidence that efficiency concerns are important, with inflated grades seemingly reducing student effort.

This paper illustrates a core market design problem, and elucidates its root cause. Whether there are effective platform design responses to this phenomenon is an open question; simultaneously-revealed ratings and anonymizing ratings through aggregation did not seem to prevent inflation from occurring in our data set. An important next step is to propose and evaluate alternative reputation mechanisms that may overcome reputation inflation. Introducing additional dimensions to a reputation system may slow down the eventual erosion of its informativeness (Chen et al., Forthcoming). Our model suggests some approaches, such as raising the benefit b to truthfully reporting feedback, or lowering the reflected cost coefficient c. One could interpret the mandatory grading curves often found in non-digital reputation systems as a policy that simultaneously affects both parameters.[17]

[17] Officer evaluation reports in the US Army limit senior raters to indicating only 50% or less of the officers they rate as "most qualified."

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