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Home Bias in Knowledge Adoption: Evidence From Location Disclosure in An Online Q&A Community

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Abstract

This study investigates whether and how answerers' location information can bias the askers' knowledge adoption decisions in online Q&A communities. Drawing on the theories underlying in-group favoritism, we propose that home bias can exist due to categorization and the expectation of better reciprocity from in-group members. We leverage the location disclosure in an online Q&A community in China as a natural experiment setting to identify home bias in knowledge adoption. We find that askers are more likely to adopt answers provided by answerers in the same location after the location disclosure. Moreover, the moderation/heterogeneity analysis suggests: (1) location information serves as a cue related to credibility, and askers rely less on it when other factors signal the answerers' credibility, and (2) askers are more favorable toward answerers in the same location when adopting an answer is associated with an expectation of better reciprocation.

Keywords: Home bias, knowledge adoption, online Q&A community, natural experiment

Introduction

Knowledge can be regarded as a critical strategic resource to sustain competitive advantage for both individuals and organizations (Cohen and Levinthal 1990; Hunter 1986; Wasko and Faraj 2000), with the higher capability to transfer knowledge leading to a more significant competitive advantage (Reagans and McEvily 2003). However, knowledge can be geographically bounded, making it hard to transfer (Hwang et al. 2015). The creation of online places can change the way how knowledge flows. Theoretically speaking, online places can eliminate geographic barriers in knowledge transfer processes. By facilitating knowledge communications between people in dispersed locations and enabling people in remote areas to utilize the knowledge provided by professionals worldwide, online places can promote social fairness in knowledge access. However, geographic frictions still exist, as home bias is frequently observed in many online places; for example, in the online lending platform, investors are more willing to lend money to borrowers from the same location (Lin and Viswanathan 2016); employers prefer employees from the same country in the online labor market (Liang et al. 2018). The same situation may occur in knowledge transfer processes when users' location information is observable online. This study aims to investigate home bias in knowledge transfer processes. Specifically, we examine the research question: whether and how home bias can exist in knowledge recipients' knowledge adoption decisions. We study the question in the context of online Q&A communities.

An online Q&A community is a special form of online place enabling knowledge transfer. The value of an online Q&A community is realized through users' voluntary participation in knowledge seeking and contribution. Previous literature has extensively investigated factors affecting knowledge contribution behaviors in online Q&A communities. However, few have looked at knowledge adoption behaviors (Chen and Walker 2022; Lee et al. 2019). Our study contributes to the literature on knowledge adoption in online Q&A communities by introducing location information as a new factor affecting knowledge adoption. The investigation of knowledge adoption is especially important for ensuring efficient knowledge utilization in online Q&A communities. One thing to note is that the answers to a question do not solely benefit the asker; instead, they can help others who are also seeking solutions to the same problem. However, the excess knowledge quantity and highly-variated knowledge quality in an online Q&A community can deter these knowledge seekers from finding the most valuable solution. Many online Q&A communities, e.g., Stack Overflow, have adopted the asker evaluation mechanism, which enables the asker to accept one of the received answers as the best answer. The best answer can serve as a screening mechanism for other knowledge seekers. Indeed, many online Q&A communities rank the best answer to the top position, which is more likely to be first noticed by other knowledge seekers. However, the evaluation mechanism relies on the askers' subjective assessment. Individual-specific preferences may affect the assessment process, making the best answer not the best for the crowd. In this study, we focus on the preference triggered by geographic location, i.e., home bias.

Drawing on the theories underlying in-group favoritism, we propose two mechanisms that may drive home bias in knowledge adoption. When location information is observable, people would use location as a categorization criterion and may perceive others from the same location as belonging to the same social group. In the online Q&A community, this categorization may drive askers to adopt group-based trust and perceive answerers from the same location as more trustworthy, affecting their perception of the answers' usefulness; this can eventually lead to home bias in askers' knowledge adoption decisions. Additionally, according to the theory of bounded generalized reciprocity, this categorization may also make askers expect better reciprocation from answerers in the same location. By accepting an answer as the best, the asker can help the answerer build reputation, which in turn may lead to reciprocity from them. Reciprocity from a local answerer can be more valuable as their relationship may extend to the offline context more easily. Therefore, askers may treat answerers from the same location more favorably by accepting their answers as the best.

The location disclosure in an online Q&A community in China provides a natural experiment to identify the impact of location information on knowledge adoption. In August 2022, the Q&A community began disclosing users' location information on their profile pages, as required by the Cyberspace Administration of China. The location information is compiled based on users' IP addresses. To identify whether there is a home bias in knowledge adoption, we examine whether askers are more likely to accept answers provided by answerers from the same location after the location disclosure. Using the difference-in-differences (DID) model, we observe that askers are indeed more willing to accept answers from answerers in the same province as the best answer. We also conduct a series of robustness tests to ensure the validity of our findings. These tests show that the observed bias is not due to potential changes in answerers' knowledge contribution behaviors or other confounding factors, supporting the existence of home bias in askers' knowledge adoption decisions in online Q&A communities.

To validate the two mechanisms we propose, we examine how other factors moderate the observed home bias. We find that the positive home bias can be mitigated by other factors that signal an answerer's credibility. Specifically, the home bias is eliminated when the answer is contributed by answerers who have been staying in the community for a longer time, or have achieved a higher community level and/or earned more badges. These findings support an informational view of the observed home bias where location information serves as a credibility-related cue. When there are other stronger signals that can be used to signal an answerer's credibility, askers rely less on the answerer's location information. Additionally, we observe an enhancement effect of monetary reward on the observed home bias, meaning that the home bias in askers' knowledge adoption decisions is more prominent when the askers pay for answers versus when they do not. This result suggests the existence of an expected reciprocity mechanism underlying the observed home bias; when an asker can expect to derive higher utility from an answerers' reciprocation, the asker is more likely to exhibit home bias in their knowledge adoption decisions, in order to protect this higher utility.

The study offers theoretical contributions. First, the study contributes to the literature on knowledge adoption in online Q&A community by introducing answerers' location information as one source of cognition bias in askers' knowledge adoption decisions. Second, the study contributes to home bias literature by expanding home bias to the knowledge adoption context. Finally, based on the theories underlying in-group favoritism, this study provides a deep understanding on the mechanisms driving home bias in knowledge adoption. The study also offers important implications for practitioners.

Research Background

In this section, we review the related literature on the home bias, online Q&A community and knowledge adoption, and in-group favoritism.

Home Bias

Home bias is a well-documented phenomenon in financial economic literature. It first referred to the geographical pattern in investors' behavior that investors tend to over-invest in domestic equities despite the potential benefits of international diversification (French and Poterba 1991; Tesar and Werner 1995). Afterward, it expands to the CEO hiring decision that firms are more likely to hire local CEOs (Yonker 2017) and credit analysts' rating behavior that analysts tend to give a more favorable rating to issuers from their home state (Cornaggia et al. 2020). These studies focus on home bias in the offline financial context. Studies have also verified the existence of home bias in online contexts. For example, Hortaçsu et al. (2009b) find a large concentration of transactions among buyers and sellers within the same city in online auction sites. Lin and Viswanathan (2016) identify that in online crowdfunding platforms, borrowers get fewer investors from their origination state and more from their destination state after their move. And Liang et al. (2018) find a positive preference for local workers in employers' decisions in online labor markets. In the online Q&A community, Hwang et al. (2015) find that users are more willing to share their knowledge with seekers in the same city. Their result signifies home bias in the knowledge contribution side. However, the home bias in knowledge adoption has not been studied yet.

Existing literature has documented two mechanisms behind home bias, rational and behavioral home bias. The rational view suggests that home bias is a result of maximizing the benefits (or minimizing the risk). The local information advantage (Coval and Moskowitz 1999) and transaction costs (Lewis 1999; Thapa and Poshakwale 2010) are adopted to explain the existence of rational home bias. The behavioral view suggests that home bias is the familiarity bias rather than the consequence of rationalized utility maximization. In financial markets, investors may over-invest local equities because they perceive investing in familiar firms as less risky, even if they obtain no real information (French and Poterba 1991; Huberman 2001; Pool et al. 2012; Zhu 2002). The survey from Strong and Xu (2003) suggests that fund managers are relatively optimistic about their home equity markets. Lin and Viswanathan (2016) find that the rationality-based mechanism cannot fully explain investors' home bias in online lending.

However, compared with the previously studied contexts, e.g., finance and labor markets, online Q&A communities differ in the two aspects. First, physical geographic proximity in the online Q&A community does not involve any information advantage or reduction in transaction costs. Second, the action process is different. In the financial and labor markets, the utility the agents finally derive is determined by their actions; thus, they have to consider the potential risk involved in each action. The nature of risk aversion leads to familiarity bias in their decisions. However, in the knowledge adoption process, the askers can observe all the available answers before making the adoption decision; they can evaluate the quality of each answer by directly applying it to solving the problem and then adopt the answer with the highest quality. The process involves less (even no) uncertainty. The differences deter us from directly applying the well-documented rational and behavioral mechanism in explaining the (potential) home bias in the knowledge adoption context. In this study, we contribute to understand the (potential) home bias in knowledge adoption basing on the theories underlying in-group favoritism.

Online Q&A Community and Knowledge Adoption

The online community offers a place for knowledge flows (Faraj et al. 2016). By enabling the knowledge transfer process, online Q&A communities can create value for the users. For example, the knowledge provider can build a reputation for their contribution (Khurana et al. 2019); the recipient can benefit by applying the knowledge to solving practical problems.

Sussman and Siegal (2003) conceptualize the elements in knowledge flows into the source (provider), the channel, and the recipient. A successful knowledge transfer process relies on the collaboration of these elements. In the context of online Q&A communities, existing literature has extensively examined the motivation behind users' knowledge contribution behavior (Chen et al. 2019; Chen et al. 2022; Goes et al. 2016; Jin et al. 2015; Lou et al. 2013; Ma and Agarwal 2007; Pu et al. 2022; Wang et al. 2022; Wasko and Faraj 2005). In addition, the embedded information and communication technology in online communities can offer channels for information exchange. However, less attention has been paid to investigating the recipients' knowledge adoption behavior in online Q&A communities.

Knowledge adoption is the utilization phase of a knowledge flow. The capability to utilize knowledge is essential to realize the value of knowledge (Grant 1996). Several studies have investigated knowledge adoption behaviors in online Q&A communities and have identified the existence of cognitive bias in adopting knowledge. Specifically, Lee et al. (2019) find that politeness bias exists in the askers' quality assessment process. Chen and Walker (2022) find that patients are unable to identify the most helpful answer; they may perceive the best answer as the worst. This study contributes to the stream of literature by introducing the knowledge providers' geographic information as a new source of cognitive bias in knowledge adoption.

In-group Favoritism

Home bias can be regarded as a type of in-group favoring behaviors; hence, this study tends to adopt the theories underlying in-group favoritism in explaining home bias in the knowledge adoption context.

Two theories have been suggested for explaining in-group favoring behaviors. One is the pure categorization (Tajfel and Turner 2004). According to the self-categorization theory, people often use objective attributes to categorize themselves with others (Turner and Reynolds 1987), and they tend to integrate the category into their self-concept (Smith and Henry 1996). Categorization can induce in-group bias. Because people always pursue a positive self, they tend to consider the social category they belong to as more positive than other social categories (Tajfel 1981). This can happen in the trust formation process, in which people would perceive demographically similar others as more trustworthy and cooperative (Brewer 1979; Levin et al. 2006; McAllister 1995; Tsui and O'reilly III 1989). Even facing strangers, people adopt group-based trust; they are more positive toward the stranger belonging to the same group (Foddy et al. 2009; Platow et al. 2012). The situation also exists in computer-mediated contexts, in which people tend to trust the information provided by similar others (Lou and Yuan 2019; Shan 2016).

Another is the theory of bounded generalized reciprocity, that is, people hold the expectation that the in-group members can better reciprocate than out-group members (Yamagishi and Kiyonari 2000). In-group favoring behaviors can be a result of maximizing one's self-interest; in this case, people tend to offer better treatment to those who are more likely to reciprocate their preferential treatment. Yamagishi and Kiyonari (2000)'s experiments show that the players cooperate more with another in-group player than with an out-group player when playing a simultaneous Prisoner's Dilemma game. However, the difference is eliminated when playing a sequential Prisoner's Dilemma game, in which the first player knows she/he can potentially induce the second player's reciprocation. They attribute the observed phenomenon to bounded generalized reciprocity, i.e., people naturally expect reciprocity from in-group members, not out-group members.

Hypothesis Development

In online Q&A communities, askers select the answer they perceive to be the most useful as the best answer. Hence, the adoption decision highly depends on the perceived usefulness of the answers. According to the information adoption model (Sussman and Siegal 2003), the evaluation of information usefulness is a dual process; aside from the information itself, source credibility (i.e., competence and trustworthy) also plays an essential role in determining one's perceived information usefulness. Self-categorization theory suggests that people tend to bond with similar other and perceive the social category they belong to as more positive. When the location information is observable, askers may use the location information to categorize themselves with the answerers. Specifically, when the askers face an answerer from the same location, the feeling of similarity can trigger them to associate themselves with the answerer as the same group; thus, they tend to develop a feeling of trustworthiness toward the answerer. Note that trustworthiness is one dimension of source credibility. The askers would perceive the answer provided by answerers from the same location as more useful and ultimately adopt the answer as the best, leading to home bias in knowledge adoption.

The theory of bounded generalized reciprocity suggests in-group favoring behaviors as the results of maximizing one's self-interest. People always expect better reciprocity from in-group members than out-group members; thus, they tend to treat in-group members better. Given this, the location disclosure may not only affect the askers' perceived credibility toward the answerers, it may also drive the askers to hold a higher expectation of reciprocal behaviors from answerers from the same location, leading the askers to treat those answerers more favorably. In the online Q&A community, accepting an answer as the best can be viewed as a rewarding behavior to the answer. This is because that many answerers contribute knowledge in the online community for gaining social capital (Wasko and Faraj 2005). The best answer can be viewed as a type of social approval and can help the answerers build a reputation[1], which may even benefit in offline contexts (Huang and Zhang 2016). Indeed, many online Q&A communities provide leaderboards, in which users are listed in the order of their reputation scores. Thus, accepting an answer as the best can help the answerer gain more recognition, and the asker can expect reciprocation from the answerer after accepting an answer as the best. Additionally, as most online Q&A communities serve people in the same industry or organization, for example, most users in the studied Q&A community are in the IT industry; the asker can expect a higher utility deriving from an answerer's reciprocation when the answerer is in the same location. Hence, an asker may also treat answerers from the same location more favorably by accepting their answer as the best. Upon on the discussion, we propose:

H1: When the location information is observable, askers are more willing to adopt answers provided by answerers from the same location (home bias).

In H1, we discuss two mechanisms that may drive home bias in knowledge adoption. The first mechanism is that location disclosure may lead an asker to utilize answerers' location information as a credibility-relate cue, affecting the askers' knowledge adoption decision. In the studied online Q&A community, aside from location information, askers can observe the answerers' community age, community level and badges in their personal page; these answerer characteristics can signal the answerer's capability to provide valuable answers. Specifically, users with a higher community age may be perceived as more experienced in the IT industry, and experience positively relates to capability; community level and badges can signal capability since the users need to acquire more knowledge to satisfy the requirements in achieving a higher level and gaining more badges. Note that competence is also a dimension of credibility (Sussman and Siegal 2003); thus, the answerers' community age, level and badges can also serve as credibility-related cues. If the first mechanism holds, the askers would rely less on location information to infer the answerers' credibility when there are other prominent credibility-related cues; thus, we would observe a weaker home bias in this case. We propose:

H2: The home bias triggered by location disclosure is weaker when there exist other prominent cues to signal the answerers' credibility (i.e., higher community age, higher community level, more badges).

The second mechanism we propose is the bounded generalized reciprocity, that is, the askers tend to offer preferential treatment to answerers belonging to the same group because of the expectation of in-group reciprocity. Reciprocity can be described as "the more you give, the more you will get"; thus, if the second mechanism holds, we expect to observe a stronger home bias in askers' knowledge adoption decisions when accepting an answer can offer the answerer more benefit. The free and paid Q&A functions in the studied online Q&A community provide us a chance to validate the bounded generalized reciprocity mechanism. In the paid Q&A, the askers set a monetary reward on the question; and reward will be given to answerers when their answers are accepted as the best. However, in the free Q&A, answerers receive no monetary reward when being accepted as the best. Thus, comparing with the free Q&A case, in the paid Q&A, the

[1] Using Stack Overflow as an example, being accepted brings the highest increment in users' reputation score. According to the regulation rule, being accepted adds 15 units to the reputation score, while being voted up only adds 10 (see https://stackoverflow.help/en/articles/4396982-reputation).

askers offer more benefit to the answerers whose answers are accepted as the best; in addition to the benefit of gaining more social capital, those answerers can receive the add-on monetary reward. We propose:

H3: The home bias triggered by location disclosure is stronger in questions offering (higher) monetary reward.

Research Methodology

Research Context

The research context is one of the largest online communities for IT professionals in China. The community is dedicated to offering a place for IT knowledge exchange among these professionals. Established in 1999, the community has attracted over 10 million registered users. Users in the community have personal pages. The personal pages show basic user information, including gender, registration date, and fields of interest. In addition, the pages also document users' community activities, including achievement (i.e., level and badges), article releasing, resource sharing, and other related activities. In December 2012, the community launched a Q&A module, which offers a community-based space for users to seek and provide answers to technical-related questions. The Q&A module works in the following ways. First, an asker initiates a question. He/she should set the title, describe the question in detail, and specify the related technical fields. Then, the Q&A community lists the question on its homepage, and others can answer the question when browsing it. The answers to a question are first listed in the ascending order of answering times. The asker can select one among the answers as the best answer, and the best answer is reordered to the top. Questions are marked as "solved" after the asker selects the best answer. In addition, the Q&A module allows viewers to upvote or downvote all the answers.

Since August 2022, the community started to disclose users' location information on their personal pages. Figure 1 shows a sampling personal page after location disclosure. The location disclosure was required in a regulation document released by the Cyberspace Administration of China[2]. The regulation change offers a clear natural experiment setting to investigate home bias in the knowledge adoption process.

Figure 1. A Sampling Personal Page (with translation) After the Location Disclosure

[2] The location disclosure was first requested in a draft regulation document released in June 2021. The formal document was released in June 2022 and came into force on August 01, 2022. The twelfth rule in the document says: "To facilitate public supervision, online information service providers should disclose location information on user information page according to Internet protocol address."

Data Collection

We developed a python crawler to retrieve the research sample in October 2022. Our data contains questions created between June 01 and September 30, 2022. We first collected basic information for each question, including the creation date, asker url, title and description, and the number of browses by the collection date. Then, we collected the answer list of the question. For each answer, we collected its' creation date, answerer url, answer content, whether being accepted as the best answer, and the number of upvotes (downvotes) by the collection date. We merged and duplicated the collected asker and answerer urls; as a result, we got the list of involved users in our data. For each user, we collected personal information (i.e., IP location, registration date, gender, level, fields of interest, and blog introduction) and historical activities (i.e., release articles, share resources, ask or answer questions, release posts and videos). In total, we got 96,625 answers to 55,997 questions. As the Q&A community has recruited some technical experts to answer the questions, we deleted the answers created by these experts in the empirical analysis. Our final dataset contains 95,023 answers to 55,997 questions, of which 11,495 questions did not get an answer from regular users.

Measurements

We conduct the empirical analysis at the answer level. The main dependent variable is $Best_{ij}$, a dummy variable indicating whether answer j in question i is accepted as the best answer. If the focal answer is the best answer, $Best_{ij}$ is 1; otherwise, it is 0. The two main independent variables are $Post_{ij}$ and $SameLocation_{ij}$. We use $Post_{ij}$ to indicate whether the focal answer is created after the location disclosure. If it is, $Post_{ij}$ is 1; otherwise, it is 0. $SameLocation_{ij}$ is the dummy variable indicating whether the answerer of the focal answer and the asker of question i are in the same location. If they are, $SameLocation_{ij}$ is 1; otherwise, it is 0[3].

We also measure a series of control variables. First, we extract answer content features, including $TextLength_{ij}$, $SolutionFormat_{ij}$, and $PositiveProb_{ij}$. $TextLength_{ij}$ is the log transformation of 1 plus the number of words in the answer. $SolutionFormat_{ij}$ is a dummy variable indicating whether the focal answer offers solutions in code or photo format. $PositiveProb_{ij}$ is the sentiment in answers. It is derived using the sentiment analysis tool in Baidu AI. $PositiveProb_{ij}$ lies in [0,1], with the value measuring the probability that the sentiment in the focal answer is positive. Second, we measure the answerer characteristics, including $Tenure_{ij}$, $Level_{ij}$, $Badge_{ij}$, and $InterestSimilarity_{ij}$. $Tenure_{ij}$ is the log transformation of the number of days that elapsed between the answerer's registration date and the creation date of the focal answer. $Level_{ij}$ is a dummy variable indicating whether the answerer's community level is above level 1. $Badge_{ij}$ is a dummy variable indicating whether the number of the answerer's badge is above the sample median[4]. $InterestSimilarity_{ij}$ is the similarity between the asker and answerer's fields of interest. It is measured as the number of mutual fields of interest the asker and answerer have. We also control for $TimeDiff_{ij}$, the log transformation of the time elapsed between the question creation time and the answer creation time. Finally, we also define two variables, $Paid_i$ and $Reward_i$, to measure the reward answerers can get when being accepted as the best in question i. $Paid_i$ is a dummy variable indicating whether the question is free or paid; it equals to one when question i is a paid question. $Reward_i$ is the monetary reward the asker set on question i. Tables 1 depicts the descriptive statistics and correlation matrix of these variables.

Variable	Mean	Std	Min	Max
$Best_{ij}$	0.204	0.403	0	1
$Post_{ij}$	0.524	0.499	0	1
$SameLocation_{ij}$	0.096	0.295	0	1
$TextLength_{ij}$	3.456	1.418	0	10.24
$SolutionFormat_{ij}$	0.236	0.425	0	1
$PositiveProb_{ij}$	0.427	0.375	0	1

[3] We adopt the locations in personal pages that were collected in October 2022 to measure $SameLocation_{ij}$. We collected the users' IP locations again in November 2022 and found only 1.290% of the involved users were in another location; this suggests that users' locations rarely change.

[4] As we only have a user's community level and badges at the collection date, not the answer creation date, we define a user's community level and badges as dummy variables.

$Tenure_{ij}$	7.159	1.346	0	8.999
$Level_{ij}$	0.701	0.458	0	1
$Badge_{ij}$	0.500	0.500	0	1
$InterestSimilarity_{ij}$	0.194	0.620	0	23
$TimeDiff_{ij}$	8.635	2.137	2.890	15.96
$Paid_i$	0.258	0.438	0	1
$Reward_i$	6.206	28.991	0	500

Table 1. Descriptive Statistics

Research Models and Estimation Results

The introduction of location disclosure in the online Q&A community offers a natural experiment setting to study home bias in askers' knowledge adoption processes. To test H1, we adopt the difference-in-difference specification and estimate the following regression.

$$logit(Best_{ij}) = \beta_1 SameLocation_{ij} + \beta_2 Post_{ij} \times SameLocation_{ij} + Controls_{ij} + WeekFE + DayofWeekFE + \varepsilon_{ij} \quad (1)$$

In Equation (1), β_2 captures the change in the location information's effect on askers' knowledge adoption behaviors after the location disclosure. If β_2 is significantly positive, we can verify that home bias exists in askers' knowledge adoption processes; they are more willing to accept answers created by answerers from their locations. The control variables in Equation (1) include the answer content features (i.e., *$TextLength_{ij}$*, *$SolutionFormat_{ij}$*, and *$PositiveProb_{ij}$*), answerers' characteristics (i.e., *$Tenure_{ij}$*, *$Level_{ij}$*, *$Badge_{ij}$*, and *$InterestSimilarity_{ij}$*), and *$TimeDiff_{ij}$*. The week and day-of-week fixed effects are used to control for the time trend in the online Q&A community. ε_{ij} is the random error term.

As the location disclosure may also change answerers' behaviors, we also conduct the propensity score matching to find more comparable samples. For each answer with *$SameLocation_{ij}$* equaling to one, we find a similar answer with *$SameLocation_{ij}$* equaling to zero as the matched answer. The matching variables include the answer content features and answerers' characteristics. Table 3 shows the balanced check on the matching variables both before and after PSM. In total, we get 16,220 matched answers.

	Before PSM				After PSM				Bias Reduct %
Variables	Mean treated	Mean control	t-stats	p-value	Mean treated	Mean control	t-stats	p-value	
TextLength	3.374	3.464	-5.77	0.000	3.407	3.414	-0.30	0.767	92.4
SolutionFormat	0.259	0.234	5.37	0.000	0.245	0.244	0.15	0.884	96.1
PositiveProb	0.447	0.424	5.45	0.000	0.441	0.443	-0.29	0.771	92.4
Tenure	6.770	7.201	-29.19	0.000	6.929	6.918	0.48	0.632	97.4
Level	0.517	0.720	-40.72	0.000	0.556	0.562	-0.63	0.527	97.6
Badgeij	0.330	0.518	-34.37	0.000	0.364	0.373	-1.24	0.216	95.0
InterestSimilarity	0.454	0.166	42.59	0.000	0.236	0.261	-2.56	0.011	91.2
TimeDiff	8.844	8.613	9.84	0.000	8.787	8.758	0.82	0.411	87.6

Table 2. Balanced Check Before and After Matching

Table 3 shows the estimations of Equation (1). Columns (1) and (2) are the estimation results on the full sample; and Column (3) and (4) are the results on the matched sample. The coefficients of the interaction term, *$Post_{ij}$*$SameLocation_{ij}$*, are significantly positive, indicating that askers are more likely to adopt answers created by answerers from the same location as the "best" answer after the location disclosure. The results signify the existence of home bias in askers' knowledge adoption decisions, supporting H1.

	(1)	(2)	(3)	(4)
VARIABLES	Best	Best	Best	Best
SameLocation	-0.013	0.017	-0.005	0.007
	(0.040)	(0.042)	(0.057)	(0.058)
Post*SameLocation	0.130**	0.135**	0.160**	0.155*

	(0.055)	(0.057)	(0.079)	(0.080)
Constant	-1.069***	-0.951***	-1.122***	-1.284***
	(0.047)	(0.079)	(0.128)	(0.191)
Controls		Yes		Yes
Week FE	Yes	Yes	Yes	Yes
Day of Week FE	Yes	Yes	Yes	Yes
Observations	95,023	95,023	16,220	16,220
Loglikelihood	-47882	-45591	-8150	-7860
Note. Robust standard errors (cluster on question) in parentheses *** p<0.01, ** p<0.05, * p<0.1				

Table 3. Estimations of Equation (1)

To test the informational mechanism of home bias (H2), we investigate how other credibility-related cues moderate the observed home bias in knowledge adoption. We estimate the following equation.

$$logit(Best_{ij}) = \beta_1 SameLocation_{ij} + \beta_2 Post_{ij} \times SameLocation_{ij} + \beta_3 Moderator_{ij} \times Post_{ij} \times SameLocation_{ij} + OtherInteractionTerms + Controls_{ij} + WeekFE + DayofWeekFE + \varepsilon_{ij} \quad (2)$$

In Equation (2), $Moderator_{ij}$ can be $Tenure_{ij}$, $Level_{ij}$, $Badge_{ij}$. Table 4 shows the estimations of Equation (2). Column (1)-(3) are the estimations on the full sample; and Column (4)-(6) are the results on the matched sample. The coefficients of the 3-way interaction terms are all significantly negative. Facing answerers who have been staying in the community longer, with a higher community level, or have obtained more badges, the askers are less likely to engender home bias in their knowledge adoption decisions. This suggests that when there exist other prominent cues to signal the answerers' credibility, the askers rely less on the answerers' location information in the decision process, confirming to our prediction in H2. The results verify the informational role of location information.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Best	Best	Best	Best	Best	Best
SameLocation	-0.191	-0.276***	-0.075	-0.218	-0.271***	-0.120***
	(0.209)	(0.066)	(0.056)	(0.312)	(0.091)	(0.077)
Post*SameLocation	0.758***	0.338***	0.205***	1.088***	0.331***	0.305***
	(0.276)	(0.091)	(0.075)	(0.417)	(0.125)	(0.105)
Tenure*Post*SameLocation	-0.091**			-0.133**		
	(0.039)			(0.058)		
Level*Post*SameLocation		-0.345***			-0.295***	
		(0.117)			(0.163)	
Badge*Post*SameLocation			-0.193*			-0.354**
			(0.116)			(0.162)
Constant	-0.968***	-0.871***	-0.946***	-1.410***	-1.163***	-1.242***
	(0.101)	(0.081)	(0.080)	(0.268)	(0.196)	(0.195)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Other Interaction Terms	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Day of Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	95,023	95,023	95,023	16,220	16,220	16,220
LogLikelihood	-45582	-45564	-45581	-7854	-7850	-7856
Note. Robust standard errors (cluster on question) in parentheses *** p<0.01, ** p<0.05, * p<0.1						

Table 4. Estimations of Equation (2)

To test the bounded generalized reciprocity mechanism (H3), we examine whether the observed home bias is moderated by the reward offered in a question. We estimated Equation (3). Table 5 depicts the estimation results. Column (1) and (2) show the results on full sample; Column (3) and (4) show the results on the matched sample. The coefficients of the 3-way interaction terms, $Paid_i$*$Post_{ij}$*$SameLocation_{ij}$ and $Reward_i$*$Post_{ij}$*$SameLocation_{ij}$, are significantly positive, indicating that the askers of paid questions are more likely to engender home bias when making adoption decisions. The results confirm to the bounded generalized reciprocity mechanism. When an asker can offer more reward to an answerer by accepting her/his answer, which is also associated with an expectation of higher interest derived from the answerer's reciprocal behavior; thus, the asker is more likely to accept answers provided in-group members for protecting the higher interest, confirming to H3.

$$logit(Best_{ij}) = \beta_1 SameLocation_{ij} + \beta_2 Post_{ij} \times SameLocation_{ij} + \beta_3 Paid_i \ (or\ Reward_i) \times Post_{ij} \times SameLocation_{ij} + OtherInteractionTerms + Controls_{ij} + WeekFE + DayofWeekFE + \varepsilon_{ij} \quad (3)$$

	(1)	(2)	(3)	(4)
VARIABLES	Best	Best	Best	Best
SameLocation	0.155***	0.122**	0.125*	0.120*
	(0.046)	(0.049)	(0.065)	(0.068)
Post*SameLocation	0.043	0.032	0.091	0.021
	(0.063)	(0.070)	(0.089)	(0.095)
Paid*Post*SameLocation	0.369**		0.196	
	(0.169)		(0.224)	
Reward*Post*SameLocation		0.045**		0.062**
		(0.021)		(0.025)
Constant	-1.126***	-1.163***	-1.437***	-1.499***
	(0.080)	(0.079)	(0.197)	(0.195)
Controls	Yes	Yes	Yes	Yes
Other Interaction Terms	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes
Day of Week FE	Yes	Yes	Yes	Yes
Observations	95,023	95,023	16,220	16,220
LogLikelihood	-44832	-45048	-7663	-7721

Note. Robust standard errors (cluster on question) in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 5. Estimations of Equation (3)

Robustness Checks

To ensure the rigor of the findings, we conduct several robustness checks. Following Fang et al. (2023), we adopt a table form (see Table 6) to summarize the robustness check we do.

Robustness Check	Reported in/Results
Relative time model to test whether parallel trend assumption holds	Figure 2
Rule out the explanation on quality change: replace the dependent variable with answer quality (i.e., vote)	Coefficient of DID term in Eq.(1): 0.005 (SE=0.015)
Control for question level characteristics (i.e., title length, number of labels)	Coefficient of DID term in Eq.(1): 0.120 (SE=0.055)
Randomized placebo test	P<0.01
Mixed logit model	Coefficient of DID term in Eq.(1): 0.173 (SE=0.084)

Table 6. Summary of the Robustness Checks

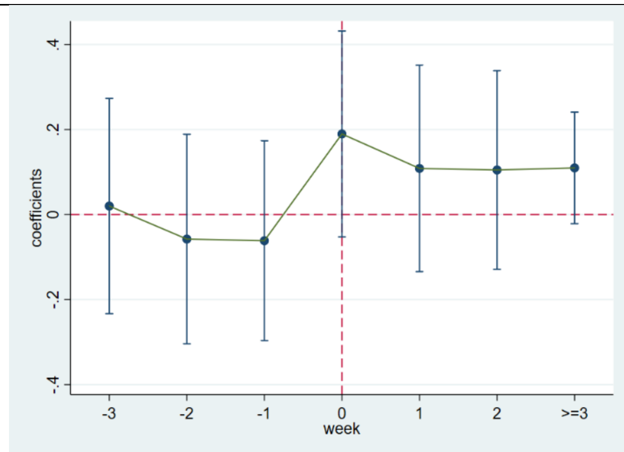

Figure 2. Coefficient Plot of Relative Time Model

Discussion and Conclusion

In this study, we investigate whether and how knowledge providers' geographic information can induce cognitive biases in knowledge seekers' adoption decisions. By leveraging the location disclosure in an online Q&A community in China as a natural experiment, we examine if the askers perceive answers provided by local and non-local answerers differently. Our DID specification identifies the existence of home bias in askers' knowledge adoption decisions; that is, the askers are more likely to adopt answers provided by local answerers after the location disclosure. This signifies location information as one source of cognition bias in knowledge adoption decisions. We also explore the mechanisms by examining how the observed home bias is moderated by other variables. We find a weaker home bias toward the answerers who have a higher community age, a higher community level, and (or) have more badges. This suggests that the askers may leverage the answerers' location as a credibility-related cue; when there are other factors signaling the answerers' credibility, the asker rely less on the location information. We also find a stronger home bias in askers' adoption decisions if the askers pay for the question. When adoption can offer the answerer more benefit, the askers tend to adopt the answer provided by local answerers. This suggests that the home bias may be partially attributed to the expectation of better reciprocity from local answerers.

Overall, this study offers both theoretical contributions and practical implications:

Theoretical Contribution

This study contributes to the previous literature in the following aspects. Firstly, this study contributes to understanding factors affecting knowledge adoption processes in online Q&A communities. Previous literature has extensively examined factors affecting users' knowledge contribution decisions (Chen et al. 2019; Chen et al. 2022; Goes et al. 2016; Jin et al. 2015; Lou et al. 2013; Ma and Agarwal 2007; Pu et al. 2022; Wang et al. 2022; Wasko and Faraj 2005); however, knowledge adoption in online Q&A communities is rarely investigated (Chen and Walker 2022; Lee et al. 2019). Our study contributes to the literature by identifying location information as another factor that can bias users' knowledge adoption decisions.

Secondly, this study contributes to the home bias literature by expanding the scope of home bias to the knowledge adoption context. Previous studies on home bias mostly focuses on the financial economic context. In the online Q&A communities, only one study has examined home bias in the knowledge contribution side (Hwang et al. 2015); however, home bias in knowledge adoption has not been studies yet. Our study contributes to the home bias literature by examining whether and how location disclosure can trigger home bias in the knowledge adoption process in online Q&A communities.

Most importantly, this study offers a deep understanding on the mechanisms underlying home bias in the knowledge adoption context. As we have discussed in the section of research background, the specific characteristics in knowledge adoption in online Q&A communities deter us from directly applying the well-documented rational and behavioral mechanisms underlying home bias in the financial and labor market contexts. We go deep to the theories underlying in-group favoritism, i.e., social-categorization and bounded generalized reciprocity, and propose two mechanisms that may drive home bias in knowledge adoption basing on the theories. Relying on the specific features integrated in the studied online Q&A community, we empirically verify the proposed mechanisms.

Managerial Contribution

This study offers managerial insights to both community operators and policy makers. The findings show that knowledge recipients are subjective to the knowledge providers' location information when making knowledge adoption decisions. This suggests that the observable location information can further threaten the knowledge management process in online Q&A communities. Knowledge quality management in most online Q&A communities relies on the askers' evaluation and the votes from other viewers, with an emphasis on the askers' evaluation. However, the askers' evaluations are biased after location information being disclosed. Thus, the community operators need to adjust their quality management strategy; for example, they can adjust their ranking mechanism by weighting between the askers' evaluation and votes from other viewers; or they can introduce the expert evaluations.

For policy makers, this study signifies a dark side of the location disclosure policy. Although the disclosure policy is originally implemented for strengthening rumor detection and facilitating public supervision; however, our results suggest disclosing location online can enlarge the geographic gap, which has been mostly eliminated by web 2.0, in knowledge transfer processes, constraining people's capability to leverage knowledge efficiently. And the negative impact may be expanded to information adoption in other online communication contexts. For example, in social media, users may also perceive other local users as more trustworthy than nonlocal users; ultimately, they are more willing to interact with local users. Hence, policy makers should consider the potential effect that location disclosure may hinder normal information communication, and implement the location disclosure policy more carefully.

Limitation and Future Direction

This study has several disadvantages, which also provide directions for future researches. First, this study only focuses on home bias brought by location information disclosure; however, since there exist stereotypes by different locations even in a country, a potential future direction is to investigate whether the location information leads to other types of geographic bias; for example, will the askers tend to judge the answerers relying on the locational stereotypes. Second, this study only investigates the impact of location information from the angle of knowledge adoption. Aside from the knowledge communication setting, future research can expand the impact in other information communication settings, for example, social medias; and investigates the effect on more general information adoption. In addition, our study investigates the impact of location disclosure basing on the argument that location information engenders geographic-based in-group favoritisms. However, social categorization may lead to both in-group favoritism and inter-group discrimination; thus, another potential future direction is to investigate whether the observable location information brings more geographic-based discriminations and conflicts (e.g., attack languages relating to geographic locations) online.

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