Invested or Indebted: Ex ante and Ex post Reciprocity in Online Knowledge Sharing Communities*

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ABSTRACT

Online communities that curate knowledge critically depend on high-quality contributions from anonymous expert users. Understanding users' motivation to contribute knowledge helps practitioners design such websites for optimal user contribution and user benefits. Researchers have studied reciprocity as a motivation for users to share knowledge online. In this study, we focus on two different types of reciprocity as drivers of online contribution: ex post and ex ante reciprocity. Ex post reciprocity refers to users who received help from others in the past, and pay back by helping others at present. Using a quasi-experiment performed via the instrumental variable method as the identification strategy, we test whether users who received more answers last week answer more questions in the current week on StackOverflow.com. We find a significant positive relationship between ex post reciprocity and knowledge contribution, and such a reciprocal motivation diminishes with time. Ex ante reciprocity refers to people helping others in expectation of future help from others. Using data from StackOverflow.com, we take advantage of a natural experiment with a difference-in-differences analysis and find evidence supporting the existence of ex ante reciprocity. This study offers a new taxonomy for reciprocity and new insights on how reciprocity drives online knowledge sharing.

CCS CONCEPTS

• Information systems → Question answering • Applied computing → Psychology • Social and professional topics → Systems analysis and design

KEYWORDS

Ex post, Ex ante, Reciprocity, Knowledge Sharing, Q&A Website

1 Introduction

User-generated content is the lifeblood of online communities, especially for question-and-answer (Q&A) websites, where high-quality answers determine whether users will continue to use the website [Lou et al. 2013]. For StackOverflow.com, a Q&A website specializing in technical programming problems, answering questions usually requires time, energy and commitment on the part of users [Wasko and Faraj 2005]. Therefore, engaging users and ensuring high-quality contributions in the form of answers to questions is critical for such websites [Wang et al. 2014]. Developing an accurate understanding of factors that facilitate and enhance user contribution enables sponsors of such websites to design better features that facilitate increased user contribution.

In this context, we explore the role of reciprocity in eliciting contributions among community members, using datasets from StackOverflow.com. Gouldner [1960] offered an early conception of the reciprocity norm; when others help us, we offer help in return. Researchers have found evidence of the operation of this concept in the virtual world. For online Q&A communities, such as StackOverflow.com, reciprocity takes the form of users' helping one another by answering questions [Wang and Lai 2006]. Iriberri and Leroy [2009] find that reciprocity is an important driving factor for user-generated content in online communities, and to the success of the community. Reciprocity can benefit an online community by facilitating exchanges of knowledge [Bock et al. 2005; Wasko and Faraj 2000], thus adding value to the platforms. However, reciprocity is a double-edged sword, since it is concerned with both contributing to others, as well as asking from others [Preece 2001]. If some users only require help from others but do not contribute, other users who contribute are much less likely to receive as much knowledge. The contributors may feel disappointed and reduce or stop contributing [Chandola et al. 2007; Fyrand 2010].

In these reciprocal exchanges, users are at times reciprocating to contributions and help given by others, but at other times, they are contributing in expectation of future help from others. To add to the rich literature of reciprocity as discussed above, we therefore suggest a new taxonomy, which classifies reciprocity along a temporal dimension: ex ante and ex post reciprocity.

Definition 1 (Investment): People experience ex ante reciprocity when they help others in anticipation of others' help later.

A person's efforts to help others under ex ante reciprocity, in anticipation of future help, can be viewed as an investment, which could pay off in the future with varying degrees of likelihood.

Definition 2 (Indebtedness): People experience ex post reciprocity when they help others after they have received help from others before.

After a person receives help from others, he/she will feel indebted, thus helping others in the future to reciprocate the help received.

Classifying reciprocity into these two types may better help us understand the role of reciprocity in encouraging online contribution. Despite studies focusing on the relationship between reciprocity and the development of online communities [Wang and Lai 2006; Chiu et al. 2006; Yang et al. 2017], findings are inconsistent about the impact of reciprocity on knowledge contribution on online communities. For example, both Wang and Lai [2006] and Ye et al. [2006]'s papers find that reciprocity has no significant influence on knowledge contribution. However, Bock et al. [2005] find a positive impact of reciprocity on knowledge sharing. Failure to distinguish between two types of reciprocity: ex ante and ex post may explain the inconsistency. Intuitively, it could be argued that ex post reciprocity will encourage contribution, whereas if the ex ante expectation of reciprocity is not realized, that could generate resentment and could harm users' contributions on the platform. Specifically, ex ante reciprocity motivates users to answer questions, in a way that these contributors expect a return from others. However, due to the existence of free riders, the contributors may fail to get what they expect, which may cause them to reduce future contributions. In this case, the existence of expectations arising from ex ante reciprocity coupled with free-riding can result in reduced user-contributions in an online community. On the contrary, the existence of ex post reciprocity may have a positive impact on users' contributions, because it is a norm leading people to offer help after they receive help from others. In summary, the effect of one type of reciprocity could cancel out the effect of the other, leading to divergent findings in the literature.

Prior research [Wasko and Faraj 2000, 2005; Jin et al. 2009] focuses on the static impact of reciprocity. Building upon this work, we focus on a potential dynamic relationship between ex post reciprocity and knowledge contribution. To be specific, users may react to reciprocal behavior immediately, when they have just received help from others. However, if users do not react to others' help in time, the impact of ex post reciprocity may diminish with time.

We focus on two groups of research questions: First, how does ex post reciprocity quantitatively influence users' contributions to online communities? Will this impact become stronger or weaker as time goes? Second, is there any evidence for the existence of ex ante reciprocity in online communities? Moreover, will the violation of ex ante reciprocity negatively influence users' motivation?

Using a quasi-experiment performed via instrumental variable (IV) method as the identification strategy, we analyze an observational dataset from StackOverflow and find consistent results that ex post reciprocity has a positive impact on knowledge sharing, and that the magnitude of this impact decreases with time. Using a different dataset from StackOverflow, we perform a difference-in-differences (DID) analysis, which shows that the violation of ex ante reciprocity may negatively affect knowledge contribution in the online community.

In this study, we first contribute to the fields of both information systems and social psychology, by adding a new taxonomy of reciprocity: ex ante and ex post. Eliciting user contribution via reciprocity in online communities is a known problem, but we explore the impact of both ex ante and ex post reciprocity in helping elicit greater user contribution. Second, we innovatively explore the dynamic impact of ex post reciprocity on knowledge contribution. Third, the observational dataset we use in this study provides insights that complement and build upon prior studies based on survey-based self-reported data [Wang and Fesenmaier 2003; Chiu et al. 2006; Jin et al. 2009]. Finally, we take advantage of two quasi-experiments to explore the causal relationship between knowledge contribution, and ex post and ex ante reciprocity.

2 Literature Review

2.1 Ex post and Ex ante Reciprocity

Reciprocity is a concept in psychology and sociology, which sociologist Alvin Gouldner [1960] described as "You should give benefits to those who give you benefit". Although sometimes implicit in prior works, no research has explicitly identified the distinction between ex ante and ex post reciprocity. Blau [1964] points out that reciprocity implies “actions that are contingent on rewarding reactions from others and that cease when these expected reactions are not forthcoming.” This description suggests why reciprocity could be a double-edged sword. On the one hand, the expectation of rewards in the future will encourage users to contribute knowledge. On the other hand, free riders' failure to reciprocate will disappoint active users. People invest in others by offering help, and at the same time, people are also expecting “dividends”, so reciprocity is not only about helping others, but also about expecting rewards.

This duality of reciprocity also happens in online communities. Preece [2001] highlights two aspects of reciprocity for online communities—giving and taking. Researchers have commonly focused on the positive side of ex ante reciprocity. Wang and Fesenmaier [2004] study an online travel community and find that there is a positive relationship between “perceived expectancy incentives” and community contribution. They explain perceived expectancy incentives as “anticipated reciprocity”, which is very similar to our definition of ex ante reciprocity. Similarly, Wasko and Faraj [2005] find that users' anticipated reciprocal relationships favor their knowledge sharing, through a field survey of managers from Korean organizations.

Apart from ex ante reciprocity, researchers have also implicitly discussed the concept of ex post reciprocity. For example, Wasko and Faraj [2000] explain reciprocity for online Q&A websites such that “if I gain some knowledge, I feel it only right to give back and help someone else”.

While much of prior work has explored ex ante and ex post reciprocity separately, there is a need to develop a unified view of both kinds of reciprocity as distinct mechanisms with potentially different outcomes. Table 1 lists some constructs related to reciprocity from prior literature. Under the column “Construct Description/Example”, we provide some quotes illustrating the relevant reciprocity construct. We then categorize these constructs into ex ante and ex post reciprocity according to our taxonomy. From Table 1, we observe that prior researchers have been studying reciprocity without making the distinction between ex ante and ex post reciprocity, sometimes leading to divergent results.

Table 1: Prior Empirical Studies on Reciprocity and Knowledge Contribution.

Construct	Construct Description/Example	Reciprocity Type	References
Reciprocity	“Good information can be learned from this newsgroup. If I gain some knowledge I feel it only right to give back and help someone else.”	Ex post	Wasko and Faraj 2000, P.165
Anticipated reciprocal relationships	“My knowledge sharing would create strong relationships with members who have common interests in the organization.”	Ex ante	Bock et al. 2005, P. 108
Perceived efficacy incentives	“Seeking future exchange from whom I provide help”	Ex ante	Wang and Fesenmaier 2003, P.716
The norm of reciprocity (NR)	“I know that other members in the BlueShop virtual community will help me, so it's only fair to help other members.”	Ex ante	Chiu et al. 2006, P.1879
Reciprocity	“Previous behavior of answering questions and helping others in online Q&A communities have influenced the contributor in receiving answers and helping in the future”	Ex post	Jin et al. 2009, P.680
Peer recognition	“Theories of reciprocity suggests that feedback from other users will have an impact on users' future participation behaviors.”	Ex post	Jin et al. 2015, P.843

2.2 Motivations for Online Knowledge Contribution

Due to the rapid development of information systems and the Internet, researchers have focused on how reciprocity drives users to contribute to online forums, especially Q&A websites [Movshovitz-Attias et al. 2013; Vasilescu et al. 2014]. Bock et al. [2005] summarize three levels of motivational forces for organizational knowledge sharing: individual benefits such as self-interest and personal gain, group benefit such as reciprocal behaviors and relationships with others, and organizational benefits such as organizational gain and organizational commitment.

For an online knowledge-sharing community, researchers draw from this prior research to construct a framework to explain users' online knowledge contribution [Wang and Lai 2006; Jin et al. 2009, 2015]. Based on their works, we summarize users' motivation to contribute knowledge in online communities into three main dimensions: individual or intrinsic benefits, external rewards, and social obligations, or reciprocity.

First, individual or intrinsic benefits occur when the motivation to contribute knowledge is self-determined or self-generated, such as self-learning [Jin et al. 2015; Lou et al. 2013] and enjoyment [Wang and Fesenmaier 2004]. Second, extrinsic motivation is driven by external rewards, including monetary rewards or virtual scores, such as badges and reputation from online communities. People are said to act out of extrinsic motivation when their behavior results in an instrumental outcome or consequence that is desirable, rather than the activity itself [Porter and Lawler 1968]. Third, social obligations, or reciprocity, refers to users' reciprocal behaviors influenced by community norms with regard to reciprocity. Most research papers agree on this point and claim that reciprocity is a factor driving users to contribute [Wang and Lai 2006; Jin et al. 2009, 2013]. This motivation comes from users' desire to be a part of the online community [Sutanto et al. 2011]. Reciprocity is a type of regulation for users to build a good relationship with others. Therefore, users will reciprocate others' help (ex post) and contribute with the expectation of others' help in the future (ex ante).

2.3 Conceptual Framework

Based on the prior research, we now build conceptual frameworks of ex post and ex ante reciprocity that describe the underlying user behaviors that we propose to study, and link the underlying behavior to potential insights about users' reciprocity-based motivation to contribute.

Ex post Reciprocity

In Figure 1a, we present a schematic of user behavior under ex post reciprocity. In this scenario, a focal user has in the past (relative to the moment of analysis) asked questions to the community (step 1 in Figure 1a), and the community has responded with answers (step 2). Depending on the number of answers received, the focal user (in the present moment–the moment of analysis) gives answers to questions by the community (step 3). If the current period answers given by the focal users in step 3 are more strongly linked to the past-period answers received by the user in step 2, after controlling for other confounders, ex post reciprocity may be a factor in the user's decision to contribute answers.

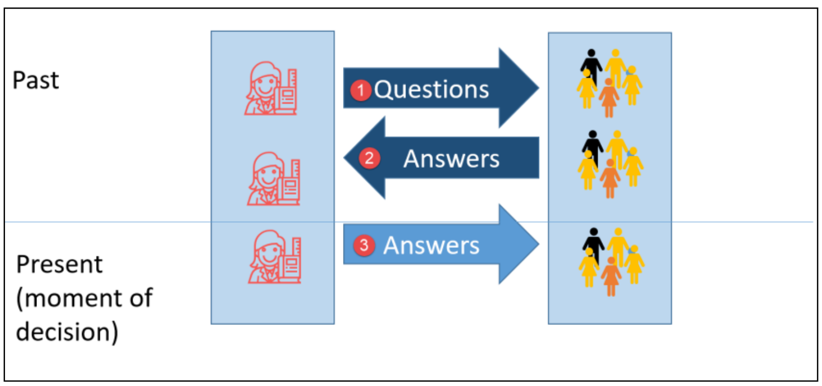

Figure 1a: User Behavior under Ex post Reciprocity.

Ex ante Reciprocity

In Figure 1b we present a schematic of user behavior under ex ante reciprocity. In this scenario, a focal user in the present moment (moment of decision, which is our moment of analysis) answers questions (step 1 in Figure 1b) posed by various members of the community. While doing so, the focal user may have expectations that when she posts questions in the future (step 2), community members will be forthcoming with answers (step 3). If there is a more and better contribution from a user with stronger ex ante expectation of future answers, ex ante reciprocity may be a factor in users' decision to contribute answers.

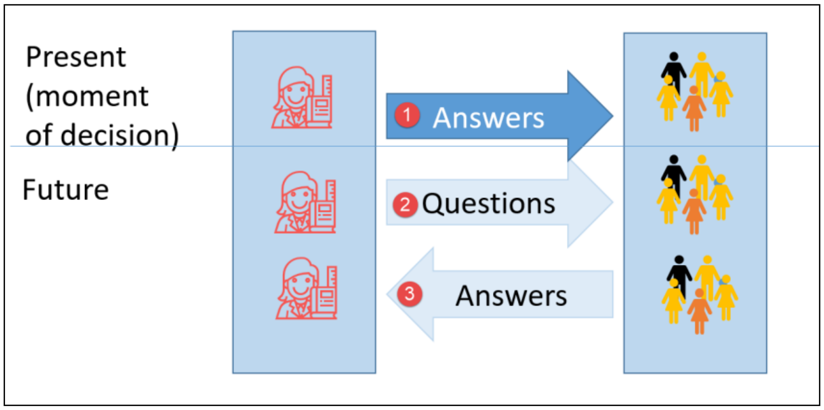

Figure 1b: User Behavior under Ex ante Reciprocity.

Simultaneous Ex ante and Ex post Reciprocity

Finally, we recognize that a user may be simultaneously subject to ex ante and ex post reciprocity. A user who is about to contribute may remember the previous answers he/she received from the community (triggering ex post reciprocity), and at the same time form expectations of future contributions from the community (triggering ex ante reciprocity). We model this situation as a unifying framework considering both ex ante and ex post at the same time.

3 Research Hypotheses

3.1 Ex post Reciprocity

As we discussed above, when users first receive help from others and then give something back in return, they engage in ex post reciprocity. On Q&A websites, answering questions is the major way to help others, and researchers use it to represent knowledge contribution [Jin et al. 2015; Xu et al. 2019]. Shumaker and Brownell [1984] find that people reciprocate the benefits from others due to a sense of indebtedness, ensuring ongoing supportive exchanges. Reciprocity has been posited as an instance of social exchange [Blau 1964; Lawler 2001]. Additionally, researchers [Jin et al. 2015] use social exchange theory [Cropanzano and Mitchell 2005] to explain how people who receive more help online will contribute more. Therefore, it is reasonable to assume that users who receive more answers may contribute more. Based on this prior literature, we posit that if ex post reciprocity works, it will have a positive impact on users' contributions. Specifically, we hypothesize that when users receive more answers in the previous period, they feel more grateful and are likely to respond with more answers to others in the current period.

H1a: The more answers a user received last week, the more answers that the user will give this week.

The impact caused by ex post reciprocity may change as time goes by. If driven by ex post reciprocity, it is likely that the user who received answers in the previous period, may post more or fewer answers in the current period, compared to the next period or subsequent periods. In H1a, we discuss ex post reciprocity between the previous period and the current period. We are interested in knowing whether our focal user demonstrates the strongest reciprocity in the period immediately after receiving help from others and whether this attenuates with time [Blau 1964]. We explore for how long after people receive help, they will continue to demonstrate reciprocity.

A sense of indebtedness may fade away after a while, so people may be driven less and less by reciprocity. Cropanzano and Mitchell [2005] finds the exchange relationships require the repayment within a particular period. As time passes after receiving help from others, those who received help in the form of answers may show a decrease in eagerness to pay back. Roberts [1998] also finds that the stability of reciprocity is problematic, indicating the impact of reciprocity could decrease as time goes by.

Therefore, it is likely that the urge to reciprocate may gradually fade with time after the event that triggered the reciprocity. In short, the longer the time elapses after a user receives others' help, the less they may pay back. We operationalize this by measuring reciprocity two weeks prior to the current period, three weeks prior, and so on. We hypothesize that the strength of reciprocity, measured by the number of answers, will become weaker as time goes on, i.e., people will be likely to post fewer answers with time.

H1b: The number of answers received more recently will have a stronger impact on the number of answers given this week.

3.2 Ex ante Reciprocity

Ex ante reciprocity emphasizes the motivation for those who help others is to get future help. On StackOverflow.com, we can infer ex ante reciprocity when people who answer others' questions expect answers from the community in the future. However, their expectations for future help could diminish due to the existence of free riders. Kollock [1998] highlights the vulnerability of online communities to free riding, where members only take from others but do not give back. Wang and Lai [2006] also discuss the potential existence of free riders in online communities, i.e., members who only ask questions, but never contribute answers. Such free-riding behaviors may limit the motivations of contributors and harm the development of online communities. For instance, Chandola et al. [2007] and Fyrand [2010] find that people get disappointed or angry if they do not receive what they expect after they help others.

If ex ante reciprocity does exist, users may reduce or stop offering help when they cannot gain help from others. On StackOverflow.com, if people cannot get answers from others, they may subsequently give fewer answers. On 9/23/2011, StackOverflow.com announced a new policy that unregistered users could no longer ask questions.[1] Before this feature change, all users could ask questions including "visitors", i.e., unregistered users. Such a situation generates a natural experiment, in which this policy is a treatment acting only on these unregistered users, but having no impact on registered users.

If we can show that before and after this date, the difference between the change in the number of answers given by unregistered users and by registered users is significantly negative, then we find evidence to support the ex ante reciprocity. To be more specific, if ex ante reciprocity does exist, when these unregistered users could not ask questions anymore, they would be less likely to answer others' questions, because they are not able to expect anything in return from others later. After the policy change, the ex ante reciprocity would only affect those unregistered users; their present contribution to the platform could no longer be reciprocated, as they are no longer allowed to pose questions.

Therefore, we put forward the following hypothesis for ex ante reciprocity.

H2: The difference of the number of answers given between registered and unregistered users before and after the policy change is negative.

4 Study 1: Ex post Reciprocity

4.1 Data Collection

We collected our dataset from http://data.stackexchange.com/. We downloaded weekly activity data of users who registered their accounts between 6/1/2010 and 12/31/2012 and whose last active dates are after 1/1/2013. We collected these users' activity from 1/1/2011 to 12/31/2012. We needed their last active dates to be after 1/1/2013, so that we could guarantee that all the users in our sample were still active all through 1/1/2011 to 12/31/2012.

In online Q&A websites, a small number of users contribute most of the answers. On StackOverflow, approximately the top 2% of users contribute more than two-thirds of the answers on the website.[2] This result appears to be the case for Quora as well, where the majority of users ask questions while a relatively smaller number of participants answer them [Parker et al. 2016]. Therefore, high-reputation users reflect the main value of this website [Movshovitz-Attias et al. 2013]. Meanwhile, low-reputation users' contributions are relatively rare, and such users are highly likely to have posted zero answers during most weeks. On the contrary, high-reputation users are more engaged, and their behaviors are more reliably observed than those of low-reputation users. We therefore filter this dataset by reputation and choose users whose current reputation is more than 10000.[3] Having this reputation cutoff increases the likelihood that the participants in the sample are reasonably active contributors. The resulting sample has 976 users, with each user's activity grouped weekly over 104 weeks.

Table 2 shows the definition of all the variables we use in the regression models for ex post reciprocity. Table 3 and Table 4 show the descriptive statistics and the correlation matrix of focal variables, respectively. From Table 3, the average answers given by a user in a week is 2.71, indicating users are fairly active on this platform. The average tenure of users is more than one year (more than 66 weeks). As expected, gold badges are rather rare (i.e., typically awarded to 1 out of 100 users per week), whereas a typical user earns a bronze badge approximately once in four weeks. From Table 4, we do not suspect multicollinearity issues as most of the correlation coefficients are sufficiently low. The variance inflation factors (VIFs) confirm the absence of multicollinearity in our analyses.

[1] https://meta.stackexchange.com/questions/59445/recent-feature-changes-to-stack-exchange
[2] The result was achieved at 7:33 PM, 9/10/2016
[3] We collected our dataset on 7/11/2016

Table 2: Variables Definition.

Variables	Explanation
Dependent Variable	
AnsGiv	The total number of answers given by a specific user (the "focal user") during a week.
Independent Variables	
AnsRec	The total number of answers received from others during a week, for questions asked by the focal user (the questions of the answers may be posted in that week or previous weeks).
AnsUpvRec	The number of answers' upvotes received during a week, for answers given by the focal user.
AnsDowRec	The number of answers' downvotes received during a week, for answers given by the focal user.
Edit	The total number of edits given by a specific user during a week.
Tenure	The number of weeks till the current date since the user created his account.
Gold	The total number of gold badges received by a specific user for a week.
Silver	The total number of silver badges received by a specific user for a week.
Bronze	The total number of bronze badges received by a specific user for a week.
Instrumental Variables	
QueUpv	The total number of upvotes of questions asked by a specific user for a week.
QueCom	The total number of comments of questions asked by a specific user for a week.
Bounties	The total number of bounties given by a specific user for a week. A bounty is a special reputation award given to answers.[a]

[a] https://stackoverflow.com/help/bounty visit time: 9:33 pm, 1/13/2019.

Table 3: Descriptive Statistics.

	Mean	SD	Min	Median	Max
AnsGiv	2.71	6.30	0	0	184
AnsRec	0.70	2.66	0	0	142
AnsUpvRec	5.54	10.93	0	2	453
AnsDowRec	0.11	0.46	0	0	15
Edit	0.10	1.87	0	0	425
Tenure	66.85	31.28	1	67	133
Gold	0.01	0.12	0	0	3
Silver	0.12	0.39	0	0	12
Bronze	0.28	0.69	0	0	42
QueUpv	0.79	3.26	0	0	618
QueCom	0.56	2.39	0	0	93
Bounties	1.04	14.23	0	0	1000

Table 4: Correlation Matrix.

(1) AnsGiv	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**
(2) AnsRec	0.05										
(3) AnsUpvRec	0.80	0.02									
(4) AnsDowRec	0.44	0.05	0.40								
(5) Edit	0.07	0.03	0.03	0.03							
(6) Tenure	-0.06	-0.06	0.04	-0.01	-0.01						
(7) Gold	0.08	0.03	0.12	0.04	0.02	0.03					
(8) Silver	0.14	0.06	0.25	0.08	0.05	0.14	0.08				
(9) Bronze	0.25	0.13	0.31	0.13	0.06	0.11	0.09	0.34			
(10) QueUpv	0.05	0.47	0.08	0.05	0.01	0.03	0.11	0.14	0.20		
(11) QueCom	0.07	0.74	0.05	0.05	0.03	-0.02	0.04	0.06	0.13	0.45	
(12) Bounties	0.04	0.11	0.04	0.02	0.02	0.01	0.01	0.03	0.10	0.11	0.10

4.2 Econometric Model

In this study, we choose users' weekly number of answers given (*AnsGiv*) by the focal user as the dependent variable. *AnsGiv* indicates users' contributions on Q&A websites [Jin et al. 2015].[4] A weekly bucketing of activity provides a good way to aggregate user behavior. Capturing all days of the week into one data point cancels out the "day of the week" effect. A week is a fairly reasonable time frame in which we can expect some contributions from active users, as not many users contribute daily. A larger aggregation interval than a week (e.g., a month) may result in too much time elapsing between periods. For independent variables, we use the number of answers received as the proxy of ex post reciprocity [Jin et al. 2015; Xu et al. 2019].

We use a two-way fixed effects model on users and weeks to estimate the effect of ex post reciprocity on users' knowledge contribution. To control for other potential factors that may have an impact on users' knowledge contribution, such as self-learning, peer influence, and users' activities, we introduce several control variables into our model. Specifically, the user fixed effects can control for users' characteristics such as self-learning and behavior patterns, which remain relatively constant as time goes by. The time fixed effects can control for the potential temporal shocks, such as peer influence. The users' tenure can control for time-variant demographic changes. We also use the number of badges received and the number of edits given to control for the external rewards and users' activities. The model is as follows:

$$log(AnsGiv)_{it} = \beta_0 + \beta_1\, log(AnsRec)_{i,t-1} + \beta_2\, log(AnsRec)_{i,t-2} + \beta_3\, log(AnsRec)_{i,t-3}$$
$$+\beta_4\, log(AnsRec)_{i,t-4} + \boldsymbol{\gamma}'\boldsymbol{X}_{it} + \delta_i + \theta_t + \epsilon_{it} \qquad (1)$$

where i and t index user and week, respectively. $\boldsymbol{X}_{it}$ represents the vector of control variables. δ_i represents user-level fixed effects that capture the effect of both observed and unobserved time-invariant characteristics of user i. θ_t represents week-level fixed effects that account for any potential temporal shocks at the weekly level. ε_{it} is the error term.

Although we are trying to use the above controls to rule out all the potential confounders, our focal variable, the number of answers received could be still correlated with the error term. For example, if a user is simply learning a lot on the site and also engaging heavily with other members on the site, he may post questions and also answers actively. We use instrumental variables to solve potential endogeneity problems.

The answers are naturally dependent on questions. Specifically, Liu et al. [2017] suggest that answers are dependent on the quality of questions. Question quality can be defined as "well-formedness, readability, utility and interestingness" [Agichtein et al. 2008], and it refers to its ability to attract users' attention, gain answering attempts, and improve the response timeliness and quality of the best answers. Therefore, a high-quality question has a higher probability of gaining answering attempts. However, the quality of questions should not have any direct impact on the dependent variable, the number of answers given. For example, some top-notch programmers rarely ask questions, but oblige to give many answers. Meanwhile, the quality of questions is more random than the number of questions. People can always ask questions, but it is difficult to control the question quality. For example, if their questions have already been asked on StackOverflow, the mediators will tag those questions as "repeated".[5] Therefore, the changes in the quality of questions are associated with the changes in the number of answers received, but do not lead to changes in the number of answers given, aside from the indirect impact; the instrument is correlated with the endogenous variable but not with the error term. We use the number of questions' upvotes as a proxy for the quality of questions because higher quality questions tend to be upvoted more by the community. We also use an alternative proxy, i.e., the number of questions' comments, giving us multiple measures of question quality.

4.3 Results of Ex post Reciprocity

Table 5a shows the two-way fixed effects regression results, based on the assumption that the focal variable $log(AnsRec)_{i,t-1}$ is exogenous. We use two models: Model (1) mainly measures the direct ex post reciprocal impact from the immediate prior period, allowing us to test H1a. Model (2) incorporates the temporal impact from previous periods' contributions, allowing us to test whether the impact of ex post reciprocity diminishes with time (i.e., hypotheses H1a and H1b).

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[4] We also use answer quality (score per answer in a week) as dependent variable in Appendix A and the results are similar to the case using answer quantity as the dependent variable, indicating ex post reciprocity affecting quantity as well as quality of answers. Since measuring quality of answers involves more uncertainty caused by, for example, other users' perception of a given answer or the inability of contributors to raise the quality of answers easily between one week and the next, we primarily rely on the more robust measure—quantity of answers rather than quality.

[5] https://meta.stackexchange.com/questions/10841/how-should-duplicate-questions-be-handled

Table 5a: Two-way Fixed Effects Regression Results.

	(1)	(2)
$log(AnsRec)_{i,t-1}$	0.134***	0.096***
	(0.008)	(0.007)
$log(AnsRec)_{i,t-2}$		0.060***
		(0.006)
$log(AnsRec)_{i,t-3}$		0.041***
		(0.006)
$log(AnsRec)_{i,t-4}$		0.048***
		(0.006)
$\log(\text{AnsUpvRec})_{i,t-1}$	0.458***	0.451***
	(0.008)	(0.009)
$\log(\text{AnsDowRec})_{i,t-1}$	0.240***	0.235***
	(0.016)	(0.016)
$\log(\text{Bronze})_{i,t-1}$	0.037***	0.040***
	(0.009)	(0.009)
$\log(\text{Silver})_{i,t-1}$	-0.004	-0.001
	(0.011)	(0.011)
$\log(\text{Gold})_{i,t-1}$	0.109***	0.105***
	(0.034)	(0.034)
$\log(\text{Tenure})_{i,t-1}$	-0.082*	-0.0611
	(0.045)	(0.056)
$\log(\text{EditGiv})_{i,t-1}$	0.228***	0.214***
	(0.020)	(0.020)
User Fixed Effects	Yes	Yes
Time Fixed Effects	Yes	Yes
Observations	100,528	97,600
R-squared	0.274	0.276
Number of Users	976	976

Notes: Robust standard errors clustered by users are reported in parentheses. p<0.01 (***), p<0.05 (**), and p<0.1 (*).

Table 5b: Test for Ex post Reciprocity and Lasting Time.

Null Hypotheses	*p*-value
$AnsRec_{i,t-1} - AnsRec_{i,t-2} = 0$	< 0.001***
$AnsRec_{i,t-2} - AnsRec_{i,t-3} = 0$	0.032**
$AnsRec_{i,t-3} - AnsRec_{i,t-4} = 0$	0.421

Notes: The test is based on Model (2) in Table 5a. *** p<0.01, ** p<0.05, * p<0.1.

From Model (1), we can conclude that ex post reciprocity has a significant positive impact on the number of answers given, supporting H1a. The result shows that when users received more answers last week, they will answer more questions in the current week. After controlling for other potential confounders such as learning effect and peer effects (measured by the non-italicized variables in Table 5a), we can claim this positive impact is caused by ex post reciprocity. From Model (2), the coefficient of the first lag of the number of answers received is significantly larger than the second lag (with *p*-value < 0.001). Table 5b shows the details about the comparison between the coefficients of different lags of ex post reciprocity. We see that the impact of ex post reciprocity diminishes as time goes by, supporting H1b. The reason for this result could be that people feel less compelled to reciprocate after a longer time when they receive help from others.

To relax the assumption of the exogeneity of our focal variable, we also run the IV regression. Table 6 shows the results of the two-stage least square (2SLS) regression for testing reciprocity. Model (1) and (2) represent the impact of the immediate ex post reciprocity, while Model (3) and (4) test the diminishing impact of ex post reciprocity from previous periods. Model (1) and (3) use the question quality, measured by the number of question upvotes, as the instrumental variable. Model (2) and (4) use the question quality, measured by the number of question upvotes as well as the number of question comments, as instrumental variables. The *p*-values of the underidentification test are all significant, which means the endogenous variable (i.e., $log(AnsRec)_{t-1}$) is correlated with our instrument(s). The overidentification test [Hansen 1982] aims at examining whether our instruments are correlated with the estimation of the error term, i.e., residual, but this test requires multiple instruments, which are available in Model (2) and (4). The *p*-values of overidentification test in both Model (2) and (4) are not statistically significant, indicating that we cannot reject the null hypotheses that all instruments are valid. The results in Model (3) and (4) are consistent with our findings of the diminishing impact of ex post reciprocity. In summary, we conclude that users will reciprocate after they receive help from others and that the strength of the impact of the ex post reciprocity weakens with time.

Table 6: 2SLS Regression Results.

	(1)	(2)	(3)	(4)
$log(AnsRec)_{i,t-1}$	0.252*** (0.016)	0.251*** (0.013)	0.189*** (0.015)	0.180*** (0.012)
$log(AnsRec)_{i,t-2}$			0.089*** (0.008)	0.091*** (0.007)
$log(AnsRec)_{i,t-3}$			0.073*** (0.008)	0.074*** (0.007)
$log(AnsRec)_{i,t-4}$			0.075*** (0.007)	0.076*** (0.007)
Control Variables	Yes	Yes	Yes	Yes
User Fixed Effects	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes
Instruments	$log(QueUpv)_{i,t-1}$	$log(QueUpv)_{i,t-1}$ $log(QueCom)_{i,t-1}$	$log(QueUpv)_{i,t-1}$	$log(QueUpv)_{i,t-1}$ $log(QueCom)_{i,t-1}$
Weak Identification Test	> 10% maximal IV size	> 10% maximal IV size	> 10% maximal IV size	> 10% maximal IV size
Underidentification p-value	0.000	0.000	0.000	0.000
Overidentification *p*-value	-	0.868	-	0.339
Observations	100,528	100,528	97,600	97,600
Number of Users	976	976	976	976

Notes: The endogenous variable is $log(AnsRec)_{i,t-1}$. The weak identification test indicates that in all the models, both Cragg-Donald Wald F statistic [Cragg and Donald 1993] and Kleibergen-Paap rk Wald F statistic [Kleibergen and Paap 2006] are larger than Stock-Yogo weak ID test critical values [Stock and Yogo 2005] at 10% maximal IV size, indicating instruments are not weak. Robust standard errors clustered by users are reported in parentheses. p<0.01 (***), p<0.05 (**), and p<0.1 (*).

4.4 Robustness Tests

In this section, we use a different instrument to test the robustness of our previous results. We also use the generalized method of moments (GMM) to include the lags of the dependent variable into the regression model.

On StackOverflow, bounties serve as bonus points, offered by question askers for answerers, when the askers are eager to get answers for their questions.[6] Offered bounties incentivize people to answer the questions, thus leading to a larger number of answers received for questions with bounties compared to questions without bounties.

As with the same logic of the quality of questions, bounties should not have any direct impact on the number of answers given, but will have a strong impact on the number of answers received. Therefore, the number of bounties given is a valid instrument for the ex post reciprocity. We show the results using bounties as the IV in Table 7, which are consistent with our previous findings. We also try other instruments for the ex post reciprocity in Appendix B and the results still hold.

[6] https://stackoverflow.com/help/bounty

Table 7: Regression Results with Bounties as IV.

	(1)	(2)
log(AnsRec)$_{i,t-1}$	0.235***	0.193***
	(0.053)	(0.062)
log(AnsRec)$_{i,t-2}$		0.038**
		(0.015)
log(AnsRec)$_{i,t-3}$		0.030***
		(0.010)
log(AnsRec)$_{i,t-4}$		0.039***
		(0.008)
Control Variables	Yes	Yes
User Fixed Effects	Yes	Yes
Time Fixed Effects	Yes	Yes
Instruments	*log(Bounties)*$_{i,t-1}$	*log(Bounties)*$_{i,t-1}$
Weak Identification Test	> 10% maximal IV size	> 10% maximal IV size
Underidentification Test *p*-value	0.000	0.000
Overidentification Test *p*-value	-	-
Observations	100,528	97,600
Number of Users	976	976

Notes: The weak identification test indicates that $log(Bounties)_{i,t-1}$ is not a weak instrument. Robust standard errors clustered by users are reported in parentheses. p<0.01 (***), p<0.05 (**), and p<0.1 (*).

For a particular focal user in a particular week, *AnsGiv* partly captures the focal user's willingness and inclination to post answers during a given week, apart from the effect of any reciprocity. We therefore adopt a dynamic panel model and include the lag of the dependent variable (*AnsGiv*) to control for a focal user's unobservable intrinsic motivations to contribute answers.

Table 8: Regression Results of System GMM.

	Estimation Method	
	One-Step	Two-Step
log(AnsRec)$_{i,t-1}$	0.039***	0.040***
	(0.009)	(0.010)
log(AnsRec)$_{i,t-2}$	0.008	0.009
	(0.007)	(0.007)
log(AnsGiv)$_{i,t-1}$	0.535***	0.533***
	(0.034)	(0.037)
log(AnsGiv)$_{i,t-2}$	0.138***	0.144***
	(0.017)	(0.019)
log(AnsGiv)$_{i,t-3}$	0.078***	0.078***
	(0.009)	(0.009)
log(AnsGiv)$_{i,t-4}$	0.070***	0.074***
	(0.008)	(0.009)
Control Variables	Yes	Yes
User Fixed Effects	Yes	Yes
Time Fixed Effects	Yes	Yes
Overidentification Test *p*-value	0.267	0.267
AR(2) Test *p*-value	0.209	0.414
Number of Observations: 97600, Number of Users: 976, Number of Periods: 104 weeks 976		

Notes: $log(AnsRec)_{i,t-1}$ is treated as a predetermined variable. The instruments are constructed based on the third to fourth lags of $log(AnsGiv)$ and the second and third lags of $log(AnsRec)$. Robust standard errors are in parentheses. p<0.01 (***), p<0.05 (**), and p<0.1 (*).

One potential problem is that the lag of the dependent variable is correlated with the error term, thus leading to an endogeneity problem. Researchers solve this problem by the GMM estimator [Arellano and Bond 1991].

To identify the causal relationship between ex post reciprocity (i.e., number of answers received in the previous period) and the number of answers given, we use a system GMM to test our hypotheses [Arellano and Bond 1991; Blundell and Bond 1998]. This method requires two assumptions: first, there should be no autocorrelation in the idiosyncratic errors. We test this assumption by examining the second-order autocorrelations in the first difference of error terms (i.e., AR(2) test). If there is no significant second-order autocorrelation, we cannot reject the null hypothesis that no autocorrelation in the error terms exists. To eliminate the potential autocorrelation, we add four lagged dependent variables into our models. As a result, the *p*-values of the AR(2) test in both models are not significant, suggesting that there is no first-order autocorrelation in the error terms. The second assumption for GMM is that there should be no correlation between the first difference of the dependent variable and the individual effect. In our context, this assumption implies that the change in the weekly number of answers given does not depend on who the user is. We show all the regression results in Table 8.

Model (1) uses a one-step GMM, i.e., two-stage least squares (2SLS) method, while model (2) uses a two-step GMM, which is more robust. As an IV estimation, GMM also allows for overidentification test when using multiple instruments. From Table 8, the validity of our instruments is supported because the *p*-values of overidentification test in Model (1) and (2) are both insignificant, which means there is no correlation between the residual and instruments in both models. Both models display consistent results for the positive impact of ex post reciprocity (H1a), and the fade-away impact as described in H1b. Therefore, our results are not likely to be disturbed by endogeneity. Additionally, we also analyze ex post reciprocity with a random sample of 223,950 users. We show the results in Appendix C and the results are consistent with our main findings.

5 Study 2: Ex ante Reciprocity

5.1 Data and Model

Next, we use DID to identify whether ex ante reciprocity drives users' contributions. By our definition, ex ante reciprocity represents that once users contribute something, they look forward to the return from others. On StackOverflow.com we define ex ante reciprocity as users' motivation to answer questions due to their expectations that others will answer their questions in the future.

Table 9: Summary Statistics of the Number of Answers by Group.

Treatment	Period	#Observations	Mean	SD	Median	Min	Max
Registered	Before	1104528	0.51	2.24	0	0	85
Registered	After	1104528	0.58	2.38	0	0	87
Unregistered	Before	239172	0.10	0.40	0	0	45
Unregistered	After	239172	0.09	0.38	0	0	74

We collected the information of 228,521 users (with 188,657 registered users, 39,864 unregistered users), who created their accounts before 3/23/2011[7] and whose "last access date" was later than 3/23/2012, thus guaranteeing that all the users were active during the whole year, and there were no shifts between these two groups. Different from Study 1, the users for the study of ex ante reciprocity include all the users regardless of their reputation scores. To make the treated and untreated groups more balanced, we removed the outliers according to users' total number of answers in our observation window (March 2011 to March 2012). We calculated the IQR (interquartile ranges) of the logarithm of the total number of answers and filtered users whose logarithm of the total number of answers is larger than the third quartile plus 1.5IQR, or smaller than the first quartile minus 1.5IQR [Tukey 1977]. Table 9 shows the summary statistics of the outcome variable, i.e., the number of answers given in one month, by treatment before and after the policy change.

Figure 2a and 2b respectively show one unregistered user's and one registered user's profile pages on StackOverflow.com. For unregistered users, StackOverflow attaches "(unregistered)" after users' names.

[7] StackeOverflow.com will allocate a "creation date" even for unregistered users.

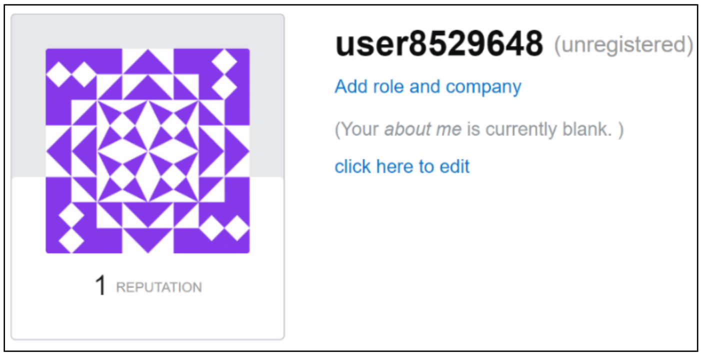

Figure 2a: An Example of an Unregistered User.

Figure 2b: An Example of a Registered User.

As we mentioned earlier, there was a policy change on StackOverflow.com such that unregistered users could not ask questions anymore after 9/23/2011. Before 9/23/2011, anyone could ask questions on StackOverflow, whether or not this user had a registered account. This policy is a treatment only on unregistered users but has no impact on registered users. Therefore, unregistered users belong to the treatment group while registered users belong to the control group. The DID model is as Equation (2) shows,

$$log(AnsGiv)_{it} = \beta_0 + \beta_1 Treated_i \times After_t + \boldsymbol{\gamma}'\boldsymbol{X}_{it} + \delta_i + \theta_t + \varepsilon_{it} \tag{2}$$

where $\log(AnsGiv)_{it}$ represents the outcome variable. $Treated_i$ indicates whether user i is in the treatment group (i.e., whether user i is unregistered). $After_t$ indicates whether StackOverflow has taken the policy change by month t. δ_i and θ_t represent user and month level fixed effects, respectively, controlling for the unobservable users' time-invariant features and temporal shocks.

5.2 DID Results

We show the DID results in Table 10. Model (1) includes all samples. To reduce the imbalance between the control and treatment group, we combine coarsened exact matching (CEM) and DID. Model (2) uses pruned samples by CEM. The outcome of CEM generates a weight for each user, so we run a weighted DID analysis, whose result is shown in Column (2). We show the detailed process of CEM in Appendix D. Both models introduce monthly time fixed effects to control for the time-variant shocks and use robust standard errors clustered by users to account for potential serial correlations [Bertrand et al. 2004]. From Table 10, we can see a consistent result of significantly negative coefficient of the interaction term in both models: the difference between the unregistered and registered users' contributions becomes larger after the policy change, supporting H2.

Table 10: Results of DID Analysis.

	Full Sample	CEM
$Treated_i \times After_t$	-0.033***	-0.029***
	(0.001)	(0.001)
log(AnsUpvRec)	0.537***	0.548***
	(0.001)	(0.002)
log(AnsDowRec)	0.453***	0.560***
	(0.004)	(0.006)
log(Bronze)	0.266***	0.334***
	(0.001)	(0.002)
log(Silver)	-0.005**	-0.018
	(0.002)	(0.012)
log(Gold)	0.026***	0.064
	(0.008)	(0.051)
log(Tenure)	0.223***	0.166***
	(0.001)	(0.002)
log(EditGiv)	0.311***	0.249***
	(0.004)	(0.006)
User Fixed Effects	Yes	Yes
Time Fixed Effects	Yes	Yes
Observations	2,687,400	2,186,460
R-squared	0.480	0.575
Number of Users	223,950	182,205

Notes: Robust standard errors clustered by users are in parentheses. p<0.01 (***), p<0.05 (**), and p<0.1 (*).

To make our results easier to understand, we use a figure to illustrate our results graphically. From Figure 3, the control group (registered users) has an increasing trend between March 2011 and March 2012. If we have the parallel trend assumption, the treated group (unregistered users) should also increase, but the actual number of answers of the treated group decreases, which could be attributed to the impact of ex ante reciprocity. When unregistered users cannot receive help from others, they are not willing to offer help as well.

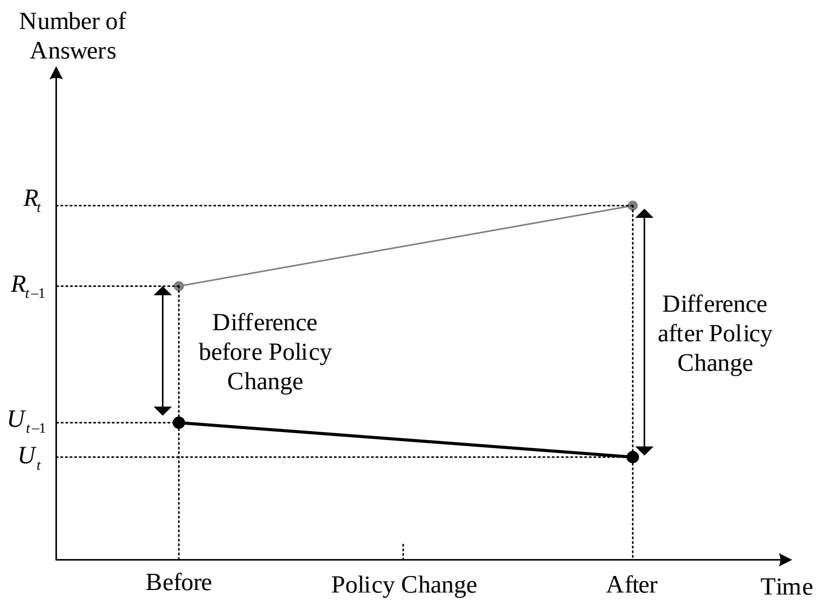

Figure 3: Illustration of the Impact of Ex ante Reciprocity by DID Analysis.

Notes: Treatment Group: unregistered users (U), Control group: registered users (R). Assumption: the same trend for both groups to give answers. The DID coefficient is $(U_t - U_{t-1}) - (R_t - R_{t-1})$, indicating the difference in differences between the number of answers for the two groups before and after the policy change.

5.3 Parallel Trend Assumption

To identify the impact of ex ante reciprocity, we need the "parallel trend" assumption [Abadie 2005; Kmenta 2010], implying that without the treatment, the change of the outcome variable (number of answers given) should be parallel in the treated and untreated groups. The parallel trend is generally not testable after the treatment due to the counterfactual outcome of the treatment group, while it is still possible to test this assumption pre-treatment.

One common approach to test the parallel trend assumption [Autor 2003; Lu et al. 2014] is to run the following model:

$$log(AnsGiv)_{it} = \beta_0 + \beta_1 Treated_i \times Month_1 + \cdots + \beta_{12} Treated_i \times Month_{12} + \boldsymbol{\gamma}'\boldsymbol{X}_{it} + \delta_i + \theta_t + \epsilon_{it} \qquad (3)$$

where $Month_t$ $(t = 1, 2, \ldots, 12)$ is a dummy variable, indicating whether it is the t^{th} month. The treatment happens in Month 6. If the parallel trend assumption holds, the coefficients before the treatment (i.e., $\beta_j, \forall j = 1, \ldots, 5$) should be statistically insignificant.

Figure 4 shows the coefficients of the interaction terms of the regression model above. From the figure we can see the coefficients are statistically insignificant before the policy change, which is consistent with the parallel trend assumption.

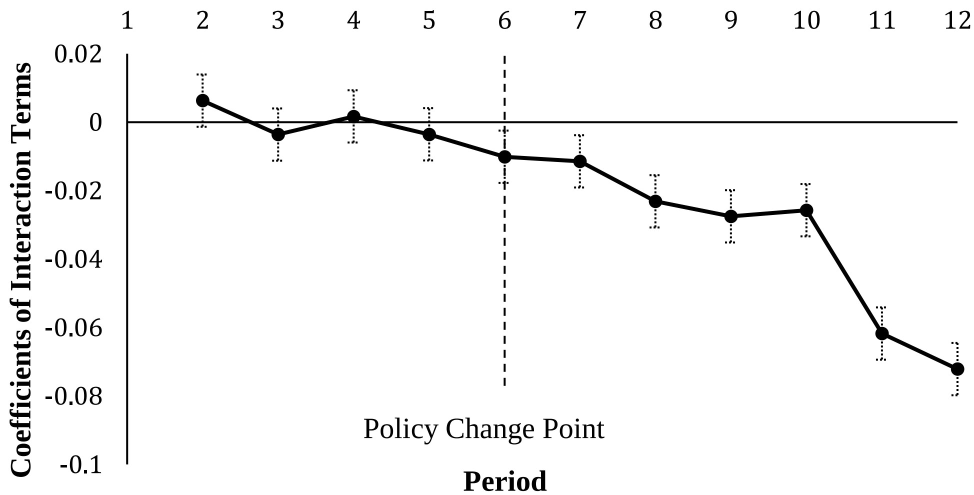

Figure 4: Test of Parallel Trend Assumption.

Notes: Each point represents the estimated coefficient of the interaction between the month dummy and the treatment dummy. The error bars are using a 99% confidence interval. The first month is omitted automatically due to multicollinearity.

5.4 Unifying Framework

Our analysis above focuses on ex post and ex ante reciprocity separately. Since both types of reciprocity may influence users' knowledge contribution simultaneously, we now model ex ante and ex post reciprocity in a unified model. In the ex ante part, we include the number of answers received last period, i.e., the proxy of ex post reciprocity, in the DID analysis. We show the results of the regression including both ex ante and ex post reciprocity in Table 11.

Model (1) in Table 11 is a DID model with two-way fixed effects, assuming $log(AnsRec)_{i,t-1}$ exogenous, and Model (3) uses $log(QueUpv)_{i,t-1}$ as the instrument of the number of answers received, as we did in Study 1. We also run the same analysis with the matching samples in Model (2) and (4). All the results significantly show a negative impact from ex ante reciprocity and a positive impact from ex post reciprocity. Therefore, both H1a and H2 are supported.

In conclusion, although it is not possible to observe users' expectations directly in observational data, we find indirect evidence of ex ante reciprocity on this platform, based on a natural experiment arising from users' reaction to a policy change. From the results of DID analysis, we conclude that the violation of ex ante reciprocity will negatively influence knowledge contribution.

Table 11: Results of Ex ante and Ex post Reciprocity.

	Linear FE		2SLS	
	(1) Full Sample	(2) CEM	(3) Full Sample	(4) CEM
$Treated_i \times After_t$	-0.038***	-0.026***	-0.038***	-0.026***
	(0.001)	(0.001)	(0.001)	(0.001)
$log(AnsRec)_{i,t-1}$	0.014***	0.011***	0.108***	0.154***
	(0.001)	(0.001)	(0.003)	(0.005)
Control Variables	Yes	Yes	Yes	Yes
User Fixed Effects	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes
Observations	2,463,450	2,004,255	2,463,450	2,004,255
R-squared	0.475	0.572	0.464	0.560
Number of Users	223,950	182,205	223,950	182,205

Notes: Robust standard errors clustered by users are in parentheses. p<0.01 (***), p<0.05 (**), and p<0.1 (*).

6 Discussion and Conclusion

This paper develops and studies two different types of reciprocity: ex post and ex ante reciprocity. In conclusion, we have three main findings from this study. First, we find consistent results for the impact of ex post reciprocity on knowledge contribution for active (high-reputation) users. For these active users, the more answers they received last week, the more answers they will contribute in the current week. Second, ex post reciprocity will fade as time passes. Answers received more recently will have a stronger impact on users' contribution. Third, we find some evidence for ex ante reciprocity, i.e., users will contribute less once they have no access to get help from others.

Our research has several limitations, which may inspire potential topics for future studies. Our results, which are based on an analysis of the technical Q&A website StackOverflow, may not generalize to other contexts, such a Quora, where the contributions are not only based on technical expertise but are also based on opinion. More research is needed for the impact of reciprocity on user contribution in other contexts such as e-commerce and social networking. In addition, the current paper mainly focuses on the statistical analysis based on the variables that can be easily measured, and the results are based on the statistical analysis with some assumptions. However, the result obtained based on the pure statistical analysis might not be enough to accurately reflect the truth in online knowledge-sharing communities. To better model the problem and get a more accurate result, it might be helpful if the future study could consider extracting the features (e.g., texture features, etc.) from the data by using some techniques such as natural language processing, machine learning, and data mining.

This study makes meaningful theoretical contributions by putting forward a new taxonomy for reciprocity: ex ante and ex post reciprocity. Although prior studies have investigated how reciprocity influences knowledge contribution, they do not show consistent results. We propose this dichotomy to explain the inconsistency in prior papers. Our findings challenge the conventional wisdom that reciprocity will positively influence an online community because the violation of ex ante reciprocity will likely harm the community. Moreover, future research in psychology and information systems behavioral studies can use our framework of ex ante and ex post reciprocity to explore other issues in reciprocity, which may bring some new findings in these research fields.

The findings in this study also have important implications for the design science [Hevner 2007] of Q&A websites and other similar knowledge-sharing platform owners and service providers. Our work throws light on the creation of the design artifact, by focusing on how reciprocity can affect the level of users' contributions. This insight can help website sponsors design better websites that facilitate greater user contribution and knowledge sharing. Specifically, for ex post reciprocity, after one user receives answers from others, the platform can highlight or push some questions for this user, thus leading the user to get familiar with ex post reciprocity norm. Meanwhile, platforms can filter rude answers and encourage polite answers to facilitate ex post reciprocity. Besides, since we have verified that the impact of reciprocity will fade away as time goes, platforms can send messages to users, indicating the number of answers received for their questions in the past few weeks. Compared to ex post reciprocity, which is concerned with the "giving" side, ex ante reciprocity is more about the "taking" side. A potential vicious circle caused by the failure of ex ante reciprocity could be as follows:

Users contribute because they expect the community to return something in the future. However, if the community does not reciprocate as they expected, they will stop contributing. This behavior will in turn result in a decreasing contribution from others arising from ex post reciprocity, exhibiting a vicious cycle.

In this case, online communities will gradually lose high-quality users, who create knowledge for the life of the platform. To avoid the violation of ex ante reciprocity, platforms can give higher priority to questions from users who contribute a lot, such as putting these questions on the top, sending other related users emails to encourage answering these questions in time, and so on. Hence, it is imperative for the designers of Q&A websites to be cognizant of the dual nature of reciprocity. Successful platforms should focus on cultivating both types of reciprocity to sustain a vibrant community.

ACKNOWLEDGMENTS

We wish to thank the Editor-in-Chief of *ACM Transactions on Management Information Systems*, Daniel Zeng, for his support during the review process. We are grateful to the associate editor and two reviewers who contribute constructive and valuable critiques, and carry out the review process in a timely manner. The final version of this paper would not have been possible without their help.

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APPENDICES

Appendix A Use Quality as Dependent Variable

To establish more robustness, we examine the changes in the quality of answers provided instead of the quantity of answers [Xu et al. 2019]. In Appendix A, we use the logarithm transformation of answer's quality given as the dependent variable to rerun our analysis for ex post reciprocity. The answer's quality is constructed by the weekly score received divided by the number of answers given, i.e., the average scores received for each answer contributed by the focal user in a week.

Table A1: Two-way Fixed Effects Regression Results Using Quality Given as Dependent Variable.

	(1)	(2)
$log(AnsRec)_{i,t-1}$	0.031***	0.022***
	(0.003)	(0.003)
$log(AnsRec)_{i,t-2}$		0.014***
		(0.003)
$log(AnsRec)_{i,t-3}$		0.008***
		(0.003)
$log(AnsRec)_{i,t-4}$		0.012***
		(0.003)
Control Variables	Yes	Yes
User Fixed Effects	Yes	Yes
Time Fixed Effects	Yes	Yes
Observations	100,528	97,600
R-squared	0.077	0.078
Number of Users	976	976

Notes: The dependent variable is quality given. Robust standard errors clustered by users are reported in parentheses. p<0.01 (***), p<0.05 (**), and p<0.1 (*).

From Table A1, the results are similar to the case using answer quantity as the dependent variable, indicating ex post reciprocity affects quantity as well as quality of answers and this impact diminishes as time goes by. Since measuring quality of answers involves more uncertainty caused by other users' perception of a given answer or the inability of contributors to raise the quality of answers easily between one week and the next, we primarily rely on the quantity of answers, which is easy to observe and measure, rather than quality.

Appendix B Alternative IV Ruling out Time Effect

In our main analyses, we use the number of questions' upvotes received as the instrument. In this section, we use the average upvotes of all the other questions that a user posed before (*AvgQueUpvOther*) as the instrument to rerun our 2SLS regression. One advantage of this instrument is that this variable is constructed by dividing the number of questions given in all prior weeks, so it can rule out the temporal effect. Table B1 shows the regression results, which are consistent with our main findings. In Model (2), although the coefficient of the second lag is insignificant, the magnitude of the impact (0.027) is statistically indifferent from that of the third lag (0.041) with *p*-value 0.504. However, the coefficient of the first lag is significantly larger than those of all the other lags, indicating a decreasing impact from the ex post reciprocity. Therefore, all our findings still hold when using *AvgQueUpvOther* as the instrument.

Table B1: Regression Results with *AvgQueUpvOther* as IV.

	(1)	(2)
$log(AnsRec)_{i,t-1}$	0.543***	0.461***
	(0.108)	(0.160)
$log(AnsRec)_{i,t-2}$		0.027
		(0.038)
$log(AnsRec)_{i,t-3}$		0.041**
		(0.021)
$log(AnsRec)_{i,t-4}$		0.049***
		(0.017)
Control Variables	Yes	Yes
User Fixed Effects	Yes	Yes
Time Fixed Effects	Yes	Yes
Instruments	$log(AvgQueUpvOther)_{i,t-1}$	$log(AvgQueUpvOther)_{i,t-1}$
Weak Identification Test	> 10% maximal IV size	> 10% maximal IV size
Underidentification Test *p*-value	0.000	0.000
Overidentification Test *p*-value	-	-
Observations	100,528	97,600
Number of Users	976	976

Notes: The weak identification test indicates that $log(AvgQueUpvOther)_{i,t-1}$ is not a weak instrument. Robust standard errors clustered by users are reported in parentheses. p<0.01 (***), p<0.05 (**), and p<0.1 (*).

Appendix C Further Robustness Tests

To further check the robustness of our results on ex post reciprocity, we rerun the analysis on ex post with the random sample for the analysis of ex ante reciprocity without filtering by reputation, including 223,950 users. The results in Table C1 indicate the conclusion about ex post reciprocity still holds. Different from the main analysis using weekly bucketing, this analysis is based on month level, which is warranted because most users contribute very infrequently. If we use weekly analysis, the data will be very sparse. However, since monthly data may result in too much time elapsing between periods, we just use it as a robustness test.

Table C1: Results of Ex post Reciprocity with All Users.

	Estimation Method	
	(1) Linear FE	(2) 2SLS
log(AnsRec)$_{i,t-1}$	0.021***	0.155***
	(0.001)	(0.005)
log(AnsUpvRec)$_{i,t-1}$	0.068***	0.035***
	(0.001)	(0.002)
log(AnsDowRec)$_{i,t-1}$	0.077***	0.054***
	(0.005)	(0.005)
log(Bronze)$_{i,t-1}$	-0.013	-0.016
	(0.009)	(0.010)
log(Silver)$_{i,t-1}$	-0.005*	-0.003
	(0.003)	(0.003)
log(Gold)$_{i,t-1}$	0.083***	0.064***
	(0.001)	(0.002)
log(Tenure)$_{i,t-1}$	0.277***	0.268***
	(0.002)	(0.001)
log(EditGiv)$_{i,t-1}$	0.113***	0.087***
	(0.005)	(0.005)
User Fixed Effects	Yes	Yes
Time Fixed Effects	Yes	Yes
Observations	2,463,450	2,463,450
Underidentification test *p*-value	-	0.000
Instruments	-	*log(QueUpv)*$_{i,t-1}$
Weak Identification Test	-	> 10% maximal IV size
R-squared	0.031	-
Number of Users	223,950	223,950

Notes: Robust standard errors clustered by users are reported in parentheses. p<0.01 (***), p<0.05 (**), and p<0.1 (*).

Appendix D Coarsened Exact Matching

To eliminate the imbalance between the control and treatment group, we leverage coarsened exact matching (CEM) with DID analysis. Table D1 outlines the pre-treatment covariates used for matching and Table D2 shows the summary statistics of these covariates.

Table D1: Description of Users' Pretreatment Features.

Variable	Description
Bronze	Average number of bronze badges received in pre-treatment periods.
Silver	Average number of silver badges received in pre-treatment periods.
Gold	Average number of gold badges received in pre-treatment periods.
Tenure	The number of months till March 2011 since the user created his account.
Edit	Average number of edits given in pre-treatment periods.
AnsUpvRec	Average number of answers' downvotes received in pre-treatment periods.
AnsDowRec	Average number of answers' upvotes received in pre-treatment periods.
QueGiv	Average number of questions given in pre-treatment periods.
AnsRec	Average number of answers received in pre-treatment periods.
QueCom	Average number of questions' comments received in pre-treatment periods.
QueUpv	Average number of questions' upvotes received in pre-treatment periods.
AboutMeLength	Number of characters of "about me" of the user account.
WebsiteURL	Dummy. Whether the user account provides a website link.
ProfileImage	Dummy. Whether the user account has a profile image.

Table D2: Summary Statistics of Users' Pretreatment Features.

Variable	Mean	SD	Min	Median	Max
Bronze	0.24	0.51	0.00	0.00	84.00
Silver	0.05	0.26	0.00	0.00	66.00
Gold	0.00	0.04	0.00	0.00	4.83
Tenure	14.35	11.35	0.00	11.00	45.00
Edit	0.06	0.92	0.00	0.00	151.50
AnsUpvRec	1.50	14.10	0.00	0.00	3542.33
AnsDowRec	0.04	0.26	0.00	0.00	26.33
QueGiv	0.28	1.03	0.00	0.00	47.33
AnsRec	1.44	8.40	0.00	0.00	542.00
QueCom	1.05	6.60	0.00	0.00	750.00
QueUpv	0.52	2.28	0.00	0.00	163.83
AboutMeLength	67.33	204.58	0.00	0.00	5966.00
WebsiteURL	0.36	0.48	0.00	0.00	1.00
ProfileImage	0.13	0.34	0.00	0.00	1.00

Table D3 shows the imbalance of all the covariates before and after matching. $\mathcal{L}1$ means $\mathcal{L}1$ statistics, which varies from 0 to 1. Perfect multivariate balance results in $\mathcal{L}1 = 0$, while $\mathcal{L}1 = 1$ indicates a complete separation of the multidimensional histograms [Iacus et al. 2009]. After the matching process, we are able to improve the imbalance measured by $\mathcal{L}1$ statistics from 0.735 to 0.406.

Table D3: Univariate Imbalance Measures.

	Before Matching		After Matching	
	Difference	$\mathcal{L}1$	Difference	$\mathcal{L}1$
Bronze	0.239	0.321	0.128	0.189
Silver	0.059	0.159	0.002	0.011
Gold	0.006	0.026	0.000	0.001
Tenure	9.507	0.490	0.009	0.028
Edit	0.068	0.076	0.013	0.026
AnsUpvRec	1.758	0.165	0.202	0.039
AnsDowRec	0.042	0.089	0.008	0.022
QueGiv	0.314	0.317	0.095	0.174
AnsRec	1.672	0.207	0.238	0.082
QueCom	1.223	0.162	0.207	0.068
QueUpv	0.608	0.330	0.091	0.132
AboutMeLength	80.031	0.189	21.783	0.080
WebsiteURL	0.159	0.159	0.000	0.000
ProfileImage	0.156	0.156	0.000	0.000
Multivariate $\mathcal{L}1$		0.735		0.406

Without loss of generality, we use Sturges' Rule [Blackwell et al. 2009] to coarsen the covariates. The matching process results in 144,129 out of 188,657 registered users (i.e., the control group) and 39,863 out of 39,864 unregistered users (i.e., the treatment group). In total, the CEM prunes 44,529 (19.5%) users from our sample.

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