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Do Noisy Customer Reviews Discourage Platform Sellers? Empirical and Textual Analysis of an Online Solar Marketplace with Deep Learning Model BERT

(Authors' names blinded for peer review)

Problem definition: What is your research problem? Academic / Practical Relevance: How is your research problem relevant to the OM research / practice community? Methodology: What is the underlying research method? Results: What are your key findings? Managerial Implications: How can academics / managers / decision makers benefit from your study?

Electricity end-users have been increasingly adopting rooftop solar panels to generate their own electricity. In this paper, we collaborated with an online solar marketplace that enables rooftop solar panel adoption by connecting customers and panel installers, and including customer reviews about installers. Considering both customer ratings and text reviews, we empirically analyze the impact of customer reviews on a sellers activity intensity and matchings on the platform. Our results indicate that the average review of a seller or its competitors do not have a consistent significant impact on the sellers activity level on the platform. However, we find that the dispersion of the sellers own reviews and the dispersion of competitors reviews both have a significant impact on the sellers activity level. Our results show that structurally, both of these dispersion measures affect the activity level of a seller in the same way. Specifically, we identify an inverted-U relationship between the sellers activity level and each of these dispersion measures. That is, an increase in either dispersion measure increases the seller activity on the platform if and only if the dispersion is low. When the dispersion is high, an increase in either dispersion measure lowers the seller activity on the platform. We also identify an inverted-U relationship between matching and the review dispersion at a local market level on the platform. Our analysis uses the advanced natural language processing model recently developed and implemented by Google AI, a state-of-the-art clustering algorithm and traditional econometrics methods.

Key words: online marketplace, customer reviews, text analysis

1. Introduction

Online marketplaces are reshaping numerous sectors, ranging from retail to clean technology. In 2019, gross merchandise sales of top online marketplaces across the globe exceeded the astonishing

$2 trillion milestone, with a 22% growth (Ali 2020). Online customer reviews, which are evaluations of a product or service by former users, are vital for online marketplaces because they are essential for customers' shopping experience. According to the Spielger Research Center (2017), nearly 95% of customers read online reviews before making a purchase. Customers pay attention to online reviews, and online reviews can significantly influence customer perception (Askalidis and Malthouse 2016, Park et al. 2007). Thus, understanding the impact of customer reviews is of paramount importance to an online marketplace operator and its sellers. This is the main focus of our work.

Online reviews can be in a rating or text format. Ratings are typically measured on a 1 to 5 scale, with 1 being poor and 5 being excellent, while text reviews include customer sentiments about the product or service in words. There is a growing interest in studying customer ratings in various contexts. The vast majority of this literature investigates how *average* customer ratings impact a *single* firm's sales. Focusing on books and movies, several studies conclude that an improvement in a product's average rating increases its sales (e.g., Chintagunta et al. (2010) and Chevalier and Mayzlin (2006)). Regarding services, Luca (2016) finds that the average rating of a restaurant has a positive impact on its revenue. There are also a few studies that show that the average ratings of a product may not have a significant impact on its sales (e.g., Duan et al. (2008)). In practice, customer ratings typically vary; it is rare to find a product or service whose ratings are all the same. Despite this, surprisingly, the implications of rating dispersion are severely understudied in the literature (see Section 1.2). Our paper contributes to the literature by studying how online review *dispersion* impacts a key behavior of online marketplace sellers and the online marketplace that consists of multiple sellers. To the best of our knowledge, there is no prior work that investigates this topic.

Our paper considers an online solar marketplace as a context. Solar energy is booming in the world, with a dazzling 34% growth worldwide in 2017 (IEA 2018). In the U.S., the annual generation from solar photovoltaics (PV) increased by nearly a factor of 4 from 2014 to 2019, and is estimated to more than triple from 2019 to 2030 (U.S. EIA 2020b,a). A key contributor to this growth is increasing solar panel adoption by electricity end-users (e.g., residential customers). By adopting solar panels, electricity end-users generate their own electricity, reducing their reliance on electric utility companies. In the U.S., the residential solar capacity increased by a factor of 4.18 from 2014 to 2019 (U.S. EIA 2020c), and is forecasted to grow 25% per year (Weaver 2019, SEIA 2019, Pyper 2018).

Online marketplaces are transforming the rooftop solar panel adoption process across the United States. An online solar marketplace is a digital platform that connects a potential panel adopter with installers, facilitating the adoption process for electricity end-users. Customers are increasingly interested in connecting with rooftop panel installers through online marketplaces. According to a recent report about a leading online solar marketplace, such an interest doubled in 11 major states of the U.S. between 2017 to 2018 (EnergySage 2019). In this paper, we analyze a novel data set we obtained from one of the largest online solar marketplaces in the United States.

The online solar marketplace we study has two salient features. First, for every incoming customer, each installer in a certain region decides whether to serve that customer or not. The installer makes a proposal (bid) if it is willing to serve the customer. Only after the installer's proposal, the installer is listed as available for the customer. This is in contrast to online marketplaces such as Amazon where sellers do not bid for a potential customer. Second, the competition among installers is local. That is, only the installers located in a particular geographical area bid for each customer, and this geographical area is not restricted to city or town boundaries. This is different from online marketplaces such as Amazon where the competition among sellers occurs at the entire marketplace level. This difference creates a unique challenge, that is, to identify *local markets* for installers. In our study, we overcome this challenge via a state-of-the-art clustering algorithm.

Our paper considers two key metrics: the number of proposals by each installer, which represents the number of customers each installer is willing to serve on the marketplace, and the number of successful proposals - i.e., *matches* - in the marketplace. The former is relevant to the growth prospect of the online marketplace, which is an important measure for investors (**REFERENCE**). The latter metric matters as it is commonly used in the financial valuation of online marketplaces (Boris 2018, Galston 2017). Hereafter, for brevity, the number of proposals by an installer will be referred to as the installer's *activity level*.

Our analysis is centered around the following three main research questions. (i) Does the dispersion in an installer's customer reviews have a significant impact on the installer's activity level? If so, what is the direction of the impact? (ii) Does the dispersion in competitors' customer reviews have a significant impact on an installer's activity level? If so, what is the direction of the impact? (iii) How does the review dispersion impact the number of matches in the marketplace? In answering these questions, we consider both ratings and text reviews made by verified buyers. To consider these two formats, in addition to traditional econometrics methods, we employ the BERT technique, which is an advanced natural language processing model developed and implemented by Google AI in late 2019. To our knowledge, our paper is the first that employs this technique in the OM literature.

1.1. Main Findings and Contributions

Our paper makes four main contributions to the literature. First, to the best of our knowledge, there is no prior work that empirically investigates how customer reviews impact a firm's activity level (i.e., number of proposals) in an online marketplace. Our paper studies this, and shows that the dispersion in an installer's reviews has a significant and inverted U-shaped impact on its activity level in the online marketplace. Thus, a firm's noisy reviews increase the firm's activity level if and only if its review dispersion is lower than a threshold; beyond that threshold, noisy reviews hurt the firm's activity level.

Second, to our knowledge, our paper is the first that studies how the dispersion in competitor reviews impacts a firm's activity level in an online marketplace. In this context, we find that the dispersion in competitor reviews has a significant and inverted U-shaped impact on the installer's activity level. This suggests that a firm's and its competitors' review dispersions have the same structural impact on the firm's activity level in the online marketplace.

Third, to our knowledge, our paper is the first to empirically analyze how the review dispersion affects the number of matches in an online marketplace where sellers have to make a proposal to win a customer. Regarding this, we identify a significant and inverted U-shaped relationship between the number of matches and the review dispersion at a local market level. This finding has a key implication for an online marketplace operator: Having all sellers with 5 stars might not be favorable to the marketplace operator. Review dispersion up to a particular level can help an online marketplace operator in terms of number of matches.

Fourth, our paper provides a showcase for a state-of-the-art advanced clustering method (OPTICS) and a very recent advanced natural language processing model (BERT). These methods have not been used in the OM literature yet, and have the potential to facilitate research in various contexts.

1.2. Related Literature

Our paper contributes to the sustainable operations literature by examining an online marketplace that facilitates solar PV adoption. Here, we will only mention the most relevant papers that includes a data analysis. Interested readers can find an excellent review in Lee and Tang (2018). In this stream, various papers analytically study solar and wind technologies while calibrating their models with real-life data (see, e.g., Singh and Scheller-Wolf (2018), Sunar and Swaminathan (2018), Sunar and Birge (2019), and references therein). There are also several papers that empirically study green technologies. These include carbon abatement technologies (e.g., Blanco et al. (2020), Blass et al. (2014)), waste exchanges (e.g., Dhanorkar et al. (2015)) and off-grid lighting solutions (e.g., Uppari et al. (2019)). To the best of our knowledge, there is no prior work that considers customers reviews and an online solar marketplace in this literature.

Our paper also contributes to the literature on online marketplaces. Moreno and Terwiesch (2014) use a transactional data set from an intermediary for software development services. The authors establish that for a seller, a superior reputation primarily increases its likelihood of winning a business. Bimpikis et al. (2019) use data from a natural experiment in a liquidation auction on a business-to-business platform, and illustrate that the design of the online platform significantly impacts the platform's revenues. Li and Netessine (2020) analyze data from an online peer-to-peer property-rental platform, and show that the market thickness can decrease the number of transactions on the platform. To our knowledge, in this stream, there is no work that studies how review dispersion impacts a firm's activity level (i.e., number of proposals) or the number of matches in an online marketplace, which are the topics of our study.

There are a few papers that study the impact of rating variability on a firm's sales. However, there is no consensus about the impact. Clemons et al. (2006) find a positive correlation between the rating dispersion and craft beer sales to provide support for a hyper-differentiation marketing strategy in the craft beer industry. In contrast, Zhu and Zhang (2010) show that the rating variation for less popular online games has a negative impact on sales. Luo et al. (2013) find that the dispersion of brand ratings can drastically hurt the firm value while Zhang (2006) concludes that the rating variation does not play a significant role in movie openings. Our paper differs from these studies in several dimensions. First and most importantly, unlike these papers, our paper takes the perspective of a marketplace operator, and studies how review dispersion impacts a key seller action and the number of matches in the marketplace. This is in contrast to the common focus in these papers, which is to understand customer-side impact of online ratings on a single firm. Second, in our setting, the seller must prepare a proposal to win its customers. Such a setting is key to our analysis and not considered by these studies. Third, we consider an online solar marketplace, which differs from studied contexts in essential ways.

Finally, our paper is related to the relative performance feedback (RPF) literature. The vast majority of this literature studies how feedback impacts an *individual worker*'s performance. Performance is context-specific, and hence is measured in different ways. For example, in a hospital setting, Song et al. (2017) measure the physician productivity by her/his patients' median length of stay, and find that public productivity measures and sharing best practices improve the productivity of low-performing physicians. There are only a few studies that consider firm-level RPF (e.g., Delfgaauw et al. (2013)). Among those, Niewoehner III and Staats (2020) is the only one that considers feedback not tied to financial incentives (e.g., any external prize or penalty as in tournaments). Niewoehner III and Staats (2020) establish that when clinics are informed about their rankings on their flu shot growth, they exhibit last-place aversion behavior, and clinics that receive ranking information performs better than the ones that do not receive such information. Our paper differs from this literature in multiple ways. First, in these studies, providing feedback refers to disclosing an entity's relative performance of interest. However, our study is interested in firms' activity levels and number of matches in an online marketplace, and customer reviews do not provide such metrics to firms. Furthermore, we study the impact of customer review dispersion. To our knowledge, there is no prior work that empirically studies how feedback dispersion affects firms' actions and marketplace operator's performance in this stream.

1.3. Organization of the Paper

The remainder of our paper is organized as follows. Section 2 states our hypotheses and describes several mechanisms by which review dispersion may impact firms' activity levels and the number of matches in the online marketplace. Section 3 explains our data and context, and includes preliminary analysis. Section 4 quantifies the impacts of an installer's and competitors' review dispersion on its activity level in the online marketplace. Section 5 studies the relationship between the market-level review dispersion and the number of matches in the online marketplace. Section 6 employs various text-mining techniques to utilize both numerical ratings and text reviews in our analysis. Section 7 provides various robustness checks, including a dynamic panel model that addresses any endogeneity issues.

2. Hypothesis Development

Online reviews have become an integral part of brand image (Chakraborty and Bhat 2018a,b), and the dispersion in brand image can drastically hurt the firm value (Luo et al. 2013). In light of this, a firm's review dispersion can impact its marketplace activity level through different mechanisms. As a statistical fact, a larger sample of reviews results in a smaller sample variation. Thus, when an installer's review dispersion increases, the installer may be willing to serve more customers to increase the number of its reviews, thereby reducing its review dispersion and improving its brand image. Based on this, the installer may make more proposals to win more customers in the online marketplace. On the other hand, a higher review dispersion may also decrease the installer's activity level through another mechanism. A higher review dispersion may imply higher differentiation of customer taste in the market (Clemons et al. 2006). In such a market, making more proposals may impose reputational risks to the installer potentially due to picky customers or additional polarized reviews. When faced with reputational risks, firms can be more selective in their project choices (Demirag et al. 2011, Hirshleifer and Thakor 1992). Thus, as the review dispersion increases, the installer may reduce the number of its proposals to be more selective about which customer to serve in the marketplace. Alternatively, the installer might reduce the number of its proposals as it might think that a higher review dispersion may damage customer perception (Zhu and Zhang 2010), and thus it is less likely to win a customer compared to its competitors. Based on these conflicting perspectives, we have the following hypotheses:

Hypothesis 1A: *An increase in an installer's review dispersion increases its activity level in the online marketplace.*

Hypothesis 1B: *An increase in an installer's review dispersion decreases its activity level in the online marketplace.*

The dispersion in competitor reviews may also impact an installer's activity level. Similar to our earlier discussion, an increase in the dispersion of competitor reviews may be perceived as a signal of a more polarized market. Thus, when competitor reviews become more disperse, to avoid any reputational harm due to variable reviews or picky customers, the firm may be more conservative in making proposals. That would reduce the installer's activity level in the online marketplace. On the other hand, a higher dispersion in competitor review might hurt the brand image of the competitor, and may negatively impact the customers' perception about the competitors' service (Chakraborty and Bhat 2018a,b, Zhu and Zhang 2010). This may increase the installer's likelihood of winning any customer compared to its competitors if the installer makes a proposal (Demirag et al. 2011, Moreno and Terwiesch 2014). Given the higher likelihood of winning, it may be favorable for the installer to bid for more customers so as to improve its sales. In light of these, we have two competing hypotheses:

Hypothesis 2A: *An increase in the review dispersion of competitors increases the installer's activity level in the online marketplace.*

Hypothesis 2B: *An increase in the review dispersion of competitors decreases the installer's activity level in the online marketplace.*

A match, i.e., an agreement between a customer and any installer, occurs only when the customer is willing to accept an available proposal. The number of available offers is a key determinant of a customer's willingness to accept any offer. Having more options might overload the customer, and can decrease the customer's motivation to accept any offer (Scheibehenne et al. 2010, Iyengar and Lepper 2000). However, it may also increase the customer's motivation to accept an offer because in a larger set of options, the customer might be more likely to find an offer that better matches to her objective (Scheibehenne et al. 2010, Baumol and Ide 1956). Based on Hypotheses 1A, 1B, 2A and 2B, it is not clear how market-level review dispersion impacts the average number of proposals per customer. This and the discussions above suggest the following two hypotheses:

Hypothesis 3A: *An increase in the market-level review dispersion increases the number of matches in the online marketplace.*

Hypothesis 3B: *An increase in the market-level review dispersion decreases the number of matches in the online marketplace.*

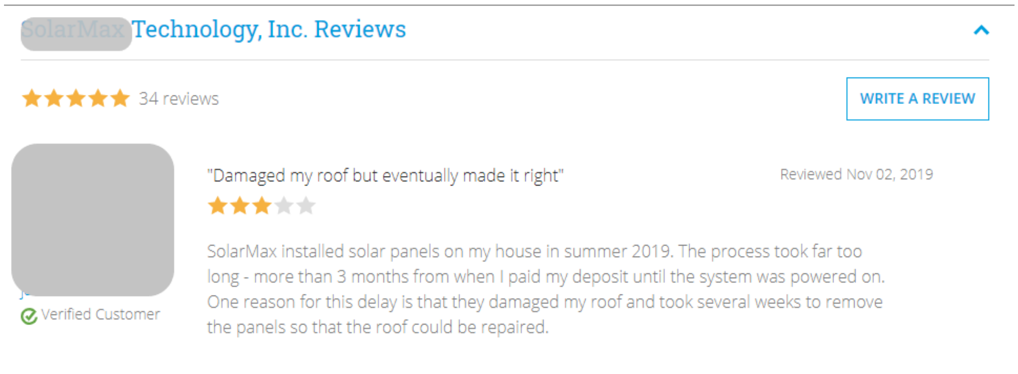

Figure 1 **A sample customer review in the marketplace.**

3. Data and Setting

For our study, we collaborated with one of the largest online solar marketplaces in the U.S., and obtained proprietary marketplace data from the company. We also complement this data set with Tracking The Sun (TTS) data set from the Lawrence Berkeley National Laboratory. TTS is a comprehensive data set on U.S. solar panel installations. Below, we will provide further details about our data and the setting of the online solar marketplace we study.

3.1. Online Solar Marketplace

The solar marketplace we study is an independent shopping website for electricity end-users (e.g., homeowners) who are interested in adopting solar panels. The marketplace operates in 33 states of the U.S., and allows solar panel installers to maintain a profile, receive information and connect with potential customers in their service areas.

The marketplace operates as follows. First, each customer visits the marketplace website and enters her information, such as the location of her property. Next, installers are informed about the customer's arrival along with her information. Each installer only serves to a particular region. If the customer's location falls into an installer's service area, the installer decides whether to make a proposal to the customer. After the customer observes installer proposals she receives, there are two possible outcomes: Either the customer agrees to work with an installer, i.e., there is a successful *match*, or the customer gives up the process, i.e., there is no matching. If the customer ends up working with the installer, she can leave a review that contains text and a rating ranging from 1 to 5 stars. The marketplace verifies customers who leave reviews. Hence, reviews are considered as authentic and not manipulated. Figure 1 provides an example of how customer reviews are displayed in the online marketplace.

As a result, the key decision for each installer in the marketplace is whether to make a proposal for a potential customer or not. In light of this, we study how the dispersion in customer reviews impacts (i) an installer's *activity level* in the marketplace, which is a logarithmic transformation of

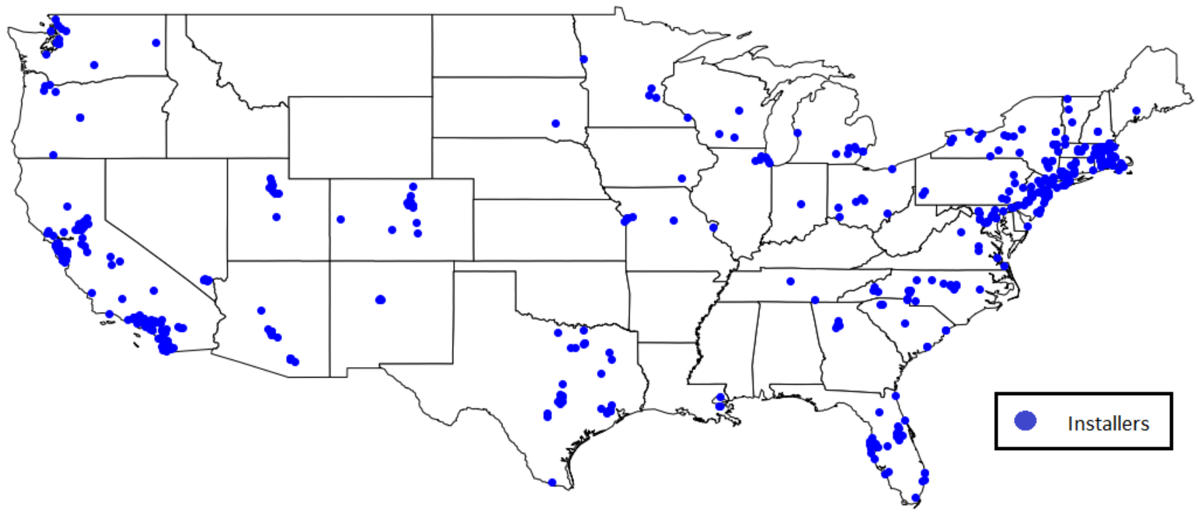

Figure 2 **Installers in our data set**

the number of proposals the installer makes in a month, and (ii) the number of monthly matches in the marketplace. For the reasons explained earlier, both of these are important metrics to the marketplace operator.

To investigate (i) and (ii), we obtained rich panel data from the online solar marketplace. Our data set contains the data of the marketplace's all vetted installers across the U.S. and full record of their customer reviews from January 2013, which is the beginning of the marketplace, up to April 2018. There are 416 installers in the marketplace, and we have each installer's monthly activities, i.e., the number of proposals made and the number of proposals won by each installer in every month, during the aforementioned time frame. Each review has a rating, text content, time stamp, and the installer ID and name with which the review is associated. We also have the location information of each installer, as illustrated in Figure 2. In the marketplace we study, there is no "closing off" or explicit exit behavior as in physical retail stores. If an installer prefers to quit the online marketplace, the installer simply becomes inactive, making no proposals to potential customers. Our analysis accounts for such behavior.

3.2. Defining Local Market

Solar installation is a combination of product and service. As part of service, installers typically visit customer site multiple times. Thus, each installer only operates within a certain geographical area, and installers compete "locally." That is, they only compete with installers that are relatively nearby. There is no data on the installers' service areas. To capture this practical element, we identify what is called *local markets* within the marketplace so that only installers in the same local market compete with each other.

To geographically segment the marketplace into local markets, we divide installers into multiple *clusters* and treat each cluster as a separate local market. Boundaries of local markets cannot be simply defined by city, county, or congressional district borders because it is common for installers to cross these artificial borders to serve customers. Instead, we use installer locations and the state-of-the-art advanced clustering algorithm called OPTICS (short for *Ordering Points To Identify the Clustering Structure*) to identify local markets.

The OPTICS routine is an unsupervised machine learning algorithm that identifies density-based clusters in spatial data. It is considered to be an extension of various commonly-used advanced clustering algorithms, such as the DBSCAN (Kanagala and Krishnaiah 2016). Among others, an important advantage of the OPTICS algorithm is that it does not require setting the number of clusters before running the algorithm as in k-means clustering; rather, it identifies the optimal number of clusters using the data. Because of its advantages, it has been applied in various contexts, ranging from political science (Davidson 2019) to geography (Teimouri et al. 2016).

In light of these, we create the geographic division of local markets with the following steps. First, we collected the 5-digit zipcode of every installer in the marketplace. Figure 2 displays the location of every installer in our data set. We then converted each zipcode to the representative coordinates based on the data provided by the US Census Bureau (2019). **IS THE FOLLOWING SENTENCE CORRECT? PLEASE CONFIRM:** This transformation is necessary to run the OPTICS algorithm on the location data. The OPTICS algorithm uses the maximum distance between two samples in a cluster as an input variable. Based on our conversations with practitioners, we learned that the majority of customers get a quote from an installer within 90 miles distance of their property. Consistent with this, we used 90 miles as the maximum distance input parameter, and the OPTICS algorithm generated 36 clusters. Each of these clusters geographically defines a local market boundary. Figure 3 illustrates the centroid of each of these 36 clusters, which represents the centroid of each local market. Hereafter, for brevity, we refer to local markets simply as "*markets*."

3.3. Measuring Dispersion in Customer Ratings

A key explanatory variable in our base regression is the dispersion in customer ratings. This section explains how we measure the rating dispersion. Later, we will also study an extended model by adding the text-based review dispersion as a separate variable in our analysis. Section 6 will explain the state-of-the-art natural language processing model we use to measure the review dispersion based on text data.

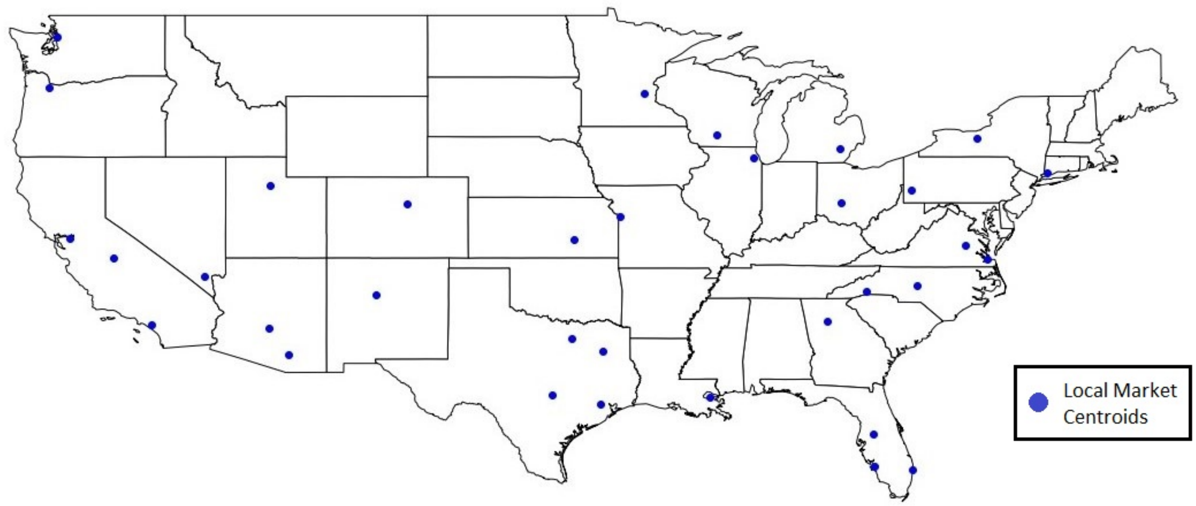

Figure 3 Local Market Centroids

We measure the rating dispersion by calculating the *entropy* of ratings. In information theory, the entropy is a common way to measure the uncertainty in a random variable's possible realizations. In our setting, because the marketplace has a 5-star rating system, the entropy of ratings is

$$H(R) = -\sum_{i=1}^{5} \text{Prob}(\text{Rating} = i) \ln(1/\text{Prob}(\text{Rating} = i)). \tag{1}$$

For example, for a set of 5 reviews each with 4 stars (out of 5 stars), the entropy of ratings $\{4,4,4,4,4\}$ is zero. Alternatively, for a set of 5 reviews with ratings $\{3,5,3,5,4\}$, the entropy of ratings is 1.0549. Although both sets have the same average rating of 4, the latter set of ratings provides more information with a higher dispersion, hence has a higher entropy.

In light of this, we create three variables that measure the rating entropy in different dimensions for each month t. First variable is Rating_Entropy_Self$_{i,t}$, which is the demeaned entropy of each installer i's own ratings. This is calculated on the set of reviews that are associated with installer i up to **PLEASE CONFIRM: and including** month t. Recalling the market defined in Section 3.2, the second variable is Rating_Entropy_Others$_{i,t}$ that is the demeaned rating entropy of all other installers in installer i's market, up to and **and including** month t. In one of our sections, we will consider the demeaned rating entropy on the market level. Thus, our third variable is Rating_Entropy_Mkt$_{m,t}$ that represents the demeaned entropy of all ratings in the local market m, up to **and including** month t. Note that these three variables are centered around their means. This is a standard procedure in setting like ours where the regression allows for both linear and quadratic versions of the same independent variable (see, e.g., (Tan and Netessine 2014)). We also checked the robustness of our findings by replacing these variables with their non-demeaned versions in all our econometric analysis, and we find that all of our insights remain the same with non-demeaned variables.

We measure the rating dispersion by calculating entropy rather than variance or coefficient of variation of ratings. The reason is two folds: First, the variance and coefficient of variance of ratings are both very highly correlated with average ratings. (The aforementioned correlation is more than 0.7.) In contrast, rating entropy exhibits a much lower level of correlation with average ratings. Thus, measuring the rating dispersion via the rating entropy enables us to include both rating dispersion and average rating as explanatory variables in our model. **PLEASE CLARIFY: Second, entropy measure provides a higher precision for our data. That is, two installers with very small difference in rating variance tend to show a larger difference in rating entropy.**

4. Installer-Level Analysis & Results

This section examines the following questions: (i) How does the dispersion in an installer's ratings affect its *activity level*, which is the logged number of proposals generated by the installer? (ii) How does the dispersion in competitors' ratings impact the installer's activity level? By studying these questions, we test Hypotheses 1a, 1b, 2a and 2b in Section 2.

We will only use numerical ratings in this section. Later, in Section 6, we will also use text reviews in our analysis. We will check the robustness of our findings in various dimensions, and address potential endogeneity concerns in an extended model in Section 7.

4.1. Regression Equation & Controls

To answer (i) and (ii) above, we run a regression model where the dependent variable is the natural logarithm of the number of proposals made by the installer. Specifically, indexing installers, months and markets by i, t and m, respectively, the dependent variable in our regression is Installer_Activity$_{i,m,t+1}$, which is equal to log(1 + number of proposals generated by installer i) in the market m during month t+1. We take the natural logarithm transformation of the number of proposals because its distribution is right-skewed. We transform the data to increase the normality of errors, thereby further improve the validity of inference. This transformation is a standard technique in the literature (see, e.g., Song et al. (2017), Tan and Netessine (2014), among others). As a robustness check, we performed the analysis without log transformation and the results are consistent.

Two of our key independent variables are Rating_Entropy_Self$_{i,t}$ and Rating_Entropy_Others$_{i,t}$, which are the rating entropy variables defined in Section 3.3. Because we have competing hypotheses, we also allow for nonlinear relationships between these independent variables and the dependent variable. Thus, we include explanatory variables $\text{Rating\_Entropy\_Self}^2_{i,t}$ and $\text{Rating\_Entropy\_Others}^2_{i,t}$ in our regression, as well:

$$\begin{aligned}\text{Installer\_Activity}_{i,m,t+1} =& \beta_0 + \beta_1 \text{Rating\_Entropy\_Self}_{i,t} + \beta_2 \text{Rating\_Entropy\_Self}^2_{i,t} \\ &+ \beta_3 \text{Rating\_Entropy\_Others}_{i,t} + \beta_4 \text{Rating\_Entropy\_Others}^2_{i,t} \\ &+ \text{Controls}_{i,m,t} + \alpha_i + \epsilon_{i,t+1}. \end{aligned} \tag{2}$$

Here, ϵ is the installer-level error term, and represents random factors that are unobservable in the data and affect the installer activity. We run two versions of (2): In one version, we consider α_i as a fixed effect whereas in the alternative version, we consider it as a random effect. To determine which model is more appropriate for our data, we run the Durbin-Wu-Hausman test where the null hypothesis is that the the random-effect model is preferred while the alternative is the fixed-effect model. With a p-value < 0.0001, we reject the null hypothesis and conclude that the fixed-effect model is more appropriate. We also establish the significance of the fixed effect in (2) with the F-test (**PLEASE ENTER THE SIGNIFICANCE VALUE**). Thus, we focus on (2) with the installer-level fixed effect α_i that controls for time-invariant characteristics of each installer.

In this regression model, the key coefficients of interests are β_1, β_2, β_3 and β_4. The values of these coefficients together with the significance of the associated variables will uncover how the rating entropy impacts the installer's activity level in the online platform.

The regression (2) includes various installer-level or market-level control variables ($\text{Controls}_{i,m,t}$). To account for the state-level renewable policy effects, we include state dummies as control variables. We have 33 such variables. We account for the impact of the solar panel prices on installers' activity levels by considering $\text{Price\_Difference}_{i,t}$ as another control variable. In practice, because solar PV systems vary in size, price per KW is a common way to represent the price of the installed solar panel. We use the TTS dataset to find each installer's price for 1 KW solar panel by matching names and zipcodes. Based on this, we compute the variable $\text{Price\_Difference}_{i,t}$ by taking the logarithm of the difference between installer i's price and the average price of its competitors that operate in the same market in month t. **As far as I remember, we did not demean these. But please confirm:** We control for the average rating of each installer i as well as the average rating of its competitors in the market for month t by including variables $\text{Average\_Rating\_Self}_{i,t}$ and $\text{Average\_Rating\_Others}_{i,t}$ in (2). We also control for the installer's experience by the control variable $\text{Experience}_{i,t}$ that is the logarithm of the number of years the installer has been installing solar systems up to (and including) month t. We collected this information from each installer's website. Another control variable in (2) is $\text{Market\_LogRevenue}_{m,t}$ that measures the logged total dollar value of all solar installations within market m during month t. To create this variable,

	Obs	Mean	SD	Min	Max
Ratings Average	4521	4.524005	1.329408	1	5
Reviews Count	4521	5.211429	6.650352	0	52
Entropy Own Reviews	4521	.0937851	.2147703	0	1.209574
Entropy Others Reviews	4521	.2098061	.1864398	0	1.070593
Experience	4521	5.693455	5.748559	0	43
Price Diff	4521	-.033842	.3810107	-2.171179	6.641788
Market Rev (Log)	4521	11.77942	8.023967	0	22.30267

Table 1 Summary Statistics Individual Level

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Entropy (Others)	1.000							
(2) Entropy (Self)	-0.075	1.000						
(3) Own Average Ratings	0.063	-0.088	1.000					
(4) Reviews Count	0.052	0.252	0.206	1.000				
(5) Others' Average Ratings	-0.514	0.022	-0.012	-0.040	1.000			
(6) Experience (Log)	0.053	-0.009	0.024	0.130	-0.092	1.000		
(7) Price (Diff)	-0.034	-0.008	0.004	-0.029	0.016	-0.033	1.000	
(8) Local Market Revenue (Log)	-0.102	-0.046	-0.029	-0.064	0.040	0.525	-0.064	1.000

Table 2 Correlation Individual Level

we augment the market boundaries identified in Section 3.2 with the TTS data. This variable aims to capture total solar installations opportunities in the market, and can be seen as a proxy for the favorableness of the solar installation market. As the final control variable, we consider $\text{Review\_Counts}_{i,t}$ which is the number of each installer i's reviews up to (and including) month t.

Tables 1 and 2 below present the summary statistics and the correlation matrix. By Table 2, correlations among explanatory variables are relatively low and do not hurt the validity of regression analysis.

4.2. Results

Table 3 presents the results estimated by three panel regression models based on the equation (2). Columns (I) through (III) of Table 3 present the estimates obtained by using different set of explanatory variables in the regression. The column (III) includes the estimates under the regression model (2), while the estimates in other columns are obtained by considering only some of these variables in the regression. In particular, we obtain the estimates in column (I) in the absence of all entropy variables in (2); column (II) presents the estimates when we exclude variables related to the installer's rating entropy from (2).

Our estimates in Table 3 identify three key results. First, the set of variables representing "noise" or dispersion of ratings have a significant impact on an installer's activity level in the marketplace. This is because in the column (III) of Table 3, all entropy variables are found to be statistically significant.

	(1)	(2)	(3)
	F.Activity	F.Activity	F.Activity
Average Rating	-0.830*	-0.788*	-0.773*
	(0.000)	(0.000)	(0.000)
Average Ratings(Others)	-0.00976	-0.00613	-0.00491
	(0.644)	(0.790)	(0.831)
Reviews Count	0.0503*	0.0473*	0.0420*
	(0.001)	(0.000)	(0.000)
Experience	0.220*	0.213*	0.213*
	(0.001)	(0.002)	(0.000)
Price Diff	0.0785	0.0798	0.0856
	(0.351)	(0.343)	(0.309)
Market Revenue	-0.0172*	-0.0168*	-0.0160*
	(0.000)	(0.000)	(0.001)
Entropy Others		1.759*	1.754*
		(0.000)	(0.000)
Entropy Others^2		-2.615*	-2.686*
		(0.000)	(0.000)
Entropy(Self)			1.743*
			(0.000)
Entropy(Self)^2			-3.356*
Constant	2.657*	2.481*	2.664*
	(0.000)	(0.000)	(0.001)
Fixed Effect	Yes	Yes	Yes
State Dummies	Yes	Yes	Yes
Observations	4200	4200	4200
r2	0.640	0.644	0.646
aic	12189.1	12156.3	12131.6
bic	12246.1	12226.0	12214.1

Table 3 Individual Level Analysis

Second, the dispersion in an installer's ratings has a positive and statistically significant first-order effect on the installer's activity level because in the column (III), the variable "Rating_Entropy_ Self" is found to be significant and its coefficient is positive ($\beta_1 =$ **ENTER**). However, we also find that an installer's rating dispersion has a negative and statistically significant second-order effect on its activity level. The reason is that in the column (III), the variable "Rating Entropy Self^2" is significant and its coefficient is negative ($\beta_2 =$ **ENTER**). Combining these two effects, the regression estimates indicate that the dispersion in an installer's ratings has a concave and non-monotone impact on the installer's activity level in the online marketplace. Specifically, an installer's rating dispersion increases its activity level in the online marketplace if and only if the aforementioned dispersion is below a threshold. When the dispersion of its ratings exceeds that threshold, any additional dispersion in the installer's ratings deters its activity in the marketplace. These provide support for Hypothesis 1A if and only if the installer's rating entropy is smaller than a threshold; otherwise, our findings are in support of Hypothesis 1B.

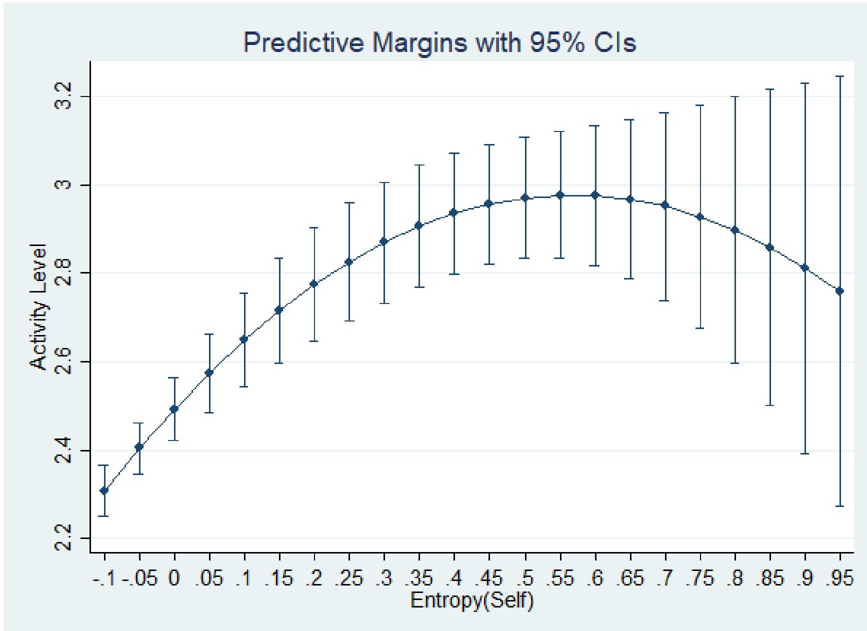

Figure 4 Marginal Impact of the Entropy of the Installer's Own Ratings on its Activity Level

Third, our estimation shows that the entropy of competitors' ratings impacts an installer's activity level in the same way as the entropy of the installer's ratings. Specifically, it has a positive and significant first-order effect (as "Rating_Entropy_Others" is significant and its coefficient $\beta_3 = \textbf{ENTER}$), and a negative and significant second-order effect (as "Rating_Entropy_Others^2" is significant and its coefficient $\beta_4 = \textbf{ENTER}$). Combining these two effects, the dispersion in competitors' ratings increases the installer's activity level if and only if the aforementioned dispersion is below a threshold. When the dispersion of competitors' ratings is above that threshold, any additional dispersion in competitors' ratings deters the installer's activity in the marketplace. This implies support for Hypothesis 2A if and only if the competitors' rating entropy is below the threshold; otherwise, our findings offer support for Hypothesis 2B.

Figures 4 and 5 illustrate the explained nonlinear effects of the rating entropy on the installer's activity level in the online marketplace. In generating Figures 4 and 5, we use the estimated regression coefficients in the column (III) of Table 3. As is apparent from these figures, on average, the installer's activity level first increases and then decreases with its rating entropy (or the rating entropy of its competitors), yielding an inverted U-shaped relationship between the two.

Finally, in all three columns of Table 3, the installer's average rating is significantly and negatively linked with its activity level. Put another way, installers appear to extend fewer proposals as their average ratings increase. One reason for this behavior could be that installers become more selective after they attain a high average rating in the marketplace. Selectiveness can emerge because the installers might think that with a higher average rating, their proposals are more likely to be

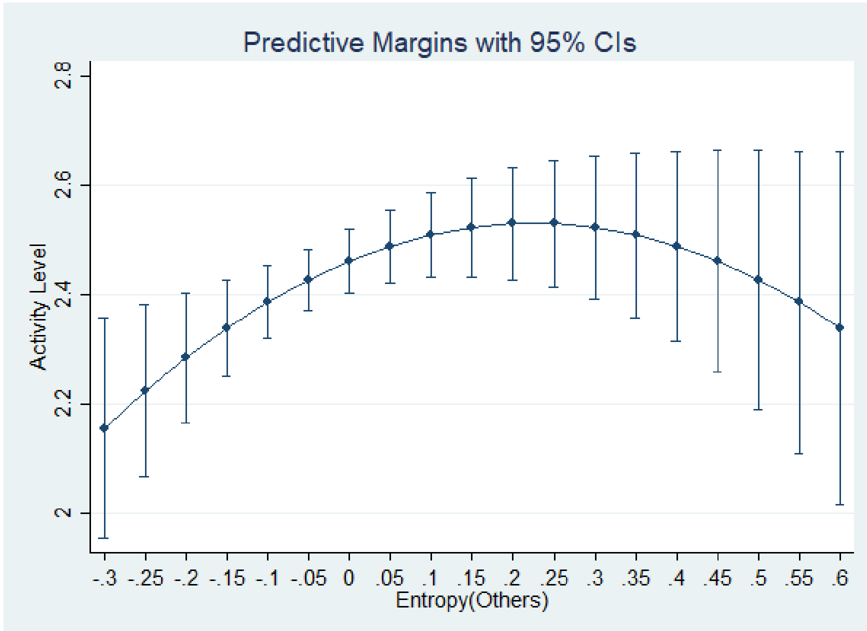

Figure 5 **[WHAT EXACTLY DO WE MEAN BY THE TERM "MARGINAL" HERE? The Marginal Impact of Other Installers' Rating Entropy (in the same market) on the Installer's Activity Level - The installer's activity level versus the rating entropy of other installers in the same market**

accepted by customers, and thus making too many offers increases their likelihood of coming across with a negative customer.

5. Market-Level Analysis & Results

An important performance metric for the marketplace operator is the number of matches (i.e., agreed proposals) between installers and customers in the marketplace. This section estimates how the market-level rating dispersion impacts the *market transaction* that is the logged number of matches in the market. With this, we test Hypotheses 3A and 3B in Section 2.

We will only use numerical ratings in this section. As an extension, Section 6 will account for text reviews in the market-level analysis. We will provide various additional robustness checks of our findings, and address potential endogeneity concerns in an extended model in Section 7.

Recalling that markets and months are indexed by m and t, respectively, we use the following regression equation for the estimation:

$$\begin{aligned}\text{Market\_Transaction}_{m,t+1} = \beta_5 + \beta_6 \text{Rating\_Entropy\_Mkt}_{m,t} + \beta_7 \text{Rating\_Entropy\_Mkt}^2_{m,t} \\ + \text{Controls}_{m,t} + \epsilon_{m,t+1}. \qquad (3)\end{aligned}$$

Performing (3) requires us to convert the installer-level monthly panel data to the market-level monthly panel data based on the markets defined in Section 3.2. Our data include the number of agreed proposals for each installer i in each month t. To create our dependent variable

Market_Transaction$_{m,t+1}$, we first calculate the total number of proposals accepted by customers in market m and month $t+1$, and then take the logarithmic transformation of that sum. Formally, Market_Transaction$_{m,t+1} = \log\left(\sum_{i \in \text{Market } m} \text{Successful_Proposals}_i + 1\right)$ in (3). We employ this standard transformation because the number of matches is right-skewed and the transformation increases the normality of errors. (As a robustness check, we also perform the analysis without log transformation and the results are consistent.)

A key explanatory variable in (3) is Rating_Entropy_Mkt$_{m,t}$, which is the entropy of all installers' ratings up to (and including) month t in the market m. Because we have two competing hypotheses about the impact of market-level rating entropy (i.e., Hypotheses 3A and 3B in Section 2), we also allow for a nonlinear relationship between the market-level rating entropy and the dependent variable. Thus, (3) also contains the quadratic term Rating_Entropy_Market$^2_{m,t}$. The aforementioned two variables are our main explanatory variables, and β_6 and β_7 are the key coefficients of interests. The values of these coefficients together with the significance of the associated explanatory variables will help us determine how the market-level rating entropy impacts market transactions.

In (3), ϵ is the market-level error term, and represents random factors that are unobservable in the data and affect market transactions. We also use various control variables (Controls$_{m,t}$) in (3). We control for the state of the market. To do that, we created 33 state dummies to represent 33 different states included in the data set. In our dataset, some markets span across more than one state (**HOW MANY MARKETS OUT OF 36 CLUSTERS SPAN MORE THAN 1 STATE?**) In light of this, each state dummy represents the fraction of installers that are located in that state within the market m. For example, suppose market 1 has 25% of installers from state X and 75% from Y. Then, we assign 0.25 to the dummy variable State_X and 0.75 to the dummy variable State_Y for market 1. Similar to the installer-level analysis in Section 4, we created the variable Average_Experience$_{m,t}$ that represents the average experience of installers in the market m up to and including month t. We calculated this by averaging installers' experience levels across the market m. In parallel to the installer-level analysis, we use the variable Average_Rating_Mkt$_{m,t}$ to control for the average rating of all installers in the market m until (and including) month t. As another control, we created the variable Review_Count_Mkt$_{m,t}$ that measures the total number of reviews by all installers in the market m up to and including month t. We also control for the difference between the average unit price of installed 1 KW solar system in the marketplace and off-marketplace, which is represented by the variable Price_Difference_Mkt$_{m,t}$. Finally, we use Market_LogRevenue$_{m,t}$ as a control where it is as defined in Section 4. Summary statistics can be found in Table 4; the correlation coefficients among variables are presented in Table 5.

VARIABLES	N	mean	p50	min	max
Entropy	611	0.201	0.169	0	1.055
Text-based Entropy	611	0.131	0.125	0.0689	0.366
Mkt Revenue	611	8.029	10.50	0	22.30
Rating Avg	611	4.866	4.988	3	5
Sentiment Score	611	0.672	0.689	0.0593	0.866
Experience(Avg)	611	5.922	6.375	0	27
Price Diff(Avg)	611	-0.0160	0	-0.504	1.312
Transaction	611	1.019	0.693	0	4.522

Table 4 Market Level Summary Statistics

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) Transaction	1.000						
(2) Activity	0.748	1.000					
(3) Entropy	0.226	0.380	1.000				
(4) Rating Avg	-0.026	-0.151	-0.601	1.000			
(5) Mkt Revenue	0.332	0.282	0.146	-0.036	1.000		
(6) Experience(Avg)	0.210	0.270	0.215	-0.111	0.484	1.000	
(7) Price Diff(Avg)	-0.116	-0.102	-0.062	0.000	-0.045	0.012	1.000

Table 5 Correlation Market Level

5.1. Results

Table 5.1**PLEASE FIX THE TABLE NUMBER** presents our regression estimates. In Table 5.1, column (I) shows the estimates obtained with the regression (3) in the absence of $\text{Rating\_Entropy\_Mkt}_{m,t}$ and $\text{Rating\_Entropy\_Mkt}^2_{m,t}$ variables, while column (II) includes the estimates obtained by running the regression (3) considering all variables in (3).

Regression estimates reveal the following key findings. First, the dispersion ("noise") in the market-level ratings has a significant and positive first-order effect on market transactions and number of matches in the market. This is because the coefficient of "Rating_Entropy_Mkt" is positive ($\beta_6 = 1.060$) and statistically significant ($p < 0.01$) in the column (II) of Table 5.1. The market-level rating dispersion also has a significant and negative second-order effect as the coefficient of the quadratic term "$\text{Rating\_Entropy\_Mkt}^2$" is negative ($\beta_7 = -1.160$) and statistically significant ($p < 0.01$) in the column (II). Combining these two effects, on average, regression estimates indicate a concave and non-monotone relationship between the market-level rating dispersion and the market transaction. Specifically, our findings indicate that the market-level dispersion increases the market transaction and number of matches if and only if the mentioned dispersion is smaller than the threshold, for any dispersion beyond that threshold, any additional dispersion on the market-level dampens the market transaction and matches. These findings support Hypothesis 3A if and only if the market-level rating dispersion is below a certain threshold; our results are in support for Hypothesis 3B for any market-level dispersion above that threshold.

	(1)	(2)
	F.Transaction	F.Transaction
Rating Avg	-0.273	-0.185
	(0.071)	(0.212)
Mkt Revenue	-0.0846	-0.0663
	(0.057)	(0.123)
Experience(Avg)	0.0197*	0.0138
	(0.013)	(0.073)
Price Diff(Avg)	0.239	0.287
	(0.282)	(0.194)
Entropy		1.060***
		(0.000)
Entropy^2		-1.610***
		(0.000)
Constant	3.443**	2.909*
	(0.009)	(0.025)
Observations	642	642
Market Fixed Effects	Yes	Yes
Weighted State Dummies	Yes	Yes
r2	0.739	0.747
aic	1075.6	1059.6
bic	1156.0	1148.9

Table 6 Market Level Analysis

Figure 6 further illustrates this nonlinear relationship via a margins plot using coefficients generated from estimates in the column (II) of Table 5.1. As we observe from this figure, on average, the market transaction (and the number of matches) first increases then decreases with the market-level rating dispersion.

Finally, market-level estimates in Table 5.1 suggest that after controlling for market conditions, installer experience, price, and state, the average rating is not significantly associated with the market-level performance.

6. Text Mining

In this section, we incorporate various methods to leverage rich text information in reviews. First, we will use the state-of-the-art advanced natural language processing (NLP) technique called BERT (i.e., *Bidirectional Encoder Representations from Transformers*) to measure the dispersion in text reviews. The BERT method was developed by Google AI in 2018, and incorporated by Google Search Engine in late 2019 (Devlin et al. 2018, Abril 2019). To the best of our knowledge, there is no other paper in operations management literature that considers this technique. Second, we will use another state-of-the-art NLP method to generate the sentiment score of each review. As the final step, we will incorporate these text-based metrics in our regression analysis to derive additional insights related to the text content.

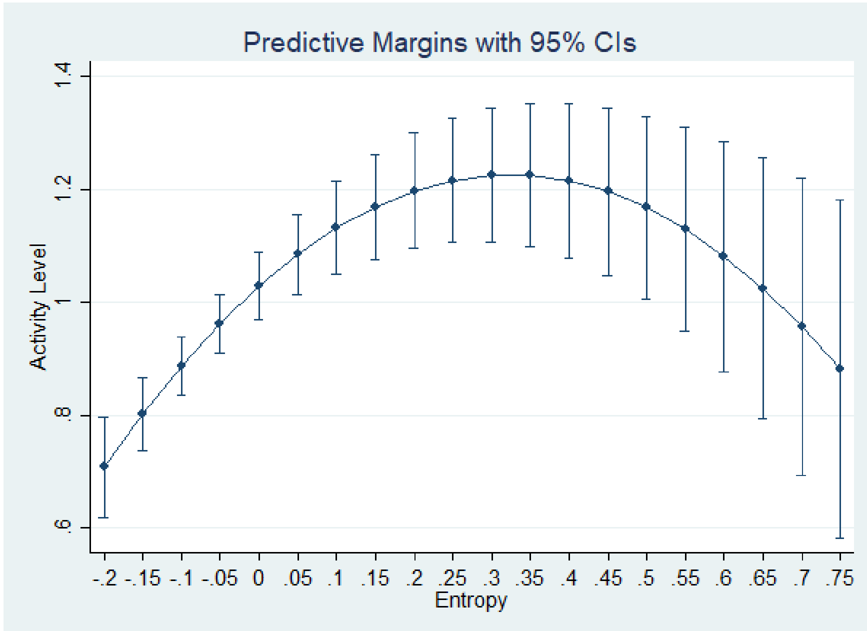

Figure 6 **Marginal Impact of Market Reviews Entropy of Reviews on Market Level Matching (IS IT NUMBER OF MATCHES OR MARKET TRANSACTION?)**

6.1. Measuring Text-Based Review Dispersion via Natural Language Processing Technique BERT

In our data set, we have **PLEASE ENTER THE NUMBER** pieces of text reviews, and we apply the following five steps to measure the dispersion in text reviews. First, we use BERT to convert each text review to a semantics-sensitive numerical vector. We will provide more details about this method later in this section. As a second step, we normalize each vector to unit length. Third, we measure the cosine similarity between any two review vectors to find the context similarity between the two. The cosine similarity between two normalized vectors V_1 and V_2 equals the inner product of two, i.e., $V_1 \cdot V_2$, and gives the cosine of the angle between the two vectors. The angle represents the similarity in the orientation of two review vectors. For example, if the angle is 0, the vectors are at the same orientation and hence the similarity is the maximum. The second and third steps above are standard in identifying the similarity between two vectors (see, e.g., Hoberg and Phillips (2016)). As the fourth step, we identify the cosine distance between every two review vectors using the fact that the cosine distance between the two normalized vectors V_1 and V_2 equals 1 minus the cosine similarity between the two. This distance reflects how much two reviews differ from each other. As the fifth and final step, we calculate the dispersion of text reviews, i.e., *text-based dispersion*, for a review set of interest by enumerating all pairwise cosine distances of reviews in that set and taking their statistical median (the 50$^{\text{th}}$ percentile). For example, for a set of 10 text reviews, we have 45 $(=\binom{10}{2})$ pairwise cosine distances. Finding the text-based dispersion for this set requires computing the median of these 45 distances. If these 10 pieces of texts are dissimilar from each other, they contain richer information and the median of these 45 distances shall be higher; and vice versa.

As a result of this procedure, similar to the rating entropy, we create the following three variables, each measuring the text-based dispersion in a different dimension: (i) $\text{Text\_Dispersion\_Self}_{i,t}$: Demeaned dispersion in installer i's own text reviews up to and including month t. (ii) $\text{Text\_Dispersion\_Others}_{i,t}$: Demeaned dispersion in text reviews of all other installers in the installer i's market up to and including month t. (iii) $\text{Text\_Dispersion\_Mkt}_{m,t}$: Demeaned dispersion in text reviews of all installers in the market m up to and including month t. Note that each of these variables is centered around its mean. We apply this standard procedure because in addition to these terms, we will also consider quadratic terms in our regression.

We now elaborate the BERT model we used to *vectorize* the text reviews. BERT is a natural language processing (NLP) model that transforms texts into numeric vectors while also preserving the meaning of texts. It belongs to the category of NLP methods called word embedding. In literature, in different contexts than ours, text data are commonly vectorized based on word counts, ignoring the semantics and word ordering (see, e.g., Hoberg and Phillips (2016) and Loughran and McDonald (2011)). However, our context involves texts that are informal writings and often contain emotions. Simply capturing word frequencies does not provide accurate results if similar emotions can be expressed with synonymous words. Thus, our analysis requires a vectorization that preserves the information and sentiment of the text reviews despite the use of synonyms and/or different styles. The BERT model achieves that. Specifically, the BERT model has two distinct advantages. First, it understands the semantics. For example, consider the 3 sentences:

Sentence 1: `they did a good job.` Sentence 2: `they did an awful job.` Sentence 3: `they did a great job.`

Considering the meaning of the sentences, we expect the distance between sentences 1 and 3, $D(1,3)$, to be smaller than the distance between 2 and 3 or 1 and 2, i.e., $D(2,3)$ or $D(1,2)$. The BERT model vectorization enables just that; it projects "good" and "great" to vectors that are closer to each other. In this example, with BERT, we have $D(1,3) = 0.03 < D(1,2) = 0.09 < D(2,3) = 0.1$. This level of distinction is not feasible without word embedding (e.g., by simply using a word counter vectorizer).

Second, the BERT model takes word ordering into account. For example, the two sentences "The food was good, not bad at all" and "The food was bad, not good at all" have the opposite meanings. Common vectorization methods (e.g., "bag-of-words" approach) are not able to capture this difference as words and number of counts are the same in both sentences. But, the BERT model can easily differentiate between these two sentences.

6.2. Sentiment Scores of Text Reviews

We use the VADER model to generate sentiment scores for text reviews. VADER is short for *Valence Aware Dictionary and sEntiment Reasoner* and developed by Hutto and Gilbert (2014) as a "parsimonious rule-based model for sentiment analysis of social media text." Since review text shares many structural similarities with the social media text, an important application area of this model is the text analysis of reviews. For each text review, VADER produces a sentiment intensity score from -1 to 1, with 1 representing very positive and -1 representing very negative sentiments.

VADER has key advantages. In contrast to models that use a polarized lexicon where a word is classified as either positive, negative or neutral, VADER is sensitive to both polarity and strength of the sentiment. The method also understands conventional syntactical and grammatical components in the text and reflects them in the sentiment intensity score it generates. Among other features, the method accounts for the exclamation mark, capitalization especially the usage of all-caps, degree adverbs such as "extremely" and "marginally", the contrastive conjunction (e.g.,"but"), conventional emojis, slangs and emoticons in its sentiment intensity score calculation.

For example, the following review, which was rated as 5-star, received a sentiment score of 0.8622 under the VADER method:

"*Mike at (...) was friendly, courteous, professional and very helpful. At first I did not know what kind of system I wanted, because my roof was too small and I had some trees in the way. Mike had never installed a tracking system but he did recommend it. It seemed like we would get the best "bang for the buck" with this system, so I went with it. Mike had all subcontractor there on time as well as all the equipment. It was up and running in less than a week. I love it.*"

As another example, the following review, which was rated as 1-star, received a sentiment score of -0.7184 under the VADER method:

"*Do not hire (...) to install a solar system. Do not hire (...) to do anything. Evan and all his various companies and names ARE NOT LICENCED OR INSURED. I was scammed by Mr. Evan (...) in December of 2013. He installed the system wrong and incomplete even though all the parts and materials were provided for him. Please take the time to do your research and check references and validate licenses and insurance information. It will save u more money than to trust a cheap con artist. All the info at (...) is fraudulent lies. Evan (...) is also known as (...).*"

Based on this method, we created three variables that represent average sentiment intensity scores in three dimensions: (i) $\text{Average\_Sentiment\_Self}_{i,t}$: The average sentiment intensity score of installer i's all text reviews up to and including month t. (ii) $\text{Average\_Sentiment\_Others}_{i,t}$: The average sentiment intensity score of competitors' text reviews up to and including month t in the installer i's market. (iii) $\text{Average\_Sentiment\_Mkt}_{m,t}$: The average sentiment intensity score of all text reviews in the market m up to and including month t.

6.3. Empirical Analysis Using Variables Derived From Text Mining

We now discuss the analysis we conducted with the review dispersion and average sentiment score measures we constructed in Sections 6.1 and 6.2. With these additional variables, we aim to examine the following questions: (i) Is the text content significant in explaining installers' activity levels and market transactions? (ii) How do the text-based dispersion and the average sentiment intensity score influence an installer's activity level and market transactions? To study these questions, we consider the following regression models:

$$\begin{aligned}&\text{Installer\_Activity}_{i,t+1}\\&= \theta_0 + \theta_1 \text{Rating\_Entropy\_Self}_{i,t} + \theta_2 \text{Rating\_Entropy\_Self}^2_{i,t} + \theta_3 \text{Rating\_Entropy\_Others}_{i,t}\\&+ \theta_4 \text{Rating\_Entropy\_Others}^2_{i,t} + \theta_5 \text{Text\_Dispersion\_Self}_{i,t} + \theta_6 \text{Text\_Dispersion\_Self}^2_{i,t}\\&+ \theta_7 \text{Text\_Dispersion\_Others}_{i,t} + \theta_8 \text{Text\_Dispersion\_Others}^2_{i,t} + \text{Controls}_{i,m,t} + \alpha_i + \epsilon_{i,t+1}.\end{aligned} \tag{4}$$

$$\begin{aligned}&\text{Market\_Transaction}_{m,t+1}\\&= \alpha_0 + \alpha_1 \text{Rating\_Entropy\_Mkt}_{m,t} + \alpha_2 \text{Rating\_Entropy\_Mkt}^2_{m,t}\\&+ \alpha_3 \text{Text\_Dispersion\_Mkt}_{m,t} + \alpha_4 \text{Text\_Dispersion\_Mkt}^2_{m,t} + \text{Controls}_{m,t} + \epsilon_{m,t+1}.\end{aligned} \tag{5}$$

In (4) and (5), all variables except text-based variables and control variables on average rating are the same as the ones in (2) and (3), respectively. An installer's text-based dispersion correlates with its rating entropy on a lower level (correlation coefficient is 0.4309). **THERE ARE THREE TYPES OF DISPERSION MEASURES - COULD YOU PLEASE REPORT THE CORRELATION COEFFICIENT FOR EACH?** Thus, (4) and (5) consider the text-based dispersion and rating entropy variables in the same regression. On the other hand, **WHAT TYPE OF AVERAGE SENTIMENT SCORE ARE WE REFERRING HERE? IS IT SELF, OTHERS OR MARKET? I ASSUMED IT WAS SELF, BUT PLEASE CONFIRM. COULD YOU PLEASE REPORT THE CORRELATION COEFFICIENTS FOR EACH?** an installer's average sentiment intensity score significantly correlates with its average rating (with a correlation coefficient of 0.8239). As a result, in (4) and (5), we will use average sentiment intensity scores and average rating variables as substitute controls.

PLEASE REVIEW THIS PARAGRAPH AND UPDATE IF NECESSARY Table 7 shows the estimation results obtained by using different set of explanatory variables in (4). In each column of Table 7, blank represents the absence of the corresponding explanatory variable in the regression.

Regression estimates in Table 7 reveal various findings. First, on average, an installer's rating entropy continues to have an inverted U-shaped impact on the installer's activity level even when the text-based dispersion is also considered. Second, an installer's text-based dispersion has a significant and positive first-order effect on the installer's activity level, whereas it has a significant and negative second-order effect on the installer's activity level (as $\theta_5 > 0$ and $\theta_6 < 0$ are both found to be significant). Combining two, on average, an installer's text-based dispersion also has an inverted-U-shaped impact on its activity level. Third, as indicated by insignificance of coefficients for "Average_Sentiment_Score_Self" and "Average_Sentiment_Score_Others", installer's average sentiment score or its competitors' average sentiment score does not have a significant impact on the installer's activity level. In fact, Table 7 indicates that an installer's average rating better explains the installer's activity level than its average sentiment score. Thus, text context can be ignored in measuring reviews' average polarity intensity while it is significant in measuring the review dispersion.

Table 8 displays the estimates obtained by using different set of explanatory variables in (5). There are three key findings. First, the market-level rating entropy continues to be significant and have an inverted-U-shaped impact on market transactions (and number of matches). Second, on average, although the text-based dispersion has an inverted-U-shaped relationship with market transactions, it has an insignificant impact on market transactions. Thus, the text content does not provide significant value in measuring the review dispersion. Third, the coefficients for the average market-level rating or average market-level sentiment score are both significant, but the text content better captures the "signal" of reviews than numerical ratings in the marketplace.

7. Robustness Check

7.1. Dynamic Panel Model

The regression model in Section 4 considers fixed effect for each installer, and that accounts for time-invariant installer-specific factors that may impact the dependent variable, i.e., installer's activity level. This section extends our regression model (2) to a dynamic panel model by including lagged dependent variables. The inclusion of these variables aims to consider time-variant unobserved heterogeneity that may influence the dependent variable. In light of this, for the installer-level analysis, the equation we estimate is extended to the following:

$$\begin{aligned}
&\text{Installer_Activity}_{i,t+1} \\
&= \gamma_0 + \gamma_1 \text{Installer_Activity}_{i,t} + \gamma_2 \text{Installer_Activity}_{i,t-1} + \gamma_3 \text{Rating_Entropy_Self}_{i,t} \\
&+ \gamma_4 \text{Rating_Entropy_Self}^2_{i,t} + \gamma_5 \text{Rating_Entropy_Others}_{i,t} + \gamma_6 \text{Rating_Entropy_Others}^2_{i,t} \\
&+ \text{Controls}_{i,m,t} + \epsilon_{i,t+1}.
\end{aligned} \tag{6}$$

However, the inclusion of the lagged dependent variable in the presence of fixed effects may cause endogeneity bias, as such an addition may lead a correlation between the regressors and the error (Nickell 1981). To overcome this, we use Arellano and Bond (1991)'s method for dynamic panel data. Arellano and Bond (1991) estimator is a general method of moments estimator that is based on dynamic panel data with first differences. It uses lagged variables as instruments to address the endogeneity bias. To avoid over-identification issues, one would need to limit the number of lags used as instruments in the regression (Bowsher 2002). Thus, we use **XY** lags of variables **XY** as instruments in our model. We think that lags of **XY** are uncorrelated with the random shock on the dependent variable. That is why we did not include those lags as additional instruments in our model. A requirement for Arellano and Bond (1991) estimation is serially uncorrelated errors. We provide support for this property in Table **XY**.

To assess the relevance of instruments, we calculated F-statistics from the first-stage 2SLS regressions of the first differences of each endogenous variable on its lagged instrument(s) (see **Table EC.XY**). The F-statistics of the considered instruments are all larger than 10. This indicates that there is no evidence on the "weakness" of the instruments. We also run the Hansen test for overidentifying restrictions, and find no evidence that our instruments violates the exogeneity assumption. **Table EC.XY** provides support for this.

We also modify the market-level model (3) to include lagged dependent variables:

$$\begin{aligned}
&\text{Market_Transaction}_{m,t+1} \\
&= \alpha_0 + \alpha_1 \text{Market_Transaction}_{m,t} + \alpha_2 \text{Market_Transaction}_{m,t-1} + \alpha_3 \text{Market_Transaction}_{m,t-2} \\
&+ \alpha_4 \text{Rating_Entropy_Mkt}_{m,t} + \alpha_5 \text{Rating_Entropy_Mkt}^2_{m,t} + \text{Controls}_{m,t} + \epsilon_{m,t+1}. \qquad (7)
\end{aligned}$$

To overcome any potential endogeneity bias in this regression, we apply similar steps as the ones explained for the analysis of the installer-level activity. In applying Arellano and Bond (1991) estimator, we use **XY** lags of variables **XY** as instruments in our model. Tables **XY** and **XY** suggest that there is no evidence that instruments are weak or violates the exogeneity assumption. Moreover, Table **XY** provides support

Tables **XY** and **XY** include our installer-level and market-level estimates. An installer's rating entropy and its competitors' rating entropy continue to have an inverted U-shaped impact on the installer's activity level. Furthermore, there is also an inverted-U-shaped relationship between the market-level rating entropy and market transaction (or number of matches). Thus, our findings are robust in this extension.

7.2. Additional Support for Inverted U-Shaped Relationship

To further validate the inverted U-shaped relationship between an explanatory variable and the response variable, one must check whether the stationary point of the explanatory variable lies within its range in our sample. This check is important to distinguish the inverted U-shaped relationship from a concave monotone relationship. The ranges of "Rating_Entropy_Self," "Rating_Entropy_Others" and "Rating_Entropy_Mkt" are provided in Tables 1 and 4. Based on our estimates in Sections 4 and 5, we calculate the stationary points for these variables as **PLEASE FILL IN BLANKS** $S_{\text{self}} \doteq -\beta_1/(2\beta_2) =$, $S_{\text{others}} \doteq -\beta_3/(2\beta_4) =$ and $S_{\text{mkt}} \doteq -\beta_6/(2\beta_7) =$. In fact, stationary point for each of these variables is also evident in Figures 4, 5 and 6. Comparing ranges and the stationary points, we conclude that in our data, the stationary point of each rating entropy variable lies within its observed data range. This provides further validation for the inverted U-shaped relationship we find in Sections 4 and 5.

We used a common criteria to identify inverted U-shaped relationships. Some researcher argue that for the inverted U-shaped relationship to be meaningful for an explanatory variable, the stationary point for that variable should not be too close to the end points of the data range or too far from the sample mean (e.g., 3 standard deviation far) Lind and Mehlum (2010). This concern does not apply our analysis as the stationary point for each rating entropy is close to its sample mean. Specifically, S_{self}, S_{others} and S_{mkt} are respectively **XY1**, **XY2** and **XY3** standard deviation away from their sample means.

7.3. Alternative Test for Inverted U-Shaped Relationship: Spline Regression

Up to this section, we identified an inverted U-shaped relationship between entropy measures and dependent variables by applying a standard technique. That is, by running a polynomial regression, showing the significance of linear and quadratic terms of entropy measure, and identifying the positive sign for the linear term and the negative sign for the quadratic term. See, e.g., Tan and Netessine (2014) and Kesavan et al. (2014) that apply this technique. We also perform spline regressions to provide robustness checks on both individual and market level analysis. This robustness check is also standard in the literature (Kesavan et al. 2014).

Spline regressions use breakpoints (*knots*) to capture the changes in coefficients for different intervals of explanatory variables. We perform spline regressions with 1 knot and with 2 knots. Knots divide data into sub-samples, and the response variable and the explanatory variable of interest are allowed to have a different linear relationship in each sub-sample. For 1 knot, we create two spline variables Rating_Entropy_Others_S1 and Rating_Entropy_Others_S2, and consider the linear term of either one only in one of the two ranges of the variable. For the installer-level analysis, we plug in either of these spline variables in place of the linear and quadratic terms of

Rating_Entropy_Others in 2. Likewise, we repeat this procedure for Rating_Entropy_Self in the installer-level analysis and for Rating_Entropy_Mkt in the market-level analysis. We also further extend this alternative testing to consider spline regressions with 2 knots, which require us to create three spline variables for each rating entropy measure.

The results are presented in Tables 14 and **PLEASE FIX THE TABLE NUMBER**A. In Table 14, we report the spline regression estimates with one knot on Rating_Entropy_Others in column (I) and with one knot on Rating_Entropy_Self in column (II). We find that the coefficient of the first spline is positive and significant while the second one (which is valid above the breakpoint) is negative and significant ($p < 0.001$), supporting the inverted U-shaped relationships between either rating entropy measure and the installer's activity levels. The conclusions are similar when we consider the case with 2 knots as shown in column (III) and (IV) of Table 14. Next, we consider the market-level analysis with results presented in Table A. For the case with 1 breakpoint for Rating_Entropy_Mkt, first positive and then negative and significant ($p < 0.001$) coefficients associated with the two splines in column (I) further validate the inverted U-shaped relationship we established on the market-level. We also find that when we move to the case with two breakpoints, the inverted U-shaped relationship is still preserved. **THIS IS BASED ON OUR CONVERSION TODAY THAT IN THE UPDATED TABLE, THIRD SPLINE WILL BE SIGNIFICANT**

7.4. Alternative Approach to Measure Text-based Dispersion

In Section 1, we measured the text-based dispersion by taking the median of cosine distances. Alternatively, one can consider the mean of cosine distances to measure the text-based dispersion. Table 16 reports the estimation results when the mean (rather than median) of cosine distances is considered in that measurement. Table 16 suggests that our findings in Section 6 continue to hold. **PLEASE INCLUDE MARKET-LEVEL TABLE, TOO**

8. Discussions

Average Ratings and Sentiment : Most the specifications concerning the impact of average ratings captured negative (yet statistically insignificant) effects. Interestingly, the model using sentiment score and Text-based dispersion measures (table 7) have shown more consistent and significant negative coefficients. After we control for other things, being rated higher or viewed more positive is associated with a lower level of activity intensity going forward.

Noise in Reviews The individual level analysis pertain to ratings and reviews dispersion all revealed an inverted-U type of impact.

Noisy Reviews and Marketplace Matching Performance : from the marketplace's perspective, dispersion in reviews also exhibits an inverted-U type of relationship with market place matches.

Methodology - text mining To analyze the reviews texts, we incorporated two text mining methods that 1) - gave reviews texts a one-dimensional sentiment score and 2) utilize word embedding model to measure texts similarity with precision. We demonstrated that the text mining tools are great complement to the quantitative data. To our knowledge, it is the first example of using deep learning based text-mining models on business settings in the operations management literature. We demonstrate the versatility of deep learning methods as a complement to traditional text-mining methods.

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	(1)	(2)	(3)
	F.Activity	F.Activity	F.Activity
Average Rating	-0.956*		
	(0.000)		
Average Ratings(Others)	-0.00337		
	(0.870)		
Avg Sentiment Score		-0.416	-0.371
		(0.106)	(0.172)
Avg Sent(Others)		-0.167	-0.181
		(0.413)	(0.369)
Reviews Count	0.0428*	0.0450*	0.0392*
	(0.000)	(0.000)	(0.000)
Experience	0.207*	0.190*	0.196*
	(0.001)	(0.001)	(0.000)
Price Diff	0.0931	0.100	0.120
	(0.302)	(0.259)	(0.179)
Market Revenue	-0.0165*	-0.0171*	-0.0164*
	(0.001)	(0.000)	(0.001)
Text-based Entropy(Self)	4.338*	4.489*	3.960*
	(0.000)	(0.000)	(0.000)
Text-based Entropy(Self)^2	-21.40*	-19.92*	-16.42*
	(0.000)	(0.000)	(0.000)
Text-based Entropy(Others)	-0.790	-0.728	-1.480
	(0.628)	(0.648)	(0.356)
Text-based Entropy(Others)^2	-40.07*	-20.20	-6.617
	(0.019)	(0.319)	(0.737)
Entropy(Self)			1.601*
			(0.000)
Entropy(Self)^2			-3.279*
			(0.000)
Entropy(Others)			0.303
			(0.123)
Entropy(Others)^2			-2.357*
			(0.000)
Constant	2.370*	2.085*	2.323*
	(0.000)	(0.000)	(0.000)
Fixed Effect	Yes	Yes	Yes
State Dummies	Yes	Yes	Yes
Observations	4109	4192	4192
r2	0.646	0.644	0.649
aic	11880.2	12094.8	12049.4
bic	11968.7	12183.5	12163.6

Table 7 Individual Level Analysis with Variables Derived from Text Analysis

Appendix. Electronic Companion

A. TABLES

	(1)	(2)	(3)
	F.Transaction	F.Transaction	F.Transaction
Rating Avg	-0.262+		
	(0.095)		
Sentiment Score		-1.322*	-1.215*
		(0.006)	(0.011)
Experience(Avg)	0.0127+	0.00856	0.00529
	(0.082)	(0.230)	(0.458)
Price Diff(Avg)	0.0877	0.127	0.127
	(0.746)	(0.640)	(0.619)
Mkt Revenue	-0.0458	-0.0296	-0.0216
	(0.253)	(0.448)	(0.574)
Text-based Entropy	7.394+	5.963	3.237
	(0.082)	(0.152)	(0.429)
Text-based Entropy^2	-19.33+	-16.31	-10.23
	(0.066)	(0.116)	(0.314)
Entropy			1.376*
			(0.000)
Entropy ^{2}			-1.379*
			(0.001)
Constant	2.900*	2.573*	2.424*
	(0.045)	(0.038)	(0.046)
Observations	611	611	611
Fixed Effect	Yes	Yes	Yes
Weighted State Dummies	Yes	Yes	Yes
r2	0.752	0.755	0.760
aic	1010.3	1001.8	992.3
bic	1098.6	1090.1	1089.4

Table 8 Market Level Analysis with Variables Derived from Text Analysis

Variable	VIF	1/VIF
Average Rating	4.59	0.22
Reviews Count	1.24	0.81
Average Rating (Others)	1.40	0.71
Entropy(others)	1.83	0.55
Entropy(others)ˆ2	1.46	0.68
Entropy(self)	7.10	0.14
Entropy(self)ˆ2	5.81	0.17
Experience	1.46	0.68
Price(difference)	1.03	0.97
Market Condition)	1.65	0.61

Table 9 VIF table: Individual Level

Variable	VIF	1/VIF
Entropy(Market)	6.67	0.149965
Entropy(Market)^2	6.21	0.160950
Average Rating	1.58	0.632615
Market Revenue	1.45	0.690279
Experience(Avg)	1.46	0.685113
Price Difference	1.01	0.986885

Table 10 VIF Table:Market level

Individual		
Order	z	prob>z
1	-9.8283	0.00
2	-0.66053	0.5089
Market		
Order	z	prob>z
1	-2.7882	0.01
2	0.04295	0.9657

Table 11 Arellano-Bond test for zero autocorrelation in first-differenced errors

	(1)	(2)	(3)
	F.Activity	F.Activity	F.Activity
Entropy Others		0.743+	0.705+
		(0.057)	(0.070)
Entropy(Others)^2		-1.302*	-1.254*
		(0.039)	(0.041)
Entropy(Self)			1.327*
			(0.004)
Entropy(Self)^2			-1.695*
			(0.031)
Activity	0.529*	0.505*	0.504*
	(0.000)	(0.000)	(0.000)
L.Activity	0.0624*	0.0377	0.0354
	(0.004)	(0.153)	(0.180)
Avg	-0.00942	-0.0701*	-0.0686*
	(0.591)	(0.000)	(0.000)
Reviews Count	0.0256*	0.0179*	0.0117*
	(0.001)	(0.006)	(0.047)
Avg(Others)	-0.199+	-0.200	-0.167
	(0.077)	(0.111)	(0.167)
Experience	-0.0230	-0.0454	-0.0548
	(0.680)	(0.415)	(0.309)
Price Diff	-0.0329	0.115	0.114
	(0.742)	(0.291)	(0.299)
Market Revenue	0.00685	0.00337	0.00376
	(0.240)	(0.618)	(0.581)
State Dummies	Yes	Yes	Yes

Table 12 Robustness Check: Individual Level with Dynamic Panel

	(1)	(2)
	F.Transaction	F.Transaction
Entropy	1.957***	1.050**
	(0.000)	(0.004)
Entropy^2	-2.456***	-1.609***
	(0.000)	(0.000)
Rating Avg	-0.207	-0.141
	(0.169)	(0.476)
Mkt Revenue	-0.0264	0.0403
	(0.502)	(0.051)
Experience(Avg)	0.0102	-0.00118
	(0.157)	(0.882)
Price Diff(Avg)	0.0349	-0.313
	(0.865)	(0.089)
Transaction		0.0238
		(0.685)
L.Transaction		-0.00533
		(0.917)
L2.Transaction		0.198**
		(0.001)
Constant	2.015**	
	(0.006)	
Fixed Effects	Yes	No
Weighted State Dummies	Yes	Yes
Observations	642	421
r2	0.726	

Table 13 Robustness Check Market Level with Dynamic Panels

	Two knots		Three Knots	
	(1) F.Activity	(2) F.Activity	(3) F.Activity	(4) F.Activity
Ent(Others)1	0.470*			
	(0.033)			
Ent(Others)2	-2.053*			
	(0.000)			
Ent(Self)1		0.738*		
		(0.003)		
Ent(Self)2		-4.207*		
		(0.000)		
Ent(Others)1			0.750*	
			(0.003)	
Ent(Others)2			-1.135*	
			(0.021)	
Ent(Others)3			-1.917*	
			(0.021)	
Ent(Self)1				1.639*
				(0.000)
Ent(Self)2				-2.616*
				(0.000)
Ent(Self)3				0.0790
				(0.959)
Same controls	Yes	Yes	Yes	Yes
Observations	4200	4200	4200	4200
r2	0.644	0.646	0.645	0.646
aic	12150.9	12130.3	12148.0	12130.4
bic	12233.3	12212.7	12236.8	12219.2

Table 14 Alternative Inverted-U Testing: Spline Regressions (Individual Level)

	Two Knots	Three Knots
	(1) F.Transaction	(2) F.Transaction
Ent(Market)1	1.197***	
	(0.000)	
Ent(Market)2	-1.144**	
	(0.008)	
Ent(Market)1		2.157***
		(0.000)
Ent(Market)2		-2.100***
		(0.000)
Ent(Market)3		0.356
		(0.606)
Observations	642	642
r2	0.720	0.732
aic	1101.0	1074.3
bic	1136.7	1114.4

	(1)	(2)	(3)
	F.Activity	F.Activity	F.Activity
Entropy	4.189**	4.290**	
	(0.003)	(0.004)	
Entropy^2	-4.066*	-4.147*	
	(0.020)	(0.018)	
Text-based Entropy			20.57
			(0.348)
Text-based Entropy^2			-61.58
			(0.332)
Rating Avg	-0.218		
	(0.695)		
Sentiment Score		-0.217	0.349
		(0.651)	(0.601)
Mkt Revenue	-0.282**	-0.288**	-0.379**
	(0.008)	(0.004)	(0.005)
Experience(Avg)	0.0559*	0.0573*	0.0740**
	(0.017)	(0.013)	(0.002)
Price Diff(Avg)	0.0970	-0.00130	-0.000982
	(0.832)	(0.998)	(0.998)
Constant	6.594*	5.596***	3.642
	(0.019)	(0.000)	(0.053)
State Dummies	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes
Observations	746	767	961
p-values in parentheses			
=”* p<0.05	** p<0.01	*** p<0.001”	

Table 15 **Market Level Use Given Quotes(instead of winning quotes)**

	(1)	(2)	(3)
	F.Activity	F.Activity	F.Activity
Average Rating	-0.436+	-0.489+	
	(0.086)	(0.062)	
Average Ratings(Others)	-0.0164	-0.0166	
	(0.468)	(0.466)	
Avg Sentiment Score			0.268
			(0.438)
Avg Sent(Others)			0.0770
			(0.802)
Reviews Count	0.0472*	0.0450*	0.0466*
	(0.000)	(0.000)	(0.000)
Experience	0.104	0.0946	0.100
	(0.124)	(0.164)	(0.144)
Price Diff	-0.00831	0.0141	0.0249
	(0.936)	(0.893)	(0.814)
Market Revenue	-0.0162*	-0.0158*	-0.0156*
	(0.002)	(0.002)	(0.002)
Text-based Entropy (Self)		11.42*	13.28*
		(0.032)	(0.016)
Text-based Entropy $(\text{Self})^2$		-34.86*	-37.87*
		(0.019)	(0.013)
Text-based Entropy (Others)	14.22+	13.10	14.26+
	(0.086)	(0.113)	(0.080)
Text-based Entropy $(\text{Others})^2$	-59.45*	-54.83+	-57.21*
	(0.035)	(0.051)	(0.039)
Constant	1.507*	0.747	0.236
	(0.029)	(0.348)	(0.782)
State Dummies	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes
r2	0.668	0.669	0.670
aic	8853.4	8849.3	8843.7
bic	8925.9	8933.9	8928.3

Table 16 Robustness Individual with Text-based Dispersion from Mean Distance

	(1)	(2)	(3)
	F.Activity	F.Activity	F.Activity
Average Rating	-0.551*	-0.524*	-0.489*
	(0.007)	(0.011)	(0.033)
Average Ratings(Others)	0.00733	0.000713	0.0000629
	(0.741)	(0.977)	(0.998)
Reviews Count	0.0504*	0.0479*	0.0436*
	(0.000)	(0.000)	(0.000)
Experience	0.136*	0.134*	0.133*
	(0.010)	(0.012)	(0.012)
Price Diff	0.188*	0.200*	0.208*
	(0.036)	(0.027)	(0.021)
Market Revenue	-0.00645	-0.00618	-0.00553
	(0.148)	(0.165)	(0.216)
Entropy(Others)		0.386+	0.358
		(0.085)	(0.108)
Entropy(Others)^2		-2.243*	-2.312*
		(0.000)	(0.000)
Entropy(Self)			1.428*
			(0.000)
Entropy(Self)^2			-2.590*
			(0.000)
Constant	2.788*	2.868*	2.995*
	(0.000)	(0.000)	(0.000)
State Dummies	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes
Observations	3472	3472	3472
r2	0.622	0.625	0.627
aic	9693.2	9670.1	9655.4
bic	9748.6	9737.7	9735.3

Table 17 Robustness Check Excluding Inactive Installers