Heterogeneous interactions in online community : economic and social impact for online sellers

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NANYANG BUSINESS SCHOOL

A thesis submitted to the Nanyang Technological University
in partial fulfillment of the requirement for the degree of
Doctor of Philosophy

2019

Statement of Originality

I hereby certify that the work embodied in this thesis is the result of original research, is free of plagiarised materials, and has not been submitted for a higher degree to any other University or Institution.

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The contributions of the co-authors are as follows:

- Dr. Boh and Dr. Mo provided the direction on the project.
- I co-designed the study with Dr. Boh.
- I analyzed the data.
- I prepared the manuscript drafts. The manuscript was revised by Dr. Boh and Dr. Mo.

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      Date   Chen Yi

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Table of Contents

Summary

The dissertation explores the heterogeneity of online interactions in the ecommerce sellers' online community. Drawing on social exchange theory, while using machine learning techniques to differentiate individuals' interactions in the online forum, we identify three types of resource exchanged in the online sellers' community: instrumental support, informational support, and emotional support. We conduct two studies to examine how the interactions of exchanging these heterogeneous types of support might impact the sellers' economic outcomes and social outcomes.

Chapter 1 introduces the background and the motivation of the dissertation and provides a brief summarization of the two studies.

Chapter 2 presents the first study of my dissertation, which examines the economic impact of receiving and providing each type of support. The findings demonstrate that receiving instrumental support, providing instrumental support, and receiving informational support in the online community are positively associated with the sellers' sales performance on the ecommerce platform. However, a seller's interactions that exchange emotional support or provide informational support are not associated with the sellers' sales performance.

Chapter 3 presents the second study of my dissertation, which explores how a seller's contribution of different types of support in the online community will trigger others' reciprocity, reflected by the responses the seller's threads receive. The findings reveal that a seller's provision of informational support is positively associated with the responses the seller's threads receive, while a

seller's provision of instrumental support is negatively associated with the responses the seller's threads receive. Moreover, the effect is moderated by the types of support sought by a particular thread.

Chapter 4 makes a conclusion on the dissertation.

Chapter 1 Introduction

The rapid growth of the internet has brought about numerous online communities in which people can interact, to expand and enrich their social networks (Butler 2001). Online forums, usually structured around certain topics or themes, are one of the earliest and most popular applications to facilitate online interactions. People interact in online forums by posting new threads and by replying to existing threads. Unlike social network application like Facebook, which assists people in building and sustaining social ties or relationships online and offline (Johnson et al. 2015), online forums are communication-oriented communities that are often constituted by anonymous strangers. Since individuals could choose to participate and interact in certain online communities on a voluntary basis, it is important to understand whether and how individual participants might benefit from their interactions in such online forums.

Existing research demonstrates the social impact of the individuals' interactions in online communities. Through receiving and providing feedback in online communities, individuals could improve their reputation among other community members (Yang et al. 2012). The messages posted by an individual also serve as a form of self-presentation, which could further enhance the individual's status within the community (Lampel and Bhalla 2007). Besides, an individual's interactions in an online community also affect the extent that the individual obtains support from the community. For instance, Wu and Korfiatis (2013) found that the individuals who have previously contributed answers to

others' questions in the Q&A community are more likely to receive responses to their own questions.

In addition, some recent research has also begun to examine the economic impact of the interactions in online communities, which is reflected in the individuals' academic, work, and financial performance. For instance, students who actively engage in discussion forums are found more likely to pass the final exams (Romero et al. 2013), while employees' knowledge sharing behaviors in online communities are positively associated with their work performance (Tseng and Huang 2011) and job-hopping (Huang and Zhang 2016). Based on a Q&A community of online sellers, Qu et al. (2013) demonstrate that contributing answers is positively associated with the sellers' sales performance, but receiving answers is negatively associated with the sellers' sales performance.

However, this stream of research has at most differentiated the impact of posting messages from the impact of receiving messages (Qu et al. 2013; Wu and Korfiatis 2013). The content of interactions does not receive much attention from the researchers. In reality, diverse types of interactions and communication often exist simultaneously in an online forum (Füller et al. 2014). Forum participants could discuss specific topics, talk about their own emotions and feelings, or directly seek tangible assistance in the community. Prior research has also noticed that patients in online health communities engage in multiple types of interactions to express emotional caring, share health-related information, and exchange tangible assistance respectively (Coulson 2005; Wang et al. 2015).

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Given that individuals could choose to engage in heterogenous types of interactions in an online forum, it is necessary to know the economic and social outcomes of these different types of interactions. Exiting literature often aggregates the interactions into a homogeneous type or focuses on just one type (e.g. exchanges of information), which might be due to the constraints of their research context (e.g. Q&A community) (Qu et al. 2013; Wu and Korfiatis 2013) or the lack of theoretical clarity on the effect of diverse interactions (Wang et al. 2013). We argue that the individuals' different types of interactions and their economic and social outcomes might be linked through different mechanisms, which deserve to be carefully discussed and examined. A deeper understanding of the impact of online interactions could guide individuals to participate in the online communities more effectively. Hence, this dissertation attempts to further investigate the economic and social impact of individuals' online interactions by exploring the heterogeneity of interactions exhibited in online communities.

In line with prior research, we characterize the interactions in online communities as forms of social exchange (Faraj and Johnson 2011), which refers to the exchange of tangible or intangible activities and resources between at least two persons (Cook et al. 2013). According to social exchange theory, the content in exchange can be broadly categorized into two types: (1) economic resource which addresses people's financial needs and (2) socioemotional resource which addresses people's esteem and psychological needs (Cropanzano and Mitchell 2005). In the literature on online communities, the economic resource is further operationalized as instrumental support (e.g. tangible actions or assistance) and

informational support (e.g. intangible knowledge), while socioemotional resource is operationalized as emotional support (e.g. affect expression or encouragement) (Coulson 2005; LaCoursiere 2001; Wang et al. 2014). Such categorization provides us a framework to identify the types of online interactions based on the types of support being exchanged.

The availability of textual data in the online forums, on the other hand, enable us to empirically segregate and examine the impact of these differing interactions. Specifically, we conduct two studies to investigate the economic and social impact of online sellers' interactions in a large online forum respectively. Forums specializing in serving online sellers are getting increasingly popular in major e-commerce platforms. We choose such forums as the context of our dissertation for two reasons: (1) diverse types of interactions among the online sellers can be observed in this context; (2) the online sellers' economic outcomes can be easily assessed with their sales performance.

The first study focuses on the economic impact of interactions in online communities. We explore how a seller's interactions in an online forum might be linked to the economic performance in the e-commerce market. Specifically, we examine how the interactions of receiving or providing instrumental support, informational support, and emotional support affect a seller's sales income respectively. The second study investigates the social impact of interactions in online communities. We examine how a seller's provision of informational support and instrumental support affects the responses s/he could receive from others, and how such differing effects of providing informational support and

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instrumental support is moderated by the type of support sought in a certain thread.

This dissertation contributes to our understanding of ecommerce sellers' online communities by identifying and differentiating the types of interactions the sellers engage in. It reveals that not all interactions are identically impactful on the sellers' economic and social outcomes. Future research might benefit from a better specificity about the interactions containing different types of content when investigating the impact of individuals' interactions in online communities. For practitioners, the way they participate in online communities should match with their economic and social needs.

Chapter 2 Economic Impact of Online Sellers' Interactions in Online Community

ABSTRACT

This study explores the economic impact of heterogeneous interactions in the Taobao sellers' online community. Drawing on social exchange theory, we differentiate sellers' interactions based on what they actually exchange. Specifically, we identify three types of support in exchange: instrumental support, informational support, and emotional support. The study examines the impact of receiving and providing each type of support on the sellers' sales. The findings demonstrate that a seller's reception and provision of instrumental support and reception of informational support are positively associated with the seller's sales performance in the e-commerce market. However, other types of interactions are not associated with the sellers' sales performance. This study contributes to both research and practice by providing a more nuanced understanding of the types of interactions in online forums and the economic impacts associated with engaging in these types of interactions.

Keywords: Online community; Social exchange; Ecommerce; Economic outcome

Economic Impact of Online Sellers' Interactions in Online Community

INTRODUCTION

Internet users today still enjoy exchanging information, chatting about their personal feelings, and discussing various topics in online forums, which is one of the most classical online social applications. Different types of forum-based communities emerged for certain groups of people with similar social identities, interests, or professions (Johnson et al. 2015). For instance, Programming communities, such as Stack Overflow, have attracted thousands of program developer to discuss issues they encounter in their daily work. Ecommerce communities, such as Taobao Forum, have been launched for online sellers to interact with each other. Given the increasing prevalence and popularity of such online forums, it is natural to ask how an individual should participate in the online forum in order to generate value and benefit effectively.

Existing research generally agree that users' participation and engagement in an online community could affect their social outcomes within the community, such as users' influence (Zhao et al. 2011) and reputation (Yang et al. 2012). For example, Himelboim et al. (2009) demonstrated that forum users who can import and combine information from different sources are more likely to create popular and influential messages, while Wu and Korfiatis (2013) found that individuals who have previously contributed to the Q&A community are more likely to receive responses when they post questions.

For participants of an online forum, the major outcomes of concern might not be constrained to the social influence within the online community. Rather, they might be more concerned about outcomes in other platforms or context. For instance, individuals participating in an online community of programmers might be more concerned about their productivity of writing codes, while individuals participating in an online community of sellers might be more concerned about their sales performance. Such economic outcomes, however, are usually more difficult to be observed, and the economic impact of individuals' interactions in online communities remains relatively unclear (Sundararajan et al. 2013). Current studies that have linked individuals' behavior in online forums to their performance have been largely limited to classroom settings (Cho et al. 2007; Romero et al. 2013; Yang and Tang 2003), with only a few studies starting to examine how individuals' interactions in online communities associate with their work performance (Tseng and Huang 2011) and career changes (Huang and Zhang 2016).

Some preliminary studies have begun to examine the economic impact of interactions in online forums by exploring how the online sellers' activities in online forums associate with their sales in ecommerce market, but their results show rather inconsistent findings. Wang et al. (2013) demonstrate that online sellers' effort in online forums does not have an impact on their shops' survival. On the other hand, Qu et al. (2013) show that the relationship is more nuanced, demonstrating that online sellers cannot achieve good sales performance through receiving answers from the online Q&A platform. Instead, sellers' contribution

behavior in online forums will increase their social capital, thus improving their sales performance. Such findings reveal that the effect of online interactions on performance is more nuanced, which highlights the need to uncover the mechanisms that link individuals' online interactions with their outcomes.

We thus provide a deeper theoretical investigation to understand how individuals' interactions in online communities and outcomes in online marketplaces are related by exploring the heterogeneity of online interactions exhibited in online forums. Existing literature on online communities has already shown that interactions and communication in the online communities can be quite diverse. For instance, prior research identifies two types of interactions in the online technical communities: task-oriented interactions that focus on sharing technical knowledge and relation-oriented interactions that focus on expressing concerns or gratitude (Faraj et al. 2015). Studies on online health communities also highlight different forms of online interactions among patients, including interactions that express emotional concern and caring, interactions that exchange health-related information, and interactions that exchange tangible assistance (Coulson 2005; Wang et al. 2015).

When investigating the economic impact of the interactions in online communities, however, researchers typically choose to regard online social interactions as homogenous or focus on just one type (Qu et al. 2013; Wang et al. 2013). Even though a study explicitly mentions that the interactions in online discussion forums help online sellers to access 4 different types of resource: market base, knowledge on running online stores, knowledge on market

dynamics, and emotional support, it still aggregates the sellers' online interactions into a general type. The effect of interactions involving different resource is not differentiated theoretically nor empirically.

Given that the interactions and communication in an online forum can be quite diverse (Füller et al. 2014), we argue that it is inaccurate to neglect the potential differentiated effect of such diverse interactions and assume that all the interactions can be aggregated into a homogeneous type. Rather, online interactions are characterized by multiple forms of social exchange, due to different motivations on the part of the online participants (Faraj and Johnson 2011). According to social exchange theory, people could exchange multiple types of economic and socioemotional resource by interacting with one another (Cropanzano and Mitchell 2005). Hence, the interactions in the online forums can be segregated into different types based on what the individuals are actually exchanging, and the mechanisms of these interactions' economic impact might also differ.

Further, the availability of rich amounts of textual data in online forums offers an opportunity to directly observe communication amongst individuals. The content flows contain information on what is actually exchanged, and can reflect whether individuals are providing and receiving certain types of support in the online community. As Sundararajan et al. (2013) stressed, although many theories are based on the assumptions that resources and influence are flowing through people's networks in specific ways, few researchers have directly used actual content flowing through network ties in their studies (Phelps et al. 2012).

Recent research has started to use the textual content of online interactions to infer individuals' different behavioral approach in developing leadership (Faraj et al. 2015; Johnson et al. 2015) and committing fraud (Li et al. 2016). We believe the diversity of textual content deserves more attention from researchers and can help uncover and explain the mechanisms linking individuals' online interactions with their economic outcomes.

To deepen our understanding of online sellers' community, it is necessary to explore the heterogeneous interactions with differing content in the online forums and the effect of these different types of interactions. This may allow us to gain a deeper and more nuanced understanding of how different ways of participating in online forums may play different roles in affecting one's economic outcomes. Thus, our research question is to understand whether and how different types of interactions and communications in the online forums may have any impact on the online sellers' economic outcomes.

Following the prior studies (Qu et al. 2013; Wang et al. 2013), we attempt to investigate the research question in the context of ecommerce community. Along with the rapid growth of C2C ecommerce, an increasing number of individual sellers started their online business (Stephen and Toubia 2010). This brings about the emergence of forums and communities specializing in serving online sellers. Major ecommerce platforms, such as Taobao, eBay, and Amazon, have all launched seller-oriented forums to facilitate interactions among the online sellers. As the participants of such forums are mostly running their own online stores, their economic outcomes can be assessed with the sales

performance in the e-commerce market. Besides, unlike traditional Q&A communities that focus on knowledge sharing (Qu et al. 2013), such forums do not constrain the content of individuals' communication. Hence, diverse types of interactions can be observed in this context. This study draws on a novel dataset on Taobao sellers, which captures both the sellers' interactions in the online forum and their sales information in the e-commerce market. We identify different forms of interactions associating with receiving or providing three types of support: instrumental support, informational support, and emotional support. Our findings reveal that not all interactions in online forums are associated with individuals' economic outcomes. Specifically, receiving instrumental support, providing instrumental support, and receiving informational support are associated with online sellers' economic outcomes – sales performance. However, providing informational support and the exchange of emotional support in the online community do not associate with the sellers' sales in ecommerce platform.

The rest of this chapter is organized as follows. The next section introduces the research context of our study. Theory and hypothesis are then explained, followed by the methodology and results. Finally, discussions on the findings and implication are presented.

RESEARCH CONTEXT

To examine our research questions, we chose Taobao (taobao.com), an ecommerce platform in China, as the research site. Taobao is the world's largest e-commerce platform that achieved a gross merchandise volume (GMV) of RMB

4,820 billion (about 710 billion USD) in the fiscal year 2018 (alibabagroup.com). About 56% of the GMV was completed on its C2C platform, Taobao Marketplace, in which most shops are owned by individual sellers instead of companies. Being the most popular ecommerce platform in China, Taobao has successfully attracted a large number of individuals to start their business online. As highlighted by an article in Economist (2015), Taobao has allowed millions in China to start selling goods at low cost, and has "reversed the fortunes of many rural people". With a large number of shops available on the platform, however, sellers also realize that it is not easy to stand out from the other shops and to earn a decent living from Taobao's online sales. There is thus a keen interest for sellers to learn how to sell on Taobao.

Given the keen competition, there is significant interest for sellers to seek assistance that may help them overcome the difficulties and improve their sales. In response to such demands, Taobao has launched an online discussion forum, Taobao Forum (bbs.taobao.com). While Taobao does not restrict forum participants to only sellers on Taobao, the forum has evolved such that many topic sections are particularly relevant to online sellers. The sellers thus become the major participators in the community. Specifically, according to the data we collected, about 82% of the participants in the forum have owned online shops in Taobao Marketplace.

This research context provides us with a unique opportunity to relate an individual's activity in the online forum with his or her performance in the ecommerce marketplace. Each forum user's online shop can be accessed through

a hyperlink displayed in their personal information in the forum, which enables us to associate the forum users with their corresponding shops in the Taobao Marketplace. The sellers' interactions and their detailed shop information can also be tracked on the two platforms respectively.

THEORY AND HYPOTHESIS

Heterogeneity of Interactions in Online Community

Social interactions in online communities allow individuals to access and exchange resources distributed in the crowd. Drawing on the social exchange theory, we regard online interactions as social exchanges (Faraj and Johnson 2011; Surma 2016), which refer to the exchanges of tangible or intangible activity and resources, more or less rewarding or costly, between at least two persons (Cook et al. 2013). As Faraj and Johnson (2011) stated, no matter what kind of resources are exchanged, the interactions in the online communities are social in nature and aim to influence or benefit from others. Social exchange theory highlights that as individuals interact with one another, the interactions form exchanges of resource that may generate future obligations (Monge and Contractor 2003).

An important focus of the social exchange theory is the content being exchanged between the exchange parties (Shore et al. 2009). According to Cropanzano and Mitchell (2005), content in exchange can be classified into two forms: economic resource and socioemotional resource. As explained in chapter 1, economic resource refers to resources that address individuals' financial needs,

and socioemotional resource refers to resources that address individuals' esteem and psychological needs. In line with this categorization, we characterize online interactions as multiple forms of social exchanges involving different economic and socioemotional resources (Faraj and Johnson 2011). Specifically, we propose that when interacting in online forums, individuals engage in 3 types of social exchange: (1) exchange of instrumental support, (2) exchange of informational support, and (3) exchange of emotional support. In particular, while the emotional support captures the socioemotional resource, the instrumental support and the informational support together constitute the economic resource. We choose to further decompose economic resource into instrumental support and informational support, because both types of support focus on solving problems and addressing economic needs (Cutrona and Suhr 1992), yet they are widely highlighted and differentiated in the literature on online communities (Coulson 2005; LaCoursiere 2001; Wang et al. 2014). While the instrumental support refers to tangible actions with some extent of direct benefit, the informational support refers to intangible advice that might provide useful guidance to its recipient. It is necessary to examine the impact of receiving or providing either support respectively. We introduce each of these 3 types of support below.

Instrumental support refers to the tangible aid, service, or activity provided for the benefit of its recipient (in the case of online sellers, for the benefit of recipient's shops) (Barrera 1986; Langford et al. 1997). Prior research sometimes also termed it as "tangible support" (Cohen and Wills 1985; Schaefer et al. 1981). In the case of Taobao, a typical example may be an appeal by Seller

B to others in the community to visit his/her shop and select some products into their favorites, with the promise of reciprocal action. Seller A may then visit seller B's shop and select some products into his or her "favorites" – behaviors that aim to increase seller B's ranking in the results displayed by Taobao Marketplace's search engine.[1] Seller A will then respond to Seller B to inform him/her of the actions taken. Seller B will reciprocate with similar behavior to Seller A. Forum messages relevant to exchanging instrumental support are often about requesting or reporting such behaviors.

Informational support represents the information, opinions, or advice related to problem-solving or other utilitarian purposes (Langford et al. 1997; Wang et al. 2014). For online sellers, informational support refers to knowledge and information that is related to running stores on e-commerce platforms. On Taobao Forum, for instance, an exchange of informational support could be initiated by a seller directly posting a thread to share his or her experience or knowledge regarding the operation of an online store. Other sellers who receive such information could post replies containing some grateful words or follow-up questions. Alternatively, an exchange of informational support could also start with a question and an illustration of the difficulties a seller encounters. Others could then post answers to the question or provide suggestions and advice.

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[1] When ranking and displaying consumers' search results, Taobao considers many factors regarding shop information, product information, product quality, and penalization. The amount of times that the shops and the products are viewed or added into favorites are among these factors. Details on the ranking rules can be found at:
https://helpcenter.taobao.com/learn/knowledge?spm=a21pp.8204670.0.0.7cf25b71Y2Wb1e&id=13532467&xttkn=1db1427703c104

Emotional support refers to the expression of affect or emotional concern to other participants (House 1981). Interactions conveying emotional support are generally affective in nature, and appeal to the feelings of the community, including showing caring or concern, encouragement, sympathy, as well as understanding and empathy. In Taobao Forum, an example of exchanging emotional support may involve a seller expressing disappointment in his or her store's business, and other sellers responding with some comforting words.

In sum, the interactions in the online sellers' community are heterogeneous as they involve providing or receiving these 3 different types of support. We further propose that engaging in different types of social exchange will provide different types of benefits.

Below, we first present the overall framework and rationale underlying the overall model, before delving into the detailed hypotheses.

Economic Impact of Interactions in Online Community

Prior research examining the motivations behind why individuals participate in online communities have identified that individuals are often motivated by an expectation of extrinsic reward, which can be broadly divided into two types: soft rewards such as personal reputation and hard rewards such as promotions (Wang and Hou 2015). In the online communities, the soft reward often refers to social benefits such as the reputation, status, or exposure the individuals gain from participating in the online communities, while the hard reward often refers to informational benefits such as the knowledge and experience possessed by others (Bateman et al. 2011; Zhou et al. 2013).

Accordingly, we expect two mechanisms to drive the online sellers' behavior in the online forum. First, those who are motivated by soft rewards would focus on promoting themselves. It helps them to improve their professional reputation or obtain more exposure (Lampel and Bhalla 2007; Tang et al. 2012; Wasko and Faraj 2005). Second, those who are motivated by hard rewards would focus on learning and acquiring knowledge in the online forum (Wasko and Faraj 2000), as the informational benefits are likely to generate concrete rewards in terms of improvements to their shops and business. Researchers found that people tend to browse and read messages posted in the online forums to acquire informational benefit (Bateman et al. 2011). We thus analyze how the two primary goals of promotion and learning could be achieved by different types of interactions.

The ***promotion mechanism*** emphasizes the actions taken by online sellers to improve their reputation and exposure while interacting with each other others. Promotion activities help sellers to become more visible or reputable, thus expanding the potential market base of the sellers' shops or products (Stephen and Toubia 2010). We propose that sellers engage in self-promotion in two ways. First, sellers can directly seek instrumental support from others. As mentioned above, the instrumental support in our context refers to a sort of tangible actions that help the receivers' shops or products to increase market exposure. Second, sellers could improve their reputation and image in the community by providing informational support to other sellers. Social commerce literature highlights that C2C ecommerce sellers possess their own market base, which can be shared

through collaboration (Stephen and Toubia 2010). Maintaining a positive image among colleagues could be helpful in attracting collaborations.

The *learning mechanism* focuses on gaining information and knowledge form others through online interactions (Armstrong and Hagel 1996; Wasko and Faraj 2005). The obtained information could guide the sellers to improve their own online business. We propose that online sellers engage in learning in two ways. First, the most straightforward way to learn is to seek informational support from others. Therefore, online sellers could learn from the messages that others posted in online forums (Bateman et al. 2011; Lampel and Bhalla 2007). Second, another way to learn is through vicarious learning or learning by observations (Chen et al. 2011). By observing others' behaviors as well as the associated consequences, an observer learns to imitate the beneficial actions and avoid the costly errors (Kim and Miner 2007; Manz and Sims Jr 1981). As individuals could observe others' shops and products when visiting and browsing others' webpages, we propose that the online sellers could learn by observation when they are providing instrumental support.

The exchange of emotional support, on the other hand, is less likely to be associated with sellers' sales performance. Unlike instrumental support and informational support that focus on problem-solving, emotional support address individuals' social and emotional needs, such as esteem, care, and affiliation (Armeli et al. 1998; Cropanzano and Mitchell 2005). Hence, the exchange of emotional support is often impactful on intrinsic outcomes, such as individuals' psychological wellbeing (House 1981). Prior literature also demonstrates that
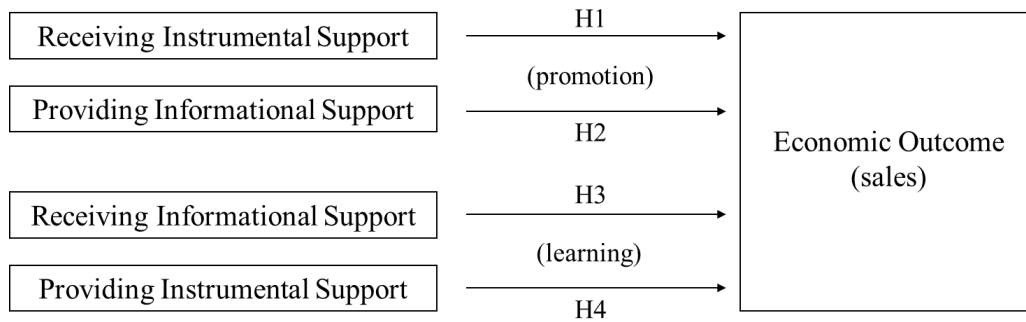
the exchange of emotional support in the online health community is effective in improving the patients' health states (Yan and Tan 2014).

To our knowledge, however, no evidence shows that individuals could achieve effective learning or promotion by exchanging emotional support in online communities. First, emotional support exchanged in the online community takes place through the expression of affect or emotional concern (House 1981), which provides symbolic value (Foa and Foa 1980). Although emotional support helps individuals better cope with depression and stress (Plaisier et al. 2007), it takes effect through consolation rather than eliminating the source of stress (Cutrona and Suhr 1992). Online sellers are thus unable to learn new information about improving their stores from receiving emotional support. Second, the exchange of emotional support in the online community is often generic and a mere formality (Wang et al. 2014). While the provision of instrumental support and informational support is associated with behavioral (e.g. browsing product page) and cognitive effort (e.g. retrieving and compiling knowledge), the cost and efforts required to provide emotional support are relatively low. The low cost and effort might thus indicate that perceptions of contribution from providing such emotional support will be correspondingly low (Falk and Fischbacher 2006). Therefore, sellers can hardly rely on providing emotional support to effectively promote themselves in an online community.

Figure 1 presents an overview of our research model. Our model attempts to explain how the different types of social exchange in the online community will impact online sellers' economic outcomes. By differentiating between

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different interactions that involve providing or receiving distinct types of support, we offer more specific and theoretical insights on how online interactions can influence online sellers' economic outcomes.

Figure 1 Overview of Research Model

Receiving Instrumental Support	H1 (promotion) →	
Providing Informational Support	H2 →	Economic Outcome (sales)
Receiving Informational Support	H3 (learning) →	
Providing Instrumental Support	H4 →	

Increasing Sales through Promotion

In a highly competitive ecommerce market, one of the sellers' major challenge is to increase their shops' exposure and accessibility to potential consumers. The extent that a shop gets promoted could significantly affect the sales revenue the shop earns. We expect that receiving instrumental support in online sellers' community will increase the recipients' exposure and accessibility. As illustrated above, instrumental support refers to tangible actions or behaviors provided for the benefit of the recipients (House 1981). In Taobao Forum, sellers post messages to report their provision of instrumental support and ask for repayment. A typical example of such message is: "I've visited your shop and put one product in my favorite. Please visit back". The exchange of instrumental support is task-focused in nature, facilitating people's collaboration and providing access to task-oriented resources, such that people can easily and efficiently obtain tangible assistance (Varella et al. 2012). In the context of

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Taobao Forum, instrumental support is mainly behaviors of visiting other sellers'

shops and behaviors of putting other sellers' products in one's own favorite list.

Obtaining such behavioral assistance can make a seller's shop or products look

more popular by the search engine of Taobao Marketplace, as popularity is one

of the factors the search engine considers in prioritizing consumers' search

results.[2] For instance, products that are put in more people's favorites are more

likely to be displayed in a higher rank. The reception of instrumental support thus

increases its recipient's opportunities to seen by consumers. Thus, receiving

instrumental support from the online forums is helpful in promoting a seller's

shop and increasing the shop's sales.

Hypothesis 1. The more a seller receives instrumental support in the online

forum, the better the seller's sales performance in the ecommerce market.

While a seller can be promoted to more consumers through receiving

instrumental support, providing informational support might help promote the

seller in the online community as well. The provision of informational support

refers to the action of sharing knowledge and experience relevant to doing online

business by posting threads or replies. An example of the textual content

containing informational support is: "You can add video on the webpage. Please

refer to this URL". We propose that the sellers' economic outcome might benefit

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[2] Videos illustrating the impact of visits (clicks) and putting in favorite on search ranking can be found in Taobao University, an official website that provide training materials for sellers. An example is
https://idaxue.taobao.com/page/class/info.jhtml?spm=a1z14.11501816.0.0.38c94a14ziZBy7&classId=4200

from providing informational support. Specifically, knowledge contribution behavior is found effective in enhancing the contributors' reputation and leadership (Faraj et al. 2015; Yang et al. 2012). Through providing information to other community members, the sellers are able to build and maintain knowledgeable and supportive images (Wasko and Faraj 2005). A positive social image will, in turn, help the focal sellers to receive useful assistance. As illustrated in prior literature, online sellers often engage in collaborative promotion by forming alliances and sharing their own market base with one another (e.g. displaying the hyperlinks of each other's shop on their own shop webpage) (Qu et al. 2013; Stephen and Toubia 2010). A seller with competent social image is likely to be perceived as a valuable and knowledgeable collaborator. Others are more likely to help and collaborate with this seller, which is helpful in increasing the seller's sales. Hence, providing informational support may indirectly help the seller to access more resources and expand market base. Thus:

Hypothesis 2. The more a seller provides informational support in the online forum, the better the seller's sales performance in the ecommerce market.

Increasing Sale through Learning

To succeed in ecommerce market, a seller needs not only a good promotion but also knowledge on many other aspects, such as store operation and market dynamics (Wang et al. 2013). One important source to acquire such knowledge is the informational support provided by other sellers in the online community. By definition, informational support in our context is mainly

relevant to doing business in Taobao. Through receiving informational support from other online sellers with diverse background and experience, the sellers could accumulate helpful information and advice related to their online business. Prior research has shown that an individual with more connections to different information sources is more capable of acquiring diverse external knowledge, thus enhancing the individual's knowledge variety and performance (Gray et al. 2011; Wong 2008). This becomes even more important in the context of Taobao, as Taobao sellers conduct their businesses independently online, and many of them have little previous experience selling online, or even selling offline. Since it is very difficult for sellers to observe or talk with each other face-to-face, communication through online channels will play a more important role in helping the sellers to access useful experience and knowledge distributed in this large and disperse crowd. The more people a seller receives informational support from, the more diverse and valuable information the seller could accumulate. Leveraging on others' knowledge and experience, the sellers could potentially avoid common mistakes, overcome difficulties others have similarly faced, and improve their business based on others' suggestions. Hence, receiving informational support is expected to positively impact individuals' performance (Rodan and Galunic 2004).

Hypothesis 3. The more a seller receives informational support in the online forum, the better the seller's sales performance in the ecommerce market.

In addition to learning from others' opinions, individuals also learn through observations (Çelen et al. 2010). When providing instrumental support,

sellers will visit and explore others' shops. This indicates that the provider of instrumental support will have chances to observe what other sellers are doing on the online shops. The literature highlights that the observers engage in two different forms of vicarious learning: (1) learning how to perform a new behavior by observing the components constituting others' behavior and (2) learning whether to adopt a behavior by observing the consequences of others' behavior (Manz and Sims Jr 1981). We propose that sellers benefit from both forms of vicarious learning when providing instrumental support to others.

First, providing instrumental support allows the sellers to learn through observations about how other sellers are operating. Sellers' activities and efforts are often reflected on their online shops. These include visual information (e.g. webpage layout, pictures, and videos) and textual information (e.g. product description) used by other sellers. Prior research has demonstrated the importance of visual and textual information in affecting online consumers' purchase intention (Kim and Lennon 2008). For a seller who actively provides instrumental support, the observation of such information may provide inspiration and valuable solutions that they may implement on their own online shops.

Second, as the economic outcomes of shops and products sellers visit are also clearly observable, providing instrumental support also enable sellers to learn about what deserves to be implemented on their online stores and what should be abandoned (Srinivasan et al. 2007). Prior research has shown that learning is most effective when observers are able to identify the outcomes

associated with different behavioral approaches (Gioia and Manz 1985). Given that observation does not require much cognitive resource, individuals are even more efficient and capable in perceiving the subtle positive and negative reinforcement cues while observing others' behaviors (Hoover et al. 2012). Based on the observed information, individuals adopt behaviors with desirable outcomes and avoid behaviors with adverse outcomes (Manz and Sims Jr 1981). In the case of Taobao, as online sellers could observe both the design of web pages and the associated sales, they are able to learn by contrasting effective practices with ineffective ones. In sum, in engaging in interactions associated with providing instrumental support, providers gain opportunities for observational learning, allowing sellers to learn how to perform better in the ecommerce market.

Hypothesis 4. The more a seller provides instrumental support in the online forum, the better the seller's sales performance in the ecommerce market.

METHODOLOGY

Data Collection

We crawled all the threads posted on Taobao Forum in the year 2014 and the replies under these threads from all topic sections relevant to the sellers. To accurately capture the interactions happening in threads posted near the end of the year, we also included replies posted between January and March 2015 for threads started in 2014. Eventually our dataset contains 1,384,255 threads and

19,308,584 responses[3]. This dataset, comprising a total of 795,593 forum users, is used to extract the activity of providing and receiving three types of supports – instrumental, informational and emotional support.

We then collected the information of online sellers' shops with the hyperlinks displayed in the forum. As the data of the products sold in these shops was large and the collection process on Taobao Marketplace is time-consuming, we were not able to collect information of all the shops. We randomly sampled 10,000 users from those who have more than four threads or ten replies in our dataset (about 170,630 users satisfy this criterion). As some of their shops are no longer open and accessible, we end up with 7,133 shops. We adopt this selection criterion to target approximately 20% of the most active individuals who intensively and consistently use the forum, so that accidental forum users are less likely to be included. As Taobao Marketplace only provides sales data of each product in the most recent month, we collected the product list and the associated sales of the sampled sellers on a monthly basis from April to June 2015. Meanwhile, we also collected the shop overview pages, which contains transaction statistics and some basic shop-level information such as the shops' creation date and primary product category.

Text Analysis to Differentiate Between Content Types

As our dataset contains more than one million threads and nearly 20 million replies, it is impossible to code all the data manually. Thus, we adopted

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[3] Note that new threads posted between January and Mar 2015 are not included.

text classification algorithms to identify whether a message contains content about one or more of the types of support we have proposed above. While such an approach is initially applied to classify English text, researchers have shown that it also generates satisfactory results with Chinese textual data (He et al. 2000). Since the types of support are reflected in the textual content of each forum message, we first generated a training and testing dataset by manually coding a random sample of 2,000 threads, classifying each thread with one or more of the three types of support. For these manually coded messages, we randomly split the sampled data into two parts, with half of the sample as the training dataset and the other half as the testing dataset. We then used a classification model, which first learns the relationships between the textual content and each type of support exhibited in the training dataset. Based on the learned relationships, the model then predicts the existence of each type of social exchange given the content of a new thread, and the testing dataset is used to check the accuracy of the model.

When coding content on informational support, we noticed that the messages seeking information are quite different from the messages sharing or providing information. This is reasonable because the exchanges of informational support are generally unidirectional. Hence, we coded the information-seeking content and information-sharing content separately. One thread can be coded as representing none, one or multiple types of content. Hence, each thread has four labels corresponding to the four types of content, with one indicating that the thread represents that type(s) of social exchange. Eventually, we identified 567

threads with content on instrumental support, 457 threads with information-seeking content, 347 threads with information-sharing content, and 385 threads that contain content on emotional support.[4]

We coded the originating thread post, as it conveys the main intent of the communication. We then code the content of replies under the threads. To capture the potential diversity of replies under different types of thread content, we sample replies under threads contain content of different types of support. Specifically, for each type of threads, 400 replies are randomly sampled to formulate the training and testing datasets, resulting in 1600 replies in total. We first apply a similar approach to reply sample as we did with the thread sample, so each reply is coded for whether it contains each type (instrumental, information-seeking, information-sharing, and emotional) of content. In addition, as replies sometimes need to be interpreted within the context of the originating message, coding them as messages independent from the originating type of thread might not sufficiently capture the flow of support, especially for replies with very short text. For instance, a reply with only a few thankful words might not be coded as containing information-seeking content by itself, but it could indicate receiving of informational support if it is under a thread with information-sharing content. Thus, for replies under each type of thread, we also manually code for whether each reply was relevant to the intent of the main thread. If a reply is not considered as relevant to any type of the thread nor containing

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[4] Since a thread could contain none of the 4 types of content or multiple types of content, the sum of the threads containing each type of content may not necessarily equal to the sample size.

any type of content by itself, it will be regarded as a spam reply (or irrelevant reply), which is not considered an effective interaction.

To ensure accuracy, an author and a research assistant coded all sampled threads and replies independently. The overall agreement between their coding results is 90.6%, and the estimated reliability is 0.901 (Perreault Jr and Leigh 1989). All inconsistently coded cases were discussed to reconcile and finalize the coding. Table 2.1 provides examples of each type of content and examples of relevant and irrelevant content shown in replies.

Table 2.1. Examples of Content being Coded

Type	Content Example	Content as relevant[5]
Instrumental	Exchange "visit" and "favorite". Must visit back.	I've seen your shop, it looks beautiful.
Info-seeking	What is the impact if I delete products with no storage? Any regulation for such deletion?	The video can be made in this way. Please refer to this URL…
Info-sharing	Today I will introduce a few helpful and necessary software and video tools for the shop web design…	Great! Thanks for sharing this.
Emotional	I'm so desperate about my shop performance	Perseverance is a victory. Taobao requires patience and will power. Come on!

We used the R package, RTextTools (Jurka et al. 2012), a popular text mining tool, to complete the classification tasks. At present, there are many

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[5] This column presents examples that are coded as relevant to the intent of the content in main thread. For instance, content that indicates information receiving is coded as relevant to information-sharing content, while content that indicates information sharing is coded as relevant to information-seeking content.

classification models. As we are not sure which model can provide the most accurate classification for our data, we followed the approach of Jurka et al. (2013), trying eight famous and popular classification algorithms - supported vector machine (SVM), general linearized model (Glmnet), maximum entropy (MaxEnt), Decision Tree (TREE), Random Forest (RF), scaled linear discriminant analysis (SLDA), LogitBoost (Boosting), and bootstrap aggregation (Bagging) - to find the algorithm with the best prediction performance for each classification task.

The text analysis package works by extracting keywords from the text for each thread[6]. Specifically, RTextTools could automatically transform all these the textual documents into a document-term-matrix, in which each row represents a document, and each column represents a distinct term. Therefore, each textual document (represented by a row) is transformed into a vector indicating the existence of the keywords, while each cell of the matrix indicates the frequency of the term appeared in the document. Based on this matrix and the manually coded labels of these documents, each algorithm or model applies its own logic to learn the relationship between the vectors of keywords and the corresponding labels. Eventually, each algorithm will formulate its own criterion that can be used to classify the rest of the text.

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[6] The forum messages are written in Chinese, which does not have spaces or delimiters between words. Before using the RTextTools to process the textual data, we segment the words of all messages with IKAnalyzer, a Java package designed for segmenting Chinese text.

For each text, we tried eight algorithms to learn the classification from the training dataset and applied each algorithm to the testing dataset. To compare the performance of each algorithm, we consider two performance measures: accuracy and ROC Area, which are often used to evaluate the performance of classification algorithms (Wang et al. 2014). The algorithm that performed the best in predicting the testing dataset was selected to complete that particular classification task (e.g. whether a thread contains content on instrumental support) on the textual messages we collected. These algorithms are trained with the dataset we manually code. In sum, the adopted classifiers achieve accuracy ranging from 0.795 to 0.946, and Roc Area ranging from 0.818 to 0.979. Details on selection of classifier algorithms are presented in Appendix A.

We further aggregate the classification results of replies. Specifically, labels of whether a reply is relevant to a particular type of thread are aggregated with labels of whether a reply contains a particular type of content if they represent flows of similar support. For instance, replies relevant to information-seeking threads are merged into replies with information-sharing content as they both indicate the provision of informational support. Similarly, replies relevant to information-sharing threads are merged into replies with information-seeking content as they both indicate receiving of informational support. The same approach also applies to replies on instrumental support and replies on emotional content. Based on threads and replies representing flows of different types of support, we construct sellers' activities accordingly.

Table 2.2 shows a summary of the aggregated classification results. To further validate the classification results, we randomly select 1000 messages (500 threads and 500 replies) and use human coder to reclassify these messages. The accuracy of machine classification is calculated by comparing it with the manual classification. The results show that the classification based on algorithm achieve an overall accuracy of 0.854 (range from 0.71 to 0.938).

Table 2.2. Summary of Aggregated Classification Results

	number of threads	As a percentage of all threads	number of replies	As a percentage of all replies
Instrumental	317,137	22.9%	11,094,124	57.5%
Emotional	223,605	16.2%	4,291,941	22.2%
Info-seeking	285,301	20.6%	1,538,964	7.9%
Info-sharing	92,858	6.7%	813,996	4.2%

Next, we explain the key dependent variables, independent variables and control variables, and how they are constructed.

Constructing Variables

Dependent Variable – Sales Performance. To measure online sellers' performance, we use sellers' total sales income (*SalesIncome*), which is operationalized as the monetary sales income that a seller earned during the 3-month period April to June 2015. Specifically, a seller's sales income is calculated based on the product price and product sales we extracted from the seller's product list every month. The dependent variable has been used to represent online sellers' economic performance on ecommerce platforms (Qu et al. 2013).

Independent Variable – Receiving and Providing Support. In online forums, an interaction happens when an individual posts a reply. A replier could

directly respond to the thread author or respond to other repliers through citing their replies. Hence, we treat a reply with citation as an interaction between the reply author and the author being cited, while a reply without citation is treated as an interaction between the reply author and the thread author. For each reply-to relationship, we use the content identified in the two authors' messages to infer how certain types of support transferred between them.

For instrumental support, if A replies to B with a message containing content of instrumental support, we consider A to provide instrumental support to B, and B to receive instrumental support from A. In addition, as mentioned before, the request of instrumental support resource is often based on a promise or norm of immediate reciprocity. We also take the potential reciprocation from the seeker to provider into account. Specifically, if B posted a message requesting instrumental support with the promise of reciprocity, and A provided the resource, we consider B to provide A with instrumental support as a reciprocation.

Unlike instrumental support, informational support is exchanged unidirectionally. One can obtain informational support from the replies he or she received. Specifically, if A replied to B with a message containing information-sharing content, we consider B to receive informational support from A. Furthermore, if A posts a message with information-sharing content, and B replied to A with a message containing content relevant to information-seeking, we consider B to receive informational support from A.

Similarly, we also consider the exchange of emotional support to be unidirectional. An effective exchange happens when someone showed emotional

need and receives emotional support from another person (Foa and Foa 1980). Specifically, if A posted a message containing emotional support, we regard it as an indicator of emotional need. If B replied to A with another message containing content of emotional support, we consider B to provide emotional support to A.

To measure the extent to which a seller has provided or received one type of support, we calculate the number of different people that the seller has interacted with. Specifically, we calculate the number of people a seller receives the following types of support from: instrumental support (*InstRec*), informational support (*InfoRec*), and emotional support (*EmoRec*). We also calculate the number of people a seller provides the following types of support to: Instrumental support (*InstPro*), informational support (*InfoPro*), and emotional support (*EmoPro*). We adopt the number of different people instead of the total number of interactions, because the resources exchanged between the same pair of people are likely to be redundant. In terms of instrumental support, for instance, if seller A's products are already put into favorite by seller B, additional interactions with seller B do not make the behaviors to be repeated again. Similarly, for informational support, a seller may post multiple messages to share similar advice and suggestions. The more people that a seller has interacted with, the greater amount of non-redundant resources s/he accesses. In sum, *InstRec*, *InfoRec*, *EmoRec*, *InstPro*, *infoPro*, *and EmoPro* represent the

instrumental support, the informational support, and the emotional support each seller receives and provides respectively.[7]

Control Variables. As sellers can post messages to start threads or replies on existing threads, we selected two variables to control for their effort made in the online forum in general. *PostThread* refers to the total number of threads initiated by the seller in 2014. *PostReply* refers to the total number of replies to others' threads posted by the seller. We also controlled the sellers' experience in the community with *ForumAge*, which refers to the number of years since the users registered in the forum.

In addition, we also consider the effect caused by the characteristics of the seller's shop. The online shops' reputation will have a significant effect on their sales, so we include the variable – *ShopLevel*, to control for such effects. *ShopLevel* is calculated based on a shops' credibility score, which is accumulated based on prior successful transactions. Besides, the feedback system could also affect sales performance. The ecommerce platform of Taobao offers three rating scores on different aspects of the shops' products and services. As these three scores are highly correlated, we calculate their average value, *AvgRating*, as a control variable. Moreover, we controlled the sellers' experience with *ShopAge*, the number of years since the shops' creation. The average price of a shop's products was controlled with *AvgPrice.* The potential competition of the sellers' major product category is controlled with *CategoryPer*, which represents the

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[7] As we do not hypothesize for the effect of receiving or providing emotional support, *EmoRec* and *EmoPro* are used as control variables in the analysis.

number of sellers in the same major product category. It is estimated based on a sample of 177,146 shops that we are able to access.

Table 2.3 presents the descriptive statistics of the variables.

Table 2.3. Descriptive Statistics of Variables

Variable	N	Mean	Median	S.D.
SalesIncome	6680	22427.1	1591.45	117043
ShopLevel	6680	5.18	5	2.38
AvgRating	6680	4.87	4.91	0.21
AvgPrice	6680	709.95	83.78	21347.19
CategoryPer	6680	31543.77	11924	27397.82
ShopAge	6680	1.92	1.35	1.66
ForumAge	6680	3.23	2.73	2.19
PostThread	6680	9.9	5	21.46
PostReply	6680	158.6	47	468.61
EmoRec	6680	12.3	1	45.19
EmoPro	6680	14.84	5	46.22
InstRec	6680	117.38	37	265.12
InstPro	6680	125.12	43	282.15
InfoRec	6680	13.4	7	28.07
InfoPro	6680	16.21	4	151.94

Note: *SalesIncome* and *AvgPrice* are measured by RMB;
    ShopAge and *ForumAge* are measured by years.

Modeling Sales Performance

We test our hypotheses by examining the relationship between the three types of support a seller receives or provides in online forums and the seller's economic performance on the ecommerce platform, represented by the following equation:

$$SalesIncome_i = \beta_0 + \beta_1 X_{con_i} + \beta_2 X_{exp_i} + \varepsilon_i$$

In the models, $SalesIncome_i$ refers to seller i's sales income achieved during the prediction period of April to June 2015. X_{exp_i} refers to seller i's

explanatory variables. X_{con_i} refers to the control variables. We take the natural

logarithmic transformation of the dependent variable and some of the

independent variables, such as *PostThread*, *PostReply*, and the explanatory

variables, as the value of these variables have highly skewed, which can be

reduced through logarithmic transformation. The model is estimated by OLS with

robust standard errors. Due to the nature of our data, reverse causality and

simultaneity bias are mitigated because we measure the forum activities prior to

sales performances, and we also have a three-month gap for the impact of

interaction and exchange to take effect. Table 2.4 presents the correlation of

variables.

Table 2.4. Correlations of Variables

	1	2	3	4	5	6	7	8
ln(SalesIncome)								
ShopLevel	0.43*							
AvgRating	0.02	-0.09*						
ln(AvgPrice)	-0.01	-0.14*	0.12*					
ln(CategoryPer)	-0.11*	-0.09*	-0.02*	0.05*				
ShopAge	0.09*	0.33*	-0.04*	0.00	-0.07*			
ForumAge	0.03*	0.17*	0.00	-0.03*	-0.04*	0.63*		
ln(PostThread)	0.04*	0.03*	-0.01	-0.01	-0.01	-0.02	-0.02	
ln(PostReply)	0.03*	0.05*	-0.02	-0.04*	-0.06*	0.02	-0.01	0.19*
ln(InstRec)	0.02	-0.04*	0.02	-0.00	-0.02	-0.08*	-0.04*	0.62*
ln(InstPro)	0.04*	-0.03*	0.01	-0.01	-0.04*	-0.06*	-0.04*	0.47*
ln(InfoRec)	0.08*	0.12*	-0.05*	-0.04*	-0.03*	0.09*	0.03*	0.32*
ln(InfoPro)	0.07*	0.12*	-0.02	-0.02*	-0.04*	0.06*	0.04*	0.39*
ln(EmoRec)	0.03*	0.06*	-0.04*	-0.04*	-0.01	0.01	0.02	0.54*
ln(EmoPro)	0.05*	0.09*	-0.04*	-0.06*	-0.04*	0.07*	0.05*	0.30*

	9	10	11	12	13	14
ln(InstRec)	0.56*					
ln(InstPro)	0.77*	0.89*				
ln(InfoRec)	0.62*	0.42*	0.54*			
ln(InfoPro)	0.67*	0.64*	0.67*	0.62*		
ln(EmoRec)	0.40*	0.58*	0.49*	0.48*	0.53*	
ln(EmoPro)	0.78*	0.53*	0.66*	0.62*	0.71*	0.52*

Note: * significant level <0.05

RESULTS

Our analysis is based on a sample of 6680 effective observations (reduced due to missing values of *AvgRating*). Model 1 includes only the control variables. The results indicate that characteristics of a seller's shop are significantly associated with the seller's sales income. While *ShopLevel*, *AvgRating*, and *AvgPrice* are positively associated with a seller's sales income, *CategoryPer* and *ShopAge* are negatively associated with sales income. These show that shops that had better ratings, higher average price, less competition and were newer tend to have greater sales income. In terms of the sellers' general forum activities, the threads a seller posts (*PostThread*) are positively associated with the seller's sales income, but the replies posted by the sellers (*PostReply*) are not significantly associated with sales income. The interactions of receiving (*EmoRec*) and providing (*EmoPro*) emotional support are not significantly associated with sales income.

We then examine the effect of the explanatory variables. Due to the reciprocal nature of instrumental support in our context, the instrumental support received (*InstRec*) and provided (*InstPro*) by a seller is highly correlated. We examine explanatory variables related to promotion (*InstRec* and *InfoPro*) and learning (*InfoRec* and *InstPro*) separately in Model 2 and Model 3. The Variance Inflation Factor (VIF) for Model 2 and Model 3 are below 4.5. To provide further validation of the results, we include all explanatory variables together in Model 4. However, the VIF for Model 4 is 10, so the results may be suffered from

multicollinearity issue. We'll focus on the results generated from Model 2 and

Model 3. Table 2.5 shows the results of the estimation.

Table 2.5. Effect on Sellers' Sales Income

	Model 1	Model 2	Model 3	Model 4
Intercept	0.24 (0.93)	0.27 (0.93)	0.15 (0.93)	0.08 (0.93)
ShopLevel	0.76*** (0.02)	0.76*** (0.02)	0.76*** (0.02)	0.76*** (0.02)
AvgRating	0.87*** (0.16)	0.85*** (0.16)	0.84*** (0.16)	0.85*** (0.16)
ln(AvgPrice)	0.18*** (0.04)	0.18*** (0.04)	0.18*** (0.04)	0.18*** (0.04)
ln(CategoryPer)	-0.28*** (0.04)	-0.28*** (0.04)	-0.28*** (0.04)	-0.28*** (0.04)
ShopAge	-0.12*** (0.03)	-0.11** (0.03)	-0.11** (0.03)	-0.11*** (0.03)
ForumAge	-0.04 (0.03)	-0.04 (0.03)	-0.04 (0.03)	-0.04 (0.03)
ln(PostThread)	0.1* (0.05)	0.04 (0.05)	0.00 (0.05)	0.03 (0.06)
ln(PostReply)	0.02 (0.05)	-0.02 (0.05)	-0.17*** (0.06)	-0.18*** (0.06)
ln(EmoRec)	-0.04 (0.04)	-0.06 (0.04)	-0.07 (0.04)	-0.05 (0.04)
ln(EmoPro)	0.03 (0.06)	0.04 (0.06)	0.00 (0.06)	0.00 (0.06)
ln(InstRec)		0.09* (0.05)		-0.11 (0.08)
ln(InfoPro)		-0.00 (0.06)		-0.02 (0.06)
ln(InfoRec)			0.14* (0.06)	0.12* (0.06)
ln(InstPro)			0.25*** (0.06)	0.37*** (0.11)
R-square	0.2037	0.2042	0.2063	0.2066

Note: $^+$p<0.1; * p<0.05; **p<0.01; ***p<0.001.

Robust standard errors are reported in ().

The results show that the instrumental support a seller receives,

represented by *ln(InstRec)*, is positively associated with the seller's sales income

(Model 2, β=0.09, p<0.5). In particular, a 1% increase in the instrumental support

received is associated with a 0.09% increase in sales income. Hence, hypothesis

1 is supported. However, the relationship becomes insignificant if the

instrumental support a seller provides is included (Model 4, β=-0.11, p>0.10).

The informational support a seller provides, represented by *ln(InfoPro)*, is not

significantly associated with the seller's sales income (Model 2, β=-0.00, p>0.1).

Hypothesis 2 is not supported.

Model 3 tests the effect of learning. The informational support a seller receives, represented by *ln(InfoRec)*, is positively associated with sales income (Model 3, β=0.14, p<0.05). Hypothesis 3 is supported. Specifically, a 1% increase in the informational support received is associated with a 0.14% increase in sales income. The relationship remains significant in Model 4 (β=0.12, p<0.05) Besides, the instrumental support a seller provides, represented by *ln(InstPro)*, is positively associated with sales income (Model 3, β=0.25, p<0.001), which supports our hypothesis 4. A 1% increase in the instrumental support provided is associated with a 0.25% increase in sales income. The relationship remains significant in Model 4 (β=0.37, p<0.001).

Robustness Checks

Different criteria for sampling active sellers. As stated above, the observations used in our analysis is sampled from the sellers who posted more than four threads or ten replies, so that each observation will have sufficient forum activities to be compared with others. The approach also helps exclude accident participants in the forum. To test the robustness of our results with another cut-off criterion, we ran a robustness test including a subsample of sellers who posted more than nine threads or eighteen replies. The results, presented in Table B.1 in Appendix, are consistent with our main analysis.

Measuring economic performance with transactions. To further validate our findings, we also use the total number of transactions (*TotalTrans*) a seller completed in the same period time (April to June) to measure the seller's economic performance. The number of transactions is also adopted as a

performance measure for online sellers in prior literature (Qu et al. 2013). We estimate the same equation with *ln(TotalTrans)* as the dependent variable. Due to missing values of *TotalTrans*, our estimation is based on a sample of 6637 effective observations. The results are presented in Table B.2. While most of the results are identical to our main analysis, we find that the association between informational support a seller receives and the seller's transactions is only marginally significant (β=0.05, p<0.1), indicating the effect of receiving informational support is weaker on the transactions volume. Compared with monetary sales income, the number of transactions suffers more from the noise of fake transactions in Taobao (Zhang et al. 2013), as such fraud is mostly committed with low-price products. Thus, the number of transactions may not reflect the economic impact of learning as well as the sales amount.

Explanatory variables based on the number of interactions. Based on the assumption that the resources obtained from the same person through multiple interactions are likely to be redundant, we construct the original explanatory variables based on the number of different people a seller exchanges a certain type of support with. Since two people might exchange different non-redundant resources through multiple interactions, we further validate our findings by reconstruct the explanatory variables based on the number of times a seller provides or receives a certain type of support. The results are presented in Table B.3, which are generally consistent with our main analysis. The informational support a seller receives and the instrumental support a seller provides remain positively associated with the seller's sales income, but the effect of receiving

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instrumental support becomes insignificant. The lack of support for the effect of receiving instrumental support is understandable, as the repeated visits from the same individual would not provide additional promotional benefits.

Constructing variables on emotional support in symmetric approach. Based on the assumption that an effective emotional exchange only happens when someone showed emotional need (Foa and Foa 1980), we consider the exchange of emotional support to be unidirectional in our main analysis. To further validate the findings, we relax this assumption and consider the emotional support to be exchanged bilaterally. The variables on emotional support (*EmoRec* and *EmoPro*) are reconstructed accordingly. Specifically, if A posts a message containing emotional support to B, we consider B to receive emotional support from A. If A posts a message containing emotional support and B replies A with a message containing emotional support, we also consider B to receive emotional support from A. The results are presented in Table B.4, which are generally consistent with our main analysis, except that receiving instrumental support becomes insignificant. Receiving informational support (β=0.15, $p<0.05$) and providing instrumental support (β=0.29, $p<0.001$) remain significant. The effect of providing emotional support and receiving emotional support is still insignificant.

Additional Analysis

An important concern regarding our argument of learning-by-observation is whether the sellers indeed pay attenttion to others' shops and products when providing instrumental support. Since we are unable to directly observe whether

a seller spend time to browse other shops' webpages, we attempt to infer the sellers' activity of oberserving from the textual content they posted in the forum. In particular, when posting replies to others, the sellers sometimes give some evaluation on others' shops or products. Such textual content indicates that the sellers have already spent some effort in browsing others' webpages. Hence, we manually code whether the 1600 replies in our trainning sample contain this type of evaluative content. A typical example of sucn type of content is "the proucts in your shop look really good, and the decoration of your shop is decent as well". Consequently, we find 198 replies containing evaluative content. Among these replies, 169 (85%) replies also conatain content on instrumental support. While not all replies providing instrumental support contain such evaluative content (19% of the replies with instrumental support contain evaluative content), it is understandable that not all who engage in such observational learning are expected to provide such evaluative content in their text. Further, our coding results did demonstrate that observational activities tend to result more from actions associated with the provision of instrumental support (only 4% of replies without instrumental support content contain evaluative content).

Futhermore, poviding evaluation can be regarded as an alternative measure for the sellers' observational activities other than providing instrumental support. To validate our findings on learning-by-observation, we examine the relationship between the sellers' activities of posting evaluation and their sales income. Following the approach explained above, we use our coding results of evaluative content to train and test algorthims. The best-performed algorithm is

applied to classify all replies in our dataset. The algorithm identifies 1,493,893 replies containing evluative content. 75% of the replies with evaluative content contain instrumental support, while 10% of the replies with instrumental support contain evaluative content.

Table 2.6. Estimation Results with *EvalPro*

	Model 1	Model 2
Intercept	0.54 (0.93)	0.47 (0.93)
ShopLevel	0.76*** (0.02)	0.76*** (0.02)
AvgRating	0.84*** (0.16)	0.84*** (0.16)
ln(AvgPrice)	0.18*** (0.04)	0.18*** (0.04)
ln(CategoryPer)	-0.28*** (0.04)	-0.28*** (0.04)
ShopAge	-0.12*** (0.03)	-0.11*** (0.03)
ForumAge	-0.04 (0.03)	-0.04 (0.03)
ln(PostThread)	0.05 (0.05)	0.04 (0.06)
ln(PostReply)	-0.15* (0.06)	-0.15*** (0.06)
ln(EmoRec)	-0.08+ (0.04)	-0.08 (0.04)
ln(EmoPro)	-0.02 (0.06)	0 (0.07)
ln(InfoRec)	0.12* (0.06)	0.14* (0.06)
ln(EvalPro)	0.26*** (0.07)	0.26** (0.08)
ln(InstRec)		-0.03 (0.06)
ln(InfoPro)		-0.07 (0.07)
R-square	0.2061	0.2062

Note: $^{+}p<0.1$; * $p<0.05$; **$p<0.01$; ***$p<0.001$.
Robust standard errors are reported in ().

With the classification results, we construct a new variable, *EvalPro*, which refers to the number of different people a seller posts evaluation to. Then, we replace *ln(InstPro)* in our regression model with *ln(EvalPro)*, and conduct the analysis again. As presented in Table 2.6, the number of people a seller posts evaluation to is positively associated with the seller's sales income (Model 1, *β*=0.26, p<0.001). Besides, the instrumental support a seller receives (*InstRec*) is still insignificant even after replacing *InstPro* with *EvalPro*. The results provide

new evidence that verifies the effectiveness and dominance of learning-by-observation.

DISCUSSION AND CONCLUSION

Our research identifies different types of resources and examines the economic impact of exchanging these resources. We measure the economic outcomes with the sellers' sales performance in the Taobao online marketplace. Specifically, we propose that the sellers' participation in online community could benefit their sales through two mechanisms: promotion and learning. In terms of promotion mechanism, we found that the instrumental support a seller receives is positively associated with the seller's sales performance. However promotion in the form of information and knowledge sharing to build one's reputation in the online community did not appear to influence sales of online sellers. This might be because the effects of reputation and image building amongst the online sellers might be too indirect. Our findings are significant as prior research has provided significant evidence that participation in online communities are likely to provide reputational impacts (Faraj et al. 2015; Wasko and Faraj 2005), but our research shows that a positive reputation or image does not necessarily translate into economic impacts and outcomes.

Furthermore, Our findings reveal that online interactions provide economic impact by providing opportunities for individuals to learn from others. The informational support a seller receives is positively associated with his or her economic performance, which indicates that the accumulated informational

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support help the sellers to perform better. Although sellers in the community are potential competitors, our results provide evidence on the value and usefulness of information and knowledge transferred in such community. Furthermore, while researchers generally agree that heterogeneous knowledge obtained from various sources could positively impact one's performance (Rodan and Galunic 2004; Wong 2008), there are also concerns regarding the cost of receiving information. For instance, Qu et al. (2013) emphasize that receiving information might signal incompetency and hurts seller's image, which will eventually cause damage on their sales. The effect could be even more salient in online context as the history of receiving informational support is highly visible. Our findings to some extent dispel such concern by showing that the benefit of receiving informational support still surpass the associated cost, if such cost really exist.

One of the more unexpecting and interesting findings of our study is the evidence of vicarious learning, or learning by observations by the online sellers. We found that by providing instrumental support, individuals are effectively engaging in learning by observations, as their visits to other online sellers and their comparison of those high vs poor performing online shops provide them with valuable information they can use to improve their online sales performance. Unlike advantages of physical stores (e.g. location, salesperson, and service), the advantages of online shops are generally more obvious and imitable. Observation is thus an efficient way for sellers to learn from their peers and competitors.

Although emotional support is often highlighted in literature on online health community (Wang et al. 2015; Yan and Tan 2014), our results do not show

the relationship between receiving or providing emotional support and sales performance. The result might imply that the impact of emotional support is constrained to individuals' psychological and intrinsic outcomes. While emotional support is important to individuals' psychological wellbeing under stress (House 1981), such effect cannot directly translate to economic outcomes.

Implications for Research

Our research contributes to existing knowledge in at least two ways. First, our research contributes to the social exchange literature by uncovering the heterogeneity of resources that occur in online sellers' forums. Existing research on online forums usually treats user interactions as homogenous. However, as we show in this study, members of an online community engage in social exchanges of various types of support. The types of support people provide and receive online are complex and diverse. It is time to pay more attention to the different types of online social exchanges based on the content of communication taking place in online forums. Drawing upon social exchange theory, we identify three types of support transferred in online forums. While instrumental support is sometimes ignored in the online community due to its tangible nature (Huang et al. 2010), we show that the tangible and reciprocal nature of such interactions is influential in providing direct and positive influence on the seller's behavior. With text classification techniques, we decompose the content of online interactions into three sub-types of support: instrumental support, informational support, and emotional support. Specifically, we focus on the effect of receiving or providing certain types of support on sellers' sales performance. Our analysis

demonstrates that the exchange of instrumental support and informational support indeed has an effect on the sellers' economic outcomes in the e-commerce market, while the exchange of emotional support does not. These findings thus reinforce the call by Phelps et al. (2012) for future research to consider the content of interactions when examining individuals' communication networks.

Second, our research enriches our understanding of the economic impacts of online interactions. By differentiating between the receipt and provision of different types of support inferred through text mining techniques, we provide a nuanced understanding of differentiating between different types of interactions and understand the consequences of online interactions. Our results appear to suggest that learning from others through the online forum appear to be more fruitful in terms of economic impact, compared to reputation building mechanism.

Implications for Practice

Our findings also have important practical implications. For online sellers, our research provides empirical evidence that not all types of support the sellers receive in online forums reap the same extent of benefits. Our results show that receiving informational support appears to provide the most significant economic benefits, in terms of improving sellers' sales on the ecommerce platform, but receiving emotional support might not be helpful at all. Moreover, providing instrumental support is positively associated with one's sales performance, which might highlight the significance of learning-by-observation. Sellers could make

use of this "side product" of providing instrumental support and could even visit others' shop and product webpages intentionally.

For organizations like Taobao, which run online forums for their stakeholders, our research highlights the nuanced effects of having individuals engage in interactions via such online forums. While organizations may intend for online forums to serve the main purpose of providing information to potential and current sellers, our research highlights the varied types of social exchanges taking place in such a forum. Task-specific experience and knowledge is not the only valuable resource in an online forum. In addition, sellers may use the online forums to engage in reciprocal exchanges of tangible behaviors, which work to help sellers to "game" the organization's rules in the ecommerce market. This is likely something that is not aligned with the organization's original intentions, since ecommerce platforms like Taobao also offer paid service for shop promotion. On the other hand, sellers also learn from observing others' shops and products, which is positive to the overall quality and revenue of the platforms. The findings highlight the opportunity for organizations to either tweak their system to prevent such behavior, or leverage on such a culture to promote new forms of interactions between sellers (such as suggestions to learn from each other's stores via visits to one another). Overall, our research shows the value in understanding the types of resources that may be taking place in an organization's online platform, and the impacts associated with individuals' engagement in each type of interactions.

Chapter 3 Impact of Heterogeneous Contribution on Reciprocity in Online Sellers' Community

ABSTRACT

This study explores how different types of resources a seller contributes in the online community will trigger others' reciprocity, reflected by the responses the seller's threads receive. Drawing on social exchange theory and machine learning techniques, we identify two important types of resources transferred in online community: informational support and instrumental support. Our findings reveal that a seller's provision of informational support is positively associated with the responses the seller's threads receive, while a seller's provision of instrumental support is negatively associated with the responses the seller's threads receive. Moreover, the effect is moderated by the types of resources sought by a particular thread. For threads that seek informational support, the effect of providing informational support becomes more positive, and the effect of providing instrumental support becomes more negative. For threads that seek instrumental support, the positive effect of providing informational support is undermined, and the negative effect of providing instrumental support becomes less negative. The study contributes to the understanding of online reciprocity by uncovering the differing impact of different contribution and its boundary condition.

Keywords: Online community; Reciprocity; Social exchange; Social outcome

Impact of Heterogeneous Prior Contribution on Reciprocity in Online Sellers' Community

INTRODUCTION

The increasing prevalence of online communities has provided plentiful and various spaces for social interactions. Forum-based communities are among the earliest and the most classical types of online communities, which have covered almost all different social or professional groups of internet users (Johnson et al. 2015). The interactions in online communities facilitate the transfer of multiple types of resources among different individuals. For instance, patients who have suffered from similar health issue could obtain various types of social support (e.g. information and emotional support) from each other in an online healthcare community (Wang et al. 2014). Such forum-based online communities are also increasingly adopted by participants in ecommerce market to access useful information and resources. For online consumers, online community act as an important source of product information generated from other consumers' experience (Bickart and Schindler 2001). For individual online sellers, online community provides channels to acquire relevant knowledge, emotional support, and market base from their peer sellers (Wang et al. 2013).

Many different individuals have benefited from the resources obtained in certain online communities. In the online healthcare community, for instance, researchers demonstrate that the social support a patient receives from others is

effective in improving the health status of the patient (Yan and Tan 2014). Similarly, in the context of ecommerce, the first study in chapter 2 also reveals that the instrumental support and the informational support an online seller obtains from a community are positively associated with the seller's sales performance in the ecommerce market. Receiving responses by itself is also valuable and meaningful for individuals participating in online community (Moon and Sproull 2008). It is found helpful in sustaining newcomers' participation, even if the received responses are not associated with the newcomers' questions (Joyce and Kraut 2006). Besides, as most online forums sort threads based on when the threads receive their newest responses, the received responses can also increase the exposure of the threads.

While the responses are the useful support that one could access in online communities, they are often not evenly distributed to all individuals engaging in the same community. A prior study on online communities of newsgroups has documented that 27% of all online posts fail to receive any response from others (Arguello et al. 2006). The value of such support in online communities and the uncertainty of actually acquiring the support raise the question: How could an individual effectively leverage the online communities to obtain support from others? In particular, what could an individual do to increase the responses s/he receives?

To answer the question, it is important to understand how the interactions in online communities are formed. Prior research regards the interactions in online communities as a form of social exchange (Faraj and Johnson 2011),

which may generate future obligations among the community members (Monge and Contractor 2003). The formation of online interactions is thus largely driven by the mechanism of reciprocity (Gu et al. 2008). Broadly speaking, reciprocity emphasizes that the contribution made in the past determines the return in the future (Gouldner 1960). The more an individual contribute to others in an online community, the more support the individual will receive from others. Specifically, an individual's prior contribution is not necessarily reciprocated by its direct recipient (direct reciprocity) but is also reciprocated by other third parties (indirect reciprocity) (Flynn 2005).

The significance and prevalence of reciprocity in online communities are widely evidenced by the literature investigating the dynamics of people's online interactions (Arguello et al. 2006). In online Q&A communities, for instance, researchers found that the more efforts an individual makes in answering questions, the more likely s/he will receive answers from others (Wu and Korfiatis 2013). Research at a community level also demonstrates that the communication patterns in online communities are characterized by reciprocity rather than preferential attachment (Faraj and Johnson 2011).

However, online community literature generally focuses on the informational aspect of individuals' contribution (Arguello et al. 2006; Wu and Korfiatis 2013). Since individuals could obtain multiple types of resources and support (e.g. informational support vs. emotional support) from an online community (Yan and Tan 2014), the resources and support one could contribute to the online community are also diverse. For instance, online leadership

literature has differentiated individuals' sociability behaviors with task-related knowledge contribution behavior, which affect others' perception of leadership through different mechanisms (Faraj et al. 2015). In terms of online reciprocity, little attention has been paid to the effect of one's contribution with content other than information. It is still unclear whether different types of contribution trigger the same extent and same type of reciprocity and returns. As community members often tend to play different roles with different behavioral patterns (Füller et al. 2014; Wang et al. 2015), differentiation between the types of their contribution could provide more nuanced understanding on why some individuals receive more support than others from the same online community. As the support is transferred through forum messages, our research question is to examine whether an individual's contribution of different resources affect the responses s/he receives in the online community.

To answer our research question, we use the dataset collected from a large forum-based online community, of which the majority of participants are online sellers doing business in a popular C2C ecommerce platform. While prior research emphasizes that online community is suitable for exchanging intangible support (e.g. informational support) due to its virtual nature (Huang et al. 2010), our context provides a unique opportunity to investigate instrumental or tangible support as well. As sellers' shops are accessible to others, many interactions in this online community are associated with some actions happening on the ecommerce platform. We rely on the textual data of the forum messages to infer different types of resources transferred among sellers. Our findings reveal that a

seller's contribution of different resources is associated with the responses s/he receives differently. While the prior provision of informational support increases the responses received, the provision of instrumental support is negatively associated with the responses received. Besides, the association between the responses a thread receives and its author's prior contribution is moderated by what types of resources the thread explicitly seeks.

Our study contributes to the understanding of both researchers and practitioners. For researchers, the study provides new evidence that could help uncover the mechanisms through which one's prior contribution triggers future returns. In addition to the reciprocity argument in existing literature, our study emphasizes that what an individual actually contributes also matters. For community participants who expect to benefit from receiving others' responses, our study provides guidance on how to participate effectively. Specifically, not all types of participation and contribution could lead to the same consequence in gaining others' responses.

THEORY AND HYPOTHESIS

Online Social Exchange and Reciprocity

As illustrated in study 1, social interactions in online community have long been characterized as a form online social exchange (Faraj and Johnson 2011), through which people could provide or receive different tangible and intangible resources. The core idea of social exchange is reciprocity. According to social exchange theory, no matter what resources are exchanged, the provider

is at least partially expecting some form of return (Blau 1964). Other people are also likely to help this provider due to their feeling of obligation to reciprocate the favor (Arguello et al. 2006; Gouldner 1960). Reciprocity in social exchange can be further divided into two forms - direct reciprocity and indirect reciprocity (Ekeh 1974; Flynn 2005). Direct reciprocity indicates that a provider of certain resources is reciprocated by the recipients. In contrast, indirect reciprocity indicates that the provider receives returns from other third parties. Both direct reciprocity and indirect reciprocity are found effective in characterizing the communication patterns in online communities (Faraj and Johnson 2011).

Reciprocity offers a useful theoretical lens to understand why people might differ in the likelihood of receiving others' responses when posting threads in the same forum. While people's contribution behaviors could be driven by diverse motivations based on either self-interest (Wasko and Faraj 2005) or altruism (Peddibhotla and Subramani 2007), reciprocity could explain why individuals make contribution to certain people rather than others. In particular, researchers highlight the importance of indirect reciprocity in linking the prior contribution and the future returns in online context (Wasko et al. 2009). Indirect reciprocity, also termed as generalized reciprocity or collective reciprocity (Ekeh 1974; Wu and Korfiatis 2013), emphasizes that a contributor is exchanging resources with the community as a whole rather than a certain group of beneficiaries. Hence, the contributor might be reciprocated by anyone in the online community in the future.

Online communities offer an ideal context for indirect reciprocity, as the communication and interactions in online communities are open and public (Wu and Korfiatis 2013). One's behaviors and contribution in an online community can be easily observed by other community participants. Hence, many people attempt to enhance their reputation and social status among other community members by contributing valuable resource (e.g. information and knowledge) in online communities (Lampel and Bhalla 2007; Wasko and Faraj 2005). Prior research indeed documents that community participants' perception and evaluation of someone are affected by this person's prior behaviors in the community, which indicates that individuals can to some extent monitor and track others' behaviors (Dahlander and O'Mahony 2011). For instance, individuals making more knowledge contribution in an online community are more likely to be recognized as leaders by other community participants (Faraj et al. 2015).

With the impression of others' behaviors, individuals can take reciprocal actions accordingly. Arguello et al. (2006) show that newcomers with little prior contribution are less likely to receive responses in the discussion forums. In some cases, community members could even track more detailed and complex information on the effort made by other individuals when participating in online communities. For instance, Wu and Korfiatis (2013) demonstrate that people who answer questions in various topic categories are more likely to receive answers to their own questions as compared to people who focus on contributing to very few topic categories.

Types of Support and Forms of Exchange

While the theory of reciprocity emphasizes that individuals could gain more responses by contributing resources that are highly valued in the online communities, prior research generally focuses on the contribution of information (Arguello et al. 2006; Wu and Korfiatis 2013). Our study takes a further step by considering the differentiated content of contribution to the community of online sellers. As shown in the first study, information is not the only valuable resource shared in online communities. Online sellers could generate economic benefit from both informational support and instrumental support obtained from others in the online sellers' community. In line with the findings of study 1, we take both the informational support and the instrumental support into consideration by examining how the one's prior contribution of these two types of support may trigger the future reciprocation from others in the communities.

Prior research highlights that the norms or rules governing the exchange of different types of resource might also differ (Cropanzano and Mitchell 2005). When providing a certain type of resource in online communities, individuals may actually engage in a certain form of social exchange (Shore et al. 2009). In general, tangible resources that can be conveyed through actual activities or goods are often exchanged in a short-term, quid pro quo fashion (e.g. negotiated exchange), while the intangible resources that are usually conveyed through languages or postures are often exchanged in an open-ended manner (e.g. generalized exchange) (Cropanzano and Mitchell 2005; Foa and Foa 1980). Since instrumental support and informational support differ a lot in their tangibility,

they are likely to be exchanged in different forms. Specifically, the informational support is expected to be exchanged in a form of generalized exchange due to its intangibility, while the instrumental support is expected to be exchanged in a form of negotiated exchange as it is highly tangible.

We propose that individuals' choice of providing instrumental support and informational support reflects their preference towards negotiated exchange and generalized exchange respectively. Prior literature highlights that individuals engaging in negotiated exchanges are mainly motivated by a strong concern of personal interests, while individuals engaging in generalized exchange are mainly motivated by the concern of collective welfare (Flynn 2005). Others are thus able to infer different intention from the provision of informational support and the provision of instrumental support. Since reciprocity is a behavioral response to the perceived cost, consequence, and intention underlying one's action (Falk and Fischbacher 2006; Stanca 2010), we would expect the reciprocation an individual could receive to be associated with what the individual actually provides in the online communities.

Although individuals also provide emotional support in the online communities (Yan and Tan 2014), we do not have hypotheses on the impact of providing emotional support. While the basic assumption of reciprocity is that the contribution is valued in the community (Mitchell et al. 2012), we argue that emotional support provides little value in our context. First, emotional support does not help to solve any problem (Cutrona and Suhr 1992). As shown in study 1, the exchange of emotional support is not associated with economic benefit,

which is the major outcome of concern in an online sellers' community. Hence, emotional support cannot offer value to people with utilitarian orientation. Second, while emotional support may provide psychological benefits (Plaisier et al. 2007), its value is largely determined by the relationship between provider and recipient (Foa and Foa 1980). For instance, the emotional support from a close family member could be very comforting and encouraging, but the emotional support from an anonymous stranger may be of little help. Prior research also argues that emotional support provided in online communities is often generic and a mere formality (Wang et al. 2014). Hence, emotional support is unlikely highly valued in an online community constituted by strangers. Given that emotional support cannot offer much economic and psychological benefit in the online sellers' community, it is unclear whether people could really memorize the provision of emotional support and how they perceive such behaviors.

In the following section, we will focus on introducing how one's contribution of informational support and instrumental support are perceived, thus affecting the responses one could receive.

Impact of Providing Informational Support

Informational support refers to the transmission of information, opinions, or suggestions (Langford et al. 1997; Wang et al. 2014). The content of informational support is quite task-oriented, and it aims to address the major concern of the community. In the context of Taobao Forum, examples of providing informational support could be posting answers to others' questions or directly sharing advice and experiences about doing business online.

While informational support might directly help its recipients in solving problems and overcoming difficulties, it does not guarantee any benefit to its providers (Wasko and Faraj 2005). The recipients do not necessarily possess valuable information or knowledge to reciprocate the providers. Due to the scarce and intangible nature of information, the exchange of informational support is best characterized by generalized exchange (Cropanzano and Mitchell 2005). People usually provide informational support voluntarily and unconditionally. Prior research demonstrates that individuals who engage in generalized exchange are mainly motivated by a concern of collective interest rather than personal interests (Flynn 2005), and they show strong willingness to take risks for the welfare of the whole community (Molm 2010). Since the information shared in online communities is public and easy to be disseminated, the providers might even lose the advantages of owning the information privately (Serenko and Bontis 2016). Due to the uncertain return and relatively high cost of providing informational support, other sellers are likely to perceive an altruistic intention underlying such contribution behaviors. This perception of good intention helps the providers to build a favorable social image in the community (Wu and Korfiatis 2013). As people generally feel obligated to reward kind intention, sellers who provide more information support are more likely to be reciprocated by others in the future.

Hypothesis 1. *The more informational support a seller provides, the more responses the seller's thread will receive.*

Impact of Providing Instrumental Support

Instrumental support refers to tangible aid, service, or activity provided for the benefit of its recipient (Barrera 1986; Langford et al. 1997). As explained in study 1, instrumental support in Taobao Forum is usually behaviors of visiting others' shop or adding others' products into favorite. Unlike information or knowledge that is often possessed by only a certain group of people (Serenko and Bontis 2016), instrumental support is not unique and can be provided by almost every seller in the community. Besides, due to the tangible nature of instrumental support (Foa and Foa 1980), sellers can easily measure and compare the instrumental supports they provide with those they receive. Thus, instrument support is mostly exchanged in a form of negotiated exchange (Cropanzano and Mitchell 2005). The major characteristic of negotiated exchange is that the benefits for the two exchange parties are usually bilateral and clearly specified and agreed upon (Molm et al. 2007; Molm et al. 2009). Contribution from one party is often accompanied with immediate reciprocation from the other party.

In the context of Taobao Forum, a seller typically provides instrumental support to people who promise to return the favor or people who have already provided instrumental support to the focal seller. The form of negotiated exchange can be verified by the textual content of forum messages. A typical thread that seeks instrumental support would explicitly promise an equivalent repayment to the providers. Similarly, a typical message reporting the provision of instrumental support would also explicitly remind the recipient to reciprocate. This is quite reasonable given that the recipients should be able to provide such instrumental support as well.

In sum, instrumental support is provided based on an assumption that the providers also benefit from the recipients equivalently. Since the provision of instrumental support often leads to bilateral benefits for both providers and recipients (Molm et al. 2007), others would not feel obligated to offer reciprocation. Moreover, Prior research highlights that the form of negotiated exchange usually attracts individuals who are motivated to act solely on their own interests, because negotiated exchange allows them to ensure the outcome of each transaction and track "the repayment of outstanding debt" (Flynn 2005). Hence, a seller's active engagement in providing instrumental support may indicate that s/he prioritize his personal interests over others'. Other sellers could perceive a self-interest intention underlying such behaviors. By providing instrumental support, a seller may create a social image that the seller contributes only when there's satisfactory return. Besides, negotiated exchange minimize the risk and uncertainty of nonreciprocity, which is necessary to the development of interpersonal trust (Molm et al. 2009). A seller's engagement in negotiated exchange reflects her/his avoidance of risk, thus preventing the seller from building strong affective bonds with the community (Molm 2010). Prior literature also demonstrates that restricted and immediate reciprocation will lead to a distrustful and brittle social relationship, resulting in low solidarity and high tension among the social group (Ekeh 1974; Uehara 1990). Thus, other sellers may perceive less and weaker emotional bonds with sellers who focus on exchanging instrumental support. Such perception eventually inhibits people from responding to the providers' threads.

Hypothesis 2. The more instrumental support a seller provides, the fewer responses the seller's thread will receive.

Moderating Effect of Thread Content

In addition to providing different types of resources in the online community, the sellers could also seek support and resources from others. The types of resources sought by a thread are usually explicitly stated in its textual content. Since informational support and instrumental support are exchanged based on different norms of reciprocity, the types of resources sought by a thread create the context for its potential responders to consider whether to respond to this particular thread. Thus, while a seller's prior contribution of different resources could impact the responses the seller's threads could receive in general, it is also important to explore whether such impact might vary across threads seeking different types of resources.

Cropanzano and Mitchell (2005) separate the concept of exchange relationship from the concept of exchange transaction. In particular, exchange relationship refers to the interpersonal attachments resulted from a series of exchange transactions. According to their typology, two parties with either social or economic relationship could engage in either social or economic transactions. While the match between the relationship and the transaction lead to a smoother exchange, the mismatch between the relationship and transaction could impede the transaction due to greater risk of psychological injury and higher emotional labor. In line with this perspective, we propose that the alignment and misalignment between what a seller contributes previously and what the seller

seeks in the current thread could affect the responses the thread receives. Specifically, a seller's provision of different resources determines how others perceive the seller's relationship with the community. As illustrated above, the provision of instrumental support indicates a relationship of negotiated exchange, and the provision of informational support indicates a relationship of generalized exchange. On the other hand, the thread content specifies the form of exchange for the current transaction the thread author is initiating. The author's contribution aligned with the current transaction will help the thread to attract more responses, while the contribution misaligned with the current transaction will inhibit the thread from receiving more responses. Next, we will introduce how the effect of sellers' different contribution on the responses their threads receive is moderated by whether the threads are seeking informational support or instrumental support.

Threads seeking informational support. Threads seeking information usually contain textual content about asking questions or requesting suggestions and advice. By posting such threads, the sellers are initiating transactions with unilateral benefits. While authors of information-seeking threads could benefit from others' responses, they can hardly reciprocate the responders with equivalent benefits immediately. The possible future benefit to the responders, if exist, is likely to be provided by some third parties (Wu and Korfiatis 2013), and neither the authors or the responders have any control over it. Hence, a thread that seeks informational support is initiating a transaction of generalized exchange. Its responders cannot be reciprocated immediately and would

experience a higher risk of non-reciprocity (Molm et al. 2007). Meanwhile, responding threads seeking information could be costly, as the disclosure of one's private information might result in the loss of informational advantage (Serenko and Bontis 2016). Since the authors of information-seeking threads attempt to acquire high-value resources without direct repayment, the potential responders will perceive higher unfairness due to the imbalanced distribution of benefit (Falk and Fischbacher 2006). In order to be reciprocated in the future, the providers of informational support would expect the recipients are similarly motivated and can sustain the forms of generalized exchange by making similar contribution to others (Flynn 2005).

The thread authors' prior contribution of informational support would be aligned with the current transactions initiated by information-seeking threads. As illustrated before, sellers engaging in generalized exchanges are more concerned about collective interests (Flynn 2005). A seller's active contribution of informational support indicates that the seller is willing to take risks for the welfare (Molm 2010). Such experience of taking risks makes others perceive more fairness when the seller tries to seek informational support from others. Specifically, if the thread authors have taken the risk of non-reciprocity, they deserve to be repaid in the same way. Hence, the positive impact of the sellers' provision of informational support is stronger in threads that seek informational support.

Hypothesis 3a. The positive association between the informational support a seller provides and the responses the seller's thread receives becomes more positive when the thread is seeking informational support.

In contrast, the thread authors' prior contribution of instrumental support would be misaligned with the transaction in information-seeking threads. As instrumental support is provided based on a norm of negotiated exchange, the provision of instrumental support indicates a self-interest intention (Flynn 2005). If a seller used to provide resources to exchange equivalent return, others will perceive more unfairness when the seller attempts to seek support without immediate repayment (Cox et al. 2007). Hence, the seller's self-interest intention is more unfavorable in information-seeking threads, and the negative impact of the sellers' provision of instrumental support is more salient.

Hypothesis 3b. The negative association between the instrumental support a seller provides and the responses the seller's thread receives becomes more negative when the thread is seeking informational support.

Thread seeking instrumental support. Threads seeking instrumental support contains content about asking for others' tangible assistance (e.g. visiting or adding to favorite) and the promise of repayment. By posting such threads, the sellers are initiating transactions characterized by the form of negotiated exchange. The benefit of exchanging of instrumental support is bilateral (Molm et al. 2007). While thread authors benefit from the responders' instrumental support, they are also required to reciprocate the responders with equivalent instrumental support. Other sellers would expect to be reciprocated with

instrumental support after responding to threads seeking instrumental support. Prior literature demonstrates that tangible rewards could reinforce one's extrinsic motivation but reduce the salience of intrinsic motivation (Deci and Ryan 1975). Similarly, the promised repayment could weaken the sellers' motivation to reward kind intention and punish unkind intention (Cox et al. 2007). Instead, when the sellers respond to threads seeking instrumental support, they are more concerned about whether the thread authors will immediately reciprocate them with promised repayment.

The thread authors' prior contribution of informational support is misaligned with transactions initiated by threads seeking instrumental support. As the major purpose of providing instrumental support is to exchange equivalent extrinsic return, the responders of instrumental threads do not care much about the kindness of thread authors' intention. The thread authors' prior contribution of informational support becomes less relevant in this scenario. Moreover, while the negotiated exchange is relatively economic and transactional, the relationship developed from exchanging informational support is more social in nature due to the providers' altruistic intention (Molm et al. 2007). Prior literature emphasizes that mismatch between the economic transaction and the social relationship will cause additional emotional labor (Cropanzano and Mitchell 2005). To avoid such emotional labor, authors with less contribution of informational support might be more preferable to the responders of instrumental threads. Thus, the positive impact of providing informational support is weakened in threads seeking instrumental support.

Hypothesis 4a. The positive association between the informational support a seller provides and the responses the seller's thread receives becomes less positive when the thread is seeking instrumental support.

The thread authors' prior contribution of instrumental support is aligned with transactions initiated by threads seeking instrumental support. As the current transactions are in a form of negotiated exchange, responders of such type of threads are motivated to obtain immediate returns (Molm et al. 2007). Although thread authors' engagement in exchanging instrumental support may indicate their self-interest (Flynn 2005), such perceived self-interest does not play an important role in the responders' decisions. Prior research highlights that negotiated exchange will make the conflictual elements more salient (Molm 2010). A seller cannot continuously find exchange patterners if s/he fails to abide by the agreement. Hence, a seller's abundant experience of exchanging instrumental support may signal her/his reliability and credibility in reciprocating others' instrumental support. Therefore, when responding to threads that request instrumental support, the responders are likely to select threads posted by authors with more experience in providing instrumental support. The impact of providing instrumental support is less negative.

Hypothesis 4b. The negative association between the instrumental support a seller provides and the responses the seller's thread receives becomes less negative when the thread is seeking instrumental support.

METHODOLOGY

Variables

Similar to the first study, we use data collected from Taobao Forum to construct variables. The unit of analysis for the present study is at the thread level, so each thread constitutes an observation. In total, our sample consists of 1,311,395 threads posted between February 2014 and December 2014. For each thread, we further track the responses it receives and its author's prior activity. In particular, in order to make sure threads posted at different time comparable, variables about a thread's responses and its author's prior activities are constructed based on a fixed time window of 30 days.

Following the same approach adopted and explained in chapter 2, we rely on the reply-to relationship and the textual classification results of forum messages' content to infer the flows of different resources transferred among sellers. The informational support and instrumental support a seller provides before posting a particular thread are thus captured accordingly. The classification results are also used to infer the resources sought by each thread. Details of variables are illustrated below.

Dependent Variable – Received Responses. The unit of analysis for this study is at the thread level. Each observation represents a thread posted by a seller. The dependent variable, represented by *NumReponses*, refers to the number of responses that the thread has received within 30 days since it was posted. For instance, if a thread is posted on July 1st, the responses that are received before July 31 will be considered, while the responses that are received after July 31 will

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be ignored. In online forum, support from others is mediated by forum messages. Hence, our dependent variable reflects the support a seller received in this particular thread. We adopt a time window of 30 days to track the responses received by a thread because it is sufficient to capture the majority of the responses. In our context, 88.5% of the responses are received within 30 days since the threads were posted. Besides, highly delayed responses might not be useful to the thread author anymore.

Explanatory Variables – Provision of Informational and Instrumental Support. We adopt reply-to relationships and the classification results of forum messages explained in chapter 2 to infer how the flows of instrumental support and informational support are transferred among people. Since our research question is about the sellers' prior contribution, we focus on the informational support and the instrumental support provided by each seller.

To provide informational support, one can either answer others' questions or directly share information. When seller A posts an information-sharing message to respond to seller B's information-seeking message, we consider it as an effective provision of informational support from A to B. When seller A posts an information-seeking message to respond seller B's information-sharing message, we consider it as an effective provision of informational support from B to A. consequently, we calculate the number of people a seller provides informational support to (*InfoPro*) to represent the seller's provision of informational support.

The provision of instrumental support is ruled by a norm of negotiated reciprocity. This indicates that individuals initiating the exchange of instrumental support will return the favor when they receive others' instrumental support. Hence, when seller A posts a message on instrumental support to respond to B's message on instrumental support, we consider an effective provision of instrumental support from A to B and an effective provision of instrumental support from B to A. We calculate the number of people a seller provides instrumental support to (*InstPro*) to represent the seller's provision of instrumental support.

Control Variables. The responses a thread could receive might be largely determined by the textual content of the thread itself. For instance, a thread explicitly seeking instrumental support might be able to attract more responses since almost everyone in the community is capable to reply it, whereas a thread seeking information might be replied by only a limited number of knowledgeable people. As our classification results identify 4 types of content in threads, we construct 4 dummy variables accordingly: *DummySeekInfo*, *DummyShareInfo*, *DummyInst*, *DummyEmo*. These dummy variables indicate whether a thread contains content about instrumental support, seeking information, sharing information, and emotional support respectively. In addition, we also control the length of the thread title and content with *TitleLen* and *ContentLen*, and the length of the text could reflect how much information a thread brings and how much effort the author made in writing the thread.

Besides, the responses received by a thread might be affected by its author's experience. A seller who has joined in the community for a longer time may be more familiar with the tastes and preferences of other community members, and thus know how to frame the threads to attract others' responses. Hence, we control the tenure of a seller upon posting a thread with *ForumAge*.

Table 3.1 and Table 3.2 present the descriptive statistics of these variables and the correlation among them.

Table 3.1 Descriptive Statistics of Variables

	N	Mean	Median	S.D.
NumResponses	116693	8.48	2	60.76
ForumAge	116693	2.55	2.07	2.20
TitleLen	116693	44.12	42	18.79
ContentLen	116693	844.71	243	2003.89
DummySeek	116693	0.20	0	0.40
DummyShare	116693	0.06	0	0.25
DummyInst	116693	0.26	0	0.44
DummyEmo	116693	0.17	0	0.37
InstPro	116693	32.94	3	92.06
InfoPro	116693	2.74	0	43.69

Note: *ForumAge* is measured by years

Table 3.2 Correlation of Variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
NumRes										
ForumAge	.01*									
TitleLen	.04*	.06*								
ContentLen	-.00*	-.01*	.01*							
DummySeek	-.02*	.02*	-.02*	-.14*						
DummyShare	.03*	.02*	.04*	.57*	-.11*					
DummyInst	.04*	-.03*	.11*	-.2*	-.24*	-.16*				
DummyEmo	.01*	-.00	-.07*	-.07*	-.01*	-.08*	-.2*			
EmoPro	.06*	-.00	-.01*	-.04*	.03*	-.03*	-.04*	.09*		
InstPro	.02*	-.03*	.06*	-.09*	-.09*	-.06*	.32*	-.06*	.59*	
InfoPro	.16*	.01*	.03*	.06*	-.01*	.09*	-.03*	-.00*	.56*	.02*

Note: * significance p<0.001

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Modeling

As shown above, the dependent variable is count data constituted of non-negative integers, and its standard deviation is much larger than its mean. This indicates that the negative binomial model is more suitable. Besides, as threads posted by the same individual could be correlated, it is important to control the individual heterogeneity. Hence, we adopt the xtnbreg procedure provided by STATA to examine the effect of a thread author's prior activity on the responses the thread receives. The procedure model the probability of count with the following equation with $\lambda_{it} = e^{X_{it}\beta}$.

$$\Pr(y_{it}|X_{it}, \delta_i) = \frac{\Gamma(\lambda_{it} + y_{it})}{\Gamma(\lambda_{it})\Gamma(y_{it} + 1)} \left(\frac{1}{1 + \delta_i}\right)^{\lambda_{it}} \left(\frac{\delta_i}{1 + \delta_i}\right)^{y_{it}}$$

y_{it} refers to the responses thread t of individual i receives. X_{it} refers to the explanatory variables and control variables observed for individual i's thread t. δ_i represents the dispersion parameter for individual i. In sum, the procedure fits conditional fixed-effects overdispersion models, and assures that the dispersion is constant across threads posted by the same individual.

RESULTS

As the explanatory variables are highly skewed, we take the natural logarithmic transformation of *InfoPro* and *InstPro*. Hence, *ln(InfoPro)* and *ln(InstPro)* are used to estimate the models. The xtnbreg procedure conducts estimation based on within-group variance. If an individual only posts one thread in our sample or an individual's multiple threads all receive 0 response, their threads are automatically dropped. Eventually, the estimation is conducted based

on 1,116,693 threads posted by 145,061 different individuals. The results are presented in Table 3.3.

Table 3.3 Estimation Results

	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	-0.715*** (0.013)	-0.689*** (0.013)	-0.7*** (0.013)	-0.656*** (0.013)	-0.668*** (0.013)
ForumAge	0.007*** (0.001)	0.006*** (0.001)	0.006*** (0.001)	0.006*** (0.001)	0.006*** (0.001)
ln(TitleLen)	0.08*** (0.003)	0.083*** (0.003)	0.082*** (0.003)	0.08*** (0.003)	0.08*** (0.003)
ln(ContentLen)	-0.073*** (0.001)	-0.076*** (0.001)	-0.075*** (0.001)	-0.077*** (0.001)	-0.076*** (0.001)
DummyShare	0.068*** (0.007)	0.067*** (0.007)	0.069*** (0.007)	0.058*** (0.007)	0.06*** (0.007)
DummyEmo	0.149*** (0.003)	0.149*** (0.003)	0.149*** (0.003)	0.153*** (0.003)	0.152*** (0.003)
DummySeek	-0.039*** (0.003)	-0.041*** (0.003)	-0.009* (0.005)	-0.04*** (0.003)	-0.06 (0.005)
DummyInst	0.427*** (0.003)	0.441*** (0.003)	0.435*** (0.003)	0.362*** (0.005)	0.37*** (0.005)
ln(InfoPro)		0.026*** (0.002)	0.021*** (0.002)	0.054*** (0.002)	0.051*** (0.002)
ln(InstPro)		-0.016*** (0.001)	-0.01*** (0.001)	-0.039*** (0.001)	-0.033*** (0.001)
DummySeek×ln(InfoPro)			0.035*** (0.004)		0.014*** (0.004)
DummySeek×ln(InstPro)			-0.04*** (0.002)		-0.024*** (0.002)
DummyInst×ln(InfoPro)				-0.089*** (0.004)	-0.086*** (0.004)
DummyInst×ln(InstPro)				0.049*** (0.002)	0.043*** (0.002)
Log likelihood	-2279157	-2278962	-2278777	-2278426	-2278364

Note: *p<0.05; **p<0.01; ***p<0.001
Standard Errors are reported in ()

Model 1 only includes control variables. The results reveal that the characteristics of thread content and the experience of the thread author are significantly associated with the responses received by the thread. In particular, threads seeking informational support are less likely to receive responses, while the threads seeking instrumental support are more likely to receive responses.

Model 2 includes the informational support and instrumental support the thread author provided before posting the thread. The results reveal that prior provision of informational support is positively associated with the responses received (β=0.026, p<0.001), which supports hypothesis 1. In contrast, prior provision of instrumental support is negatively associated with the responses received (β=-0.016, p<0.001). Thus, hypothesis 2 is supported.

In Model 3, we interact *DummySeek* with *ln(InfoPro)* and *ln(InstPro)* to examine whether the effect of providing informational and instrumental support would vary in threads that seek informational support. The results demonstrate that the positive association between prior provision of informational support and the responses received is more strengthened in threads that explicitly seek informational support (β=0.035, p<0.001), which supports hypothesis 3a. Similarly, the negative association between prior provision of instrumental support and the responses received is strengthened in threads that seek informational support (β=-0.04, p<0.001), which supports hypothesis 3b.

We then interact *DummyInst* with *ln(InfoPro)* and *ln(InstPro)* in Model 4 to examine whether the effect of providing informational support and instrumental support is different in threads seeking instrumental support. The results also support hypothesis 4a and hypothesis 4b. In threads seeking instrumental support, the positive association between the provision of informational support and the received responses becomes less positive (β=-0.089, p<0.001), and the negative association between provision of instrumental support and the received responses is less negative (β=0.049, p<0.001).

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We further validate the findings by including all four interactions in Model 5. The estimation results are still consistent. In addition, we also compare our fixed-effect model with the random-effect model. The results of the Hausman test reject the null hypothesis that the difference between the two models is not systematic, indicating the fixed-effect model is a superior choice.

Robustness Check

Reconstructing dependent variable based on number of responders. In online forum, a thread could receive multiple responses from the same responder. Thus, the responses a thread receives could be driven by a few active and talkative responders. As these multiple responses from the same individual sometimes bring redundant resources, our dependent variable, the number of responses, may not accurately reflect the support the thread author receives. Hence, we also try to use the number of responders a thread attracts as dependent variable. Results are presented in Table C.1 in Appendix. The results are consistent with our findings in Table 3.3.

Reconstructing explanatory variables based on number of interactions. Our original explanatory variables are constructed based on the number of people a thread author has provided certain types of resources to. Hence, multiple interactions between the same pair of sellers are aggregated. Since other sellers might be impressed by the number of times a thread author provides resources rather than the number of people the author provides support to, we reconstruct the explanatory variables based on the number of times the thread author provides

a certain type of resources. Results are presented in Table C.2 in the Appendix. The results are consistent with our findings.

Different time window to generate activities and responses. As explained above, we track a seller's prior activity and the responses of a thread based on a time window of 30 days. To examine whether our findings are sensitive to the time window we choose, we further calculate the number of responses (*NumResponses*) and the prior provision of informational support (*InfoPro*) and instrumental support (*InstPro*) based on a time window of 90 days. In other words, this new *NumResponses* captures responses received by a thread in 90 days, while new *InfoPro* and *InstPro* reflect a seller's activity in 90 days before posting the thread. We conduct the analysis with these new variables. The results (shown in Table C.3) are consistent with our findings.

Controlling the effect of providing emotional support. Since prior study highlights the prevalence and importance of emotional support in online health community (Wang et al. 2014; Yan and Tan 2014), we also attempt to conduct robustness check with the effect of providing emotional support (*EmoPro*) being controlled. Similar to *InfoPro* and *InstPro*, *EmoPro* refers the number of people a seller provides emotional support to. In particular, we consider the main effect of providing emotional support as well as the interactions between providing emotional support (*EmoPro*) and thread types (*DummyInfo* and *DummyInst*). The results, presented in Table C.4 in the Appendix, are still consistent with our findings.

Controlling the seasonal effect. In the online forum, the general activeness may differ in different months, because the sellers could be very busy in certain time periods or seasons. As a result, it could be more difficult for sellers to receive responses in certain months due to the low activeness across the whole community. We try to control the seasonal effect by adding a set of dummy variables to represent different months. Specifically, 10 dummy variables are added to represent Feb to Nov, while Dec will be the reference group. The results, presented in Table C.5 in the Appendix, are consistent with our main analysis.

Additional Analysis

To further validate whether the effect of the prior contribution of informational support and instrumental support varies in threads with different content, we conduct subgroup analysis. Firstly, we divide the whole sample into information seeking group (*DummySeek*=1) and non-information seeking group (*DummySeek*=0). Estimations are then conducted with these 2 subsamples respectively. The results are shown in Model 1 and Model 2 of Table 3.4. In both subgroups, the provision of informational support is positively associated with the number of responses, while the provision of instrumental support is negatively associated with the responses. However, the results of the two subgroups differ in their effect size. For the provision of informational support, the 95% confidence interval of its estimated coefficient is [0.04, 0.059] in information seeking group, while the 95% confidence interval of its estimated coefficient is [0.018, 0.026] in the non-information seeking group. Hence, the association between the provided informational support and the received

responses is more positive in threads seeking informational support. For the provision of instrumental support, the 95% confidence interval of its estimated coefficient is [-0.036, -0.024] in the information-seeking group, while the 95% confidence interval of its estimated coefficient is [-0.013, -0.009] in the non-information seeking group. Hence, the association between the provided instrumental support and the received responses is more negative in threads seeking informational support. The results are consistent with hypothesis 3a and 3b.

Table 3.4 Estimation Results for Subgroup Analysis

	Model 1 DummySeek=1	Model 2 DummySeek=0	Model 3 DummyInst=1	Model 4 DummyInst=0
N	179059	874303	265268	806268
Intercept	-0.81*** (0.033)	-0.686*** (0.015)	-0.248*** (0.025)	-0.699*** (0.016)
ForumAge	-0.002 (0.002)	0.008*** (0.001)	0.01*** (0.002)	0.004*** (0.001)
ln(TitleLen)	0.033*** (0.008)	0.092*** (0.003)	0.101*** (0.006)	0.063*** (0.004)
ln(ContentLen)	0.009* (0.004)	-0.088*** (0.002)	-0.089*** (0.003)	-0.056*** (0.002)
DummyShare	-0.059$^+$ (0.035)	0.01*** (0.007)	-0.163$^+$ (0.086)	0.056*** (0.007)
DummyEmo	0.089*** (0.008)	0.153*** (0.04)	-0.033** (0.011)	0.17*** (0.003)
DummySeek			-0.185*** (0.012)	-0.011** (0.003)
DummyInst	0.25*** (0.014)	0.438*** (0.004)		
ln(InfoPro)	0.049*** (0.005)	0.022*** (0.002)	-0.002 (0.004)	0.024*** (0.002)
ln(InstPro)	-0.03*** (0.003)	-0.011*** (0.001)	-0.01*** (0.002)	-0.018*** (0.001)

Note: *p<0.05; **p<0.01; ***p<0.001
Standard Errors are reported in ()

Similarly, we also divide the whole sample into an instrumental support group (*DummyInst*=1) and a non-instrumental support group (*DummyInst*=0).

Estimation results are shown in Model 3 and Model 4 of Table 3.4. The effect of providing informational support on responses is insignificant for threads that seek instrumental support (Model 3, β=-0.002, p>0.1), but the effect is significant and positive in the non-instrumental support group (Model 4, β=0.024, p<0.001). Hence, the association between the provided informational support and the received responses is less positive in threads seeking instrumental support. Moreover, the effect of providing instrumental support on responses is negative and significant in both instrumental support group and non-instrumental support group, but it differs in the effect size. The 95% confidence interval of the estimated coefficient is [-0.013, -0.007] in the instrumental support group and [-0.02, -0.015] in the non-instrumental support group. Hence, the association between the provided instrumental support and the received responses is less negative in threads seeking instrumental support. The results are generally consistent with hypothesis 4a and 4b.

DISCUSSION AND CONCLUSION

Based on the context of online sellers' community, the present study demonstrates that sellers' provision of different types of resources affects the likelihood of receiving responses in different ways. Specifically, the provision of informational support increases the likelihood of receiving responses. This indicates that other people may perceive a positive and kind intention from a seller's informational contribution, which could, in turn, trigger the reciprocal behaviors from others. In contrast, the provision of instrumental support

decreases the likelihood of receiving responses, indicating that others in the community may perceive a relatively unfavorable intention from a seller's behaviors of providing instrumental support. Such perceived intention inhibits others to reciprocate the seller, resulting in fewer responses.

In addition, our findings also show that the effect of one's prior activity could vary across threads with different content. For threads explicitly seeking information, the positive effect of providing informational support becomes more positive, and the negative effect of providing instrumental support becomes more negative. In contrast, the positive effect of providing informational support is undermined in threads seeking instrumental support, while the negative effect of providing instrumental support is less negative for threads seeking instrumental support. The findings reveal that one's prior activity does not always trigger the same extent of reciprocity from others. The effect also depends on the alignment or misalignment between the content of a thread and the activity of the thread author.

Implication for Research

Our study contributes to our knowledge of online community and social exchange in two ways. First, the study enhances our understanding of reciprocity in online context by differentiating the types of resource one could contribute. Prior literature typically focuses on knowledge contribution in online community and demonstrates that making contribution can trigger indirect reciprocation from others (Arguello et al. 2006; Wu and Korfiatis 2013). Our study shows more nuanced finding, which reveals that contribution by itself does not necessarily

lead to positive reciprocity. Instead, different contribution could trigger different reciprocity. While contributing information and knowledge may indeed increase the responses one could receive, providing instrumental support shows an opposite effect. Future research on online reciprocity may benefit from a better specificity about content exchanged through online interactions.

Second, our study contributes to the social exchange literature by differentiating the long-term relationship of exchange from the current transaction of exchange and investigating the alignment between them. Prior literature proposes that the current transactions or exchanges an individual is engaging in may not necessarily match with the relationships the individual builds with the exchange parties (Cropanzano and Mitchell 2005). Our study examines the impact of this potential mismatch by associating the types of resources in exchange with different forms of exchange. Specifically, instrumental support is exchanged in a negotiated form, while informational support is exchanged in a generalized form. Consequently, one's prior contribution of certain types of support affects the types of exchange relationships s/he builds. The support sought by a thread specifies the form of exchange for the current transaction. The findings of our study reveal that the mismatch between exchange relationship and the current transaction indeed impede the obtainment of others' support. For instance, sellers who actively engage in exchange instrumental support may less likely to receive informational support from others.

Implication for practice

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Our findings also provide guidance to practitioners on how to participate in online community. Specifically, our findings demonstrate that how an individual participates in the online community could affect the responses s/he receives. The strength of the effect varies depending on the types of resource the individual is seeking. As many individuals may be more interested in acquiring a particular type of support in online community, they need to ensure that the contribution they made matches with the resource they desire. If an individual wants to obtain information and knowledge from others, s/he should try to be active in providing informational support and avoid engaging in exchanging instrumental support. If an individual wants to obtain instrumental support, s/he may not need to contribute informational support.

For organizations who operate online communities, our study could help them improve the design of their communities. Specifically, our findings reveal that the engagement in exchanging instrumental support has a negative impact on the responses one could receive, and such impact is more salient when the focal individual is seeking information. This indicates that the negotiated exchange of instrumental support might impede the generalized exchange of informational support. Given that the form of generalized exchange is important to the sustainability and solidarity of the community (Faraj and Johnson 2011; Molm et al. 2007), organizations should carefully balance the amount of instrumental support and informational support exchanged in the community. For instance, organizations could develop separate sub-forums for different types of communication, so that the exchange of instrumental support in one sub-forum

may have less impact on the exchanges of informational support in another sub-

forum.

Chapter 4 Conclusion

The increasing number of individual ecommerce sellers has triggered the development of the online sellers' community. In recent years, a lot of major ecommerce platforms (e.g. Taobao, Amazon, and eBay) have launched online forums for the sellers to interact with each other. To enhance our knowledge of online sellers' community, my dissertation investigates the economic and social impact of sellers' interactions in the online community. In particular, while existing research does not pay much attention to the diverse resources exchanged in the online sellers' community, my dissertation explores the impact of the sellers' heterogeneous interactions involving different types of resources. Drawing on social exchange theory, we identify three types of resources: informational support, instrumental support, and emotional support.

Since sales are likely to be the major outcome of concern for online sellers, the first study of my dissertation examines how a seller's interactions of receiving or providing different economic and socioemotional resources affect the seller's sales income. The findings reveal that not all interactions in the online sellers' community can benefit the sellers' sales. Only the interactions of receiving informational support and the interactions of providing instrumental support are positively associated with the seller's sales performance on the ecommerce platform. This indicates that learning in the online sellers' community could effectively benefit the sellers' sales, but promotion in the community might be much less effective.

While the first study uncovers the economic value of exchanging instrumental support and informational support in online sellers' community, the second study of my dissertation explores the social impact of the sellers' activities and interactions. Specifically, we examine how a seller's provision of informational support and instrumental support affects the responses the seller's threads receive from others. The findings show that the provision of informational support increases the responses received, while the provision of instrument support reduces the responses received. Furthermore, the effect is moderated by the type of resources sought by a thread. The positive effect of providing informational support is strengthened in threads seeking informational support but undermined in threads requesting instrumental support. The negative effect of providing instrumental support becomes more negative in threads seeking informational support but less negative in threads requesting instrumental support. The findings highlight the importance of alignment between one's prior contribution and the current request.

Overall, my dissertation demonstrates that a better specificity about the types of resources exchanged among the online sellers can provide more nuanced understanding on the economic and social impact of the seller's interactions in the online communities.

Reference

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Appendix A: Classification Process and Evaluation

Before training and testing algorithms with the textual data we manually coded, we need to transform the text data into a suitable form. Unlike English, Chinese text does not have space between each pair of words, so our first step is to segment all the Chinese text into separated words. We adopt a popular open-source Java segmentation algorithm, IKAnalyzer (Lin, 2012), to conduct the segmentation task. Thus, all threads and replies are transformed into a new text form with space between words.

Then, the R package, RTextTools, could automatically transform all these the segmented documents into a document-term-matrix, in which each row represents a document, and each column represents a distinct term. Therefore, each cell of the matrix indicates the frequency of the term appeared in the document. Based on this matrix and the manually coded labels of these documents, the package could train the classifiers with the provided algorithms.

We compute two measures to evaluate the classifiers' performance. Accuracy refers to the proportion of documents that are correctly classified by this classifier. ROC Area refers to the area under the ROC curve, which is drawn by contrasting the true positive rate to false positive rate and different cut-off point. This measure reflects how well a classifier separates true signals from the noise. The ROC Area will equal to 1 for a perfect classification and equal to 0.5 for a worthless or random classification. The performance measures of all classifiers we trained tested are listed in the following tables, with the selected

one being bold. In sum, the adopted classifiers achieve accuracy ranging from 0.795 to 0.946, and Roc Area ranging from 0.818 to 0.979.

Table A.1. Classifying Threads with Instrumental Support Content

	SVM	Glimnet	MaxEnt	TREE	**RF**	SLDA	Boost	Bagging
Accuracy	.799	.842	.834	.852	**.868**	.786	.841	.868
Roc Area	.835	.898	.887	.778	**.899**	.815	.876	.865

Table A.2. Classifying Threads with Information-seeking Content

	SVM	Glimnet	**MaxEnt**	TREE	RF	SLDA	Boost	Bagging
Accuracy	.775	.834	**.823**	.813	.827	.748	.809	.818
Roc Area	.789	.84	**.826**	.734	.824	.761	.795	.792

Table A.3. Classifying Threads with Information-sharing Content

	SVM	Glimnet	MaxEnt	TREE	**RF**	SLDA	Boost	Bagging
Accuracy	.863	.86	.826	.833	**.868**	.835	.86	.863
Roc Area	.831	.83	.683	.757	**.877**	.731	.788	.86

Table A.4. Classifying Threads with Emotional Support Content

	SVM	Glimnet	**MaxEnt**	TREE	RF	SLDA	Boost	Bagging
Accuracy	.833	.822	**.824**	.822	.82	.77	.811	.824
Roc Area	.833	.814	**.818**	.737	.793	.714	.762	.768

Table A.5. Classifying Replies with Instrumental Support Content

	SVM	Glimnet	MaxEnt	TREE	**RF**	SLDA	Boost	Bagging
Accuracy	0.924	.928	.88	.901	**.941**	.886	.911	.926
Roc Area	.963	.969	.946	.923	**.979**	.946	.948	.966

Table A.6. Classifying Replies with Information-seeking Content

	SVM	Glimnet	MaxEnt	TREE	RF	SLDA	**Boost**	Bagging
Accuracy	.939	.945	.908	.953	.941	.939	**.946**	.953
Roc Area	.765	.817	.786	.786	.835	.857	**.872**	.782

Table A.7. Classifying Replies with Information-sharing Content

	SVM	Glimnet	MaxEnt	TREE	**RF**	SLDA	Boost	Bagging
Accuracy	.910	.908	.863	.891	**.914**	.906	.905	.899
Roc Area	.740	.818	.736	.74	**.878**	.794	.776	.854

Table A.8. Classifying Replies with Emotional Support Content

	SVM	Glimnet	MaxEnt	TREE	**RF**	SLDA	Boost	Bagging
Accuracy	.831	.895	.858	.9	**.898**	.888	.876	.891
Roc Area	.881	.918	,870	.87	**.935**	.905	.881	.886

Table A.9. Classifying Replies Relevant to Instrumental Support Threads

	SVM	Glimnet	**MaxEnt**	TREE	RF	SLDA	Boost	Bagging
Accuracy	.855	.845	**.88**	.84	.835	.85	.85	.84
Roc Area	.913	.853	**.933**	.887	.656	.861	.926	.634

Table A.10. Classifying Replies Relevant to Information-seeking Threads

	SVM	Glimnet	**MaxEnt**	TREE	RF	SLDA	Boost	Bagging
Accuracy	.82	.735	**.83**	.72	.725	.805	.77	.805
Roc Area	.885	.811	**.904**	.729	.855	.888	.815	.85

Table A.11. Classifying Replies Relevant to Information-sharing Threads

	SVM	Glimnet	**MaxEnt**	TREE	RF	SLDA	Boost	Bagging
Accuracy	.805	.82	**.85**	.8	.825	.7	.58	.83
Roc Area	.887	.842	**.887**	.79	.9	.861	.852	.856

Table A.12. Classifying Replies Relevant to Emotional Support Threads

	SVM	Glimnet	**MaxEnt**	TREE	RF	SLDA	Boost	Bagging
Accuracy	.755	.72	**.795**	.675	.715	.77	.755	.695
Roc Area	.871	.835	**.901**	.754	.822	.802	.82	.74

Table A.13. Classifying Replies with Evaluative Content

	SVM	**Glimnet**	MaxEnt	TREE	RF	SLDA	Boost	Bagging
Accuracy	.919	**.946**	.881	.94	.936	.939	.93	.945
Roc Area	.92	**.945**	.804	.886	.966	.956	.921	.947

Appendix B: Robustness Check for Chapter 2

Table B.1. Sample Based on Top 15% Active Seller

	Model 1	Model 2	Model 3	Model 4
Intercept	0.17 (0.94)	0.22 (0.94)	0.02 (0.95)	0.07 (0.95)
ShopLevel	0.76*** (0.02)	0.77*** (0.02)	0.77*** (0.02)	0.77*** (0.02)
AvgRating	0.86*** (0.16)	0.83*** (0.16)	0.82*** (0.16)	0.83*** (0.16)
ln(AvgPrice)	0.2*** (0.04)	0.2*** (0.04)	0.2*** (0.04)	0.2*** (0.04)
ln(CategoryPer)	-0.27*** (0.05)	-0.27*** (0.05)	-0.27*** (0.05)	-0.27*** (0.05)
ShopAge	-0.12** (0.04)	-0.11** (0.04)	-0.11** (0.04)	-0.11** (0.04)
ForumAge	-0.03 (0.03)	-0.03 (0.03)	-0.03 (0.03)	-0.03 (0.03)
ln(PostThread)	0.1* (0.05)	0.03 (0.06)	-0.02 (0.05)	0.02 (0.06)
ln(PostReply)	0.02 (0.05)	-0.03 (0.06)	-0.18** (0.06)	-0.2** (0.07)
ln(EmoRec)	-0.04 (0.04)	-0.06 (0.04)	-0.07 (0.04)	-0.04 (0.05)
ln(EmoPro)	0.01 (0.06)	0.01 (0.07)	-0.03 (0.06)	-0.03 (0.07)
ln(InstRec)		0.11* (0.05)		-0.13 (0.09)
ln(InfoPro)		0.01 (0.07)		-0.02 (0.07)
ln(InfoRec)			0.16** (0.06)	0.14* (0.06)
ln(InstPro)			0.28*** (0.06)	0.43*** (0.11)
R-square	0.2045	0.2052	0.2079	0.2083

Note: $^{+}p<0.1$; * $p<0.05$; **$p<0.01$; ***$p<0.001$.
Robust standard errors are reported in ().

Table B.1 presents robustness check with observations sampled from the top 15% of active sellers who posted more than 9 threads or 18 replies (compared to top 20% who post more than 4 threads or 10 replies in the main analysis). As shown in the table, the relationship between receiving instrumental support and the seller's sales income was positive and significant (Model 2, $\beta=0.11$, $p<0.05$), but it became insignificant in Model 4. Receiving informational support was significantly and positively associated with the seller's sales income (Model 3, $\beta=0.13$, $p<0.05$). Similarly, providing instrumental support was positively associated with the seller's sales income (Model 3, $\beta=0.28$, $p<0.001$). Both

InfoRec and *InstPro* remained significant in Model 4. However, providing informational support was not significantly associated with the seller's sales income. In sum, the results were consistent with the results in our main analysis.

Table B.2. Dependent Variable Based on Transactions

	Model 1	Model 2	Model 3	Model 4
Intercept	0.02 (0.52)	0.08 (0.52)	-0.02 (0.52)	0.00 (0.52)
ShopLevel	0.55*** (0.01)	0.55*** (0.01)	0.55*** (0.01)	0.55*** (0.01)
AvgRating	0.43*** (0.09)	0.41*** (0.09)	0.41*** (0.09)	0.41*** (0.09)
ln(AvgPrice)	-0.23*** (0.02)	-0.23*** (0.02)	-0.23*** (0.02)	-0.23*** (0.02)
ln(CategoryPer)	-0.08*** (0.02)	-0.08*** (0.02)	-0.08*** (0.02)	-0.08*** (0.02)
ShopAge	-0.12*** (0.02)	-0.12*** (0.02)	-0.12*** (0.02)	-0.12*** (0.02)
ForumAge	-0.01 (0.01)	-0.01 (0.01)	-0.01 (0.01)	-0.01 (0.01)
ln(PostThread)	0.06* (0.03)	0.02 (0.03)	0.01 (0.03)	0.02 (0.03)
ln(PostReply)	0.03 (0.03)	-0.01 (0.03)	-0.07* (0.03)	-0.08* (0.04)
ln(EmoRec)	-0.01 (0.02)	-0.03 (0.02)	-0.03 (0.02)	-0.02 (0.02)
ln(EmoPro)	-0.04 (0.03)	-0.05 (0.04)	-0.06 (0.03)	-0.07^{+} (0.04)
ln(InstRec)		0.06* (0.03)		-0.05 (0.04)
ln(InfoPro)		0.04 (0.04)		0.03 (0.04)
ln(InfoRec)			0.05^{+} (0.03)	0.04 (0.03)
ln(InstPro)			0.14*** (0.03)	0.19** (0.06)
R-square	0.3237	0.3245	0.3252	0.3259

Note: $^{+}$p<0.1; * p<0.05; **p<0.01; ***p<0.001.
Robust standard errors are reported in ().

Table B.2 presents the estimation results with the number of transactions as the dependent variable. Receiving instrumental support was positively associated with the seller's total number of transactions (Model 2, β=0.06, p<0.05), but the association became insignificant in Model 4. Providing instrumental support was positively associated with the seller's total number of transactions (Model 3, β=0.14, p<0.001), and it remained significant in Model 4 (β=0.19, p<0.01). Providing informational support are not significantly

associated with the seller's transactions. These findings are consistent with the results of our main analysis. However, the association between receiving informational support and the seller's number of transactions was only marginally significant (Model 3, $\beta=0.05$, $p<0.1$), and it became insignificant in Model 4. This is inconsistent with our main analysis.

Table B.3. Explanatory Variables Based on Number of Interactions

	Model 1	Model 2	Model 3	Model 4
Intercept	0.23 (0.93)	0.24 (0.93)	0.06 (0.93)	0.02 (0.93)
ShopLevel	0.76*** (0.02)	0.76*** (0.02)	0.76*** (0.02)	0.76*** (0.02)
AvgRating	0.87*** (0.16)	0.86*** (0.16)	0.85*** (0.16)	0.85*** (0.16)
ln(AvgPrice)	0.18*** (0.04)	0.18*** (0.04)	0.18*** (0.04)	0.18*** (0.04)
ln(CategoryPer)	-0.28*** (0.04)	-0.28*** (0.04)	-0.28*** (0.04)	0.28*** (0.04)
ShopAge	-0.12*** (0.03)	-0.11** (0.03)	-0.11*** (0.03)	-0.12*** (0.03)
ForumAge	-0.04 (0.03)	-0.04 (0.03)	-0.04 (0.03)	-0.03 (0.03)
ln(PostThread)	0.1* (0.05)	0.06 (0.05)	-0.02 (0.05)	0.04 (0.05)
ln(PostReply)	0.02 (0.05)	-0.01 (0.05)	-0.14* (0.06)	-0.16* (0.06)
ln(EmoRec)	-0.04 (0.04)	-0.06 (0.04)	-0.07 (0.04)	-0.05 (0.04)
ln(EmoPro)	0.02 (0.06)	0.02 (0.06)	-0.01 (0.06)	-0.01 (0.06)
ln(InstRec)		0.06 (0.05)		-0.1 (0.08)
ln(InfoPro)		0.01 (0.06)		-0.01 (0.06)
ln(InfoRec)			0.13** (0.05)	0.11* (0.05)
ln(InstPro)			0.21*** (0.06)	0.32** (0.1)
R-square	0.2037	0.2041	0.2061	0.2063

Note: *p<0.1;**p<0.05;***p<0.01.
Robust standard errors are reported in parentheses.

Table B.3 presents the results of robustness check, in which the explanatory variables (*InstRec*, *InstPro*, *InfoRec*, and *InfoPro*) were constructed based on the number of times a seller provides or receives certain types of resources. For instance, *InstPro* here represents the number of times a seller provides instrumental support. Thus, the instrumental support provided to the

same person through different interactions was not aggregated. While the original explanatory variables in our main analysis assumed that a certain type of support exchanged between the same pair of sellers is redundant, this new set of explanatory variables helped us to verify the findings based on a contrary assumption. The results demonstrated that receiving informational support (Model 3, β=0.13, p<0.01) and providing instrumental support (Model 3, β=0.21, p<0.001) were significantly and positively associated the sellers' sales performance. Such effects remain significant in Model 4. However, receiving instrumental support was not significantly associated with the sellers' sales performance, which is inconsistent with our main analysis.

Table B.4. *EmoRec* and *EmoPro* Constructed in Symmetric Approach

	Model 1	Model 2	Model 3	Model 4
Intercept	0.24 (0.93)	0.25 (0.93)	0.14 (0.93)	0.08 (0.93)
ShopLevel	0.76*** (0.02)	0.76*** (0.02)	0.76*** (0.02)	0.76*** (0.02)
AvgRating	0.88*** (0.16)	0.86*** (0.16)	0.84*** (0.16)	0.85*** (0.16)
ln(AvgPrice)	0.18*** (0.04)	0.18*** (0.04)	0.18*** (0.04)	0.18*** (0.04)
ln(CategoryPer)	-0.28*** (0.04)	-0.28*** (0.04)	-0.28*** (0.04)	0.28*** (0.04)
ShopAge	-0.11*** (0.03)	-0.11** (0.03)	-0.11** (0.03)	-0.11** (0.03)
ForumAge	-0.04 (0.03)	-0.04 (0.03)	-0.04 (0.03)	-0.04 (0.03)
ln(PostThread)	0.04 (0.05)	0.02 (0.05)	-0.01 (0.05)	0.01 (0.05)
ln(PostReply)	0.00 (0.06)	-0.01 (0.06)	-0.15* (0.06)	-0.16* (0.07)
ln(EmoRec)	0.08 (0.08)	0.02 (0.10)	0.05 (0.09)	0.02 (0.10)
ln(EmoPro)	-0.02 (0.11)	0.00 (0.11)	0.06 (0.11)	-0.08 (0.11)
ln(InstRec)		0.07 (0.06)		-0.13 (0.09)
ln(InfoPro)		-0.01 (0.06)		-0.01 (0.06)
ln(InfoRec)			0.15*(0.06)	0.12* (0.06)
ln(InstPro)			0.29*** (0.07)	0.41*** (0.11)
R-square	0.2038	0.2040	0.2062	0.2065

Note: +p<0.1; * p<0.05; **p<0.01; ***p<0.001.
　　Robust standard errors are reported in parentheses.

Table B.4 presents the results of the robustness check, in which the variables on emotional support (*EmoRec* and *EmoPro*) were constructed in a symmetrical approach. Specifically, if A posts a message containing emotional support to B, we consider B to receive emotional support from A. If A posts a message containing emotional support and B replies A with a message containing emotional support, we also consider B to receive emotional support from A. The results demonstrated that receiving informational support (Model 3, β=0.15, $p<0.05$) and providing instrumental support (Model 3, β=0.29, $p<0.001$) were significantly and positively associated the sellers' sales performance, which is consistent with our main analysis. However, receiving instrumental support was not significantly associated with the sellers' sales performance, which is inconsistent with our main analysis. Besides, both receiving and providing emotional support (*EmoRec* and *EmoPro*) was not associated with sales.

Appendix C: Robustness Check for Chapter 3

Table C.1. Dependent Variable Based on Number of Responders

	Model 1	Model 2	Model 3	Model 4
Intercept	-0.586***	-0.584***	-0.555***	-0.561***
	(0.013)	(0.013)	(0.013)	(0.013)
ForumAge	0.006***	0.005***	0.005***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)
ln(TitleLen)	0.081***	0.079***	0.079***	0.078***
	(0.003)	(0.003)	(0.003)	(0.003)
ln(ContentLen)	-0.076***	-0.075***	-0.077***	-0.076***
	(0.001)	(0.001)	(0.001)	(0.001)
DummyShare	0.065***	0.061***	0.057***	0.055***
	(0.007)	(0.007)	(0.007)	(0.007)
DummyEmo	0.151***	0.153***	0.154***	0.155***
	(0.003)	(0.003)	(0.003)	(0.003)
DummySeek	-0.045***	0.002	-0.043***	-0.011*
	(0.003)	(0.005)	(0.003)	(0.005)
DummyInst	0.437***	0.426***	0.361***	0.37***
	(0.003)	(0.003)	(0.003)	(0.005)
ln(InfoPro)	0.032***	0.041***	0.059***	0.062***
	(0.002)	(0.002)	(0.002)	(0.002)
ln(InstPro)	-0.019***	-0.007***	-0.041***	-0.029***
	(0.001)	(0.001)	(0.001)	(0.001)
DummySeek × ln(InfoPro)		0.034***		0.016***
		(0.004)		(0.004)
DummySeek × ln(InstPro)		-0.037***		-0.024***
		(0.002)		(0.002)
DummyInst × ln(InfoPro)			-0.083***	-0.075***
			(0.004)	(0.004)
DummyInst × ln(InstPro)			0.047***	0.038***
			(0.002)	(0.002)
Log likelihood	-2199946	-2199392	-2199179	-2199079

Note: *p<0.05; **p<0.01; ***p<0.001
    Standard Errors are reported in ()

Table C.1 presents results of robustness check with the number of responders as the dependent variable. The results are consistent with our main analysis. The provision of informational support is positively associated with the number of responders (Model 1, β=0.032, p<0.001), while the provision of instrumental support is negatively associated with nthe umber of responders (Model 1, β=-0.019, p<0.001). For threads seeking informational support, the

effect of providing informational support becomes more positive (Model 2, β=0.034, p<0.001), and the effect of providing instrumental support becomes more negative (Model 2, β=-0.037, p<0.001). For threads seeking instrumental support, the effect of providing informational support becomes less positive (Model 3, β=-0.083, p<0.001), and the effect of providing instrumental support becomes less negative (Model 3, β=0.047, p<0.001).

Table C.2. Explanatory Variables Based on Number of Interactions

	Model 1	Model 2	Model 3	Model 4
Intercept	-0.689***	-0.7***	-0.656***	-0.668***
	(0.013)	(0.013)	(0.013)	(0.013)
ForumAge	0.006***	0.006***	0.006***	0.006***
	(0.001)	(0.001)	(0.001)	(0.001)
ln(TitleLen)	0.083***	0.082***	0.08***	0.08***
	(0.003)	(0.003)	(0.003)	(0.003)
ln(ContentLen)	-0.076***	-0.075***	-0.077***	-0.076***
	(0.001)	(0.001)	(0.001)	(0.001)
DummyShare	0.067***	0.069***	0.058***	0.06***
	(0.007)	(0.007)	(0.007)	(0.007)
DummyEmo	0.149***	0.149***	0.153***	0.152***
	(0.003)	(0.003)	(0.003)	(0.003)
DummySeek	-0.041***	0.009*	-0.04***	-0.006
	(0.003)	(0.005)	(0.003)	(0.005)
DummyInst	0.441***	0.435***	0.362***	0.37***
	(0.003)	(0.003)	(0.005)	(0.005)
ln(InfoPro)	0.026***	0.021***	0.054***	0.051***
	(0.002)	(0.002)	(0.002)	(0.002)
ln(InstPro)	-0.016***	-0.01***	-0.039***	-0.033***
	(0.001)	(0.001)	(0.001)	(0.001)
DummySeek × ln(InfoPro)		0.035***		0.014***
		(0.004)		(0.004)
DummySeek × ln(InstPro)		-0.04***		-0.024***
		(0.002)		(0.002)
DummyInst × ln(InfoPro)			-0.089***	-0.086***
			(0.003)	(0.004)
DummyInst × ln(InstPro)			0.049***	0.043***
			(0.002)	(0.002)
Log likelihood	-2278962	-2278777	-2278462	-2278364

Note: *p<0.05; **p<0.01; ***p<0.001
Standard Errors are reported in ()

Table C.2 presents the results of the robustness check, in which explanatory variables are constructed based on the number of times a seller

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provides or receives certain types of resources. The results are consistent with our main analysis. The provision of informational support is positively associated with the number of responders (Model 1, β=0.026, p<0.001), while the provision of instrumental support is negatively associated with nthe umber of responders (Model 1, β=-0.016, p<0.001). For threads seeking informational support, the effect of providing informational support becomes more positive (Model 2, β=0.035, p<0.001), and the effect of providing instrumental support becomes more negative (Model 2, β=-0.04, p<0.001). For threads seeking instrumental support, the effect of providing informational support becomes less positive (Model 3, β=-0.089, p<0.001), and the effect of providing instrumental support becomes less negative (Model 3, β=0.049, p<0.001).

Table C.3 presents results of the robustness check, in which both dependent variables and explanatory variables are constructed based on a time window of 90 days instead of 30 days. Using a longer time window will cause a reduction of sample size, as we need to make sure we have sufficient data to track each thread author's activity. Eventually, the estimation is conducted based on a sample of 954,951 threads. The results reveal that the change of time window does not affects our results. The effect of providing informational support is positive and significant (Model 1, β=0.021, p<0.001). Such effect is strengthened for threads that seek information (Model 2, β=0.04, p<0.001) but undermined in threads that seek instrumental support (Model 3, β=-0.078, p<0.001). On the other hand, the prior provision of instrumental support is negatively associated with the received responses (Model 1, β=-0.026, p<0.001), which is more

negative for threads seeking information (Model 2, β=-0.043, p<0.001) and less

negative in threads that seek instrumental support (Model 3, β=0.054, p<0.001)

as well.

Table C.3. Robustness Check with Time Window of 90 Days

	Model 1	Model 2	Model 3	Model 4
Intercept	-0.61***	-0.622***	-0.564***	-0.577***
	(0.014)	(0.014)	(0.014)	(0.014)
ForumAge	0.006***	0.006***	0.005***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)
ln(TitleLen)	0.08***	0.079***	0.078***	0.077***
	(0.003)	(0.003)	(0.003)	(0.003)
ln(ContentLen)	-0.082***	-0.081	-0.083	-0.082
	(0.001)	(0.001)	(0.001)	(0.001)
DummyShare	0.046***	0.048***	0.037***	0.039***
	(0.007)	(0.007)	(0.007)	(0.007)
DummyEmo	0.139***	0.139***	0.143***	0.143***
	(0.003)	(0.003)	(0.003)	(0.003)
DummySeek	-0.047***	0.015**	0.045**	-0.008
	(0.003)	(0.005)	(0.003)	(0.005)
DummyInst	0.455***	0.448***	0.352***	0.362***
	(0.003)	(0.003)	(0.006)	(0.006)
ln(InfoPro)	0.021***	0.016***	0.05***	0.045***
	(0.002)	(0.002)	(0.002)	(0.002)
ln(InstPro)	-0.026***	-0.02***	-0.053***	-0.046***
	(0.001)	(0.001)	(0.001)	(0.001)
DummySeek× ln(InfoPro)		0.04***		0.02***
		(0.003)		(0.004)
DummySeek× ln(InstPro)		-0.043***		-0.025***
		(0.002)		(0.002)
DummyInst× ln(InfoPro)			-0.078***	-0.074***
			(0.004)	(0.004)
DummyInst× ln(InstPro)			0.054***	0.048***
			(0.002)	(0.002)
Log likelihood	-1987671	-1987484	-1987140	-1987083

Note: *p<0.05; **p<0.01; ***p<0.001
    Standard Errors are reported in ()

Table C.4 presents the results of the robustness check, in which the

emotional support a seller provides (*EmoPro*) is also included. The results reveal

that controlling the effect of emotional support does not change our findings. The

provision of informational support is positively associated with the number of

responders (Model 1, β=0.043, p<0.001), while the provision of instrumental

support is negatively associated with nthe umber of responders (Model 1, β=-0.007, p<0.001). For threads seeking informational support, the effect of providing informational support becomes more positive (Model 2, β=0.015, p<0.01), and the effect of providing instrumental support becomes more negative (Model 2, β=-0.05, p<0.001). For threads seeking instrumental support, the effect of providing informational support becomes less positive (Model 3, β=-0.016, p<0.001), and the effect of providing instrumental support becomes less negative (Model 3, β=0.069, p<0.001).

Interestingly, the results also show that the effect of providing emotional support is negative for threads seeking instrumental support (Model 3, β=-0.086, p<0.001). It further confirms that misalignment between prior contribution and current transaction will inhibit the sellers from receiving responses. The long-term social image or relationship resulted from providing emotional support is highly social and affective, while the transaction in threads seeking instrumental support is highly economic. The mismatch between the economic transaction and the social relationship leads to higher emotional labor (Cropanzano and Mitchell 2005), which, in turn, reduces others' inclination to respond to the threads.

Table C.4. Robustness Check with Emotional Support

	Model 1	Model 2	Model 3	Model 4
Intercept	-0.673*** (0.013)	-0.682*** (0.013)	-0.664*** (0.013)	-0.675*** (0.013)
ForumAge	0.006*** (0.001)	0.006*** (0.001)	0.005*** (0.001)	0.005*** (0.001)
ln(TitleLen)	0.081*** (0.003)	0.08*** (0.003)	0.078*** (0.003)	0.078*** (0.003)
ln(ContentLen)	-0.076*** (0.001)	-0.075*** (0.001)	-0.075*** (0.001)	-0.074*** (0.001)
DummyShare	0.05***	0.06***	0.06***	0.062***

	(0.007)	(0.007)	(0.007)	(0.007)
DummyEmo	0.152***	0.153***	0.152***	0.152***
	(0.003)	(0.003)	(0.003)	(0.003)
DummySeek	-0.04***	-0.002	-0.038***	-0.005
	(0.003)	(0.005)	(0.003)	(0.005)
DummyInst	0.434***	0.427***	0.383***	0.391***
	(0.003)	(0.003)	(0.005)	(0.005)
ln(InfoPro)	0.043***	0.041***	0.049***	0.047***
	(0.002)	(0.002)	(0.002)	(0.002)
ln(InstPro)	-0.007***	-0.001	-0.044***	-0.038***
	(0.001)	(0.001)	(0.001)	(0.002)
ln(EmoPro)	-0.027***	-0.031***	0.01***	0.01***
	(0.001)	(0.002)	(0.002)	(0.002)
DummySeek × ln(InfoPro)		0.015**		0.012***
		(0.004)		(0.004)
DummySeek × ln(InstPro)		-0.05***		-0.023***
		(0.002)		(0.003)
DummySeek × ln(EmoPro)		0.031***		0.000
		(0.003)		(0.003)
DummyInst × ln(InfoPro)			-0.016***	-0.014***
			(0.005)	(0.005)
DummyInst × ln(InstPro)			0.069***	0.064***
			(0.002)	(0.002)
DummyInst × ln(EmoPro)			-0.086***	-0.086***
			(0.003)	(0.003)
Log likelihood	-2278800	-2278592	-2277933	-2277876

Note: *p<0.05; **p<0.01; ***p<0.001

Standard Errors are reported in ()

Table C.5 presents the results of the robustness check, in which seasonal effect is controlled by a set of dummy variables. After ruling out seasonal effect, the results are still consistent with our main analysis. The provision of informational support is positively associated with the number of responses (Model 1, β=0.028, p<0.001), while the provision of instrumental support is negatively associated with the number of responses (Model 1, β=-0.017, p<0.001). For threads seeking informational support, the effect of providing informational support becomes more positive (Model 2, β=0.034, p<0.001), and the effect of providing instrumental support becomes more negative (Model 2, β=-0.039, p<0.001). For threads seeking instrumental support, the effect of

providing informational support becomes less positive (Model 3, β =-0.084, p<0.001), and the effect of providing instrumental support becomes less negative (Model 3, β=0.046, p<0.001).

Table C.5. Robustness Check with Seasonal Effect

	Model 1	Model 2	Model 3	Model 4
Intercept	-0.639***	-0.652***	-0.623***	-0.635***
	(0.014)	(0.014)	(0.014)	(0.014)
ForumAge	0.005***	0.005***	0.005***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)
ln(TitleLen)	0.082***	0.082***	0.08***	0.08***
	(0.003)	(0.003)	(0.003)	(0.003)
ln(ContentLen)	-0.076***	-0.075***	-0.076***	-0.076***
	(0.001)	(0.001)	(0.001)	(0.001)
DummyShare	0.057***	0.059***	0.051***	0.052***
	(0.007)	(0.007)	(0.007)	(0.007)
DummyEmo	0.15***	0.151***	0.153***	0.153***
	(0.003)	(0.003)	(0.003)	(0.003)
DummySeek	-0.04***	-0.008	-0.039***	-0.006
	(0.003)	(0.005)	(0.005)	(0.005)
DummyInst	0.438***	0.432***	0.364***	0.373***
	(0.003)	(0.003)	(0.003)	(0.005)
ln(InfoPro)	0.028***	0.024***	0.054***	0.05***
	(0.002)	(0.002)	(0.002)	(0.002)
ln(InstPro)	-0.017***	-0.011***	-0.039***	-0.033***
	(0.001)	(0.001)	(0.001)	(0.001)
DummySeek× ln(InfoPro)		0.034***		0.014***
		(0.004)		(0.004)
DummySeek× ln(InstPro)		-0.039***		-0.024***
		(0.002)		(0.002)
DummyInst× ln(InfoPro)			-0.084***	-0.081***
			(0.004)	(0.004)
DummyInst× ln(InstPro)			0.046***	0.041***
			(0.002)	(0.002)
Log likelihood	-2278337	-2278168	-2277933	-2277808

Note: *p<0.05; **p<0.01; ***p<0.001
    Standard Errors are reported in ()
    Dummy variables representing different months are omitted