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Estimating the effects of Covid-19 and 5G in the submarkets of internet and mobile shopping

Seungmi Yang^{*}, Youngsun Kwon[†]

Abstract

This paper aims to examine how two recent external shocks—the Covid-19 pandemic and 5G services—are transforming online shopping submarkets in Korea by estimating the effects of these two shocks on mobile shopping sales and conversion, which refers to substitution for shopping over fixed internet (termed internet shopping). Key findings are: Covid-19 boosted sales in 14 mobile shopping submarkets and decreased sales in two submarkets; 5G services also helped sales increases in 13 submarkets, while mobile technologies altogether contributed to sales increases in 14 submarkets; and mobile shopping conversions in online shopping submarkets have been driven mostly by mobile technologies, including 5G, and not by Covid-19.

Keywords: Covid-19, 5G, Mobile, Online, Shopping, Conversion

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1. Introduction

External shocks, including technologies and the Covid-19 pandemic, have been reshaping the online shopping landscape worldwide (Lamberton and Stephen, 2016; Grewal, Roggeveen and Nordfält, 2017). Mobile phones, especially smartphones, supported by anywhere and anytime wireless connections to the internet, enhanced the convenience of online shopping (Spaid and Flint, 2014; Zhongmei, Yu-Che and Cui, 2020). Online shopping dates back to telephone shopping (Cox and Rich, 1964), but we limit the focus of this research to shopping via wired (fixed) and wireless internet. In this paper, we define internet shopping as shopping via fixed internet and mobile shopping as shopping through mobile applications (apps) and mobile webs. Often customers use desktop computers for internet shopping and smart devices, including smartphones and tablets, for mobile shopping. Our definition of mobile shopping here does not mean literally shopping on the go, and includes the usage of smartphones for shopping, even at homes and offices.

Recently, the structural change (conversion) toward mobile shopping in online shopping channels has become more vivid due to two exogenous shocks: the Covid-19 pandemic (WHO, 2020) and the spread of 5G services globally as well as in Korea. The effects of the two external shocks on sales, however, are likely to be different across products and services sold online. The Covid-19 pandemic unevenly affected the submarkets of online shopping because consumers' consumption sets were regulated differently across products and services in location and time by the government, whereas enhanced convenience due to 5G services would not distort consumption sets in product and service space. In other words, if 5G had affected consumer behavior, that effect would be an even one, i.e. being neutral among submarkets, whereas Covid-19 would have affected sales in submarkets unevenly.

This paper aims to examine the effects of these two exogenous shocks on mobile

shopping in order to understand how they affected consumption (sales) in submarkets. In order to attain this objective, this research uses data from 21 submarkets of Korean internet and mobile shopping. This paper finds that Covid-19 boosted sales in 14 mobile shopping submarkets and decreased sales in two submarkets, 5G services also led to sales increases in 13 submarkets, and mobile technologies, including 5G, contributed to sales increases in 14 submarkets. Covid-19 affected differentially the sales of mobile shopping submarkets and a notable finding is that mobile conversion in online shopping submarkets have been driven mostly by mobile technologies, including 5G, not by Covid-19. As the 5G subscription rate rises, the mobile shopping conversion rate will also continue to rise in the online shopping submarkets. Thus, one managerial implication we can suggest to retailers is that mobile shopping conversion in online shopping will continue even after the Covid-19 pandemic, so retailers should closely monitor mobile shoppers' behavioral changes and be active in developing mobile marketing strategies that are effective on 5G based smartphones.

The remaining structure of this paper is as follows. The next section first sets forth the research questions and then overviews the developments and changes in the Korean internet and mobile shopping submarkets over the past four years. During that period, the center of Korean online shopping shifted from internet to mobile shopping. Section 3 reviews the literature on internet and mobile shopping, finding that there has been no study on the effects of both 5G and Covid-19 on internet and mobile shopping. This lack of research is mainly due to the fact that the two shocks are very recent events. Section 4 explores the characteristics of data and introduces the estimation models used for analyses, and section 5 reports and discusses the outcomes of the analyses. Section 6 closes the paper with discussion of managerial implications.

2. Research questions and key characteristics of Koran online shopping submarkets

2.1 Research questions

The Covid-19 pandemic, which started in Korea on January 20, 2020, drove people to prefer online shopping over offline shopping. Consumers chose online shopping because they could buy goods and services without coming into contact with salespersons and other consumers and could also avoid various space and time constraints placed on consumption by governments. After Covid-19 broke out, consumers' consumption sets were constrained by various local and global regulations. For example, traveling within and between nations was sometimes prohibited, gatherings of people in public places and shopping in offline stores were regulated, and shop opening hours were also controlled by governments worldwide (WHO, 2020). In addition, employees and students began to work from home and take online classes, which also changed purchase intentions by forcing them to stay home. Covid-19 truly strengthened the advantage of online shopping over offline shopping, freeing consumers from space and time constraints. As summarized in the next subsection, the sales of some submarkets have increased dramatically after Covid-19 while those of others have declined. The spread of Covid-19 in Korea, as shown in Fig. 1, has not been even over time but went through three bursts and troughs for the past fourteen months and currently is on the verge of the fourth burst, implying that there have been variations in its effects on internet and mobile shopping over time. These variations across submarkets over time enable us, we believe, to estimate the differential effects of Covid-19 on the sales of internet and mobile shopping submarkets in Korea.

===== Insert Fig. 1 around here =====

Since April 2019, when South Korea launched 5G services, becoming the first country to provide 5G services commercially in the world, 5G services have quickly spread

worldwide. As of the end of 2020, 24 countries in Europe were offering 5G services¹ and, globally, 61 countries were offering 5G services commercially as of January 2021.² Three mobile network operators (MNOs) in Korea garnered 12.9 million 5G subscription lines, and their combined 5G market share reached 18.2% as of the end of January, 2021.³ Given that 4G services in Korea overtook 3G services in subscriber lines within seven quarters after its launch in 2011, it is true that 5G performance in Korea for the past seven quarters might look disappointing. Yet, even though the migration speed to 5G services in terms of subscriber lines does not look vigorous, the transition to 5G that occurred in wireless traffic volume is notable because the traffic volume created by 5G services was 319.8 petabytes in January 2021, only 15%p smaller than that of 4G services, 374.9 petabytes. This implies that a 4G subscriber line generates on average 7.2 gigabytes monthly while a 5G subscriber line generates 24.9 gigabytes. In short, 5G services are actually catching up to 4G services, at least in terms of traffic generation in Korea and this will soon become a common trend globally.

Even though more and more countries have launched 5G services, the 5G services currently offered fall short of what was envisioned when 5G standards were initially announced in late 2017 (ITU, 2019; Zhongmei et al., 2020).⁴ Three types of 5G services were initially envisioned (Zhongmei et al., 2020): eMBB (Enhanced Mobile Broadband), mMTC (Massive Machine Type Communications), and URLLC (Ultra-reliable, Low Latency Communications), but 5G standards (Release 16) with specifications for the latter two

¹ European 5G observatory (<https://5gobservatory.eu/market-developments/5g-services/>).

² GSA (<https://gsacom.com/paper/nts-update-february-2021-status-snapshot/>).

³ As of the end of January 2021, 4G, 3G, and 2G subscriber lines took up 73.4%, 7.8%, and 0.6% of total subscriber lines in Korea, respectively (Source: Korea Ministry of Science and ICT, <https://www.msit.go.kr/>).

⁴ The 5G standards released in late 2017 (Release 14) were non-standalone radio specifications which operated in integration with LTE networks, and most current 5G services are based on this specification. Release 15 of 5G standards, announced by 3GPP in December, 2018, was the first full set of 5G standards, enabling standalone 5G networks (<https://www.3gpp.org/release-15>).

services—mMTC and URLLC—were finally published in July 3, 2020. Therefore, it is no wonder that current 5G services, running on the 5G networks based on Release 14 of 5G standards, are just enhanced 4G services and center around eMBB services (Samdanis and Taleb, 2020). According to the telecommunications service coverage and quality evaluation report published in December 30, 2020 by Korean MSIT (Ministry of Science and ICT), the average download speed of 5G, measured at 221 places in Korea, was 690.47 Mbps and that of LTE, measured at 364 places, was 153.10 Mbps, implying that 5G subscribers can use the internet content at roughly a four and a half times faster speed than 4G subscribers.⁵ An interesting fact is that the average download speed of the first-tier wired broadband service (Giga internet) was 363.66 Mbps, showing that 5G has already surpassed even wired broadband internet in download speed. This means that consumers subscribing to 5G services are more likely to use 5G-based mobile broadband services than wired broadband services even at home. Put differently, as Einav, Levin, Popov and Sundaresan (2014) stated in their paper, a large share of mobile shopping is likely to be done at home, facilitating mobile conversion in online shopping.

2.2 Recent developments in the Korean online shopping submarkets

Statistics Korea, the Korean statistical office, publishes monthly online shopping sales data by 23 commodity and service groups, termed submarkets here, for internet and mobile shopping.⁶ The online shopping sales data are collected by Statistics Korea from 1,077 online shopping malls sampled from a population of 19,087 B2C online shopping malls.⁷ This population includes online only malls and mixed malls using both online and

⁵ In terms of the average upload speed, 5G (63.32 Mbps) was measured to be just 1.6 times faster than 4G (39.31 Mbps).

⁶ Statistics Korea homepage url is <http://kostat.go.kr>.

⁷ Those with sales less than 24 million Korea Won (1\$ = about 1,100 Korea Won) are excluded from the population but their aggregated sales cover only 0.04% of the total Korean online shopping sales.

offline distribution channels, and sales values comprise sales to both domestic and foreign consumers.⁸ Internet shopping sales are the sales from pc-based online transactions and mobile shopping sales are the sales from mobile app or mobile web.⁹ In other words, the sales from mobile shopping are also separately counted and collected, so total online shopping sales are simply the addition of the two sales. This paper uses the data of 21 submarkets out of 23 submarkets, and Table 1 presents 21 submarkets and their main sale items. The unused two submarkets, “miscellaneous services” and “others,” are not used for analyses because their unknown heterogeneous compositions of sale items hinder our understanding and explanation of the submarket data.

===== Insert Table 1 around here =====

For the past three years, the year-over-year growth rates of mobile shopping have recorded, on average, 27.1% per year, while those of internet shopping have remained at 7.5%.¹⁰ Owing to the persistent and strong growth of mobile shopping, the aggregated sales of internet and mobile shopping has grown 19.3% per year for the same three year time period as the year-over-year growth rate, and the share of mobile shopping in online shopping has increased from 53.6% in January 2017 to 70.5% in January 2021. Fig 2 illustrates this drastic structural change, conversion to mobile shopping, in the Korean online shopping industry. This big picture of online shopping does not reveal the ups and downs of submarkets in online shopping that have occurred in Korea between 2017 and 2020, and the next subsection investigates those details.

⁸ In collecting sales data for mixed malls, Statistics Korea counts only online shopping sales by excluding offline sales.

⁹ This definition of mobile shopping was also used in the previous studies (Einav et al., 2014).

¹⁰ Four year monthly data are used for the year-over-year growth rate, so the calculated growth rates exist for only three years from 2018 to 2020.

===== Insert Fig. 2 around here =====

2.3 Changes in the composition of Korean online shopping submarkets

For the past four years, as summarized in Tables 2 and 3, the Korean online shopping industry has experienced drastic ups and downs in the growth rates and the rankings of internet and mobile shopping submarkets. Table 2 presents the average monthly sales growth rates of 21 submarkets for the three time periods distinguished by the two events— 5G and Covid-19, and Table 3 shows the average sales and rankings of the submarkets. This section reports several notable changes that have occurred in the Korean online shopping industry over the past four years. First, over the whole period, as shown in the group mean of Table 2, the monthly growth rates of mobile shopping in the submarkets exceeded, on average, those of internet shopping, which resulted in the widening gap between internet and mobile shopping seen in Fig. 2. From the increases over time in the standard deviation statistics of the growth rates in Table 2, we can also notice that 21 submarkets have been differentially affected by the two events.

Second, in order to explore the substitution of mobile shopping for internet shopping, we categorize the 21 submarkets into two groups: mobile shopping substitutes for internet shopping (MsI) and, inversely, internet shopping substitutes for mobile shopping (IsM). In examining mobile conversion in online shopping, we can use two approaches: one is to compare two ratios of mobile shopping sales to internet shopping sales calculated for submarkets for the two time points, January 2017 and January 2021, and the other is to calculate and compare growth rates of mobile and internet shopping sales for submarkets and sub-periods. It is easy to show the mobile shopping conversion in the former approach, but it ignores the transition process in between the two time periods. As shown in Fig. 3, the ratios of mobile shopping sales to internet shopping sales in “Cosmetics” and “Shoes” submarkets

have declined, implying that they are IsM cases. “Shoes,” however, can be seen as an MsI case because its ratios at the two points of time were greater than 1. Looking at the ratio, we can consider “Computer” as a case of IsM because its values were also less than 1, even though the ratio has become larger, in the two points of time. In terms of the latter approach, MsI is the case in which mobile shopping average growth rates are greater than internet shopping average growth rates in a given period, and IsM is the opposite case of MsI, i.e., mobile shopping average growth rates are less than or equal to internet shopping average growth rates. Growth rates in bold fonts in Table 2 stand for IsM cases and all others are MsI. We can easily confirm that during the first sub-period, from January 2017 to March 2019 (right before 5G services launched in Korea), MsI was the norm in all 21 submarkets. In the second sub-period, we can identify six submarkets of IsM, and two representative submarkets of them, “Cosmetics” and “Shoes”, continued to be the same cases of IsM in the third sub-period, in which the effects of 5G and Covid-19 mingled. As shown in Fig. 4, during the third sub-period, “Cosmetics,” “Shoes” and “eCoupon” submarkets made greater strides in internet shopping than in mobile shopping. To sum up, MsI has occurred widely and consistently in the Korean online shopping industry, except for “Cosmetics” and “Shoes.”

===== Insert Tables 2 and 3, and Figs. 3 and 4 around here =====

Third, during the Covid-19 pandemic, mobile shopping substitution for internet shopping was most vivid in the submarkets of the second quadrant in Fig. 4, in which the growth rates of mobile shopping submarkets were positive whereas those of internet shopping submarkets were negative: “FoodServ,” “Autoparts,” “Petsupp,” “Sports,” and “Stationary.” Among the submarkets in the first quadrant of Fig. 4, those above the dotted diagonal line are also cases within the category of MsI even though they are less conspicuous than those in the second quadrant.

Fourth, travel and transportation services (“Travel”) had been the largest submarket in terms of sales in both internet and mobile shopping markets but, after Covid-19 broke out, its monthly sales of internet shopping decreased by 13.8% per month on average and that of mobile shopping by 6.5% on average. Because of these marked downturns, as shown in Table 3, the rankings of first in both internet and mobile shopping for “Travel” submarkets in January 2017 fell to twelfth and eighth, respectively, in January 2021. As a result of these changes, the market shares of “Travel” also decreased in both internet and mobile shopping submarkets from 17.8% and 15.6% in January 2017, respectively, to 2.1% and 3.8% in January 2021. Covid-19 also had a severely negative impact on “Culture” and “Clothing” submarkets. “Culture” submarkets, representing online reservation services for artistic performances, such as films, operas, musicals and ballets, ranked eleventh and sixteenth in January 2017 in internet and mobile shopping, respectively but as cinemas and theaters were closed after Covid-19, “Culture” submarkets’ rankings fell to the lowest rank, 21st of the 21 submarkets, in January 2021.

The internet and mobile shopping submarkets for “Clothing,” which ranked second in January 2017, fell to sixth in internet shopping and fifth in mobile shopping in January 2021. In addition, “Bag” and “Accessory” submarkets also experienced falls in their rankings in both internet and mobile shopping markets. These significant changes in online shopping after Covid-19 were also similarly observed in other countries (Deloitte, 2021; OECD, 2020; Statista, 2021).

===== Insert Table 3 around here =====

Fifth, Table 3 also reveals that ranking rises in mobile shopping were most vivid in “FoodServ” and “eCoupon” submarkets and moderately conspicuous in “Electronics,” “Agrofishe,” and “Book” for the past four years. In internet shopping, ranking rises were

most striking in “eCoupon,” “FoodServ,” “Furniture” and “Cosmetics” submarkets and moderately conspicuous in “Shoes,” “Food,” “Electronics,” “Necessities” and “Kid” submarkets. The big strides of those submarkets in the rankings of mobile and internet shopping did not share common causes. The mobile “FoodServ” submarket, providing cooked food such as pizza and chicken, for example, continued to have strong growth over the past four years, not just in the period of Covid-19, whereas the internet “FoodServ” submarket barely grew at all during the Covid-19 period, implying that Covid-19 and mobile technologies including 5G differentially affected internet and mobile shopping.

3. Literature review

Over the past two decades, research papers on online shopping and marketing proliferated and their research concerns have covered various dimensions of online shopping (Lamberton and Stephen, 2016; Grewal et al., 2017). Here, this literature review on online shopping focuses on the areas that are related to our research question development, and is therefore neither complete nor comprehensive. As discussed earlier, technologies were the main driver of structural changes in online shopping. Conversion to mobile shopping from internet shopping is facilitated by the flexibility of wireless connections in space and time dimensions (Luo, Andrews, Fang and Phang, 2014). At the dawn of the twenty first century, when 2G mobile networks were full blown, academic research on mobile commerce began to emerge (Zhongmei et al., 2020). Balasubramanian, Peterson, and Jarvenpaa (2002) formally conceptualized mobile commerce and illustrated how traditional commerce activities would evolve in a space-time matrix. They predicted that mobile commerce would bring forth rapid innovation in location specific and time critical commerce activities. Comparing internet and mobile shopping, Ghose, Goldfarb, and Han (2013) argued that search costs were higher in mobile shopping because of small screen size and thus ranking effects of mobile ads were

greater on mobile phones than on desktop computers. In addition, they argued that mobile shopping could be more complementarily used for local offline shopping than for online shopping from distant stores. As the studies above predicted, wireless internet reduced space and time constraints and enhanced flexibility in retail business for sellers and buyers. Xu, Chan, Ghose and Han (2016) conducted an empirical research study supporting mobile conversion in online shopping and reported that tablets functioned as a substitute for the PC channel but as a complement for the smartphone channel.

The most popular research subject on online shopping has been behavioral studies on user adoption and customer experience in online shopping. Bhatnagar, Misra and Rao (2000) proposed two constructs, convenience and risk, based on the consumer theory of microeconomics to investigate who uses and does not use online shopping. As Bhatnagar et al. (2000) stated, the two constructs were not new ones but were identified in earlier research by Cox and Rich (1964) on telephone shopping. Bhatnagar et al. (2000) found that the two constructs affected consumers' purchase behavior and these effects varied with product categories and demographic variables. Since Bhatnagar et al. (2000) was published, extensive research papers on consumer behavior in online shopping, especially on consumer attitudes and purchase intentions, have been published in the literature: some prominent studies are Bart, Stephen and Sarvary (2014), Chopdar and Balakrishnan (2020), Forsythe and Shi (2003), Kim, Wang and Roh (2021), Lee and Tan (2003), Li, Zhao, Xu and Pu (2020), Nysveen, Pedersen and Thorbjørnsen (2005) and Wang, Malthouse and Krishnamurthi (2015).

Smartphones have been the key media of marketing for mobile shopping (Spaid and Flint, 2014; Xu et al., 2016). Marketing spending on mobile shopping has increased globally over time as smartphones became prevalent and their applications (apps) also became easier

to use. Therefore, there have been many studies on the role of mobile marketing on mobile shopping performance. Luo et al. (2014) found that temporal and geographical targeting increased sales, and Bart et al. (2014) analyzed the effects of mobile display advertising on consumers' attitudes and purchase intentions and found that the effects were statistically positive when products were utilitarian (not hedonic) and were characterized by higher involvement, requiring consumers' active engagement for purchase decisions. Chopdar and Balakrishnan (2020) is different from other papers in that their paper addressed the effects of mobile application characteristics on repurchase intention in mobile shopping. Online retailers offered various reward coupons, discounts and location specific shopping information to entice mobile shoppers to make repurchases and impulse buying (Mattia, Di Leo and Principato, 2021). Chopdar and Balakrishnan (2020) studied the positive effects of app incentives and provision of contextual information on impulse buying and Dickinger and Kleijnen (2008) studied positive and negative effects of mobile coupons on coupon redemption.

4. Data and the model

4.1 Data and descriptive statistics

This paper drew on monthly sales data from January 2017 to January 2021 for 21 submarkets of internet and mobile shopping. Submarket sales data of mobile shopping (Mshop) and the mobile shopping conversion ratios (MCR), defined by mobile shopping sales divided by internet shopping sales, are used as dependent variables, and the explanatory variables are mobile internet subscriber lines (MSL), the number of 5G service subscriber lines (5G), Covid-19 confirmed cases (Covid), cyclical component of composite coincident index (CCCI), income (*I*: credit card payments were used as a proxy variable), the number of employed (EMP), and monthly seasonal effects (Month). Nominal monetary values, sales

values and credit card payments, were deflated by CPI (consumer price index) in order to remove common inflation effects. All variables are monthly data, which actually constrained our choice of explanatory variables because many data are not collected monthly. The reason for using data from 2017 in this paper is that data collection methods for online shopping were changed in 2017, and the current administration in Korea, which dramatically changed government policies, started in early 2017. Descriptive statistics of independent variables and their correlation coefficients matrix are reported in Table 4. In most cases, correlation coefficients are not high, so we expected that the multicollinearity problem, if any, would not be serious even though pairwise coefficient checking is not enough to avoid that problem. The descriptive statistics of dependent variables are not presented in Table 4 because they were already introduced in the previous Tables and Figures.

===== Insert Table 4 around here =====

4.2 Analytical models

Each submarket of online shopping is a collection of commodities and services, so the sales values of submarkets are aggregated sales of individual commodities and services. Therefore, by deflating the sales values we obtained real values of sales and used them as dependent variables. In order to identify the effects of Covid-19 and 5G services on submarket sales of mobile shopping and mobile conversion ratios, this paper utilized reduced form linear regression models, as shown in Equation (1). Real sales values (equilibrium quantities), Y_{it} , are a function of exogenous variables, X_{it} , which are composed of six explanatory variables and 11 monthly dummies. In the regression analyses based on Equation (1), the endogeneity problem is not likely to exist between the dependent variables and the six independent variables because mobile shopping submarkets are only a small part of the Korean national economy, but all six independent variables are measured at national level.

$$Y_{it} = \alpha_i + \sum_{j=1}^k \beta_{ij} X_{jt} + \varepsilon_{it} \text{ ----- (1)}$$

where Y is a dependent variable with a submarket index $i = 1, \dots, 21$, X stands for independent variables with an index $j = 1, \dots, k$, α is constant, β is regression coefficients and t is time index which ranges from January 2017 to January 2021. X does not have i submarket index because there are no submarket specific independent variables used in the regressions, and it also includes 11 dummies for controlling monthly seasonal effects. Each submarket can be seen as a separate market in a cluster market (Kwon and Cho, 2015). As the same independent variables are used for explaining submarkets sales and MCR, we ran regressions separately for individual submarkets: 21 regressions of real mobile shopping sales on explanatory variables and another 21 regressions of mobile conversion ratios on the same explanatory variables.

All regressions are time-series analyses, so, in order to control for an autocorrelation problem, we checked the Durbin-Watson statistic and, when autocorrelation was detected, corrected standard errors with autocorrelation robust standard errors based on the Newey-West method, provided in R, in calculating t-statistic and p-value. Table 5 reports the outcomes of mobile shopping submarket sales regressions and Table 6 reports those of mobile conversion ratio regressions. In the last columns of Tables 5 and 6, we also report the coefficients of determination and the Durbin-Watson statistic. For the sake of readability, we provided p-values, based on autocorrelation robust standard errors, of regression coefficient estimates instead of standard error or t-statistic. All analyses were done with the R statistical program and the coefficients of dummy variables for controlling monthly seasonal effects are omitted to save space in Tables 5 and 6. The coefficients in bold font in Tables 5 and 6, are those statistically significant at the 5 percent level of significance.

5. Outcomes and discussion

As discussed earlier, the development of mobile communication technologies, including 5G, and the rapid global spread of the Covid-19 pandemic, facilitated adoption of mobile shopping, resulting in rapid growth of mobile shopping sales and conversion of internet shopping to mobile shopping. In the previous section, we ran two groups of regressions to estimate the effects of two external shocks on mobile shopping. One reason for using multiple regressions in statistical analyses is to estimate partial (net) effects of independent variables. In addition to the two exogenous shock variables, we therefore used additional control variables, such as income, economic cycle and national employment level data. For example, Covid-19 could affect mobile shopping directly as well as indirectly, through its impacts on general economic activities and employment. If we do not control indirect effects by omitting economic cycle and employment, Covid-19's direct effect would be overestimated. One example of this case is the "Clothing" mobile shopping sales in Table 5. After Covid-19 pandemic spread, people were forced to stay at home and newspapers reported that people bought fewer clothes because they did not have to dress up while at home. The results of analyses, however, do not support this assertion. Table 5 shows that mobile shopping of clothing was not affected by Covid-19, but mostly by income and employment and marginally by mobile subscription lines, implying that statistically a direct effect of Covid-19 was non-existent, but it could have generated indirect effects.

===== Insert Tables 5 and 6 around here =====

Key findings of the regression results are summarized and discussed as follows. First, the Covid-19 pandemic turned out to be statistically positively correlated with the sales of the mobile submarkets, "Computer," "Electronics," "Book," "Stationary," "Bag," "Cosmetics," "Kid," "Food," "Agrofishery," "Necessities," "Autoparts," "Furniture," "eCoupon," and "FoodServ," negatively correlated with the sales of two submarkets,

“Travel” and “Culture,” and had no correlation with “Clothing,” “Shoes,” “Accessory,” “Sports” and “PetSupp” submarkets. In other words, the Covid-19 pandemic induced consumers to use mobile shopping more in 14 submarkets and less in two submarkets. This outcome is not an unexpected result because Covid-19 led people to favor non-contact shopping to offline shopping. An interesting finding is that, controlling for other factors, Covid-19 did not foster conversion to mobile shopping from internet shopping, as shown in Table 6. In 13 submarkets, Covid-19 was neutral in mobile conversion and revealed positive effects in only two submarkets, “eCoupon” and “Cosmetics,” while showing negative effects in six submarkets.

Second, mobile technologies, including 5G, were found to boost mobile shopping sales by and large and to have strongly driven mobile conversion for the past four years in Korea. The mobile subscriber line variable in Table 5 contributed to sales increases in 14 submarkets and the 5G service subscription line variable did the same in 13 submarkets, out of which both variables contributed concurrently to sales increases in 10 submarkets.¹¹ Another interesting finding is that the mobile subscription line variable has been the main factor promoting mobile conversion in the Korean online shopping submarkets for the past four years. In 19 of the 21 submarkets, mobile technology represented by mobile subscription lines accelerated mobile substitution for internet in online shopping. This conversion was vividly observed in “FoodServ,” “Culture,” “Travel,” “PetSupp,” “Autoparts” and “Shoes.” 5G subscriber lines turned out to contribute to mobile conversion in six submarkets: “FoodServ,” “eCoupon,” “Food,” “Stationary,” “Book” and “Travel.” In other words, in those six submarkets, 5G subscriber lines affected positively mobile conversion concurrently with

¹¹ Ten submarkets are “Book,” “Stationary,” “Sports,” “Food,” “Agrofishery,” “Necessities,” “Furniture,” “PetSupp,” “eCoupon” and “FoodServ.”

mobile subscriber lines.

Third, the income variable was shown to contribute to mobile shopping sales increases in the submarkets, “FoodServ,” “Travel,” “Cosmetics,” “Clothing,” “Bag,” “Accessory,” “Shoes” and “Stationary,” most of which could possibly be classified as normal (not inferior) goods. The business cycle turned out to have a strong positive relationship with the sales of “Travel” and “Culture” submarkets and a strong negative relationship with those of “FoodServ,” “Necessities,” “eCoupon,” “Kid,” “Shoes” and “Autoparts.” Employment seems to have no relationship or a negative one (“Electronics,” “Sports,” “Clothing,” “Computer” and “Furniture”) with sales in most mobile shopping submarkets, except for “Cosmetics,” “eCoupon” and “Kid” with positive relationship.

Fourth, it is also an interesting finding that income in 13 mobile submarkets is negatively correlated with mobile conversion ratios and positively correlated with mobile conversion ratios in only two submarkets, “eCoupon” and “Cosmetics.” This result suggests that income is not a factor inducing consumers to use mobile shopping more than internet shopping. Business cycle and employment are also not driving mobile conversion either negatively or positively in online shopping submarkets, except for a few cases such as “Shoes,” “Furniture,” “Culture,” “Autoparts,” “Sports” and “Stationary.”

6. Conclusion

This paper finds that Covid-19 boosted sales in 14 mobile shopping submarkets and decreased sales in two submarkets. 5G services also helped sales increase in 13 submarkets, while mobile technologies altogether contributed to sales increases in 14 submarkets. A notable finding is that mobile conversion in online shopping submarkets have been driven mostly by mobile technologies, including 5G, and not by Covid-19, implying that Covid-19 was neutral in increasing sales in many internet and mobile shopping submarkets.

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Fig. 1 Monthly confirmed Covid-19 cases in Korea

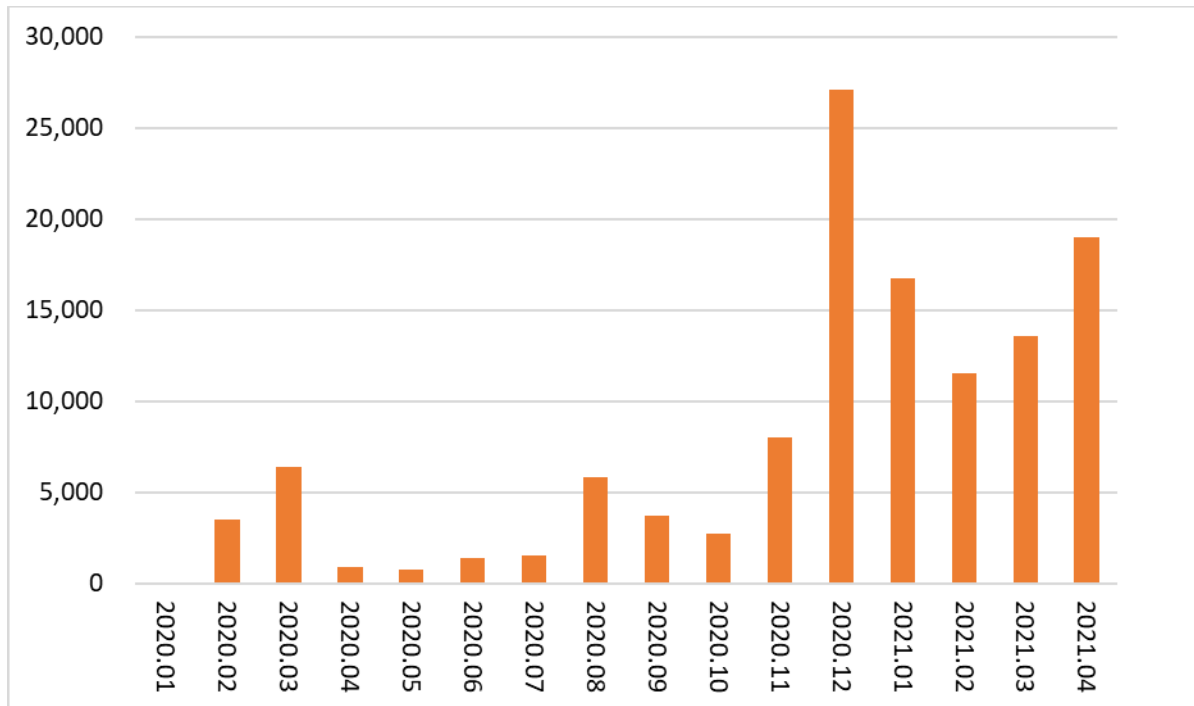
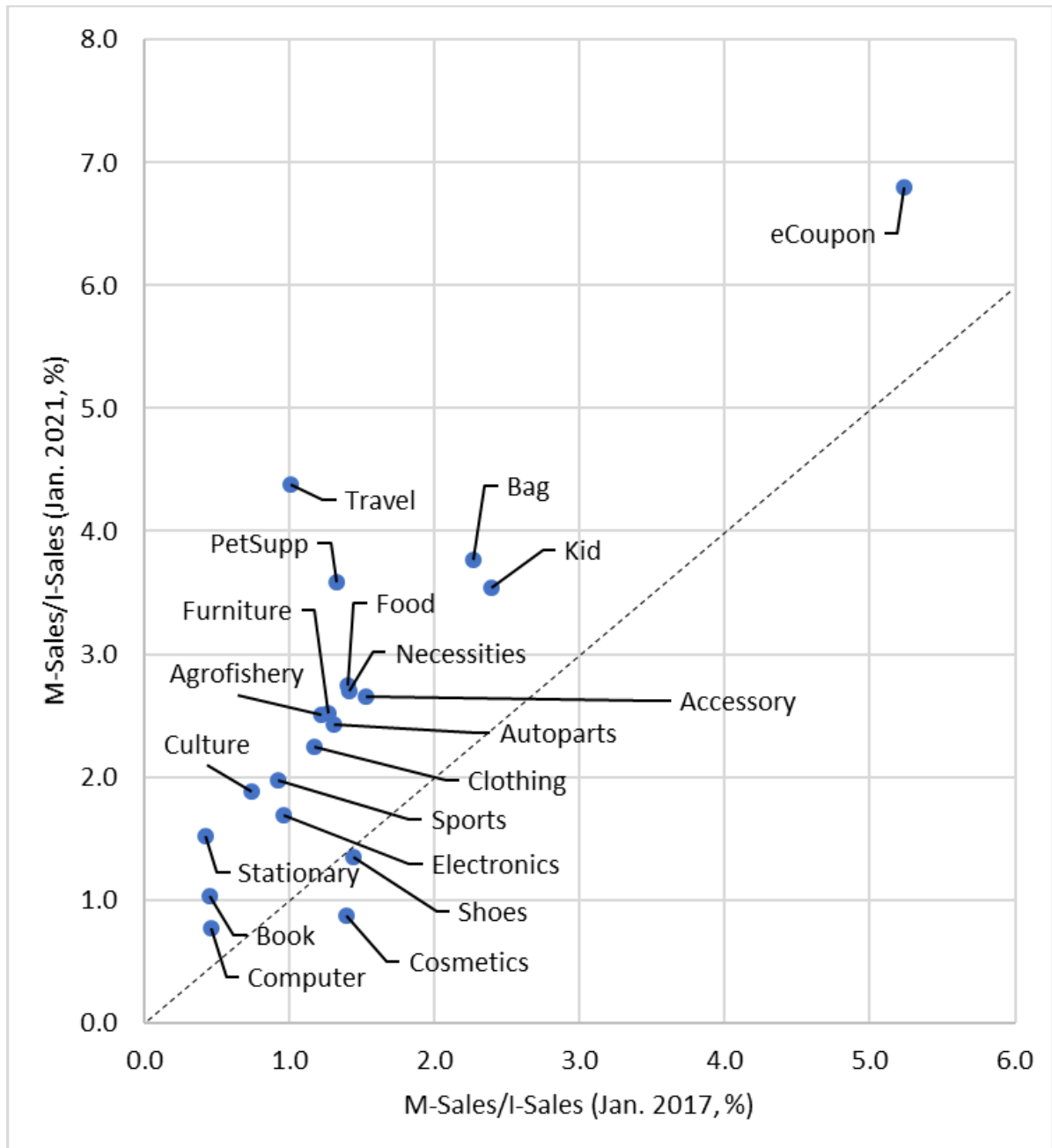


Fig. 2 Structural change in the Korean online shopping industry



* 1,100 Korea Won \approx 1 US dollar

Fig. 3 Online shopping conversion to mobile shopping between 2017 and 2020 in Korea



* "FoodServ" submarket is not shown in the above Fig 4., because its M-sales/I-Sales ratio changed drastically from 4.6 to 28.7 between Jan. 2017 and Jan.2021.

Fig. 4 Average monthly sales growth rates of online shopping submarkets after Covid-19

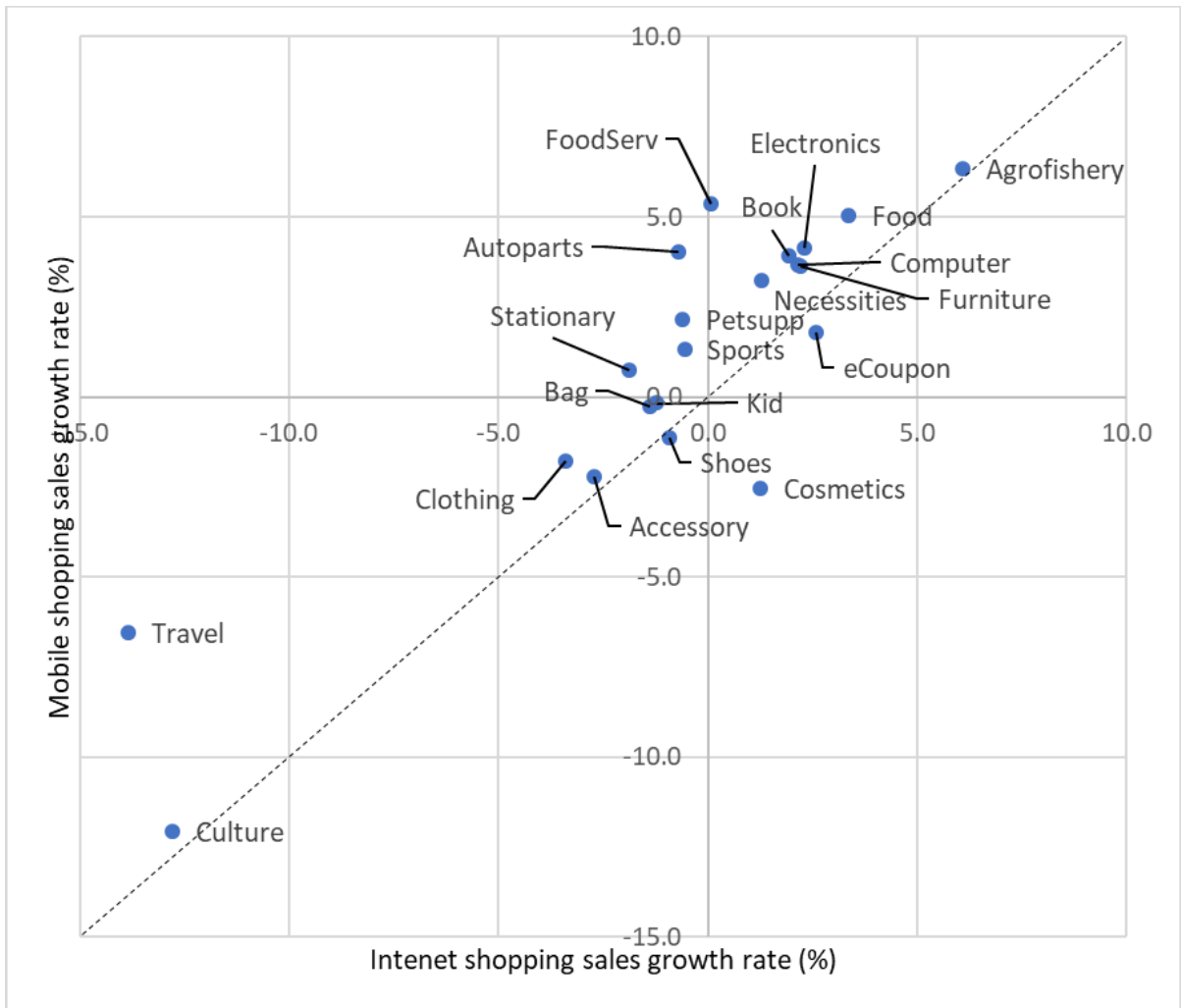


Table 1 Online shopping commodity and service groups and their major items

Groups (Abbreviation)	Major items
Computers and parts (Computer)	Personal computers, notebook computers, printers, speakers, software, etc.
Home appliances and Electronics (Electronics)	TV, refrigerator, air conditioner, washer and dryer, digital camera, cellphone, etc.
Books (Book)	Books except e-books
Stationaries (Stationary)	Office supplies, stationaries, papers, pencils, etc.
Clothing (Clothing)	Clothing for men and women, sportswear, etc.
Shoes (Shoes)	All kinds of shoes, sandals, slippers, etc.
Bags (Bag)	Purses, suitcases, backpacks, etc.
Fashion items and accessories (Accessory)	Hats, caps, gloves, scarfs, watches, rings, earrings, and other accessories
Sports and leisure items (Sports)	Sports and outdoor items, hiking items, miscellaneous items for leisure activities
Cosmetics (Cosmetics)	Cosmetics, perfumes, miscellaneous items for makeup
Goods for kids and infants (Kid)	Diapers, strollers, baby walkers, beds and car seats for babies, dolls and toys, etc.
Food and beverages (Food)	Coffee, tea, water, cereal, beverages, sugar, cooking oil, kimchi, canned food, etc.
Agro-fishery-livestock products (Agrofishery)	Grain, meat, corn, fish, vegetables, fruits, etc.
Daily necessities (Necessities)	Cooking appliances, bedding, soap, shampoo, toilet paper, detergent and cleanser, flower, vase and flower pots, etc.
Automobiles and parts (Autoparts)	Cars, motorcycles, driving guide system, vehicle black box camera, engine oil, windshield wiper fluid, other auto-parts and supplies
Furniture (Furniture)	Desks, chairs, tables, bed, etc.
Pet supplies (PetSupp)	Pet food, cleaning supplies, pet toys, pet shoes and clothing, etc.
Travel and transportation service (Travel)	Bus and train tickets, airplane ticketing and reservation, rental car, hotel and accommodations, etc.
Culture services (Culture)	Film, opera, musical, ballet, cinema reservation services
E-coupon services (eCoupon)	All kinds of gift cards or coupons
Food services (FoodServ)	Cooked and delivered food (pizza, chicken, etc.) services

* Source: Online shopping survey (Statistics Korea)

Table 2 Average monthly sales growth rates of 21 submarkets by sub-periods

Group Abbr.	Jan. 2017~ Mar. 2019		Apr. 2019 ~ Dec. 2019		Jan. 2020~Jan. 2021	
	Internet shopping	Mobile shopping	Internet shopping	Mobile shopping	Internet shopping	Mobile shopping
Agrofishery	-1.189	1.177	1.676	2.547	6.080	6.333
FoodServ	1.984	5.723	2.387	4.989	0.072	5.364
Food	0.624	2.211	1.439	2.117	3.366	5.031
Electronics	2.394	3.691	-1.015	-0.939	2.309	4.133
Autoparts	0.859	1.299	1.531	0.437	-0.703	4.011
Book	0.385	2.131	-1.598	-0.333	1.936	3.921
Computer	0.320	1.910	0.909	-0.215	2.147	3.657
Furniture	0.875	2.594	-0.027	0.762	2.220	3.623
Necessities	0.656	1.985	0.289	0.933	1.283	3.236
Petsupp	-0.182	2.057	1.418	2.168	-0.603	2.147
eCoupon	3.450	4.314	1.860	2.388	2.585	1.786
Sports	1.096	2.684	0.266	1.428	-0.559	1.329
Stationary	0.616	3.400	1.473	3.850	-1.881	0.760
Kid	0.219	1.303	3.321	2.977	-1.237	-0.152
Bag	0.777	2.218	0.752	0.697	-1.375	-0.275
Shoes	2.243	2.969	2.829	0.289	-0.920	-1.135
Clothing	0.625	1.946	1.202	2.252	-3.385	-1.787
Accessory	0.609	1.992	0.493	1.988	-2.705	-2.234
Cosmetics	1.630	1.826	1.897	1.552	1.250	-2.535
Travel	-0.146	1.030	1.102	2.273	-13.837	-6.546
Culture	-0.953	1.481	-0.785	1.388	-12.785	-12.073
Group Mean	0.804	2.378	1.020	1.598	-0.797	0.885
Standard Dev.	1.060	1.109	1.195	1.383	4.609	4.243

* The numbers in bold fonts are used for IsM (internet shopping substitutes for mobile shopping).

Table 3 Online shopping submarkets sales and their ranking

Group Abbr.	Annual internet sales mean (Bil. Won)	Annual mobile sales mean (Bil. Won)	Mobile sales of 2021.01 (Bil. Won)	Rank by mobile sales of 2021.01	Rank by mobile sales of 2017.01	Rank by internet sales of 2021.01	Rank by internet sales of 2017.01
FoodServ	608.4	8157.7	1956.0	1	8	14	19
Food	4084.4	8820.1	1591.6	2	3	3	5
Electronics	5728.9	7569.1	1175.7	3	6	1	3
Necessities	3422.2	6825.7	951.2	4	5	5	7
Clothing	5291.4	8417.3	745.2	5	2	6	2
Agrofishery	1223.7	2601.7	537.2	6	9	7	8
Cosmetics	4934.0	5761.0	501.4	7	4	2	6
Travel	5885.9	8468.3	405.5	8	1	12	1
eCoupon	393.7	2345.4	383.7	9	15	15	21
Furniture	1223.2	2346.4	348.9	10	11	8	12
Computer	3536.7	2298.8	342.9	11	10	4	4
Kid	1000.7	2976.4	327.4	12	7	11	13
Sports	1676.0	2461.7	260.2	13	13	9	9
Bag	603.4	1785.5	181.1	14	12	17	15
Book	1138.7	789.5	131.2	15	18	10	10
Accessory	748.1	1549.9	129.0	16	14	16	14
Shoes	824.4	1400.8	116.0	17	17	13	16
Autoparts	622.7	768.4	110.1	18	19	18	18
Petsupp	272.2	639.0	82.1	19	20	20	20
Stationary	487.6	408.1	59.0	20	21	19	17
Culture	826.6	977.5	21.8	21	16	21	11
Group Mean	2120.6	3684.2	493.2	-	-	-	-

* Annual internet and mobile sales mean values are average values of four-year sales values from 2017 to 2020.

Table 4 Descriptive statistics and correlation coefficients of independent variables

		MSLI	5G	Covid	CCCI	I	Emp
Descriptive statistics	unit	thousand	thousand	person	2015=100	Real value (bil. Won)	thousand
	mean	66437.1	2689.0	1602.2	100.4	47429.1	26885.8
	standard deviation	2792.5	3833.8	4716.0	1.3	2948.8	205.9
	min	61518.2	0.0	0.0	97.2	39810.2	26571.2
	max	70690.0	12869.9	27115.0	102.1	53186.8	27474.9
	count	49	22	13	49	49	49
Correlation coefficients	MSLI	1					
	5G	0.834	1				
	Covid	0.475	0.708	1			
	CCCI	-0.854	-0.740	-0.308	1		
	I	0.718	0.453	0.156	-0.523	1	
	Emp	0.520	0.190	-0.003	-0.223	0.4559	1

Table 5 Regression results of mobile shopping submarket sales

Submarkets	Independent variables (dependent variable: real values of mobile shopping submarket sales)						
	MSL	5G	Covid	CCCI	I	EMP	
Computer (p-value)	0.0245 (0.0000)	-0.0011 (0.2136)	0.0011 (0.0322)	2.5971 (0.4442)	-0.0069 (0.0015)	-0.0409 (0.0134)	$\bar{R}^2=0.946$ DW=1.66
Electronics (p-value)	0.0599 (0.0000)	0.0080 (0.0605)	0.0091 (0.0023)	10.681 (0.3224)	0.0084 (0.1642)	-0.1730 (0.0002)	$\bar{R}^2=0.960$ DW=2.34
Book (p-value)	0.0053 (0.0001)	0.0011 (0.0006)	0.0008 (0.0000)	-1.2659 (0.1901)	-0.0022 (0.0124)	-0.0006 (0.8960)	$\bar{R}^2=0.956$ DW=2.10
Stationary (p-value)	0.0014 (0.0148)	0.0009 (0.0000)	0.0006 (0.0000)	-1.2312 (0.0325)	0.0007 (0.0040)	0.0030 (0.1957)	$\bar{R}^2=0.976$ DW=1.98
Clothing (p-value)	0.0127 (0.0808)	0.0033 (0.1547)	-0.0006 (0.6434)	-13.729 (0.1693)	0.0197 (0.0000)	-0.0545 (0.0445)	$\bar{R}^2=0.953$ DW=2.15
Shoes (p-value)	0.0002 (0.8729)	0.0017 (0.0002)	0.0002 (0.3270)	-4.7384 (0.0057)	0.0031 (0.0000)	0.0006 (0.9108)	$\bar{R}^2=0.942$ DW=1.83
Bag (p-value)	0.0030 (0.0376)	0.0003 (0.7312)	0.0006 (0.0398)	-2.2776 (0.0926)	0.0056 (0.0000)	-0.0060 (0.4769)	$\bar{R}^2=0.907$ DW=1.49
Accessory (p-value)	0.0029 (0.0911)	-0.0023 (0.0041)	0.0005 (0.0553)	1.3370 (0.4439)	0.0044 (0.0000)	0.0106 (0.2601)	$\bar{R}^2=0.847$ DW=1.06
Sports (p-value)	0.0119 (0.0008)	0.0049 (0.0000)	-0.0003 (0.5727)	-4.7554 (0.2165)	0.0031 (0.1113)	-0.0745 (0.0000)	$\bar{R}^2=0.968$ DW=1.66
Cosmetics (p-value)	-0.0169 (0.1219)	-0.0092 (0.0003)	0.0068 (0.0000)	-10.075 (0.3490)	0.0343 (0.0000)	0.2458 (0.0000)	$\bar{R}^2=0.872$ DW=1.09
Kid (p-value)	0.0015 (0.5830)	0.0046 (0.0000)	0.0015 (0.0001)	-11.419 (0.0003)	0.0001 (0.9281)	0.0362 (0.0168)	$\bar{R}^2=0.964$ DW=1.89
Food (p-value)	0.0641 (0.0000)	0.0304 (0.0000)	0.0008 (0.0000)	-10.527 (0.1712)	-0.0091 (0.1754)	-0.0183 (0.7152)	$\bar{R}^2=0.978$ DW=1.97
Agrofishery (p-value)	0.0192 (0.0003)	0.0119 (0.0000)	0.0027 (0.0018)	-3.3433 (0.4456)	-0.0059 (0.0831)	-0.0064 (0.7558)	$\bar{R}^2=0.949$ DW=2.03
Necessities (p-value)	0.0257 (0.0219)	0.0177 (0.0000)	0.0049 (0.0003)	-35.209 (0.0028)	-0.0063 (0.2176)	-0.0399 (0.5053)	$\bar{R}^2=0.964$ DW=1.35
Autoparts (p-value)	-0.0003 (0.8371)	0.0031 (0.0000)	0.0011 (0.0000)	-4.5531 (0.0002)	0.0003 (0.7147)	-0.0012 (0.8213)	$\bar{R}^2=0.945$ DW=1.80
Furniture (p-value)	0.0168 (0.0000)	0.0049 (0.0000)	0.0011 (0.0066)	-2.6895 (0.3316)	-0.0029 (0.1264)	-0.0396 (0.0047)	$\bar{R}^2=0.969$ DW=1.56
PetSupp (p-value)	0.0036 (0.0013)	0.0010 (0.0020)	0.0002 (0.2482)	0.9838 (0.3909)	0.00005 (0.8895)	-0.0044 (0.2788)	$\bar{R}^2=0.945$ DW=1.56
Travel (p-value)	0.0101 (0.4840)	-0.0311 (0.0000)	-0.0047 (0.0263)	58.980 (0.0000)	0.0544 (0.0000)	0.0073 (0.9427)	$\bar{R}^2=0.877$ DW=1.69
Culture (p-value)	0.0148 (0.0000)	-0.0112 (0.0000)	-0.0018 (0.0180)	11.665 (0.0036)	0.0025 (0.1059)	-0.0352 (0.0629)	$\bar{R}^2=0.811$ DW=1.55
eCoupon (p-value)	0.0147 (0.0103)	0.0032 (0.0077)	0.0024 (0.0005)	-14.297 (0.0090)	0.0034 (0.090)	0.0665 (0.0018)	$\bar{R}^2=0.967$ DW=1.42
FoodServ (p-value)	0.0492 (0.0000)	0.0534 (0.0000)	0.0225 (0.0000)	-49.568 (0.0000)	0.0139 (0.0002)	0.0370 (0.2599)	$\bar{R}^2=0.995$ DW=1.31

* Constant term and monthly dummies are omitted for the sake of readability and the numbers in parentheses are p-values.

Table 6 Regression results of mobile conversion ratios by submarkets

Submarkets	Independent variables (dependent variable: mobile convergence ratio)						
	MSL	5G	Covid	CCCI	I	EMP	
Computer (p-value)	0.0001 (0.0000)	-0.00002 (0.0000)	-0.000005 (0.0045)	0.0599 (0.0002)	-0.00003 (0.0000)	-0.0002 (0.0004)	$\bar{R}^2=0.880$ DW=1.74
Electronics (p-value)	0.0001 (0.0000)	-0.00001 (0.0280)	-0.000004 (0.2460)	0.0521 (0.0376)	-0.00002 (0.0793)	-0.0003 (0.0003)	$\bar{R}^2=0.893$ DW=1.80
Book (p-value)	0.00006 (0.0000)	0.000004 (0.0008)	-0.000001 (0.1494)	0.0058 (0.3008)	-0.00001 (0.0002)	0.00002 (0.3095)	$\bar{R}^2=0.986$ DW=1.77
Stationary (p-value)	0.00007 (0.0000)	0.00002 (0.0000)	0.000002 (0.1979)	-0.0495 (0.0000)	-0.00001 (0.0040)	0.0002 (0.0005)	$\bar{R}^2=0.982$ DW=1.85
Clothing (p-value)	0.0001 (0.0000)	-0.000002 (0.8420)	-0.00001 (0.0044)	0.0287 (0.2337)	-0.00004 (0.0000)	-0.00007 (0.5480)	$\bar{R}^2=0.858$ DW=1.49
Shoes (p-value)	0.0003 (0.0000)	-0.0001 (0.0000)	-0.00002 (0.0112)	0.2316 (0.0000)	-0.00007 (0.0002)	-0.0010 (0.0000)	$\bar{R}^2=0.707$ DW=1.30
Bag (p-value)	0.0001 (0.0005)	-0.000007 (0.4732)	-0.000002 (0.7005)	0.0569 (0.0725)	0.00001 (0.5515)	-0.0002 (0.2409)	$\bar{R}^2=0.907$ DW=2.02
Accessory (p-value)	0.0001 (0.0001)	-0.000007 (0.4027)	-0.000002 (0.5861)	0.0569 (0.0552)	0.00001 (0.4284)	-0.0002 (0.1048)	$\bar{R}^2=0.894$ DW=1.66
Sports (p-value)	0.00002 (0.0000)	-0.000007 (0.1397)	-0.000007 (0.0169)	0.0627 (0.0018)	-0.00003 (0.0021)	0.0005 (0.0000)	$\bar{R}^2=0.950$ DW=1.54
Cosmetics (p-value)	-0.00004 (0.2630)	-0.00007 (0.0000)	0.00002 (0.0090)	-0.0087 (0.8656)	0.00005 (0.0003)	0.0005 (0.0127)	$\bar{R}^2=0.815$ DW=1.08
Kid (p-value)	0.0002 (0.0000)	-0.00001 (0.1295)	-0.000007 (0.2222)	-0.0096 (0.8304)	-0.00006 (0.0012)	0.00002 (0.9288)	$\bar{R}^2=0.856$ DW=1.89
Food (p-value)	0.0001 (0.0000)	0.00002 (0.0017)	-0.000003 (0.2511)	-0.0172 (0.5515)	-0.00005 (0.0000)	-0.00005 (0.7066)	$\bar{R}^2=0.941$ DW=1.48
Agrofishery (p-value)	0.0001 (0.0122)	-0.000006 (0.6952)	0.000005 (0.5889)	0.0060 (0.9175)	-0.00002 (0.3716)	0.000007 (0.9712)	$\bar{R}^2=0.753$ DW=2.12
Necessities (p-value)	0.0002 (0.0000)	0.000002 (0.6909)	-0.000004 (0.0333)	0.0300 (0.1138)	-0.00004 (0.0000)	-0.0002 (0.0389)	$\bar{R}^2=0.971$ DW=1.21
Autoparts (p-value)	0.0003 (0.0005)	-0.00009 (0.0000)	0.000002 (0.8643)	0.2035 (0.0084)	-0.00004 (0.2374)	-0.0014 (0.0248)	$\bar{R}^2=0.375$ DW=2.42
Furniture (p-value)	0.0002 (0.0000)	-0.00001 (0.0209)	-0.000007 (0.0356)	0.0533 (0.0164)	-0.00003 (0.0003)	-0.0002 (0.0145)	$\bar{R}^2=0.966$ DW=1.58
PetSupp (p-value)	0.0003 (0.0000)	-0.00003 (0.1810)	-0.000003 (0.6327)	0.0724 (0.1718)	-0.00005 (0.0031)	-0.0007 (0.0084)	$\bar{R}^2=0.919$ DW=1.54
Travel (p-value)	0.0003 (0.0000)	0.00009 (0.0000)	-0.000004 (0.6112)	-0.0739 (0.1058)	-0.0002 (0.0000)	-0.0010 (0.0000)	$\bar{R}^2=0.961$ DW=1.82
Culture (p-value)	0.0004 (0.0000)	-0.0001 (0.0000)	-0.00001 (0.1863)	0.3382 (0.0000)	-0.00005 (0.0088)	-0.0015 (0.0000)	$\bar{R}^2=0.664$ DW=1.61
eCoupon (p-value)	-0.0007 (0.0019)	0.0001 (0.0280)	0.0001 (0.0019)	-0.7793 (0.0004)	0.0003 (0.0032)	0.0044 (0.0000)	$\bar{R}^2=0.516$ DW=1.92
FoodServ (p-value)	0.0018 (0.0002)	0.0003 (0.0033)	0.0002 (0.0531)	0.8658 (0.1183)	0.0001 (0.4899)	-0.0034 (0.0931)	$\bar{R}^2=0.953$ DW=1.71

* Constant term and monthly dummies are omitted for the sake of readability and the numbers in parentheses are p-values.