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Digital Item Purchase Model in SNS Channel Applying Dynamic SNA and PVAR*

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Abstract

Purpose: Based on previous researches on social factors of digital item purchase in digital contents distribution platforms such as SNS, we aim to develop the integrated model that accounts for the dynamic and interactive relationship between social structure indicators and digital item purchase**. Research design, data and methodology:** A PVAR model was used to capture endogenous and dynamic relationships between digital item purchase and network indicators. **Results:** We find that there exist considerable endogenous and dynamic relationships between digital item purchase and network structure variables. Not only lagged in-degree and out-degree but also in-closeness and out-closeness centrality have significant and positive impacts on digital item purchase. Lagged clustering has a significant and negative effect on digital item purchase. Lagged purchase has a significant and positive impact just on the present in-closeness and out-closeness centrality; but there is no significant effect of lagged purchase on the other two degree variables and clustering coefficient. We also find that both closeness centralities have much higher carryover effect on digital item purchase and that the elasticity of both closeness centralities on the purchase of digital items is even higher than that of other network structure variables. **Conclusions:** In-closeness and out-closeness are the most influential factors among social structure variables of this study on digital item purchase.

Keywords: Digital Items, Digital Contents Distribution Platforms, Social Network Service (SNS), Panel Vector Autoregression (PVAR), Impulse Response Function.

JEL Classification Code: C33, C55, C81, M31.

1. Introduction

Although the main revenue source of major SNS (social network services) including Facebook and Twitter is advertising, SNS providers are trying to diversify revenue sources by selling digital items to SNS members (Kim, Gupta, & Koh, 2011; Koh & Kim, 2003). Statistics show that the sales of digital items to SNS service users have rapidly increased and diversified. According to statistics, Facebook has reported that its 2014 annual total revenue is \$12.5 billion of which \$1.0 billion takes digital items (Fiegerman, 2015). Line that is a Korean mobile based social messenger service reported \$80million revenue of digital items out of \$4.1 billion which is its total revenue. The Guardian, a British daily reported that branding of "Sticker," the name of digital items of Line, has become the critical factor for attracting western customers (Dredge, 2014). In Spain, stickers of Rafael Nadal, a famous Spanish professional tennis player and soccer clubs including Real Madrid and FC Barcelona are circulated. Not only has Line executed charging of stickers, but it also has realized a platform in which users can make and sell stickers themselves. "LINE Creators Market" which started in April 2014 earned \$1.1million for three months since its open. "LINE friends", which is a representative sticker, was expanded into offline character business and has created additional value (Moon, 2014). KakaoTalk, another popular mobile instant messenger, launched branded emoticons in April 2017. In 2018, they have been distributing 565

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different brand emoticons with an annual growth rate of 167% (Kakao, 2018).

The success of social network services mainly depends on network effects originating from users' spontaneous participation. The more people use an SNS, the more values of the SNS can be created. Digital items can also play a critical role in users' participation in SNS and can indirectly contribute to increasing advertising revenue of SNS.

Considering such importance of digital item market and business, consumers' buying process of digital items and related factors has been identified by a number of researchers (Kim et al., 2011; Mäntymäki & Salo, 2011). More specifically, business practitioners and researchers have been interested in what factors are significantly associated with the purchase of digital items (e.g., Kim et al., 2011; Kim, Chan, & Kankanhalli, 2012; Koh & Kim, 2003; Wohn, 2014; Lee & Bae, 2019). However, the previous studies have mainly focused on finding psychological antecedents of the purchase of digital items (Kim et al., 2011; Kim et al., 2012; Koh & Kim, 2003). Exceptionally, Wohn (2014) examine 'actual' purchase of digital items in SNS. Unlike the previous studies on the factors of the purchase of digital items, this study examines the dynamic and endogenous relationships between social structure indicators and the purchase of digital items using panel vector autoregression model (PVAR) which has not been dealt with by other studies.

And our study has another distinction in focusing on the role of closeness centrality and clustering coefficient which were little dealt with in previous studies.

The remainder of this study is constructed as follows. We present the previous literature on the intention of digital item purchase in SNS, marketing and sociology researches on social network analysis (SNA) in Section 2. In Section 3, we draw and discuss the model specification for this study and social network indicators. Section 4 details data collection and empirical results with managerial implications. In Section 5, we conclude this paper with contributions, limitations and further research directions of this study.

2. Literature Reviews

Our study draws on two previous research streams. The one is marketing and e-commerce researches on the intention of digital item purchase in SNS. The other stream is the researches based on social network analysis.

2.1. Digital Item Business

Digital items are usually classified as an intangible objects (Yang, Huang, & Su, 2018), and composed of background music, emoticon, online avatars, online game items and decorative ornaments (Kim et al., 2011). And digital item business can be categorized as fallowing; subscription, retail distribution, and freemium (Koeder & Tanaka, 2017; Yang et al., 2018). First, in subscription business model, SNS uses pay a subscription fee to gain the right to use the service. While, in retail distribution business model, SNS providers sell to digital items via either an online or physical channel. Finally, in freemium business models, consumers can use or access the service free, but they have to be paid for using premium version or for digital items.

2.2. The Sale of Digital Items in Social Media Distribution Platform

Social media play roles not only as a digital contents generation platform but also as a digital contents distribution platform (Susarla, Oh, & Tan, 2012). Social media deliver new types of time and space such as self-expression, link, self-creation in the digital era (Livingstone, 2008). Digital items are new media products used and distributed by social media members for self-representation, self-expression, and communication (Kim et al., 2011; Jung & Kim, 2016). Digital items usually can be fall into following two categories; graphical and musical digital items. Graphical digital items include avatars, accessories for avatars, items for decorations and game items, etc. Musical digital items are composed of music and songs.

First real-money trade for digital items began between players in massively-multiplayer online games (MMOs) in 1999 (Hamari & Lehdonvirta, 2010). Game users exchange their game possessions with other gamers (Lehdonvirta, 2008). Lehdonvirta (2005) finds that users' intention to purchase digital items is related to their motivations such as advancement in a status hierarchy, advantageous competitive settings, self-expression etc. Lehdonvirta, Wilska, and Johnson (2009) point out that digital items are distributed and consumed as social signs to make distinctions between "haves" and "have-nots" and to construct and communicate self-identity to other community members.

Customer value is a primary motivation factor of consumer purchase behavior (Sweeney & Soutar, 2001; e.g. Babin, Darden, & Griffin, 1994; Dodds, Monroe, & Grewal, 1991; Kim, Chan, & Gupta, 2007; Sheth, Newman, & Gross, 1991; Zeithaml, 1988). Customer value is classified into functional, emotional, and social value, denoting perceived utility of enhancing or sustaining a person's social capital. Kim et al. (2011) suggest that there are self-expression and relationship support in social value. As for self-image expression, consumers want to purchase and consume products to show their self-image as desirable appearance in the eyes of others. By using digital items, SNS users and social game members can express and strengthen their self-image. Self-presentation theory can also explain the reason why people try to demonstrate desirable views of themselves to others (Goffman, 1959; Leary, 1996). Concerning self-presentation, there are two critical motives (Schlenker, 2003). People intend to influence others and find similar people to build relationships by self-presentation. Primary ways of offline self-presentation are language, behavior, looks, and belongings, while online self-presentation mainly depends on textual, symbolic, and aural methods (Schau & Gilly, 2003).

Social relationship support indicates a perceived capability to help form, sustain and enhance relationships among people. Through SNS, people can exchange emotional aid, companionship, and sympathy. People open their timeline to maintain and enhance current relationships (Walker, 2000). SNS users try to attract more friends or visitors and strengthen relationships with them by embellishing their timeline using diverse digital items. That is, SNS members use digital items to build and strengthen their social relationships with their friends and they are motivated to buy digital items. Thus, an SNS member who has more friends compared to her neighbours will tend to buy digital items to decorate her online background, leading to maintaining and enhancing her status in SNS. Through the above discussion, we can infer that the need for maintaining and strengthening social value can lead to consumers' purchasing digital items in SNS. Kim et al. (2011) find that social relationship support has a positive and significant association with the intention to purchase digital items in SNS.

2.3. Research Concerning Influential Factors of Social Network Structure

A lot of researchers from a variety of fields such as sociology, computer science, economics, and management have examined the relationship between people's behaviors (e.g., product adoption) or performances (e.g., profitability) and social network structure indicators which shows a person's social influence power in her social network (Burt, 1992, 2004; Wasserman & Faust, 1994; Bhattacharya, Phan, & Bai, 2019). Although there are lots of social network structure variables, several indicators are mainly used as important ones in social science area such as sociology, economics, business etc. Those variables are degree, closeness centrality, and clustering coefficient and the existing research on those variables are as follows.

2.3.1. Degree

In social networks, a node that has much higher degree than other nodes is called a hub (Goldenberg, Han, Lehmann, & Hong, 2009). Hub has been a main research topic and received research interest from various academic spheres on social networks. Watts and Dodds (2007) claim that the role of hubs is limited in diffusing innovation and the critical mass of early adopters of information play an important role in initial adoption of innovation. In contrast, Goldenberg et al. (2009) argues that hubs are critical in the adoption of innovation. The authors classify hubs into innovative hubs that affect the speed of adoption and follower hubs that influence market size.

Stephen and Toubia (2010) examine the relationship between social network structure and the profitability of social commerce distributors. A big network is formed by linking each store with other online stores. They find that distributors' revenue can grow up by building a network among other online stores. In particular, in-degree has a significant and positive impact on online distributors' revenue, while out-degree has a significant and negative effect on online distributors' revenue.

Katona, Zubcsek, and Sarvary (2011) show that having a high-degree neighbor (i.e. hub) decreases the probability of adoption, while a high-degree person has a higher likelihood of adopting innovation than others. A hub cannot pay much attention and spend much time to her each friend because she has so many friends. Thus, the amount of interest one of her friends takes would be limited on average.

2.3.2. Closeness Centrality

Closeness centrality shows how close distance between a focal node and every other node excluding a focal one in a social network (Wasserman & Faust, 1994). If a node can easily contact with other nodes in her proximal area and get some news more quickly than others, she is likely to be influential in terms of closeness. She can communicate news such as new product launching with other nodes efficiently, which may have an impact on her neighbors' activities such as product adoption (Beauchamp, 1965). Stephen and Toubia (2010) show that in-closeness centrality positively and significantly influence online distributors' revenues while a high-degree person has a higher likelihood of adopting innovation than others.

2.3.3. Clustering Coefficient

The clustering coefficient shows how densely a node is interconnected with other nodes in a social network (Watts & Strogatz, 1998). Girvan and Newman (2002) suggested that highly clustered networks are tightly-knit and distinctive communities. This indicator might be associated with cases in which every social network actor influences other nodes. Network closure theory explains that if two actors who know each other have the same friend in common in a social network, they can have greater impact on that shared person than when they are not interlinked (Burt, 2004; Coleman, 1988).

3. Empirical Model

3.1. Panel Vector Auto Regression (PVAR) Model

To capture endogenous, dynamic, and interactive relationships between the purchase of digital items and network structure indicators, we use a PVAR model. This model integrates the typical Vector Autoregression (VAR) methodology, setting all the variables of the dynamic system as endogenous, and panel data, controlling for unobserved individual heterogeneity. If a sufficient number of time-series data available, VAR parameters can be easily estimated, and the long-term impact of an unanticipated shock from one variable on the others in the system may be obtained. To date, VAR model, a time series model, has been used in various marketing-mix settings (for a review of this approach, see Dekimpe & Hanssens, 2003). In addition, our model of this study deals with cross sectional characteristics by using each panel's data, which is our model's differentiation point from the other marketing researches applying VAR model. We specify a PVAR model as follows:

$$y_{it} = \sum_{l=1}^{L} A_l y_{i,t-l} + f_i + d_t + e_{it},$$
$$e_{it} \sim iid\, N(0, \Sigma_e)$$
$$i = 1,2,3,\ldots\ldots, N, \qquad t = 1,2,3,\ldots, T_i$$

where $\boldsymbol{y_{it}}$ is an endogenous dependent variable vector, A is a parameter matrix to be estimated, f_i specifies unobserved heterogeneity, and d_t indicates time effect. e_{it} is an error term supposed to be identically and independently distributed (*i.i.d.*) following $N(0, \Sigma_e)$ and needs to follow an orthogonal condition as follows:

$$(2)\ E[y_{is}e_{it}] = E[f_i e_{it}] = E[d_t e_{it}] = 0\ \ (s \neq t)$$

This orthogonal condition shows that lagged variables are eligible for instrumental ones in estimating equation (1). However, unobserved heterogeneity, f_i should be calculated to estimate parameters of equation (1) by using the orthogonality condition in equation (2).

In applying VAR model to panel data, we need to set the constraint that the latent structure is the same for every cross-sectional unit. Because this restriction can be violated in reality, one method to solve the constraint problem on parameters is to permit "individual heterogeneity" in the variable levels by using fixed effects, indicated by f_i in the model. If the fixed effects were associated with the regressors because of lags of the dependent variables, biased coefficients would be created by the mean-differencing method usually used to remove fixed effects. To overcome this problem, we apply forward mean-differencing, also referred to as the "Helmert procedure" (Arellano & Bover, 1995). This procedure removes only the forward mean — that is, the mean of all the future observations available for each firm-year (Love & Zicchino, 2006). That transformation holds the orthogonality between lagged regressors and transformed variables, lagged regressors can be applied as instruments and the coefficients can be calculated through system generalized method of moment (GMM). Our model also considers individual-specific time dummies, d_t which can be removed by taking away the means of each variable computed for each month. As in traditional VAR, PVAR not only deals with all variables as endogenous, but also makes estimation for lots of cross sections of data possible, which is impossible in traditional VAR. The impulse response functions (IRFs) analysis supplements The PVAR analysis by elucidating the dynamics in the interested relationships. IRFs mean the response of one variable to one standard deviation shock on other variables in the dynamic system, while controlling for all other shocks at zero. We can visualize the dynamic pairwise relationships by using IRFs. IRFs can capture the impact of product purchase to a network structure variable shock while other variables remain constant.

3.2. Social Network Structure Indicators

There are two kinds of social network according to whether a social network relationship has a direction or not: undirected network and directed one. Friendship network of Facebook is a representative example of an undirected network and Twitter is a typical directed network composed of follower and following relationships. A communication network showing relationships of visitors and hosts is also a directed network. In addition, a communication network also has a characteristic of weighted network. Frequency of visits to and from a node's friends is reflected in calculating social network structure variables in communication networks. Our study deals with weighted directed social network dataset unlike the previous studies using undirected social network (Katona, Zubcsek, & Sarvary, 2011) and directed but unweighted network (Stephen & Toubia, 2010; Yoganarasimhan, 2012). Network structure indicators are calculated on a monthly basis (12 months) and per each node and construct panel data as follows. Based on the discussion about the concepts and studies of social structure variables, we calculate those social structure indicators as follows.

3.2.1. Degree

Degree of a directed network can be classified into "in-degree" and "out-degree." By transforming Wasserman and Faust (1994) and considering weight, we calculate weighted in-degree and out-degree as follows:

(3) $wind_{it} = \sum_{j=1}^{N} W_{ij,t} \cdot L_{ij,t}$

(4) $woutd_{it} = \sum_{j=1}^{N} W_{ji,t} \cdot L_{ji,t}$

$wind_{it}$ and $woutd_{it}$ represent weighted in-degree and out-degree of node i in period t. $W_{ij,t}$ is the frequency of visits from j to i in period t, $W_{ji,t}$ is a number of visits from i to j in period t. If a relationship from i to j exists, $L_{ij,t}$ is 1 or 0 in period t and if a relationship from j to i exists, $L_{ji,t}$ is 1 or 0 in period t.

3.2.2. Closeness Centrality

Weighted in-closeness and out-closeness centrality considering visit frequency can be computed as follow:

(5) $winclose_{it} = \sum_{i \neq j} W_{ij,t}/d_{ij,t}$, $i = 1,2,3,\ldots,N$

(6) $woutclose_{it} = \sum_{j \neq i} W_{ji,t}/d_{ji,t}$, $i = 1,2,3,\ldots,N$

$d_{ij,t}$ represents a smallest distance from j to i ($i \neq j$) in period t, and

$d_{ji,t}$ demonstrates a smallest distance from i to j ($j \neq i$) in period t.

3.2.3. Clustering Coefficient

We can calculate a weighted clustering coefficient as folows. A graph $G(V,E)$ in which V is a set of vertices (nodes). $V = \{v_1, v_2, \ldots\ldots\}$. And E represents a set of edges $E = \{e_1, e_2, \ldots\}$ as the following:

(7) $e_{ij,t} = \begin{cases} 1, & if(i,j) \in E \\ 0, & otherwise \end{cases}$

A set of neighbors of i in period t are assumed as the following:

(8) $N_{i,t} = \{j | i,j \in V,\ e_{ij,t} = 1 \,\&\, (i,j) \in E\}$

Weighted clustering coefficient can be calculated as the following (9)

(9) $wclustering_{i,t} = \dfrac{\sum_{(i,j) \in N_{i,t}} e_{ij,t} \cdot \dfrac{W_{ij,t}}{\sum_{(i,j) \in N_{i,t}} W_{ji,t}}}{\sum_{i,j \in N_{i,t}} 1}$

4. Empirical Analysis

4.1. Data Description

We collected data from a Korean social network service provider. We sampled 23,395 nodes by snowball sampling and data period is from Oct. 2011 to Sep. 2012. The network type we examine is a communication network reflecting both weight (i.e., visit frequency) and direction.

The first dependent variable is the purchase quantity of digital items used mainly for decorating SNS members' individual timeline. We log-transform the purchase data. Other dependent variables including in-degree, out-degree, in-closeness centrality, out-closeness centrality, and clustering coefficient are set by calculating communication network values following measures introduced in section 3.2. We construct panel vectors combining those dependent variables. Table 1 shows descriptive statistics of all endogenous variables.

Table 1: Descriptive statistics

Variable	Mean	Min.	Max.	Std. Dev.
ln_pu (log of purchase)	1.71	0	12.23	2.92
wind	118.73	0	65,011	601.43
woutd	118.73	0	14,082	316.68
winclose	.001	0	.0069	.0008
woutclose	.001	0	.0147	.00085
wclustering	.0008	0	.07	.0025

4.2. Model Estimation

To investigate endogenous and dynamic response as well as interactions between product purchase and network structure variables, we estimated equation (1). Equation (1) is estimated as the following procedures using network structure variables and log of purchase. First, we conduct empirical analysis by testing for stationarity versus evolution of variables (Enders, 2004).

For this, we perform panel unit root tests like the tests of Im, Pesaran, and Shin (1997), Levin and Lin (1992), and ADF-Fisher and PP-Fisher. Table 2 presents the results of these tests which show that all variables are stationary (every p-value <.00). This means that model can be estimated with each variable in levels.

Table 2: Panel unit root test results

	Levin, Lin and Chu t*		Im, Pesaran and Shin W-stat		ADF		PP	
	test-statistic	p-value	test-statistic	p-value	test-statistic	p-value	test-statistic	p-value
ln_pu	-572	.00	-248	.00	110,585	.00	126,325	.00
wind	-4,280	.00	-293	.00	84,123	.00	97,133	.00
woutd	-10,695	.00	-1,176	.00	93,196	.00	10,625	.00
winclose	-4,970	.00	-4,843	.00	39,470	.00	44,881	.00
woutclose	-67	.00	-655	.00	42,396	.00	46,130	.00
wclustering	-6,067	.00	-367	.00	48,687	.00	55,409	.00

Next, we conduct Granger-causality test to decide whether there exist endogenous and bi-directional causality relationships between dependent variables. The results for the test are reported in Table 3 and show obvious proof of bi-directional causality in each pairwise variables but for weighted in-degree and weighted clustering coefficient at 5% significance level (.068, significant at 10% level). This supports our approach of analyzing the variables as a "full dynamic system" through PVAR analysis (Trusov, Bucklin, & Pauwels, 2009).

Table 3: Granger causality results

DV is Granger Caused by	ln_pu	wind	woutd	winc-lose	woutc-lose	const-raint
ln_pu		.00	.01	.00	.00	.00
wind	.00		.00	.00	.00	.00
woutd	.00	.00		.00	.00	.00
winclose	.00	.0003	.00		.00	.00
woutclose	.00	.006	.00	.00		.00
wclustering	.00	.068	.004	.00	.00	

Table 4: Optimal lag length

lag	AIC	BIC
lag1	5.12	5.14
lag2	5.08	5.14
lag3	**5.02**	**5.13**
lag4	5.05	5.16
lag5	5.08	5.18
lag6	5.21	5.30
lag7	5.43	5.51

Then, we choose the appropriate lag length L using Akaike's Information Criterion (AIC) and Bayesian Information Criterion (BIC) (for details, see Greene, 2008), following the standard approach in the VAR literature (e.g., Holtz-Eakin, Newey, & Rosen, 1988; Love & Zicchino, 2006). The results are shown in Table 4. According to the results, lag3 has the lowest values in terms of AIC and BIC; thus, three is chosen as an optimal lag length.

Based on the above results, we conduct PVAR model estimation using equation (1). In more detail, equation (1) can be presented as the following equation (10).

$$(10)\quad \begin{bmatrix} ln\_pu_{it} \\ wind_{it} \\ woutd_{it} \\ winclose_{it} \\ woutclose_{it} \\ wclustering_{it} \end{bmatrix} = \sum_{l=1}^{3} \begin{bmatrix} \beta_{11}^{l} & \beta_{12}^{l} & \beta_{13}^{l} & \beta_{14}^{l} & \beta_{15}^{l} & \beta_{16}^{l} \\ \beta_{21}^{l} & \beta_{22}^{l} & \beta_{23}^{l} & \beta_{24}^{l} & \beta_{25}^{l} & \beta_{26}^{l} \\ \beta_{31}^{l} & \beta_{32}^{l} & \beta_{33}^{l} & \beta_{34}^{l} & \beta_{35}^{l} & \beta_{36}^{l} \\ \beta_{41}^{l} & \beta_{42}^{l} & \beta_{43}^{l} & \beta_{44}^{l} & \beta_{45}^{l} & \beta_{46}^{l} \\ \beta_{51}^{l} & \beta_{52}^{l} & \beta_{53}^{l} & \beta_{54}^{l} & \beta_{55}^{l} & \beta_{56}^{l} \\ \beta_{61}^{l} & \beta_{62}^{l} & \beta_{63}^{l} & \beta_{64}^{l} & \beta_{65}^{l} & \beta_{66}^{l} \end{bmatrix} \begin{bmatrix} ln\_pu_{it-l} \\ wind_{it-l} \\ woutd_{it-l} \\ winclose_{it-l} \\ woutclose_{it-l} \\ wclustering_{it-l} \end{bmatrix} + \begin{bmatrix} e_{ln\_pu,it} \\ e_{wind,it} \\ e_{woutd,it} \\ e_{winclose,it} \\ e_{woutclose,it} \\ e_{wclustering,it} \end{bmatrix}$$

After the time dummy and the fixed effects have been eliminated, the system coefficients are estimated.

The main results from the PVAR analysis equation (10) are reported in Table 5.

Our major interest lies in examining dynamic and endogenous relationships between the purchase quantity and network structure indicators. We intend to examine whether (a) network structure indicators has a significant impact on lagged purchase quantity of digital items and (b) vice versa.

As in Table 5, some lagged network structure variables have significant impacts on the present purchase. As we expect, lagged in-degree in *t-1* period (β=.04, p-value<.05) and out-degree in *t-1* period (β =.003, p-value<.05) have a significant and positive and impact on the purchase of digital items in current *t* period.

Table 5: Panel vector auto regression results

	Dependent Variable					
	ln_pu	**wind**	**woutd**	**winclose**	**woutclose**	**wclustering**
ln_pu(t-1)	.20*** (41.67)	.0002 (.24)	-.63 (-1.23)	.003*** (4.81)	.002*** (2.74)	.001 (.49)
ln_pu(t-2)	.10*** (24.66)	.0002 (.34)	.21 (.53)	.002*** (2.64)	.002*** (3.04)	.001 (.76)
ln_pu(t-3)	.06*** (16.06)	-.0007 (-1.07)	-1.12*** (-3.12)	-.0001 (-.21)	.001** (2.52)	-.005*** (-2.81)
wind(t-1)	.04** (2.18)	.61*** (10.89)	-4.04 (-.69)	-.04*** (-6.58)	.06*** (3.78)	.13 (1.5)
wind(t-2)	-.04 (-1.52)	.02 (.32)	-1.12 (-.21)	-.02*** (-3.13)	-.04** (-2.3)	-.17*** (-2.61)
wind(t-3)	.02 (1.34)	.08 (1.31)	4.51 (.98)	-.002 (-.61)	-.003 (-.2)	.05 (1.19)
woutd(t-1)	.003*** (4.80)	-.00001 (-.85)	.51*** (20.79)	.0001*** (12.6)	.000007 (.57)	.00002 (.25)
woutd(t-2)	-.000008 (-.16)	.000003 (.19)	.06*** (4.21)	-.00003*** (-3.79)	-.00004*** (-3.87)	.00007 (1.16)
woutd(t-3)	-.00005 (-1.05)	-.00002* (-1.73)	.06*** (4.77)	-.00001 (-1.33)	-.00001 (-1.53)	-.00008 (-1.59)
winclose(t-1)	.19*** (7.79)	.0009 (.11)	4.03 (1.08)	.35***(62.04)	.07*** (13.62)	-04*** (-2.66)
winclose(t-2)	.03 (1.51)	.002 (.46)	.47 (.18)	.13*** (24.59)	-.007* (-1.68)	-.02 (-1.52)
winclose(t-3)	.04* (1.86)	-.009* (-1.90)	3.24 (1.16)	.1*** (20.47)	.006 (1.53)	-.02 (-1.2)
woutclose(t-1)	.23*** (7.98)	.0004 (.03)	15.84*** (4.44)	.17*** (30.63)	.43*** (55.14)	.08*** (3.32)
woutclose(t-2)	.06** (2.24)	.006 (.59)	-4.46 (-1.30)	.01*** (2.65)	.18*** (26.55)	.02 (1.16)
woutclose(t-3)	.03 (1.27)	.02 (1.18)	4.5 (1.4)	.03*** (6.24)	.13*** (23.7)	.03 (1.6)
wclustering(t-1)	-0.000003 (-.00)	.02* (1.79)	11.4*** (2.78)	-.006** (-2.18)	-.0006 (-.19)	.64*** (24.04)
wclustering(t-2)	-0.03** (-2.31)	-.01** (-2.06)	-.81 (-.33)	-.007*** (-3.27)	.18*** (26.55)	.07*** (3.81)
wclustering(t-3)	-0.02** (-2.20)	.009(1.38)	-.27(-.12)	-.005***(-2.71)	-.006***(-3.16)	.08***(5.1)

Notes: *, **, *** - significant at the 10%, 5%, and 1% level, respectively. The values in parentheses are t-values

Lagged in-closeness in *t-1* period has a significant and positive impact on the present purchase (β =.19, p-value<.05), and Lagged out-closeness in *t-1* and *t-2* periods has a significant and positive effect on the present purchase (β =.23, p-value<.05 in *t-1* period and β =.06, p-value<.05 in *t-2* period).

Lagged clustering coefficients are negatively associated with the purchase of digital items (β =-.03, p-value<.05 in *t-2* period and β =-.02, p-value<.05 in *t-3* period). High clustering can interrupt information flow between communities (Watts & Strogatz, 1998) and may have a negative long-term effect on the purchase of digital items. Thus, we can infer that the lagged highly clustering might have negative effect on the purchase by obstructing product information flow to her local network. However, clustering coefficient of t-1 period is not significantly related to the digital item purchase, which means that the effect of lagged clustering does not occur instantly and takes considerable time to influence the purchase. Although it's not easy to reveal the reason in this study, it can be very interesting topic to examine why clustering coefficient affects purchase or other consumer behaviors after substantial time in the future research.

To quantify the interaction effect between the purchase of digital items and each social structure indicator, we compute and present Impulse Response Functions (IRFs) based on the estimated PVAR system parameters. IRFs are good to interpret with the calculated results (Joshi & Hanssens, 2010; Trusov, Bucklin, & Pauwels, 2009; Villanueva, Yoo, & Hanssens, 2008). When analyzing IRFs, we estimate their 95% confidence intervals. Because the IRF matrix is set up from the calculated VAR coefficients, standard errors should be considered. Thus, we compute IRFs' standard errors and generate confidence intervals through Monte Carlo simulations. A draw of coefficients of the model are randomly generated applying the estimated coefficients and variance-covariance matrix and the impulse-responses are re-computed. This procedure is repeated 500 times. The 5^{th} to 95^{th} percentiles of the distribution are generated and are applied as the impulse-responses' confidence interval.

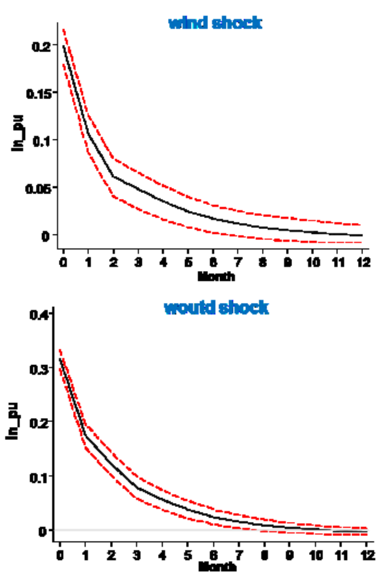
The IRFs present the gradual impact of a one-standard deviation shock in social network structure variables on the future purchase values. These enable us to examine carryover effect of each variable on the purchase while fully accounting for the indirect effect of these variables in a dynamic system. Figure 1 and Figure 2 demonstrate the results. Figure 1 shows the shock impacts of network structure variables on the future purchase of digital items, and Figure 2 represents the shock impacts of purchase on the future network structure indicators.

IRFs for the effect of in-degree, out-degree, in-closeness centrality, in-closeness centrality, and clustering coefficient on the purchase over time are presented in Figure 1.

There is a positive and significant impact of a one-standard deviation shock of in-degree and out-degree on the digital item purchase over time. While in-degree has a carryover impact on the purchase for 6 months, out-degree has a carryover effect on the purchase for about 7 months.

Shocks in in-closeness centrality and out-closeness centrality also positively influence on the future values of the purchase of digital items over time dynamically. The positive and significant carryover impacts continue over 12 months. However, a one-standard deviation shock of clustering coefficient positively impacts the present purchase, but a negative impact on the future purchase consistently over 12 periods.

Figure 2 represents the results of the gradual impact of a one-standard deviation shock in the purchase of digital items on the future values of network structure indicators. A shock in the purchase of digital items presents insignificant carryover impacts on in-degree and out-degree including clustering coefficient. On the other hand, a shock in the purchase of digital items positively impacts in-closeness and out-closeness centrality. That is, just in - and out -closeness centrality values out of network structure indicators cause and are caused by the purchase of digital items.



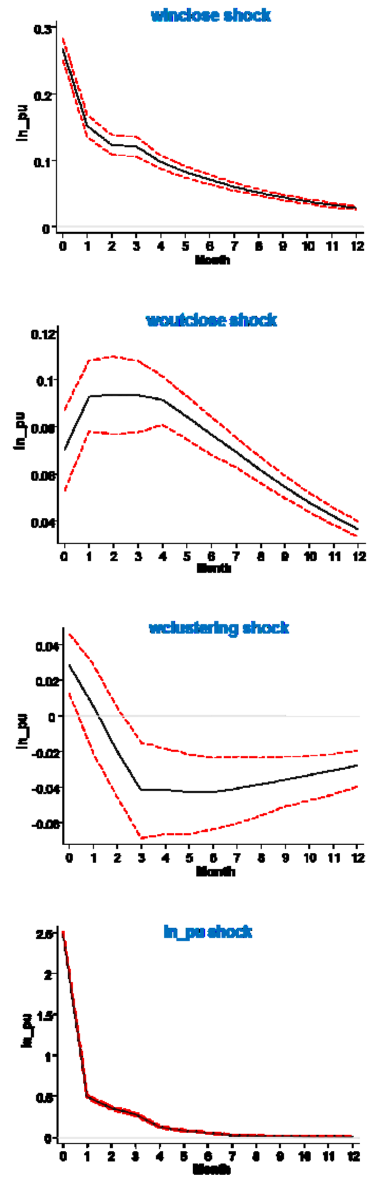
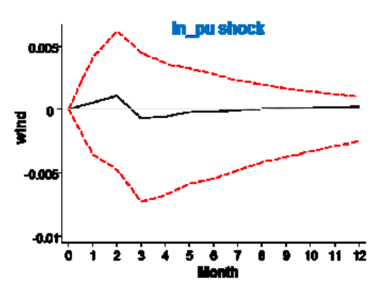


Figure 1: IRFs results: the shock of NS (Network Structure) variables



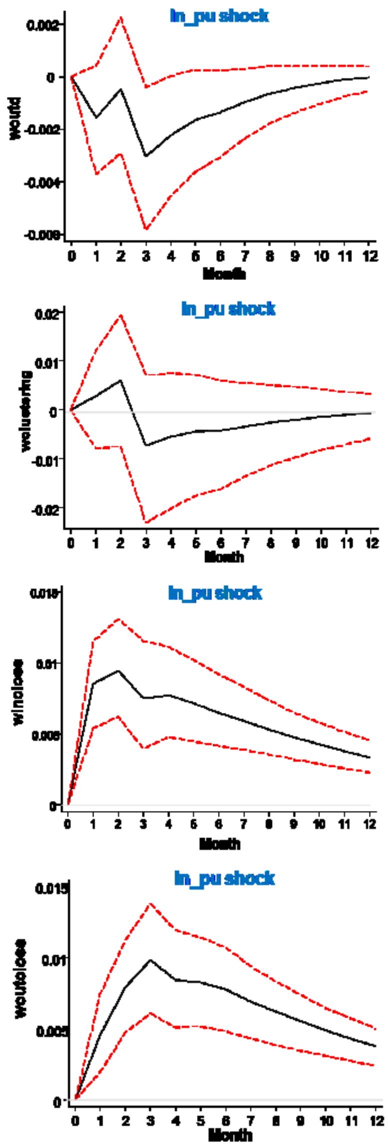


Figure 2: IRFs results: the shock of the purchase of digital items on NS (Network Structure) variables

We also compute short-term and long-term elasticities for each social structure indicator on the purchase of digital items following the computation method that Trusov, Bucklin, and Pauwels (2009) present. Table 6 shows elasticities of each period (one, three, six, nine, and twelve month respectively). From the results of Table 6, we can obtain several important implications. First, (in and out -) closeness centrality of SNS users has much more impact on the purchase of digital items than (in and out -) degree does. The one month's elasticity of in-closeness centrality (.116) is 10 times higher than that of in-degree (.012) and 3 times higher than that of out-degree (.038). And the one month's elasticity of out-closeness centrality (.069) is 5.7 times higher than that of in-degree and 1.8 times higher than that of out-degree. Moreover, the difference increases over time. The 12 month's elasticity of in-closeness centrality (.686) is 19 times higher than that of in-degree (.036) and 6 times higher than that of out-degree (.114). And the 12 month's elasticity of out-closeness centrality (.63) is 17.5 times higher than that of in-degree and 5.5 times higher than that of out-degree. Increasing closeness centrality of an SNS user is a much more effective way for the sale of digital items than increasing degrees of her (i.e., increasing the number of friends). That is, making an SNS community smaller world can be a very effective policy to increase the purchase of digital items. Second, although the immediate (one month) elasticity of clustering is positive, the long-term (12 month) elasticity of that is negative, which is the same result as that from IRFs.

Table 6: Short-term vs. long-term elasticity of purchase to social structure values

	One Month	Three Months	Six Months	Nine Months	One Year
In-degree	.012	.025	.033	.036	.036
Out-degree	.038	.082	.108	.115	.114
In-closeness	.116	.302	.493	.611	.686
Out-closeness	.069	.209	.397	.536	.630
Clustering	.001	-.010	-.034	-.055	-.072

5. Conclusions

5.1. Summary and Contributions

This study examines the dynamic and endogenous relationships between social structure indicators and the purchase of digital items using panel vector autoregression model (PVAR). The previous studies have primarily examined psychological factors that influence the intention of purchasing digital items. Even empirical studies using field data set unrealistic model specifications such as time invariant and undirected social structure variables. However, our model specifies time variant and directed social structure variables. By applying PVAR, controlling for individual's unobserved heterogeneity, we are also able to consider bi-causality and endogenous relationships between digital item purchase intention and social structure variables which is one of our study's differentiated contributions from the previous related studies.

From the empirical results, we find that there exist considerable endogenous and dynamic effects between the purchase of digital items and network structure variables over time. Not only lagged in-degree and out-degree but also lagged in-closeness and out-closeness centrality positively and significantly influence the present digital item purchase. While, there is a significant and negative impact of lagged clustering coefficient on the present digital item purchase. In addition, lagged purchase has a significant and positive impact just on the present in-closeness and out-closeness centrality; but there is no significant impact on in-degree and out-degree variables including clustering coefficients. We also find that both closeness centralities have much higher carryover effect on the purchase of digital items and that the elasticity of both closeness centralities on the purchase of digital items is even higher than that of other network structure variables. Based on the results of this study, in-closeness and out-closeness are the most influential among social network structure variables of this study on the purchase of digital items.

5.2. Implications

From the empirical results of this study, we can derive academic and practical implications as following. First, academically, we can set more realistic model which can consider dynamic, time variant, endogenous, and interactive relationships between social structure variables and digital item purchase while controlling for unobserved individual heterogeneity.

Second, marketing managers of social network service providers can apply the results of this study to their marketing strategy. Practitioners can find cause and effect relationships between network structure indicators and the purchase of digital items (i.e., endogenous relationships) by applying the PVAR model to their company's social media data. Practitioners can also consider the carryover and time lag effects of social structure values on the purchase of digital items (i.e., dynamic relationships). Degree, closeness and clustering have a significant impact on the digital item purchase for over one year. Specifically, the effect of out-degree on the purchase of digital items appears after a considerable time lag. SNS marketers or firms' practitioners can also use the result of this study to target customers for purchasing digital items in SNS. Through this study, we find that lagged in- and out- closeness centralities are much more influential factors on the purchase of digital items than other social structure indicators including degree centrality. We also find that just in-closeness and out-closeness centrality are influenced by the purchase of digital items and thus, we can verify a positive feedback loop between closeness centrality and purchase. Hence, closeness centrality can be one of the most important network structure variable to be managed properly through time. In sum, it can be more effective for practitioners to target a communicator, a node who has much higher closeness centrality than others (Jeong, 2014), rather than a hub in social network or make social networks small world in order to promote the sale of digital items. That is, when a marketing manager intends to find a suitable influencer to promote the sales of newly developed digital items to consumers, if she can obtain information both on the number of degree and distance from other consumers of a node in a social network, she might get more effective results when she targets one who has the shortest distance among others rather than one who has the highest degree. However, conclusions should be made after several empirical studies on who is a better target customer, which would be a good future research topic.

5.3. Limitations and Future Research

Although this study has important contributions and implications, it has some limitations that can be good research topics in the future. Frist, the dataset we use in this study includes just one-year of observations, thus making it difficult to exclude seasonal effects such as the year-end holidays.

Second, the dataset for this study is calculated on a monthly basis. Braha and Bar-Yam (2006) show the picture in which social network structure indicators fluctuate severely on a daily basis. At first, we intended to calculate social network structure variables on a weekly or a daily basis. However, weekly or daily basis dataset have too much sparseness, thus, we aggregate network structure indicators on a monthly basis. In the future research, by using shorter periods of dataset, our model can be analysed.

Finally, the results of this study cannot be generalizable to other types of products other than digital items that are a symbolic and low-involvement product. The appropriate network structure for product adoption can be different according to each product type (Choi, Kim, & Lee, 2008). Thus, it can be another interesting topic to investigate what social values significantly affect the purchase of other types of products.

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