Social Structure and Trust in Massive Digital Markets

Completed Research Paper

David Holtz
MIT Sloan School of Management
30 Memorial Drive, Cambridge, MA 02142
dholtz@mit.edu

Diana Lynn MacLean
Facebook, Inc.
1 Hacker Way, Menlo Park, CA 94025
malcdi@fb.com

Sinan Aral
MIT Sloan School of Management
30 Memorial Drive, Cambridge, MA 02142
sinan@mit.edu

Abstract

Embedding games in networks creates trust when the network is sufficiently dense and/or the players are sufficiently central. But, while much existing research examines how formal reputation signals, like ratings or reviews, enhance trust and facilitate market transactions, almost no research explores the role of networked social signals in generating trust in such marketplaces. Here, we measure the extent to which situating transactions in networks can generate trust in online marketplaces with an empirical approach that provides external validity while eliminating many potential confounds. Using micro-level data on ~1.6M sales posts in Facebook buy and sell groups, we find that both increased network density and seller degree centrality increase two-sided interest in transacting. These results suggest that network structure can produce trust in marketplace transactions and imply that network-based trust mechanisms can offer an appealing alternative to formal reputation systems in mitigating moral hazard and adverse selection in digital marketplaces.

Keywords: Electronic marketplace, 06. Peer-to-Peer and Crowd Markets, Peer-to-peer, Networks, Trust/online trust

Introduction

Over the past two decades, the internet has facilitated the emergence of numerous informal, peer-to-peer marketplaces such as Craigslist, eBay, and Facebook Marketplace. These new informal marketplaces are particularly susceptible to adverse selection and moral hazard because they provide less comprehensive information about shoppers, sellers and products. They therefore depend on trust between shoppers and sellers to facilitate transactions much more than traditional markets. Traditional models of economic activity in informal markets take either an “oversocialized” approach of generalized morality or an “undersocialized” approach of reliance on formal institutions and contracts. In contrast, Granovetter (1985) argues that economic action is embedded in social networks, and that the social embeddedness of economic activity should encourage trust between potential transaction partners, reducing the probability of malfeasance. The importance and effects of offline marketplaces’ social embeddedness has been documented empirically, for example in sociological studies of Middle Eastern bazaars (Geertz 1978) and an economic study of the Marseille fish market (Weisbuch et al. 2000).

Given the ubiquity of informal digital marketplaces, understanding how to effectively generate trust in informal marketplaces is more relevant now than ever. For instance, an October 2016 Facebook press release notes that 450 million Facebook users visit Facebook buy and sell groups every month (Ku 2016). There is a sizable academic literature on the use of reputation systems and reviews to mitigate moral hazard and adverse selection in digital marketplaces (Cripps et al. 2004; Dellarocas 2003; Dellarocas 2005). But, reputation systems have known issues. For instance, shopper or seller quality estimates obtained from reputation systems are often biased due to sorting (Dellarocas and Wood, 2008; Fradkin et al. 2017), feedback reciprocity (Bolton et al. 2013; Fradkin et al. 2017) or social influence (Muchnik et al. 2013). Given the design difficulties that reputation systems present, it is worth considering whether alternative mechanisms exist for reducing moral hazard and adverse selection in digital marketplaces.

Reputation systems are a natural choice for establishing trust in many informal digital markets, because transactions are not embedded in any sort of existing social context. For example, an eBay shopper and seller do not know anything about each other's identity or background. However, the emergence of popular social networks such as Facebook, Twitter, and LinkedIn presents an opportunity to embed informal digital marketplace activity in an established online social context. Facebook buy and sell groups and Facebook Marketplace do just that. Facebook buy and sell groups are informal marketplaces where Facebook users post a wide range of items for sale including, but not limited to, clothes, furniture, electronics, and cars. Notably, even though Facebook buy and sell groups do not currently employ any formal reputation or review system, they provide a useful venue to trade a wide range of items at a variety of price points.

The extent to which social relations and networks generate trust in marketplaces has long been a subject of interest in both the theoretical (Ali and Miller 2013; Buskens 1998; Fainmesser 2012; Karlan et al. 2012; Kinateder 2008; King 2015; Lahno 1995; Lahno 1995a; Raub and Weesie 1990) and empirical (Burt and Knez 1995; Chandrasekhar et al. 2014; Chandrasekhar and Breza 2016; Gallo and Yan 2015; Glaeser et al. 2000; Johnson et al. 2002; Karlan et al. 2012; Rand et al. 2011; Uzzi 1999) literature. However, both the theoretical and empirical literature still contain several unanswered questions. In the theoretical literature, the effect that network structure and agents' network position have on trust varies, depending on the exact functional form of the model being examined. Studies in the empirical literature have been limited to lab experiments, observational studies, and small-scale in vivo experiments. Furthermore, it is unclear in both literatures which network is the "relevant network" when studying the network embeddedness of economic transactions. While some work focuses on a network of past transactions or commerce-related interactions, others focus on a network of social connections (e.g., family members, friends and acquaintances).

Using an observational dataset describing Facebook buy and sell group activity over one month in early 2017, this paper quantifies the extent to which the social connections in Facebook buy and sell groups establish trust and facilitate trade. We operationalize the concept of trust by measuring the amount of two-sided interest a given item posted in a Facebook buy and sell group receives (i.e., the number of shoppers who would be interested in transacting with the seller with whom the seller is also willing to transact). To measure two-sided interest, we use the "double interact" as a measure of two-sided interest between sellers and shoppers. The double interact, first introduced by Weick (1979), is a pattern of interaction that has been used to proxy for "transactions" in studies of online dating markets (Bapna et al. 2016), where offline outcomes of interest (i.e., dates) are not observable.

The link between trust and two-sided interest is justified nicely by Tadelis (2016), which presents a simple game in which a shopper chooses whether or not to engage with a seller, who is either honest or opportunistic. The shopper's decision depends on the probability the she assigns to the seller being honest, i.e., to what degree the shopper trusts the seller. In a peer-to-peer marketplace, sellers face a similar decision and will decide whether to respond based on the probability with which they believe the shopper is honest. It follows that an increase in trust (i.e., an increase in the perceived likelihood that transaction partners are honest) should lead to a greater number of instances where there is two-sided interest in transacting. Although measuring actual sales would be preferable to measuring two-sided interest, reliably determining that an item has been sold (and, subsequently, who an item has been sold to) in our setting is extremely difficult. When two parties choose to transact, they often meet offline, and carry out payment using cash or an alternative payment platform.

Our empirical strategy takes advantage of the fact that many sellers will cross-post items to multiple Facebook buy and sell groups. This allows us to control for observed and unobserved attributes of both the seller and the item being sold, and to obtain less biased estimates of the impact that network structure has on market outcomes. Using both the Facebook social graph and the history of interactions in each buy and sell group, we can perform this analysis for both the network that characterizes social connections *and* the network that characterizes past commerce-related interactions. This enables us to determine whether one of these networks more or less effectively generates trust than the other. We also compare the bivariate distributions of shopper- and seller-level network characteristics for shopper-seller dyads where there *is* two-sided interest, and shopper-seller dyads where there *is not* two-sided interest. This analysis provides preliminary insight into the importance of shopper-level network characteristics in establishing facilitating trade.

We find that increased seller centrality in either the network comprised of commerce-based interactions or the network comprised of Facebook friendships is associated with a greater amount of two-sided interest in transacting. Furthermore, we see weak evidence that increased network density can lead to greater levels of trust, and that higher levels of shopper network centrality can also drive trust in informal marketplaces. Most importantly, these results suggest that network structure can produce trust in the absence of a formal reputation or review system and imply that network-based trust mechanisms may offer an appealing alternative to review- and evaluation-based reputation systems, in mitigating moral hazard and adverse selections in informal marketplaces.

This research contributes to the existing literature in numerous ways. First, it is the first in vivo study of a massive digital informal marketplace that is embedded in a social network. This allows us to compare the impact of social tie-based and economic transaction-based network structure. Second, the fact that we observe a single seller with different network positions in multiple marketplaces allows us to move closer to the econometric gold standard of a randomized experiment, while still maintaining a degree of external validity. Finally, while there is an existing literature suggesting network-based trust is important in offline interactions, our work is among the first to examine how well these results translate to a *digital* setting.

The paper proceeds as follows. First, we contextualize the contribution of this work by reviewing the existing literature on trust in informal marketplaces and economic activity embedded in social structure. We then describe the setting for our study and the data used for analysis. Next, we discuss our methodological approach and present our findings. Finally, we discuss the results and possible extensions to the work.

Literature Review

Facebook buy and sell groups can be thought of as digital versions of flea markets, bazaars, and souks found in the physical world. Geertz's study of the Sefrou bazaar (Geertz 1978) provides the first economic treatment of marketplaces that incorporates the sociocultural context in which the market is embedded. Geertz notes that the bazaar economy is a "distinctive system of social relationships centered around the production and consumption of goods and services," and that information in the bazaar economy is "poor, scarce, maldistributed, inefficiently communicated, and intensely valued."

The low information nature of informal marketplaces creates an environment with high levels of information asymmetry and the potential for moral hazard to run rampant. Every possible transaction between a shopper and seller can be thought of as a "trust game," in which a transaction only occurs if both agents decide they can trust the other (Dasgupta 1988; Kreps 1990; Kreps 1996). Consequently, unless there is sufficient trust between shoppers and sellers, the market will fail. To justify the fact that there are many informal marketplaces that do not fail, early schools of thought relied on an "oversocialized" economic approach that incorporated a generalized sense of morality, or an "undersocialized" approach that relied on formal institutions and contracts to generate trust. In a departure from both approaches, Granovetter (1985) argues that the embeddedness of economic actions in social networks should generate trust between economic agents and discourage malfeasance.

Over the past 30 years, healthy theoretical and empirical economic studies have expanded and tested Granovetter's initial proposal. In the theoretical literature, the simplest models of trust in repeated games do not involve a network at all. In these models, the same shopper and seller play the trust game repeatedly. The shopper can punish poor behavior by withdrawing their trust in subsequent rounds, while the seller can build up a reputation for trustworthiness. Two-player models in this style have a cooperative equilibrium in which both the shopper and seller trust each other in every round (Dasgupta 1988; Kreps 1990; Kreps 1996; Lahno 1995; Lahno 1995a). Extensions to these simple models which embed trust games into a social context with third party observers find that cooperation remains an equilibrium (Burt and Knez

1996; Dasgupta 1988; Raub and Weesie 1990). Even more sophisticated models explicitly embed economic activity into a well-defined network, in which trust is often established through the flow of information about previous transactions through network edges per a specified transmission model.

In many of these models, particular network structures and/or network positions can make the cost of unsavory behavior so high that agents are incentivized to cooperate. However, different game specifications, diffusion models, and network definitions have produced a range of different predictions, many of which do not agree with one another. Theoretical studies have argued that denser networks can induce trust (Ali and Miller 2013; Buskens 1998; Kinateder 2008), that centrality can induce trust (Buskens 1998; King 2015), that balanced competition, sparseness of the network, and segregation of the network tend to lead to greater levels of cooperation under community enforcement in bipartite networks (Fainmesser 2012), and that dense networks allow for transacting valuable assets, whereas loose networks better facilitate the exchange of low value items and favors (Karlan et al. 2009).

In the empirical literature, some of the earliest evidence for the importance of social structure in generating trust comes from Burt and Knez (1995), which finds through the analysis of a survey of managers at a high-tech firm that third parties have a strong amplifying effect on trust, and that different forms of connection with third-parties are responsible for both negative and positive effects on trust. Since then, observational studies have found, across a wide range of settings such as fish markets, Peruvian shantytowns, and the middle-market banking industry, that markets embedded in networks help agents choose who to transact with (Weisbuch et al. 2000), determine who is trustworthy enough to lend to (Karlan et al. 2009), and receive lower interest rates on loans (Uzzi 1999). Lab experiments online and offline have found that socially close individuals are more likely to trust one another (Glaeser et al. 2000), that cooperation is maintained in repeated cooperation games in dynamic networks through network rewiring (Rand et al. 2011), and that cooperation is associated with the emergence of dense and clustered networks with highly cooperative hubs and separate communities for cooperators and non-cooperators (Gallo and Yan 2015). Finally, field experiments conducted in rural Indian villages have found that pairs of people are more likely to cooperate when they are socially close and that individuals with more central partners are better behaved (Chandrasekhar et al. 2014; Chandrasekhar and Breza 2016).

Signaling and warrant theory also suggest social networks may help to establish trust in informal marketplaces. Empirical studies (Li et al. 2009; Van Der Heide et al. 2013) have found that credibility signals (e.g., seller ratings, product photos, and money back guarantees) can increase bidding activity and result in higher sale prices in online auctions. Donath and Boyd (Donath 2007; Donath and Boyd 2004) suggest that social network signals (e.g., who someone is "connected to" in a social network) should serve as good credibility signals, since they are difficult to fabricate. Donath and Boyd also argue that that social networks help enforce norms by making agents aware that others are observing their actions.

We build on this literature in multiple ways. First, our setting allows us to estimate the amount of trust generated by two different networks – the network of interactions in buy and sell groups and the network of Facebook friends. Additionally, the fact that Facebook users cross-post items across multiple buy and sell groups enables us to more accurately estimate the generalizable causal effect of network structure than was possible in previous observational or experimental lab studies because we can effectively hold all seller and product characteristics constant in fixed effects specifications. This is also the first study of network-generated trust in massive digital social networks, which are exceptionally sparse. Beyond contributing to the literature on trust and networks, we believe our findings are useful to marketplace designers, who may wish to leverage social structure to generate trust and facilitate transactions.

Institutional Details and Data

Institutional Details

Facebook buy and sell groups provide a setting for Facebook users to exchange a wide range of goods and services with their peers. Each buy and sell group has its own Facebook page, the centerpiece of which is its group timeline. Group members can post to the group timeline, which at any given moment includes recently posted, modified, or commented on items. Buy and sell groups on Facebook have one of three privacy levels: "open," "closed," or "secret." The privacy level of a group determines how easily new

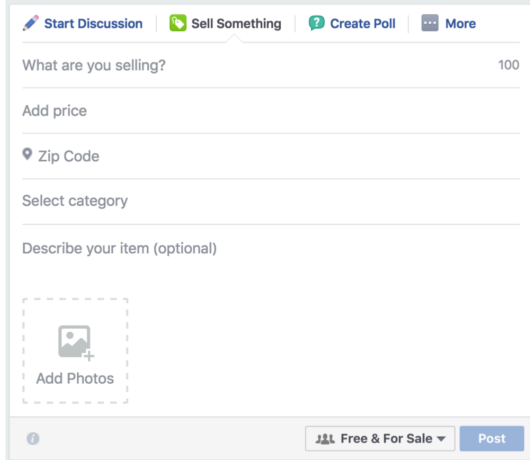

Figure 1. The Facebook buy and sell group composer window at the time of this study. Sellers are asked to provide a title and description for the item. They also specify a price, item category, and location (zip code) for the item, and can add photos to the post.

members can join a group, who can see posts in the group, and who can find the group in search. A more detailed description of group privacy settings can be found in ("What are the privacy settings," n.d.).

There are a handful of differences between the process of posting an item in a buy and sell group and the process of writing a post in any other Facebook group. First, in addition to photos and a description of the item, the composer window in a buy and sell group includes fields for a seller to indicate the price, location, category, and title of the item for sale. Figure 1 shows a screenshot of the buy and sell group composer window.

It is not uncommon for a seller to "cross-post" an item. A seller does this by posting the exact same item (with the same price and title) to multiple groups on the same day. For instance, a seller might post the same bicycle to both "Bicycle Bazaar" and "Wheelers and Dealers Boston."[1] Serious sellers often cross-post to expose their item to as many shoppers as possible and to increase the likelihood that their item is sold.

A shopper has several ways to show interest in an item, including liking or commenting on a seller's post, or sending the seller a private message via Messenger. In comments, shoppers will often request further item details, or simply write "Interested" to indicate they have some level of interest in an item. Conversation topics could include further discussion of item details, or transaction logistics and details.

Once a seller has sold an item, they can optionally mark it "sold". Once an item has been marked sold, that item will no longer appear in the buy and sell group's timeline. However, no further details (e.g. whether the item was sold on Facebook or on a different platform; who the buyer was; etc.) are collected. This can lead to false positives – for instance, a seller may mark an unsold item sold, or may mark an item sold after transacting with a non-Facebook buyer. This can also lead to false negatives – for instance, a seller may never mark a sold item as such, or delete an item rather than mark it sold. In fact, deleting sold items is encouraged in many groups.

Datasets

Our primary dataset is aggregated and de-identified data collected from Facebook buy and sell groups over a 31-day period spanning from January 15, 2017 to February 14, 2017 (inclusive). Our empirical strategy,

---

[1] Both "Bicycle Bazaar" nor "Wheelers and Dealers Boston" are synthesized examples.

Table 1. Group Summary Statistics			
	Group-level sampling	Item-level sampling	Statistically Significant?
Number of groups	1,788	713,586	
Average Group Size (Members)	4,151.257 (11,172.5)	7,182.365 (12,727.38)	***
Average Group Density (Friendships)	0.024 (0.042)	0.012 (0.021)	***
Average Group Density (interactions)	0.001 (0.004)	0.001 (0.003)	***
Average % Isolates (Friendships)	0.177 (0.180)	0.140 (0.139)	***
Average % Isolates (Interactions)	0.883 (0.127)	0.846 (0.135)	***
Standard deviations in parentheses *** p<0.01, **p<0.05, *p<0.1			

Table 1. Group-level summary statistics for both the dataset consisting of cross-posted items sampled at the item-level and items sampled at the group-level. The third column indicates whether the difference between the two groups is statistically significant at the 95% confidence level, as calculated with a Monte Carlo permutation test (B=10,000).

which we will soon discuss in more detail, relies on sellers cross-posting items to multiple groups. Considering this, we build a dataset comprised entirely of items from this timespan that are cross-posted.

Our primary dataset, which is sampled at the item-level, is constructed as follows. We first created a hashed ID for every item from its title, local currency price, and seller user ID. If a hashed ID appears in more than one group on the same day, it is considered cross-posted. Given these hashed IDs, we draw a 1% sample of all hashed IDs that are cross-posted to 2 or more groups between January 15 and February 14, and then keep only hashed IDs that still qualify as cross-posted after filtering out groups that have fewer than 3 members or more than 6 million members. The lower bound is imposed because groups with fewer than 3 members do not contribute meaningfully to the study of trust and social structure. The upper bound is imposed because the computation of group-level network statistics for extremely large groups (i.e., more than 6 million members) is prohibitively expensive. This process produces a dataset with 4,833,699 posts, 715,284 unique items, 700,310 unique groups and 661,025 unique sellers.

We further restrict our dataset in the following ways. First, we filter out any hashed IDs that have more than one distinct price, product category, or number of photos across postings. Hashed IDs satisfying these criteria may be spam, or may correspond to generic titles being used to sell a variety of items (e.g., "Tons of free stuff!"). We also remove any items that have a listed price of $0 and $1. Both $0 and $1 are used to signal special cases of pricing, such as free items. Finally, we filter out any items posted from countries that do not have posts to more than one unique group ID or posts corresponding to more than one hashed ID in the sample. This produces a final dataset with 1,651,491 posts, 299,179 unique items, 432,995 unique groups, and 284,090 unique sellers.

Given that we are interested in studying the impact of network structure on trust and transactions, we also need to identify the relevant network(s) to study in Facebook buy and sell groups. One network is simply the Facebook friendship graph. We define a buy and sell group's friendship graph as the induced subgraph of the entire Facebook graph containing the members of that group. In addition to the friendship graph, we are also interested in the graph arising out of past commerce-related interactions. To define such a graph, we look at activity in Facebook buy and sell groups in the three weeks prior to the beginning of our study (December 25, 2016 to January 14, 2017). We then create an edge between two members of a given buy and sell group if, during that three-week period, they interacted with one another in that buy and sell group (i.e., one of them liked the other's post or they messaged each other regarding an item) at least once. Finally, to analyze messaging behavior between shoppers and sellers in our dataset, we count messages sent between sellers and any shopper who has interacted with one of their products in the past five days, within three days of each buy and sell group post being made.

One natural concern is that the sellers and items in our sample are not representative of all sellers and items in Facebook buy and sell groups, since sellers who cross-post may be more professional, or more likely to

Table 2. Item/Seller Summary Statistics			
	Group-level sampling	Item-level sampling	Statistically Significant?
Average Groups/Item	1.003 (0.059)	5.473 (4.915)	***
Avg. Double Interacts (D.I.) (3) / Post	0.022 (0.311)	0.171 (0.759)	***
% posts receiving ≥ 1 D.I.	0.012 (0.0002)	0.107 (0.0002)	***
Average Number of Photos	2.914 (4.501)	3.281 (4.377)	***
% Sellers Female	0.521 (0.001)	0.557 (0.001)	***
Average Seller Age (Where Available)	31.896 (11.245)	31.996 (11.457)	***
Average Seller Facebook Friends	836.706 (1,015.489)	798.069 (1,007.794)	***
Most Common Product Category	Apparel	Apparel	N/A
Avg. Seller Degree Centrality (Friends)	0.009 (0.042)	0.007 (0.029)	***
Avg. Seller Degree Centrality (Interactions)	0.006 (0.026)	0.003 (0.011)	***
Standard deviations in parentheses *** p<0.01, **p<0.05, *p<0.1			

Table 2. Item- and seller-level summary statistics for both the dataset consisting of cross-posted items sampled at the item-level and items sampled at the group-level. The third column indicates whether the difference between the two groups is statistically significant at the 95% confidence level, as calculated with a Monte Carlo permutation test (B=10,000).

post to certain groups. To understand the ways in which our sample is similar and dissimilar to the general population of sellers and items in Facebook buy and sell groups, we also created a dataset consisting of all item postings in a randomly drawn sample of Facebook buy and sell groups. This sample consists of all items posted to a small, random sample of buy and sell groups between January 15, 2017 and February 14, 2017.[2] Restricting the dataset to posts in groups with more than 3 members and fewer than 6 million members produces a dataset of 561,282 posts, 528,660 unique items, 1,788 unique groups and 181,951 unique sellers. Applying the same price, category, and country filters to this dataset as were applied to the primary dataset produces a final dataset of 434,538 posts, 430,086 unique items, 1,754 unique groups, and 154,784 unique sellers in a this sample of Facebook buy and sell groups. We then generated friendship and commerce graphs using the same methodology as described above.

Table 1 compares the groups that appear in both samples. Groups in the primary dataset tend to be 75% larger than the average buy and sell group, with friendship graphs that are about half as dense. Our primary dataset also contains groups that have fewer friendship graph isolates (i.e., group members with no friends in the group). While the average interaction graph density is of the same order of magnitude in the two samples, groups appearing in our primary dataset also tend to have fewer commerce interaction graph isolates.

Table 2 compares the posts appearing in both samples. Our sample has multiple notable differences relative to posts from a random sample of buy and sell groups. Items in our sample are cross-posted to ~5 times as many groups (as expected). The average item receives ~8 times as many double interacts, and ~10 times more items receive at least one double interact. The average item in our sample has about 0.3 more photos, and the sample of sellers includes about 3% more female users. The average seller is slightly older, and has about 40 fewer Facebook friends. The degree centrality of an average seller is about 22% lower in the friendship graph, and about 50% lower in the interaction graph. Despite these differences, we believe the cross-posted item sample is worth studying, as during the time of our study, cross-posted items account for

[2] We are unable to share the exact sampling rate for confidentiality reasons.

Table 3. Predicting the probability an item is marked as sold or deleted		
	Dependent Variable	
	% Marked as sold (1)	% Marked as sold or deleted (2)
# of Double Interacts	0.027*** (0.003)	0.025*** (0.002)
Constant	0.316*** (0.001)	0.389*** (0.001)
Observations	70	71
R^2	0.599	0.615
Standard errors in parentheses *** p<0.01, **p<0.05, *p<0.1		

Table 3. Coefficients obtained from a weighted least squares regression of the probability that an item is marked as sold or deleted on the number of double interacts that item receives.

a non-trivial proportion of items posted in buy and sell groups and large share of the posts in buy and sell groups.

Empirical Analysis

Methodology

As transactions are not directly observed in Facebook buy and sell groups, we measure the number of "double interacts" a particular item receives as a proxy or leading indicator of transactions. The double interact is a measure developed by Weick (1979) and considered to be a "sense-making process that people use when they organize in a variety of contexts" (Bapna et al. 2016). A double interact can be described as a pattern of messaging activity in which agent A messages agent B, agent B responds to agent A, and agent A responds to agent B's response. Double interacts were also used as an outcome metric in a recent paper by Bapna et al. (2016), which studied search costs and search signals in online dating markets. In many ways, the data limitations of an online dating site and the data limitations of Facebook buy and sell groups are similar. While we are able to observe both implicit and explicit signs of shopper interest in an item and whether or not messaging occurs between a shopper and seller, we are unable to observe the offline outcome of interest (in our case, a shopper and seller successfully completing a transaction). Bapna et al. (2016) validate the use of the double interact by noting that it is an industry standard for online dating firms, and point out that the mean and median length of double interact conversations in their dataset agree with data collected by Hitsch et al. (2010), who parsed the text of messages sent on an online dating site to determine at which point users exchanged offline contact information or agreed to meet up offline. Another benefit of using double interacts rather than the marked as sold (or deleted) indicator is that we are better able to differentiate varying levels of demand across items, as many shoppers may be interested in the same item.

Although the marked as sold label does not provide a reliable indication of whether an item has been sold, we do expect it to be correlated with an item being sold. Thus, if we see a positive correlation between the number of double interacts an item receives and the likelihood that it is marked as sold, we have evidence that the number of double interacts is a reasonable outcome metric. As noted previously, some buy and sell groups encourage shoppers to delete items when they are sold. Thus, we conduct the following analysis using two definitions: the first only considers an item being marked as sold, the second considers an item being marked as sold or deleted. Figure 2 shows the distribution of double interact lengths across a secondary dataset consisting of aggregated and de-identified Facebook buy and sell group activity between May 28, 2016 to June 26, 2016. Note that the minimum length of a double interact in the plot is 3 messages because of the double interact definition. The mean number of messages sent in a double interact is 33.04, while the median is 14. Figure 3 shows the likelihood that an item will be marked as sold (or deleted) within

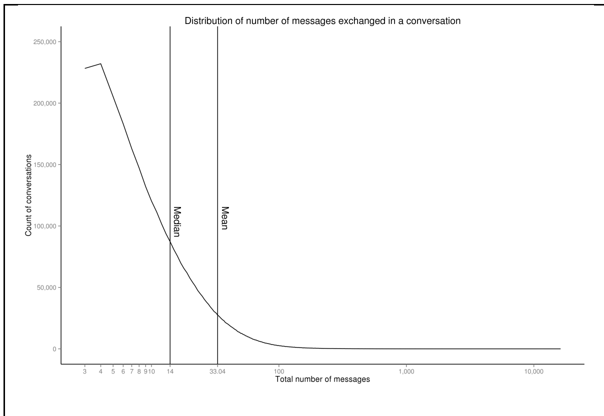

Figure 2. The distribution of the length of double interact conversations. The mean conversation length conditional on double interact is 33.04 messages, and the median is 14 messages. This figure includes all double interact conversations occurring in buy and sell groups between May 28, 2016 and June 26, 2016.

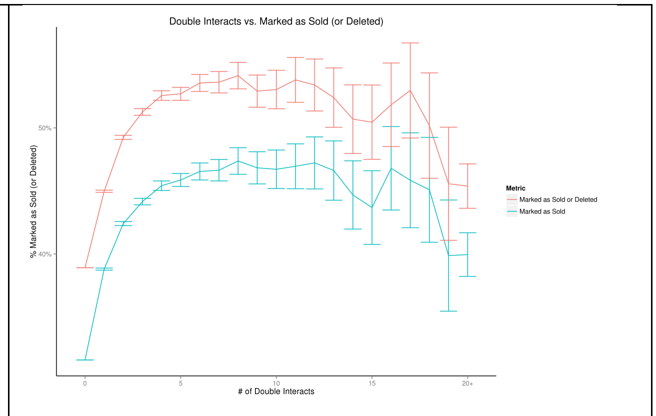

Figure 3. The likelihood that an item is marked as sold or marked as sold or deleted within 14 days of being posted as a function of how many double interacts it receives within its first 3 days. This figure includes all items posted to all buy and sell groups between May 28, 2016 and June 26, 2016.

14 days of being posted as a function of the number of double interacts it receives in its first three days on Facebook during the same period. For both outcomes, there is a positive correlation between the number of double interacts and the likelihood of being marked as sold or deleted, although this likelihood does plateau after about 8 double interacts.

Table 3 contains the coefficients obtained by performing an inverse-variance weighted least squares regression of the percentage of items either marked or sold as deleted on the number of double interacts an item received,

$$pct_{mas/del} = \alpha + \beta DI + \varepsilon \quad (1)$$

Whether the outcome variable is percent of items marked as sold or the percent of items marked as sold or deleted, the coefficient on # of double interacts is positive and statistically significant (p = 0.003 and p = 0.002, respectively), suggesting that double interacts are in fact correlated with transaction events. Having established the double interacts are a reasonable proxy for two-sided interest in transacting, we can now focus on the relationship between the number of double interacts a given item receives, the network structure of the group in which the item is being sold, and the network position of the seller who is selling that item. We use normalized degree centrality (Freeman 1978),

$$DC_i = \frac{d_i}{|G|-1} \quad (2)$$

as a measure of the seller i's centrality in the network G. d_i indicates seller i's degree, and $|G|$ represents the number of members in group G. One common critique of degree centrality is that it does not capture a given node's location in the network, just the number of ties it has. However, many other network centrality measures (e.g., betweenness centrality or eigenvector centrality) rely on networks with one connected component. Many of the groups in our sample contain 2 or more components, making degree centrality a natural choice.

To measure the causal effect of network structure and a seller's network attributes on the number of double interacts a given item receives, we would ideally like to estimate a model of the form

$$DI_{ij} = \alpha + \beta DC_{ij} + \delta\rho_j + \gamma\zeta_j + \xi X_i + \upsilon_{ij} + \varepsilon_{ij}, \quad (3)$$

where DI_{ij} is the number of double interacts item i receives in group j, α is a constant, DC_{ij} is the degree centrality of seller i in group j, ρ_j is the density of group j, ζ_j is a vector of group-level covariates (e.g., number of members, privacy setting, etc.), X_i is a vector of seller- and item-level covariates (e.g., seller age, item

Table 4. Regression results for both the OLS and OLS with fixed effects (commerce interactions graph)		
	Number of double interacts (3 messages)	
	OLS (1)	OLS w/ F.E. (2)
Seller degree centrality: $3\times10^{-5} - 1.8\times10^{-4}$	0.005** (0.002)	0.002 (0.002)
Seller degree centrality: $1.8\times10^{-4} - 4.9\times10^{-4}$	0.010*** (0.002)	0.015*** (0.002)
Seller degree centrality: $4.9\times10^{-4} - 1.2\times10^{-3}$	0.012*** (0.002)	0.030*** (0.002)
Seller degree centrality: $1.2\times10^{-3} - 2.8\times10^{-3}$	0.021*** (0.002)	0.054*** (0.003)
Seller degree centrality: $2.8\times10^{-3} - 7.4\times10^{-3}$	0.039*** (0.002)	0.081*** (0.003)
Seller degree centrality: $7.4\times10^{-3} - 7.5\times10^{-2}$	0.136*** (0.004)	0.156*** (0.004)
Group density: $2\times10^{-5} - 3\times10^{-5}$	0.020*** (0.002)	0.001 (0.002)
Group density: $3\times10^{-5} - 5\times10^{-5}$	0.037*** (0.003)	0.009*** (0.003)
Group density: $5\times10^{-5} - 7\times10^{-5}$	0.054*** (0.003)	0.017*** (0.003)
Group density: $7\times10^{-5} - 1\times10^{-4}$	0.072*** (0.004)	0.019*** (0.003)
Group density: $1\times10^{-4} - 1.4\times10^{-4}$	0.102*** (0.004)	0.039*** (0.004)
Group density: $1.4\times10^{-4} - 2\times10^{-4}$	0.118*** (0.005)	0.043*** (0.004)
Group density: $2\times10^{-4} - 3.1\times10^{-4}$	0.130*** (0.005)	0.047*** (0.005)
Group density: $3.1\times10^{-4} - 5.5\times10^{-4}$	0.145*** (0.006)	0.054*** (0.006)
Group density: $5.5\times10^{-4} - 6\times10^{-1}$	0.167*** (0.008)	0.061*** (0.007)
Constant	-0.090 (0.064)	
Observations	1,651,417	1,651,447
R^2	0.041	0.438
Product- and seller-level controls	YES	NO
Group-level controls	YES	YES
Date posted controls	YES	YES
Robust standard errors in parentheses *** p<0.01, **p<0.05, *p<0.1		

Table 4. Results from estimating the models in equations (5) and (6). Network statistics are calculated on the commerce interaction graph.

category, etc.), υ_{ij} is an unobserved idiosyncratic term which represents how well-suited item *i* is to group *j* (e.g., a beanbag chair might sell well in a college buy and sell group), and ε_{ij} is the residual.

Unfortunately, estimating this model accurately given a purely observational dataset is difficult. Particularly in settings like Facebook buy and sell groups, where there is a large amount of item-level heterogeneity, it may be impossible to control for all relevant item-level attributes. Furthermore, network formation may be endogenous, making it difficult to cleanly identify the causal effect of network structure. Our empirical strategy is to focus on items that are cross-posted to many groups, allowing us to estimate a model with item-level fixed effects. This allows us to control for both observed and unobserved item characteristics. Furthermore, we observe the same seller participate in multiple different buy and sell groups, in which they have different degree centralities. This allows us to control for any endogenous relationship between

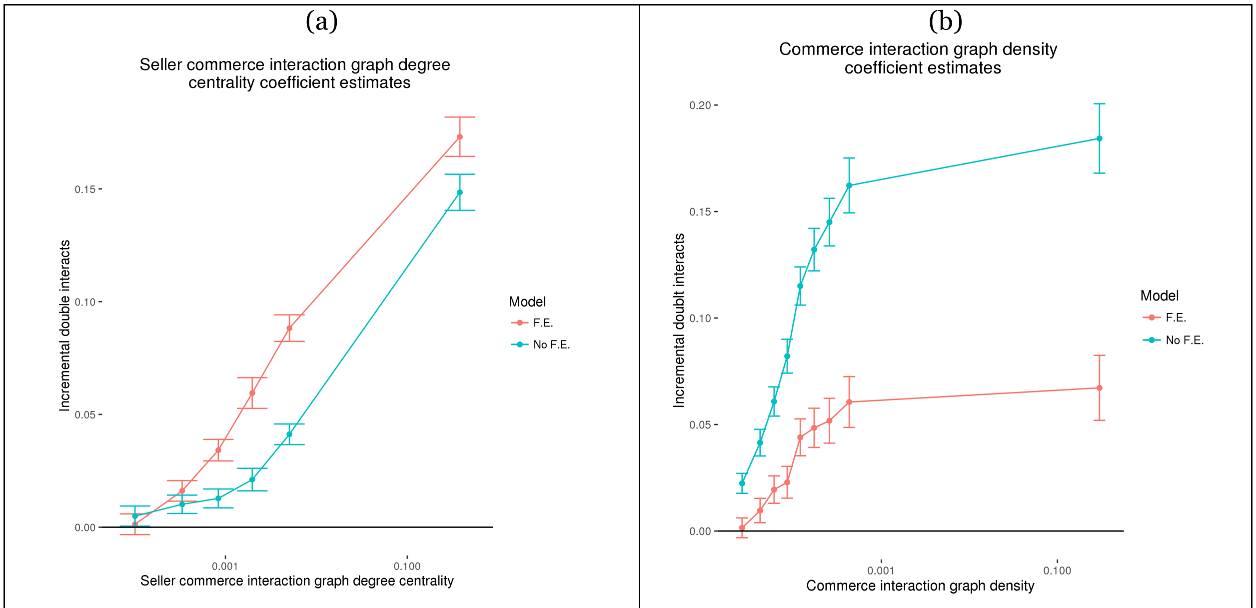

Figure 4. Estimated coefficients, along with 95% confidence intervals, for (a) seller commerce interaction graph degree centrality and (b) commerce interaction graph density. Outcome variable is the number of double interacts the item receives.

network position and observed or unobserved seller characteristics (e.g., more gregarious sellers may be more likely to be high degree across multiple buy and sell groups).

This empirical strategy has some precedent in both the sociology and economics literatures. Burt studies the degree to which role-specific network structure (rather than personality-specific network structure) influences achievement by taking advantage of variation in the network structure across roles for players who have multiple avatars in the MMORPG Everquest 2 (Burt 2012). Einav et al. (2015) measure the effect of different auction starting prices, auction reserve prices, and shipping fees by identifying eBay sellers who simultaneously auction off many copies of the exact same item with different auction parameter choices. With this strategy, a model we might estimate is instead

$$DI_{ij} = \alpha_i + \beta DC_{ij} + \delta\rho_j + \gamma\zeta_j + \varepsilon_{ij}. \quad (4)$$

Finally, we would like to capture any non-linear effects in both seller degree centrality and group density, since this study focuses on trust that emerges out of social structure. To do so, we split both seller degree centrality and group density into quantiles, and assign each item a dummy variable corresponding to the seller's degree centrality and the group's density. This modification produces the model that we *do* estimate,

$$DI_{ij} = \alpha_i + \sum_{q_{DC}} \beta_{q_{DC}}\, \delta\left(DC_{ij} \in q_{DC}\right) + \delta \sum_{q_\rho} \beta_{q_\rho}\, \delta\left(\rho_j \in q_\rho\right) + \gamma\zeta_j + \varepsilon_{ij}. \quad (5)$$

We cluster errors at the item-, seller- and group-level. Because our dataset has 299,179 unique items, the right-hand side of our model contains many item-level fixed effects. Considering this, we estimate our model using an algorithm introduced in Gaure (2013), which estimates linear models with multiple high-dimensional categorical variables.

To quantify the benefit of this approach, we also estimate an OLS model without fixed effects in which we control for as many item- and seller-level covariates as possible:

$$DI_{ij} = \alpha + \sum_{q_{DC}} \beta_{q_{DC}}\, \delta\left(DC_{ij} \in q_{DC}\right) + \delta \sum_{q_\rho} \beta_{q_\rho}\, \delta\left(\rho_j \in q_\rho\right) + \gamma\zeta_j + \xi X_i + \varepsilon_{ij}. \quad (6)$$

To understand whether the friendship graph, the commerce activity graph, or both are important for generating trust, we estimate the models details in equations (5) and (6) using network statistics calculated on both graphs. As a robustness check on our definition of double interacts, we also estimate equations (5) and (6) for different definitions of the double interact metric in which a shopper and seller must have

Table 5. Regression results for both the OLS and OLS with fixed effects (Facebook friendship graph)		
	Number of double interacts (3 messages)	
	OLS (1)	OLS w/ F.E. (2)
Seller degree centrality: $6\times10^{-5} - 2.1\times10^{-4}$	0.003 (0.003)	-0.005* (0.003)
Seller degree centrality: $2.1\times10^{-4} - 4.2\times10^{-4}$	0.036*** (0.003)	0.023*** (0.004)
Seller degree centrality: $4.2\times10^{-4} - 7.4\times10^{-4}$	0.064*** (0.003)	0.053*** (0.003)
Seller degree centrality: $7.4\times10^{-4} - 1.2\times10^{-3}$	0.084*** (0.003)	0.074*** (0.004)
Seller degree centrality: $1.2\times10^{-3} - 2.1\times10^{-3}$	0.105*** (0.003)	0.099*** (0.004)
Seller degree centrality: $2.1\times10^{-3} - 3.5\times10^{-3}$	0.129*** (0.003)	0.125*** (0.004)
Seller degree centrality: $3.5\times10^{-3} - 6.4\times10^{-3}$	0.155*** (0.003	0.151*** (0.004)
Seller degree centrality: $6.4\times10^{-3} - 1.5\times10^{-2}$	0.191*** (0.004)	0.185*** (0.005)
Seller degree centrality: $1.5\times10^{-2} - 1\times10^{0}$	0.250*** (0.004)	0.230*** (0.005)
Group density: $4\times10^{-4} - 6.8\times10^{-4}$	0.020*** (0.005)	0.006 (0.005)
Group density: $6.8\times10^{-4} - 1\times10^{-3}$	0.024*** (0.005)	0.003 (0.005)
Group density: $1\times10^{-3} - 1.4\times10^{-3}$	0.028*** (0.005)	0.007 (0.005)
Group density: $1.4\times10^{-3} - 2\times10^{-3}$	0.028*** (0.005)	0.005 (0.005)
Group density: $2\times10^{-3} - 2.8\times10^{-3}$	0.032*** (0.005)	0.007 (0.005)
Group density: $2.8\times10^{-3} - 4.1\times10^{-3}$	0.033*** (0.005)	0.005 (0.005)
Group density: $4.1\times10^{-3} - 6.2\times10^{-3}$	0.038*** (0.005)	0.006 (0.005)
Group density: $6.2\times10^{-3} - 1.1\times10^{-2}$	0.042*** (0.006)	0.006 (0.006)
Group density: $1.1\times10^{-2} - 9\times10^{-2}$	0.043*** (0.007)	0.005 (0.007)
Constant	-0.927*** (0.083)	
Observations	1,651,417	1,651,447
R^2	0.042	0.445
Product- and seller-level controls	YES	NO
Group-level controls	YES	YES
Date posted controls	YES	YES
Robust standard errors in parentheses *** p<0.01, **p<0.05, *p<0.1		

Table 5. Results from estimating the models in equations (5) and (6). Network statistics are calculated on the Facebook friendship graph.

exchanged either 3, 4, 5, or 7 messages. Bapna et al. (2012) perform a similar check when using double interacts as an outcome variable.

In addition to group-level network structure and seller network position, we are also interested in the attributes of shopper-seller dyads. Although we are not able to make any causal claims, we observe the bivariate distributions of shopper degree centrality and seller degree centrality for dyads who begin interacting, but do not generate a double interact and dyads who begin interacting and *do* generate a double interact. To compare these distributions, we use a statistical test introduced by Duong et al. (2012), which

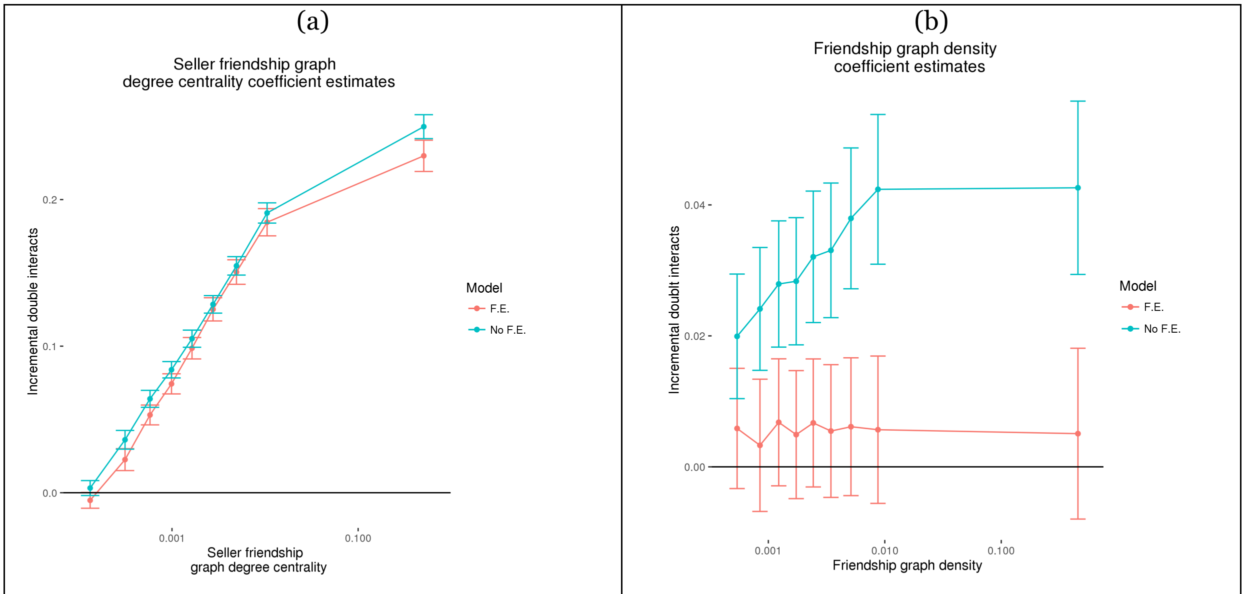

Figure 5. Estimated coefficients, along with 95% confidence intervals, for (a) seller Facebook friendship graph degree centrality and (b) Facebook friendship graph density. Outcome variable is the number of double interacts the item receives.

uses a kernel-based estimator to test the null hypothesis that the two distributions are the same (i.e., $f_1 = f_2$) by comparing intrasample pairwise differences and intersample pairwise differences.

Results

Table 4 contains coefficient estimates obtained by estimating equation (5) and equation (6) using our primary dataset, which is sampled at the item-level, with the 3-message double interact as our outcome variable. Network-level statistics are calculated using the commerce-related interaction graph. Column 1 provides estimates obtained using the OLS model *without* hashed ID-level fixed effects, whereas column 2 provides estimates obtained using the fixed effects. Table 5 contains coefficients obtained estimating the same models on the same dataset, but with network-level statistics calculated from the Facebook friendship graph. Again, column 1 provides estimates obtained using the OLS model *without* hashed ID-level fixed effects, whereas column 2 provides estimates obtained using fixed effects. Figure 4 shows estimates of the incremental number of double interacts generated as sellers become more central in the commerce interaction graph (a) and as the commerce interaction graph becomes denser (b). Figure 5 shows estimates of the incremental number of double interacts generated as sellers become more central in the friendship graph (a) and as the friendship graph becomes denser (b). Both figures display estimates from the model that incorporates item-level fixed effects (red) and the model that does not incorporate item-level fixed effects (blue). Recall that in our sample, the average number of double interacts that an item receives is 0.171, so on average an increase of 0.01 double interacts represents a 5.8% increase in the amount of two-sided interest in transacting.

We find that controlling for group-level observables, the number of double interacts that an item receives increases as the seller becomes more central in either the commerce-related activity graph (Figure 4a and Table 4) or the Facebook friendship graph (Figure 5a and Table 5). This result is robust to the inclusion or exclusion of item-level fixed effects, suggesting that the impact of unobserved seller- or item-level attributes on the number of double interacts a given item receives is not substantial. Note that the inclusion of item-level fixed effects allows us to focus on marginal effects from variation in centrality and density across groups, controlling for most of the variance explained by the social popularity of the seller.

OLS without item-level fixed effects predicts that the number of double interacts an item receives increases as a buy and sell commerce-related activity graph becomes denser (Figure 4b and Table 4) and as its Facebook friendship graph becomes denser (Figure 5b and Table 5). However, inclusion of item-level fixed effects substantially reduces the effect of increased commerce interaction graph density and renders the

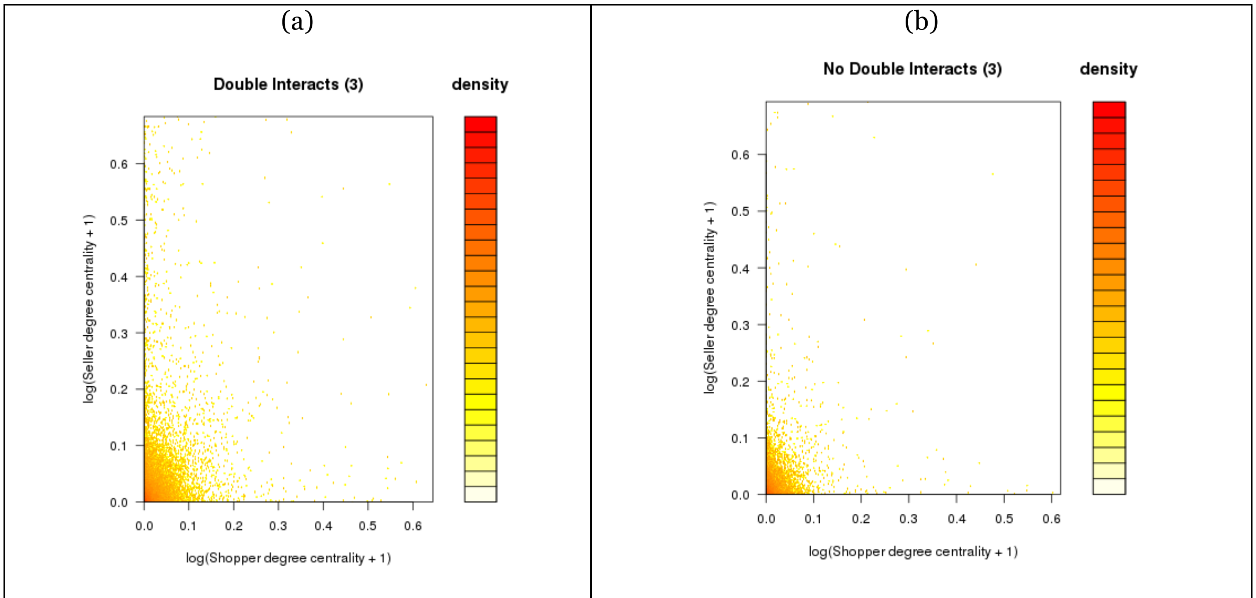

Figure 6. Bivariate distribution of shopper and seller degree centralities in cases where (a) a message thread resulted in a double interact and (b) a message thread did not result in a double interact. Degree centralities are calculated on the Facebook friendship graph.

benefit of friendship graph density statistically insignificant. This suggests that group level friendship dynamics may be may be less important that group level commercial interaction dynamics in fostering trust between shoppers and sellers. We note however that omitted group-level characteristics that may bias our estimates of group density coefficients in these analyses.

Using the statistical test introduced by Duong et al. (2012), we also compare the bivariate distributions of shopper and seller degree centrality for conversations that do and do not result in a double interact. We perform this comparison using both degree centrality in the Facebook friendship graph and the commerce interaction graph. For both the Facebook friendship graph (z = 32.48; p < 0.001) and the commerce interaction graph (z = 579.94; p < 0.001), the difference between the two distributions is statistically significant. Figure 6 shows the smoothed bivariate distribution of shopper and seller degree centralities in the friendship graph for conversations that (a) did or (b) did not result in a double interact. Message threads that resulted in a double interact tended to feature sellers with higher degree centrality. Figure 7 shows the smoothed bivariate distribution of shopper and seller degree centralities in the commerce interaction graph for message threads that (a) did or (b) did not result in a double interact. Conversations that result in a double interact tended to have both shoppers and sellers with higher degree centrality.

Discussion

Our empirical results suggest that social network features and network centrality in particular are important in generating trust in informal online marketplaces. Our results suggest that increases in the degree centrality of an item's seller, either in the Facebook friendship graph or in the commerce interaction graph, can lead to significant increases in the amount of two-sided interest a given item will receive. Interestingly, the results from our fixed effects model specification suggest that while denser commerce interaction graphs predict more double interacts for a given item, any analogous effect with respect to the Facebook friendship graph vanishes after including item-level fixed effects. The first result is somewhat intuitive – for a given buy and sell group to have a dense commerce interaction graph, the group must have been recently active, which makes it unsurprising that shoppers and sellers remain engaged. On the other hand, the fact that increased Facebook friendship graph density does not increase trust is surprising, and merits more attention in a future study. Nonetheless, one aim of this study was to determine which of these two networks was relevant for generating trust in informal marketplaces, and we have found that both networks provide useful signals for predicting the amount of two-sided interest an item will receive. Although it is beyond the scope of this paper, it is worth considering how these two networks are related – if the Facebook

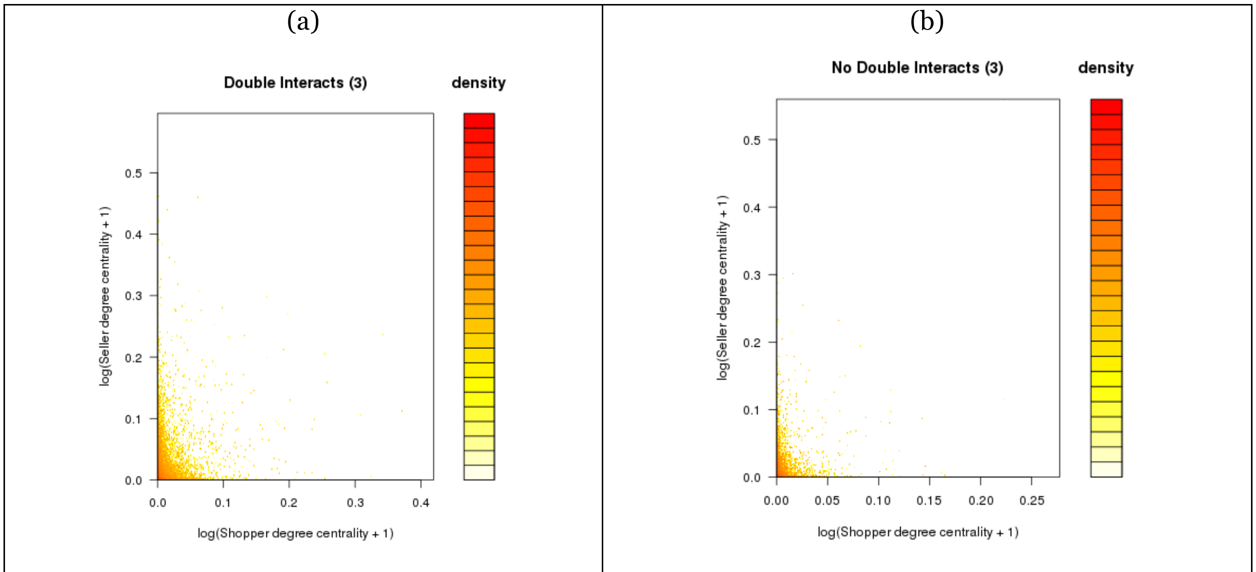

Figure 7. Bivariate distribution of shopper and seller degree centralities in cases where (a) a message thread resulted in a double interact and (b) a message thread did not result in a double interact. Degree centralities are calculated on the commerce interaction graph.

friendship network does in fact generate trust, the commerce interaction graph that emerges over time should be related to the Facebook friendship network.

We were also able to compare the bivariate distributions of shopper and seller degree centrality in cases where conversations did result in double interacts and in cases where conversation did not result in double interacts. We find that conversations that result in double interacts tend to have sellers who are more central in the Facebook friendship network, and both shoppers and sellers who are more central in the commerce interaction graph. Although our empirical strategy exploits cross-posting behavior on the part of sellers, this result suggests that shopper centrality may also be important for determining trust.

This work has significant managerial implications for those designing online marketplaces. Both the academic literature and industry practice suggest that centralized reputation systems are the most common mechanism for generating trust in online settings. However, designing an effective reputation system is difficult; ill-conceived reputation systems are susceptible to distortions, such as sorting, feedback reciprocity, and herding. Furthermore, a reputation system's success is contingent on buyer/seller participation and a marketplace composed of repeat transactors. Our results suggest that an alternative path, which generates trust by leveraging pre-existing social structure, offers an appealing alternative to the status quo. Networked social signals generate trust in online markets without relying on user-generated feedback and do not display as much sensitivity to strategic or irrational user behavior. Exploiting networked social signals is natural for Facebook buy and sell groups, which are embedded in a vast social network. However, even standalone marketplaces can employ social structure-oriented trust-building mechanisms by taking advantage of the APIs offered by many large social networks.

This study represents the first investigation of network-based trust in massive digital marketplaces. It contributes to a rich theoretical and empirical literature that contains many promising results that have not yet coalesced into a coherent narrative. We quantify trust by measuring the number of double interacts an item receives within 14 days of being posted in a Facebook buy and sell group. We find that increased seller centrality in the network leads to greater trust levels. Furthermore, we find weak evidence that increased network density increases trust. Our results provide evidence that the social network in which market is embedded and the network composed of past commerce-related interactions both play a role in generating trust. Finally, our findings indicate that shopper centrality may also be important for generating trust. Not only do these results suggest that network structure can produce trust in the absence of a formal reputation system; they imply that network-based trust mechanisms may offer an appealing alternative to review-based reputation systems, which can mitigate moral hazard and adverse selections issues in a marketplace. Future work might focus on more cleanly identifying the role of network structure in massive digital marketplaces, either by exogenously modifying the network structure itself or by modifying the salience of network-based trust signals in a marketplace's user interface.

Acknowledgements

We are grateful to Alex Dow and Justin Hepler for helpful comments and discussion.

References

Ali, S.N., and Miller, D.A. 2013. "Enforcing Cooperation in Networked Societies," *Working Paper*.

Bapna, R., Ramaprasad, J., Shmueli, G., and Umyarov, A. 2016. "One-Way Mirrors in Online Dating: A Randomized Field Experiment.," *Management Science* (62:11), pp. 3100-3122 (doi: 10.1287/mnsc.2015.2301).

Burt, R.S. 2012. "Network-Related Personality and the Agency Question: Multirole Evidence from a Virtual World.," *American Journal of Sociology* (118:3), pp. 543-591.

Burt, R.S., and Knez, M. 1995. "Kinds of Third-Party Effects on Trust.," *Rationality and Society* (7:3), pp. 255-292.

Burt, R.S., and Knez, M. 1996. "Trust and Third Party Gossip," in *Trust in organizations: Frontiers of theory and research*, Kramer, R.M. and Tyler, T.R. (eds)., Thousand Oaks, CA: Sage, pp. 68-69.

Buskens, V. 1998. "The Social Structure of Trust.," *Social Networks* (20:3), pp. 265-289.

Chndrasekhar, A.G., and Breza, E. 2016. "Social Networks, Reputation and Commitment: Evidence from a Savings Monitors Experiment," *Working Paper*.

Chandrasekhar, A.G., Kinnan, C., Larreguy, H. 2014. "Social Networks as Contract Enforcement: Evidence from a Lab Experiment in The Field," *NBER Working Paper* (No. w20259).

Cripps, M.W., Mailath, G.J., and Samuelson, L. "Imperfect monitoring and imperfect reputations.," *Econometrica* (72:2), pp. 407-432.

Dasgupta, P. 1988. "Trust as a commodity," in *Trust: Making and breaking cooperative relations*, Gambetta, D. (ed.), Oxford, UK: Basil Blackwell, pp. 49-72.

Dellarocas, C. 2003. "The digitization of word of mouth: Promise and challenges of online feedback mechanisms.," *Management Science* (49:10), pp. 1407-1424.

Dellarocas, C. 2005. "Reputation mechanism design in online trading environments with pure moral hazard.," *Information Systems Research* (16:2), pp. 209-230.

Dellarocas, C., and Wood, C.A. 2008. "The sound of silence in online feedback: Estimating trading risks in the presence of reporting bias.," *Management Science* (54:3), pp. 460-476.

Donath, J. 2007. "Signals in Social Supernets.," *Journal of Computer-Mediated Communication* (13:1), pp. 231-251 (doi: 10.1111/j.1083-6101.2007.00394.x).

Donath, J., and Boyd, D. 2004. "Public displays of connection.," *bt technology Journal* (22:4), pp. 71-82.

Duong, T., Goud, B., and Schauer, K. 2012. "Closed-form density-based framework for automatic detection of cellular morphology changes.," *Proceedings of the National Academy of Sciences of the United States of America* (109:22), pp. 8382-8387.

Einav, L., Kuchler, T., Levin, J., and Sundaresan, N. 2015. "Assessing Sale Strategies in Online Markets using Matched Listings.," *American Economic Journal: Microeconomics* (7:3), pp. 215-247 (doi: 10.1257/mic.20130046).

Fradkin, A., Grewal, E., and Holtz, D. 2017. "The Determinants of Online Review Informativeness: Evidence from Field Experiments on Airbnb.," *Working Paper*.

Fainmesser, I. 2012. "Community Structure and Market Outcomes: A Repeated Games in Networks Approach," *American Economic Journal: Microeconomics* (4:1), pp. 32-69 (doi: 10.1257/mic.4.1.32)

Freeman, L.C., "Centrality in social networks conceptual clarification," *Social Networks* (1:3), pp. 215-239.

Gallo, E., and Yan, C. 2015. "The Effects of Reputational and Social Knowledge on Cooperation.," *Proceedings of the National Academy of Sciences of the United States of America* (112:12), pp. 3647-3652 (doi: 10.1073/pnas.1415883112).

Gaure, S. 2013. "OLS With Multiple High Dimensional Category Variables.," *Computational Statistics & Data Analysis* (66), pp. 8-18 (doi: 10.1016/j.csda.2013.03.024)

Geertz, C. 1978. "The Bazaar Economy: Information and Search in Peasant Marketing.," *The American Economic Review* (68:2), pp. 28-32.

Glaeser, E.L., Laibson, D.I., Scheinkman, J.A., and Soutter, C.L. 2000. "Measuring Trust," *The Quarterly Journal of Economics* (115:3), pp. 811-846 (doi: 10.1162/003355300554926).

Granovetter, M. 1985. "Economic Action and Social Structure: The Problem of Embeddedness.," *American Journal of Sociology* (91:3), pp. 481-510.

Hitsch, G.J., Hortasçu, A., and Ariely, D. 2010. "Matching and Sorting in Online Dating.," *American Economic Review* (100:1), pp. 130-163 (doi: 10.1257/aer.100.1.130)

Karlan, D., Mobius, M., Rosenblat, T., and Szeidl, A. 2009. "Trust and Social Collateral," *The Quarterly Journal of Economics* (124:3), pp. 1307-1361.

Kinateder, M. 2008. "Repeated Games Played in a Network," *Unpublished*.

King, M. "Whom Can You Trust? Reputation and Cooperation in Networks," *Working Paper*.

Kreps, D.M. 1990. *A Course in Microeconomic Theory*, Princeton, NJ: Princeton University Press.

Kreps, D.M. 1996. "Corporate Culture and Economic Theory," in *Firms, Organizations and Contracts: A Reader in Industrial Organization*, Buckley, P.J., and Michie, J. (eds.), Oxford, UK: Oxford University Press, pp. 221-275.

Ku, M. 2016. "Introducing Marketplace: Buy and Sell with Your Local Community", *Facebook*, (available at https://newsroom.fb.com/news/2016/10/introducing-marketplace-buy-and-sell-with-your-local-community/; retrieved April 7, 2017).

Lahno, B. 1995. "Trust and Strategic Rationality.," *Rationality and Society* (7:4), pp. 442-464.

Lahno, B. 1995. "Trust, Reputation and Exit in Exchange Relationships.," *Journal of Conflict Resolution* (39:3), pp. 395-510.

Li, S., Srinivasan, K., and Sun, B. 2009. "Internet Auction Features as Quality Signals.," *Journal of Marketing* (73:1) pp. 75-92.

Muchnik, L., Aral, S., and Taylor, S.J. 2013. "Social Influence bias: A randomized Experiment," *Science* (341:6146) pp. 647-651.

Rand, D.G., Arbesman, S., and Christakis, N.A. 2011. "Dynamic social networks promote cooperation in experiments with humans.," *Proceedings of the National Academy of Sciences of the United States of America* (108:48), pp. 19193-19198 (doi: 10.1073/pnas.1108243108).

Raub, W., and Weesie, J. 1990. "Reputation and Efficiency in Social Interactions: An Example of Network Effects," *American Journal of Sociology* (96:3), pp. 626-654.

Tadelis, S. 2016. "Reputation and feedback systems in online platform markets," *Annual Review of Economics* (8), pp. 321-340.

Uzzi, B. 1999. "Embeddedness in the Making of Financial Capital: How Social Relations and Networks Benefit Firms Seeking Financing," *American Sociological Review* (64:4), pp. 481-505.

Van Der Heide, B., Johnson, B.K., and Vang, M.H. 2013. "The Effects of Product Photographs and Reputation Systems on Consumer Behavior and Product Cost on eBay.," *Computers in Human Behavior* (29:3), pp. 570-576 (doi: 10.1016/j.chb.2012.11.002).

Weick, K.E. 1979. "Cognitive processes in organizations.," *Research in Organizational Behavior* (1:1), pp. 41-74.

"What are the privacy settings for groups?" (n.d.). *Facebook Help Center,* Facebook, Inc. (available at https://www.facebook.com/help/220336891238465; retrieved April 26, 2017).

Weisbuch, G., Kirman, A., and Herreiner, D. 2000. "Market Organisation and Trading Relationships," *The Economic Journal* (110:April), pp. 411-436.