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Abstract

Social Commerce sites are in vogue enough to be recognized as a new trend in online shopping arena. Social Commerce can be defined as the electronic commerce triggered by social media. It has been growing very rapidly with enormous discount rate, quality services and precise information. This research analyzes effects of posted numeric information on daily sales volumes. Hetrosckedasticity arises with the real transaction data that was acquired from TicketMonster which is one of the biggest Social Commerce sites in Korea. Therefore, GLS model was applied to have results that original price, discounted price, minimum quantity to have discounted price, and maximum units of sales are statistically significant. Minimum quantity of sales to meet the requirement to have discounted prices has threshold effect on the purchase of consumers like the ways they have group buying on the Internet. However, additional studies are required to identify if this correlated information can be results of reasonable estimates by the vendors and the intermediary or play a role of signal to attract sales. More research opportunities are addressed on services types, consumer groups and information richness.

Keywords

Social Commerce, Threshold effect, GLS

1.Introduction

With development of ICT (Information and Communications Technology), new paradigms for commerce have been emerged such as e-Commerce and m-Commerce. These kinds of commerce have changed the market mechanism and then lead the economic prosperity by lowering cost, reducing delivery time and offering more information. As like e-Commerce, Social Commerce also has similar role in the society. Moreover social commerce also revive regional economy activation by promoting mom and pop stores.

B2C commerce agenda on Internet is in vogue again in recent days with the sky-rocketing popularity of Social Commerce sites (Tracy 2010). At the moment, Groupon in U.S. is one of the best known and largest one of these sites. It features a daily deal for each city it operates in, offering consumers a significant discount for a local business or event, 50% or less than the retail price. Consumer buying the Groupon must pay its price upfront, and they have a certain amount of time to use it.

Social Commerce is emerging electronic commerce market. Still, however, defining Social Commerce is controversial issue (Venrock 2005, Edelman 2005, Raito 2007, Stephen and Toubia 2008, IBM 2009). As the first definition, Beach (2005), product manager at Yahoo shopping, suggests that the shoposphere and pick lists are examples of Social Commerce. He believes the community of shoppers is one of the best sources for product information and advice. Recently, Cecere (2010), partner of Altimeter group, mentions Social

Commerce as the use of social technologies to connect, listen, understand, and engage to improve the shopping experience.

Even though the Social Commerce is not easily defined as one sentence, we can find some unique characteristics of Social Commerce. First, Social Commerce generally sells the service products such as mom and pop restaurants, café and healthcare, while other e-commerce sites deal mostly with durable products. Second, without prior notice, they sell one product for one day, called "one deal a day". Third, as the part of the promotion, they sell their product with more than 50% discount rate. Finally, with growth of social network service (e.g. Twitter, Facebook etc.), Social Commerce makes use of social network services that enable consumers buy as a group socially.

Not an exception in the popularity of Social Commerce is Korea where lots of tech-savvy early adopters exploited the idea typically via Web portal sites or Internet auction sites. As the mobile micro-blogging service like Twitter became popular, virtual community of people flock together instantly to catch volume discount offers. Among 200 Social Commerce sites in Korea as of December 2010, TicketMonster leads the market, having cumulative revenue more than $2 million in just the past 8 months. Most of the current Social Commerce services in Korea mimic the business model of Groupon to provide 50 percent or larger discount coupons on a variety of products and services for restaurants, movies, performing arts, leisure activities and beauty services. These services are reshaping electronic commerce and strengthening the offline connections between the companies and buyers.

Social Commerce is similar with existing electronic commerce; on the other hand, it also has some unique features. Even though research on consumer group behavior has been conducted, it is hard to find studies on social commerce itself. In this research, we would find factors which have influence on sales with the real transaction data that was acquired from TicketMonster. Generally, price, promotion and word-of-mouth are expected to be possible factors for sales. The rest of this paper proceeds in four sections.

Section 2. Literature review will explain the related theories. Section 3. Data and model will follow to describe our data and discusses econometric specification. Section 4. Results then presents the empirical results of our GLS model. Finally, Section 5. Summary and discussion summarize the findings and explore the opportunities of the further research on Social Commerce.

2. Literature Review
2.1 Social Commerce
Majority of people understand Social Commerce as the 'social shopping' of electronic commerce, one of trendy concept of these days. However, Social Commerce has some special characteristics which have totally distinguished from general e-commerce. It deals with service product while e-commerce usually provides durables. Social Commerce focuses on selling non-popular brand, called "mom and pop" – that is the reason why customer can have more uncertainty in Social Commerce shopping. Additionally, Social Commerce actively uses social network service such as Twitter and Facebook. In this point of view, the Social Commerce is not only the one part of e-commerce, but also new mechanism for e-commerce.

Whereas Social Commerce becomes a popular mechanism of electronic commerce, there are only few academic studies. Stephen and Toubia (2010)'s research is the only paper published in authority journals, which shows the value of Social Commerce with analytical analysis. However, this research does not analyze normally accepted Social Commerce

sites; rather the research object is close to classic electronic commerce market. Dholakia's working paper (2010) suggests how to promote in Social Commerce website with survey data from vendors working with Groupon, the most famous Social Commerce site in United States.

2.2 Group-buying

Group-buying has existed as a unique form of electronic commerce and analyzed in many studies. Group-buying has the mechanism that price goes down to the pre-determined level when enough number of consumers purchase certain quantity for durable goods. There have already been a number of studies for group-buying (Chen et al. 2002, 2007, Kauffman and Wang 2001, Anand and Aron 2003). The main issue of group-buying research is threshold effect around point of discount. Price threshold indicates proximity in order quantity terms to the quantity-price combination that reflects a drop in price to the lower-tier. Before and after threshold, consumer behavior and selling patterns may be changed from this point on (Kauffman and Wang 2001).

In Social Commerce, matters setting the minimum quantity point for discount. Kauffman and Wang (2001) shows that in group-buying sites the threshold effect exist; especially people tend to buy more right before and after threshold.

2.3 Deadline Effect

In auction mechanism, customers are crowded in the last minutes, called deadline effect or end effect (Roth and Ockenfels 2002, Roth et al. 1998). Suppose that consumers consider purchasing product, at the end, they have tendency to buy if they do not have enough time to evaluate their decisions to buy or not. In Social Commerce, the vendors and the intermediary set the maximum quantity of sales that take effect on consumer behavior.

2.4 Price in e-commerce

In many IS researches already studied the price level in e-commerce (Brynjolfsson and Smith 2000, Chun and Kim 2005) and price dispersion (Baye et al. 2004, Brynjolfsson and Smith 2000). Brynjolfsson and Smith (2005) mentions that online prices are normally lower than offline ones, because through the online, vendor does not have to pay for huge amount of fee for store, logistics and employee. Moreover, some research presented price dispersion in online (Ancarani and Shankar 2004, Baye et al. 2004, Brynjolfsson and Smith 2000). However, level of price dispersion is reduced when more companies exist in the market. Even though online usually offers lower price of product, lower price is not always a solution to sell it. Brand, trust and awareness are some factors can differentiate the price dispersion (Brynjolfsoon and Smith 2000).

Wang et al. (2008) study about "one deal a day" site and check the effect of price. They enumerate price elasticity for physical good in one deal a day site.

3. Data and model

We collected transactional data from TicketMonster from 12th May to 8th December, 2010. TicketMonster is the first Social Commerce site in Korea and launched at May of 2010 and sells wide range of services product from restaurant, café, healthcare, etc.

Total number of product is 536. To secure same analysis condition, however, we rule out product sold more than 1 day. Additionally, we remove some products which have zero and exceptional prices from the list. Finally, we get 471 products and most of these products are services.

As shown in Table 1, TicketMonster sold a variety of services products with price ranging from 750 to 990,000 Korean Won. TicketMonster sells the product with the average discount rate of 55.29%. On average, the number of sales of each item is 1,075. Customer has average 86.81 days to exercise their coupon. TicketMonster sets the minimum quantity of sales and if total sales of each product exceed this threshold, the product will be sold at discounted price. If not, product will not be sold. Among 536 products, there were less than 5 products which did not meet the requirement for discounted sales. We also present the skewness and kurtosis statistics for the variables and from these results; we find that the data are not normally distributed.

	Mean	SD	Min	Max	Skewness	Kurtosis
Sales	1,075.28	1,468.63	41	27,194	12.38	213.64
Original Price	46,32.85	41,492.46	1,500	305,000	2.18	6.50
Discount Rate	55.29	6.45	50	81	1.47	1.60
Discounted Price	19,519.64	15,819.70	750	99,000	1.90	4.33
Duration	86.81	47.72	-	458	2.01	14.66
Min_Quantity	88.40	74.95	15	1,000	8.62	96.28
Max_Qunatity	1,847.28	2,632.03	165	31,000	7.14	61.24

TABLE 1: Sample descriptive statistics, N = 471

Figure 1 shows the average hourly percentage of products sold in the Social Commerce. At the first of 1st hour, more portions of consumers than other time periods purchase the product. From 9 A.M. to 12 A.M., more than 30% of sales happen. At the end period of the day, we think that there is the deadline effect as well.
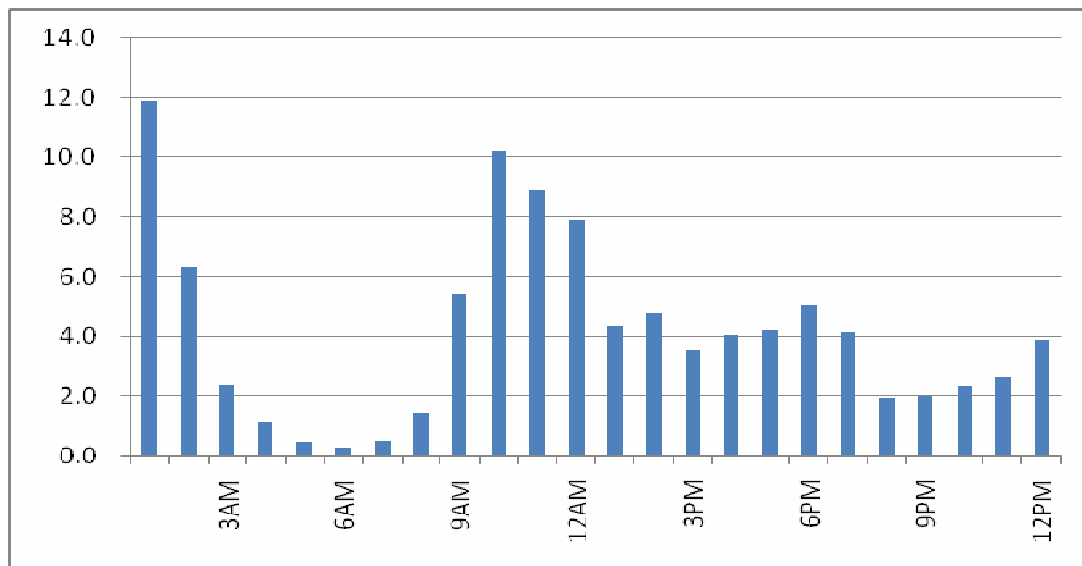

Figure 1: Average Percentage of Sales Quantity

While each vendor posts product information themselves in e-commerce websites and consequently those postings lack unity, TicketMonster, the intermediary, controls whole information on the web site and display it with same framework. Therefore, we assume that

there are no differences in amount of product information and layouts and the only differences are numeric information such as price, discount rate, minimum and maximum quantity. From this assumption and given data, we derive our basic model as follows:

$$Y_i = \alpha_i + \beta_1 \ln(Original\ Price_i) + \beta_2 \ln(Discount\ Price_i) +$$
$$\beta_3(Min\ Quantity_i) + \beta_4(Max\ Quantity_i) + \varepsilon_i \qquad (1)$$

In our model, we use original price instead of discount rate because we can find the impact of discount rate by comparing original price and discounted price and easily compare the effects of original price and discounted price as well. We use logarithm value of prices, original price and discounted price, since the gap between high price and low price are too big. Wang et al. (2009) also used logarithm to adjust this effect.

Variable	Definition
Dependent Variable	
Sales (Y_i)	Total quantity of sales for product i
Independent Variables	
ln(Original Price$_i$)	The natural logarithm of original price for product i
ln(Discounted Price$_i$)	The natural logarithm of discounted price for product i
Min_Quantity$_i$	The amount of minimum quantity to discount for product i
Max_Quantity$_i$	The amount of maximum quantity of sales for product i

TABLE 2: Variable Definitions and Descriptive Statistics

In cross-sectional estimation, we should take into account a heteroskedastic random error term (ε_i). Heteroskedasticity occurs when $E(\varepsilon_i^2) = \sigma_i^2$ for i = 1, . . ., n and $\sigma_i^2 \neq \sigma_t^2$ for some t > 1. With heteroskedasticity, the ordinary least squares (OLS) coefficient estimator is known to be unbiased and inefficient. A modified version of White's (1980) test strongly supports heteroskedasticity. Therefore, we tested hetroskedasticity as shown at Table 3, to understand that there exists hetroskedasticity under .01 significant level.

White's test for Ho: homoskedasticity

$Chi^2(14)$	$Prob > Chi^2$
458.40	.00

Cameron & Trivedi's decomposition of IM-test

Source	Chi^2	df	p
Heteroskedasticity	458.40	14.00	.00
Skewness	107.48	4.00	.00
Kurtosis	1.38	1.00	.24
Total	567.26	19.00	.00

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity

$Chi^2(1)$	$Prob > Chi^2$
9228.09	.00

TABLE 3: Test for hetroskedasticity

In order to resolve heteroskedastic issues, generalized least squares (GLS) estimation specifies $\sigma_i^2 = \sigma^2 [E(Y_i)])$ where sales volumes predicted by OLS is a consistent estimator of $E(Y_i)$. Table 4 reports both the OLS and GLS results.

	Sales (n=471)	
Variables	OLS	GLS
ln(Original Price)	477.84	477.84
	$(.265)^{a*}$	$(.265)^{***}$
ln(Discounted Price)	-766.61	-766.61
	$(-.399)^{***}$	$(-.399)^{***}$
Min_Quantity	8.55	8.55
	$(.436)^{***}$	$(.436)^{**}$
Max_Quantity	.20	.20
	$(.351)^{***}$	$(0.351)^{**}$
Constant	2337.80	2337.80
	$(-)^{***}$	$(-)^{*}$
R^2	.562	.562

a. The values in parentheses are z-statistics. All tests are two-tailed with * = 10%, ** = 5%, and *** = 1% significance.

TABLE 4: Ordinary and Generalized Least Squares Results

4. Results

The GLS results are emphasized because heteroskedasticity is present in the volume of sales. Sales of items is correlated with original price and discounted price, minimum quantity to have discounted price and maximum limit of sales volume. P values of all the variables except the constant are less than .05, which means the estimates will be statistically significant with .95 confidence level. The interesting thing in this result is that the effects from original price and discounted price have different direction. People buy more when product price is cheaper; this is common sense of demand curve. The standard coefficient is -.40 in .01 significant level. However, original price also has impact on sales. Product that has higher original price is sold more with .27 standard beta value. The coefficients of log value of original price and discounted price have different signals, positive for original price and negative for discounted price. This can be interpreted as consumers on Social Commerce tend to purchase more if original price is high and discounted price is low, that is, the discount rate is high.

As original price estimate in the OLS model is not statistically significant. The results indicate a high price level generally yields a high value variance. Typically Social Commerce deals with various types of service such as restaurant, pub, café, and exhibition and so on. Higher original prices are, higher variance values are, we expect. With GLS model, original price estimate is statistically significant as the variances of price levels are considered.

We find that sales and minimum quantity of sales have positive correlation; standard coefficient is .44 with .05 significant level. We can interpret this result to mean that more people buy this product to achieve the price discount, as threshold point is higher. And maximum quantity also has positive effect on sales, standardized beta is .35 in .05 significant level.

From these results, we derive the conclusion that people prefer cheaper product according to the basic economic theory. However, they also concern original price and when products have same sales price; people tend to appreciate more value on product which has higher original price.

5. Summary and Discussion

In this paper, we have empirically test a GLS model that explains the correlation between the volume of sales and posted numeric information in Social Commerce website. The formal model generates predictions about the quantity of item sales as a function of item's discounted price, maximum number of sales and the minimum number of sales to apply pre-determined discount rate. This model takes into consideration all the figures on the Social Commerce web site. The empirical results reveal three major insights about the proposed model.

First, we find that the volume of sales is correlated with original price, discounted price, maximum number of sales, and minimum number of sales. This point can be explained by both that vendor and the intermediary are estimating appropriate number of sales and that the numeric information plays a role to attract the sales accordingly. The discrimination between both effects left to be reserved for our next research.

Second, it is clear that minimum quantity of sales to meet the requirement to have discounted prices has threshold effect on the purchase of consumers like the ways they have group buying on the Internet. For more precise analysis, the concept of velocity to reach the minimum quantity point should be taken into account in the following studies.

Third, we came to know that the vendors and the intermediary could make use of the original price information on the web site. Statistically, standardized coefficient of discounted price is bigger than that of original price, which means discounted price is more correlated with sales volume than original price is. Therefore, the vendors and intermediary could control the original price to make consumers appreciate more values. For example, higher prices will have consumers feel that they are consuming better services at lower prices with the presentation of higher discount rates. Experimental research opportunities can be found to verify this kind of price adjustment.

Our study can be evaluated as one of the very first empirical research on Social Commerce. We deal with posted numerical information and actual sales data. Services quality and information other than numerical ones are not covered in this research. Ultimately, more models are needed that characterize the nature of Social Commerce. We have focused here only on the posted numeric information and the results of sales, however, there definitely are more aspects to research such as consumer profiles, differences among the product types, variations of sales through time including deadline effect, and the impact of other information at the web site. More rigorous methodology should be adopted to explain the differences between original price and discounted price. Such studies are important not only to understand the mechanism of Social Commerce, but also to be able to predict the potentials of "so growing" commerce site.

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