The Rise of E-commerce and Generational Consumption Inequality: Evidence from COVID-19 in South Korea*

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Abstract

This paper investigates how the local COVID-19 outbreak, acting as a sudden negative shock to mobility, led to a significant generational disparity, with younger people benefiting disproportionately from the ability to transition to online consumption. Employing credit card transaction data linked to cardholders' demographic characteristics, we construct online spending shares by age group to study the generational disparity in online consumption when consumer mobility was constrained. We estimate a difference-in-difference model based on an exogenous regional outbreak of COVID-19 in South Korea. Our results show that when the mobility costs to offline stores unexpectedly increased due to the pandemic, middle-aged and older adults (aged 45 and above) were less likely to shift their spending online than younger adults (aged 20-44). The limited shift to the online consumption of older people resulted in decreases in their total consumption, while that of younger ones changed little, thereby increasing generational consumption inequality. With the rising trend in e-commerce, our findings emphasize the growing importance of generational differences in adapting to new shopping technologies.

Keywords: COVID-19, Online Shopping, Mobility, Consumption Inequality

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1 Introduction

This study investigates the generational disparities in online consumption during the COVID-19 pandemic, which caused a sudden negative mobility shock. With the fear of infection and policies restricting mobility (Koster et al., 2022), the pandemic increased mobility costs (Brinkman and Mangum, 2022) and caused a sudden surge in online shopping (Bounie et al., 2020; Relihan et al., 2020; Chang and Meyerhoefer, 2021; Agrawal and Shybalkina, 2022).[1]. However, the rapid transition to online shopping has been more challenging for many older people due to a lack of digital knowledge, which causes non-negligible inequality between them and younger generations. Moreover, as older people's spending tends to be more concentrated on essential goods relative to the spending of younger generations, this decline in consumption directly leads to an even greater welfare loss.

Identifying the impacts of e-commerce on the generational consumption disparity is challenging due to the gradual increase of online shopping shares and the lack of data. This paper overcomes this empirical challenge by leveraging credit card transaction-level data with the demographic information of cardholders, combined with a local COVID-19 break as an exogenous force to shift to online shopping. Specifically, we use a local COVID-19 outbreak in the Daegu and Gyeongbuk areas (DG areas hereafter) in South Korea caused by the gatherings of a religious sect as an exogenous shock, which enables us to estimate a difference-in-difference (DID) model.

We find that the COVID-19 pandemic has accelerated the shift to online shopping. During a local outbreak in the DG areas, the increase in the online spending share was 2.3 percentage points greater in the treated areas than in the other regions. Given that the online share has increased on average at an annual rate of 1.5 percentage points during the last decade in South Korea, a 2.3 percentage point increase means that a 1.5-year online transformation occurred in two months due to the pandemic. More critically, the shift to

[1] Life has increasingly moved online during the COVID-19 pandemic. More people work from home (Barrero et al., 2021; Althoff et al., 2022; Delventhal et al., 2022), more students take online courses (Bacher-Hicks et al., 2021), and more consumers buy online. However, the sudden adaptation to relying on the internet for daily activities has widened the "digital divide"—a phenomenon describing the disparities in access and use of information technologies across different populations. For example, students in low-income families are unequally harmed by the shift to online learning (Bacher-Hicks et al., 2021), and older patients are less likely to receive care via telemedicine (McCullough et al., 2021). Working from home has also been an important online transition during the pandemic. For example, more educated workers have had an easier time shifting to remote work than low-paid service workers, intensifying the employment and wage inequality by education level (Dingel and Neiman, 2020; Mongey et al., 2021). Footnote 8 provides more multidisciplinary literature on the digital divide

online shopping widened the generational online consumption gap by 50%. Specifically, younger people (20-44) increased their online spending share within the treated areas by 4.9 percentage points, while the share of older people (45 and older) was not significantly changed. The generational gap is more significant for people aged 60 and older than those aged 45–59.

As a result, we find that older people decreased their total consumption by 9.8 percentage points, while there was not much change in the total consumption of younger people. The impact on overall expenditure confirms that the limited accessibility to online consumption made older people purchase fewer goods during the pandemic. Given that the expenditure peaks in middle age and then decline thereafter (Aguiar and Hurst, 2013), and the expenditure of older people tends to be concentrated on essential goods (see Appendix Figure A1), these results could imply even more significant welfare loss for older people.

Finally, we delve into the local recovery effects of COVID-19 in DG areas, which occurred from August 2020 to October 2020, coinciding with the disappearance of mobility constraints as the local outbreak subsided. During this period, we observed a significant 40% reduction in the generational online consumption disparity that had emerged during the peak of the local outbreak of COVID-19. However, it's important to note that a notable portion of this divergence in online shopping habits persisted even six months after the pandemic's peak. This implies the potential for longer-term welfare loss for older populations, despite the improvement in the short-to-medium-term outlook for generational consumption disparities.

This paper contributes to the literature on the rise of e-commerce during COVID-19 and generational consumption inequality.The COVID-19 pandemic, marked by the fear of infection and consequent mobility-restricting policies, has considerably escalated mobility costs (Koster et al., 2022; Brinkman and Mangum, 2022). This has catalyzed a pronounced shift towards online shopping (Bounie et al., 2020; Relihan et al., 2020; Chang and Meyerhoefer, 2021; Agrawal and Shybalkina, 2022). Yet, the question of how the advantage of e-commerce is heterogeneously distributed across different demographic groups within cities remains largely unexplored, due to the constraints on data and research setting. This paper bridges this gap in the literature by utilizing South Korean credit card data and factoring in a localized COVID-19 outbreak as an unexpected stimulus that compelled consumers towards online shopping. Our novel contribution lies in illustrating how the digital divide accentuated consumption inequality within cities, especially between the younger and older populations, following the COVID-induced disruptions in South Korea.

This paper's longer run implication is related to the literature on retail apocalypse due to the rise of e-commerce. Prior literature underscores that spatial mobility is pivotal in shaping consumption patterns (Glaeser et al., 2001; Forman et al., 2009; Couture, 2013; Agarwal et al., 2017; Coibion et al., 2021; Miyauchi et al., 2021). Furthermore, the advent of e-commerce has revolutionized the consumer landscape by allowing access to stores that may be geographically distant (Dolfen et al., 2023). This transformative shopping technology enhances overall consumer welfare and diminishes spatial consumption inequalities by significantly cutting down trade costs across locations (Fan et al., 2018; Couture et al., 2021; Relihan, 2022). Our findings highlight potential inequality issues that could emerge if access to offline stores significantly diminishes, due to a potential 'retail apocalypse' in urban areas (Gupta et al., 2022; Van Nieuwerburgh, 2023; Chun et al., 2023).

The remainder of this paper is organized as follows. Section 2 briefly describes the pattern of local COVID-19 outbreaks and online shopping by generation in South Korea. Section 3 explains our data and Section 4 describes our empirical specification. Section 5 reports our results and Section 6 concludes.

2 Background

The spread of COVID-19 in South Korea started in February 2020, driven by a sudden and exogenous local outbreak in the Daegu-Gyeongbuk[2] (hereafter DG) regions (Aum et al., 2021). This outbreak was caused by a gathering of Shincheonji, a religious sect founded in South Korea that has more than 200,000 followers.[3] Before February 2020, only 30 patients were confirmed nationwide, and no confirmed case was reported in the DG areas. On February 17, the 31st confirmed patient attended a religious gathering held

[2]Daegu is the fourth biggest city in South Korea with a population of 2.4 million, following Seoul, Busan, and Incheon (City of Daegu, 2021). Gyeongbuk is a province surrounding Daegu, which forms the Daegu-Gyueongbuk metropolitan area.

[3]Shincheonji is a denomination of a new Christian religious movement established in South Korea and is considered a heresy by the mainstream church. The followers of Shincheonji are spread all over the country, and thus, the DG area is not more susceptible to this religious sect.

by Shincheonji in the city of Daegu.[4] Being reluctant to reveal themselves, Shincheonji followers who attended the gathering refused COVID-19 tests, leading to the spread of COVID-19 in the DG areas.

[Figure 1 about here]

Panel (a) of Figure 1 shows the number of cases in DG and non-DG areas from January to October 2020. By the end of February, COVID-19 cases exploded to 2,337, with 85.1% of the cases in the DG area. The first COVID-19 wave was highly local and subsided in April 2020. The local outbreak in the DG areas decreased mobility due to the fear of infection and policies restricting mobility. Panel (b) of Figure 1 shows the differences in monthly mobility[5] between the DG and non-DG areas from October 2019 to October 2020. Before January 2020, mobility in the DG areas was not significantly different from that in the non-DG areas. However, following a local outbreak in the DG areas, mobility in these areas decreased sharply, dropping by almost 30% compared to the non-DG areas by March 2020. The disparity in mobility between the DG and non-DG areas dissipated after May 2020. This change coincided with the spread of COVID-19 in the non-DG areas and the subsiding of the disease in the DG areas, as depicted in Figure 1, Panel (a).

[Figure 2 about here]

Along with the negative impacts on mobility, the local outbreak of COVID-19 disproportionately accelerated the shift to online shopping[6] in the DG areas. Panel (a) of Figure 2 shows that the online spending shares in the DG and non-DG areas had highly similar levels and trends before the outbreak. However, online shares rose more rapidly in the DG area than in the other areas during the outbreak in February and March 2020. Specifically, by March 2020, the online shopping share of the total expenditure increased by almost 10 percentage points in the DG areas but by 4.5 percentage points in the non-DG areas. The statistics indicate that residents in the DG area, which had a high number of

[4]Because South Korea publicly disclosed detailed location information (e.g., "X Supermarket in Y District in Seoul") about individuals who tested positive for COVID-19, it is possible to detect an exact superspreader individual and/or event. The information on the confirmed cases was widely transmitted to mobile phones, which was a way to reduce the number of cases (Shin et al., 2021; Argente et al., 2022).

[5]The mobility data come from SK Telecom's mobile data, which encompasses around 50% of the telecom networks in South Korea. The mobility of a district is defined as a count of users with signals located outside their residential districts for more than 30 minutes.

[6]Online spending shares in South Korea (around 21% in 2019) is similar to those of the UK (around 19% in 2019), higher than the share of the US (around 11% in 2019) (see Appendix Figure A3).

COVID-19 cases, feared going outside to shop and thus replaced the activity faster with online alternatives.

Importantly, there have been generational disparities in the rate of adaptation to online shopping. Panel (b) of Figure 2 illustrates the generational digital divide[7] (Goldfarb and Prince, 2008; Prieger and Hu, 2008) in online shopping. Even before COVID-19 (before January 2020), younger generations' online shares were higher than older generations' in DG areas. Given that 99.4% of elderly households aged 60 and older in 2020 had full access to the internet (National Information Society Agency, 2020), such generational digital divide in South Korea seems to be primarily due to differences in internet literacy or internet usage habits.[8]

When local COVID-19 restrictions limited accessibility to offline shops in February 2020, the online spending share of younger people in the DG area during the outbreak increased more than that of their older counterparts, thereby widening the generational gap in online shopping. In particular, the online shares of the younger generation in the DG areas increased from 35% to 47%, whereas the online shares for older people increased from 22% to 27% after the local outbreak. In other words, the benefits of online shopping rose due to the limited mobility during the outbreak, older adults were less likely than younger adults to shift their shopping from offline to online. This suggests that the lack of digital skills for the older groups might be an obstacle to increasing their low online shopping rate, widening the generational consumption inequality. Given that older people's consumption is more concentrated on essential goods (see Figure A1), the welfare implications for the increased generational gap in consumption could be significant.

After May 2020, as the number of COVID-19 cases began to decrease in DG areas, online spending shares reverted to their previous levels on average in these areas, as seen in Figure 2, Panel (a). However, a closer examination of the differences between the older and younger demographics within the DG areas, as presented in Figure 2, Panel (b), reveals a nuanced trend. While the older population in the DG areas returned to their

[7] The digital divide across various socio-demographic groups has been a focal point of research across various disciplines, the methodology typically hinges on survey data or focused group research (Van Deursen et al., 2015; Friemel, 2016; Delello and McWhorter, 2017; Yu et al., 2017; Scheerder et al., 2017; Yoon et al., 2020; Eger et al., 2021). Together, these studies provide a holistic view of the digital divide across different populations. This paper contributes to the existing multi-discipline literature by directly quantifying the effect of e-commerce on generational consumption inequality, credit card transaction data which provides detailed transaction quantities and prices at each location at a given time, which provides an advantage over the survey data.

[8] Delving deeper into the nuances, while intriguing, is beyond the immediate scope of this paper. We defer this exploration to future research.

previous levels of online spending, the younger population did not fully revert to pre-COVID online consumption shares, which prolonged the generational gap that occurred during the pandemic.[9]

3 Data

We use credit card transaction data to measure online spending shares. While survey data provides valuable insights into the online shopping behaviors of various demographic groups, and highlights the diminished internet usage among the older population, our credit card data presents unique advantages in capturing generational consumption disparities, especially within our research context. Its precision is unparalleled; it records exact monetary transactions, as opposed to surveys which may only provide estimates of shopping frequencies without detailed expenditure information. Furthermore, our credit card data offers a level of granularity that surpasses that of standard South Korean surveys, such as Internet Usage Survey (Korea Internet and Security Agency), or the Digital Divide Survey (Institute of Information and Communications Technology Planning and Evaluation). Crucially, for the design of our study—which requires observations at a county-age-monthly level—credit card transaction data provides the necessary detail to accurately assess generational disparities in online shopping during the COVID-19 pandemic.

The dataset is provided by BC Card, which is representative of credit and debit card transactions in South Korea.[10] The company has the second-largest transaction network, which includes 11 credit card companies and banks as member issuers. The company has 36 million cardholders—corresponding to approximately 80% of the adult population in South Korea—and 450 million transactions per month. The unit of observation is a transaction, which includes the time and date of the transaction, the transaction amounts, and the detailed four-digit categories of spending.

Unlike the credit card transaction data (e.g., VISA or MasterCard in the US setting)

[9]Figure A4 illustrates the online penetration trends for the younger and older age groups in both DG and non-DG areas. The divergence observed in the medium term (Aug 2020 - Oct 2020) between these age groups' online shopping shares during the post-COVID period raises questions about the potential long-term persistence of this trend.

[10]The credit card market in South Korea is mainly composed of five major companies, and each company has a market share of approximately 15%–20% (The Credit Finance Association). As a comparison, Visa debit and credit cards cover 24% of spending in the United States (Einav et al., 2021).

used in the previous studies (Mian et al., 2013; Dolfen et al., 2023),[11] the company provides a merchant-cardholder-linked dataset, which enables us to identify the demographic information of consumers (e.g., age, sex, residential address) for transactions so that we can measure age-specific online spending shares. We construct monthly online spending shares by age (five-year age groups; 20-24, 25-29, . . . , 65 and older) $\times$ sex (female or male) $\times$ county (229 counties) cell level from October 2018 to March 2020.

We define online spending using the category numbers 4076 (internet PG), 4077 (internet total), and 4078 (internet mall)[12]. Online spending share is defined by dividing online spending by the sum of online and offline spending, and online transactions are defined as those made through the internet. To make online and offline spending comparable, we exclude some products (from the total of 243 categories) sold offline only (e.g., gasoline, pharmaceuticals) in the South Korean setting. Each online and offline spending amount is aggregated by a specific age-sex group living in a county. Because the dataset is provided at the consumer level, we can decompose changes in spending into changes in the number of consumers, the number of frequencies, and the amount per transaction.

[Table 1 about here]

Table 1 and Appendix Table A1 present a summary statistics of our sample. Panel A of Table 1 shows online spending shares by age group and treatment area. The average online spending share is 26.13%, but online shares between the younger and middle-aged or older groups show a large gap of almost 12 percentage points. Both the treated DG area and the control area show highly similar online shares, suggesting that the COVID-19 outbreak in the DG area might not be related to local confounding factors determining the online consumption pattern. Panel B of Table 1 shows that 14% of counties belong to the DG regions. Each young and old group accounts for 50% of the sample.

We also construct the following control variables: the county-level monthly income data obtained from the Korea Credit Bureau and the county-level population density for each month from the Resident Registration. Moreover, we construct the (age $\times$ sex)

[11] To the best of our knowledge, the transaction data utilized in previous studies encompassed details about the merchants' industry and address, along with the transaction amount and type. However, this data did not include information pertaining to the cardholders, such as age and sex.

[12] The four-digit categories provided by the credit card data include expenditures on online delivery platforms and other forms of online food orders. For instance, when a cardholder places a food delivery order directly through a restaurant's website, it is categorized as online consumption. Conversely, orders made over the phone are classified as offline consumption, as they align with the Point of Sale (POS) machine criteria.

cell-level monthly income variable for each county.

4 Empirical Specification

To identify the effect of the increased online shopping on generational consumption inequality, we exploit the local outbreak of COVID-19 in the DG regions in a DID framework. As we saw in the previous figures, the first COVID-19 wave was highly localized in the DG areas and subsided by April 2020. The sudden and localized outbreak of COVID-19 was unrelated to local socioeconomic factors, which enables us to perform the DID analysis. Before February 2020, mobility patterns (Figure 1) or online spending shares (Figure 2) were not different in the DG and non-DG areas, which validates our DID empirical strategy.

Specifically, we use the following DID specifications at the county-demographic cell level:

$$Y_{i,a,g,t} = \beta Post_t \times DG_i + X'_{i,a,g,t}\gamma + \mu_i + \tau_a + \theta_g + \lambda_t + \epsilon_{i,a,g,t}, \tag{1}$$

$$Y_{i,a,g,t} = \beta_y Post_t \times DG_i + \beta_o Post_t \times DG_i \times Older_a + X'_{i,a,g,t}\gamma + \mu_i + \tau_a + \theta_g + \lambda_t + \epsilon_{i,a,g,t}. \tag{2}$$

Subscripts i, a, g, and t denote county (229 counties), age group (20–24, 25–29, ..., 65 and older), sex (female or male), and month (from October 2018 to March 2020), respectively.

Equation (1) estimates the effect of COVID-19 on online consumption, while Equation (2) estimates different responses by age group. $Y_{i,a,g,t}$ is the outcome variable (e.g., online spending shares, the log of offline or total spending per capita) of cardholders living in county i and belonging to sex g and age group a at year-month t. The observation unit is county $\times$ age $\times$ sex $\times$ year-month cell. $Post_t$ and DG_i are dummy variables to capture the COVID-19 treatment period and area, respectively. $Post_t$ equals 1 if t belongs to February 2020 or March 2020, and DG_i equals 1 if a county belongs to the DG area.

In Equation (2), $Older_a$ equals 1 if the age is 45 and older. $X_{i,a,g,t}$ is a control variable, including the log of average income in each cell, the log of income in each county, and the population density of each county. μ_i are county fixed effects, τ_a are age fixed effects, θ_g are sex fixed effects, and λ_t are $(year \times month)$ fixed effects, respectively. Standard errors are clustered at the county level.

In Equation (1), the coefficient β represents the DID estimate of the COVID-19 impact on the online spending share of individuals in the treatment DG area. In Equation (2), the coefficient β_y is the DID estimate of the COVID-19 effect on the online spending share for young (baseline) individuals in the treatment area. In contrast, β_o captures the disparity in effects between younger and older people within the treatment area. Therefore, a negative value of β_o suggests that older people in the treatment area are less inclined to shift to online consumption compared to their younger counterparts in the same area.

5 Results

5.1 Event Study

[Figure 3 about here]

Figure 3 presents an event study graph illustrating the evolution of online shares in the DG areas compared to the non-DG areas, both before and after January 2020. As observed, the surge in online shares in the DG area corresponds with a decrease in mobility within those regions, and this trend dissipates by May 2020. Starting from August 2020, when the non-DG areas witness a surge in virus cases, the online shares in DG areas fall below those in the non-DG areas. We will delve deeper into these dynamics using regression results in the subsequent sections, separating short (or immediate) run (Feb 2020 – Mar 2020) in Section 5.2 and medium run (Aug 2020 – Oct 2020) analysis in Section 5.3.

5.2 Short Run Analysis: Local COVID-19 Outbreak

Panel A of Table 2 shows the effects of COVID-19 on online spending shares. Columns (1) and (2) report the COVID-19 effects on online spending shares in the treated DG area, while columns (3) to (4) present the effects on online shares by age group within the treatment area. The DID estimate of the COVID-19 effect on the online share in column (1) is 2.304 and statistically significant at the 1% level. The local outbreak in February and March 2020 increased the online spending share in the DG areas by 2.3 percentage points, implying a faster online transformation in the treatment area than in the other areas. Given that the online share has increased on average at an annual rate of 1.5% during the last decade in South Korea, a 2.3 percentage point increase means a 1.5-year online transformation occurred in two months due to COVID-19. The result does not change after adding the control variables in column (2).

[Table 2 about here]

However, the fast online transformation has not occurred for older people in the DG area. Column (3) shows that the local outbreak increased the online share of young people (baseline) by 4.9 percentage points, i.e., a 15.29% increase in their online share, given that the mean of the online spending share of young people is 32.05% (Table 1). But the effect on the online share of older people is 5.3 percentage points smaller than the effect on the younger ones. This nearly offsets the baseline effect, implying that the local COVID-19 outbreak did not change the online shares of older people in the DG area compared to those in other areas. In response to the local outbreak of COVID-19, younger people increased their online shopping, while older ones did not, thereby increasing the generational gap in online shopping. The widened generational gap is 5.3 percentage points, equivalent to a 45% increase in the existing generational gap.[13] The results change slightly after adding the control variables in column (4); however, the overall implications stay the same.

The significant disparities in online consumption patterns between older and younger generations during the local COVID-19 outbreak are not solely due to younger individuals spending more on goods and services online. Panel C of Table A2 demonstrates the changes in online exposure attributable to these effects, both before and after COVID-19. Notably, our data indicate a more substantial increase in 'online exposure' (i.e., the percentage of consumption baskets that are sold online) among older individuals post-COVID-19 (4.34% for older vs. 1.27% for younger individuals). This trend is primarily due to an increased reliance on online shopping for food and beverage purchases, a category predominantly consumed by older individuals. This implies that the proportion of online shopping within the consumption baskets of older people has risen more significantly compared to that of younger individuals, which suggests that the welfare consequences for the elderly could potentially be severe.

This observation raises a critical question: Did older people's total consumption decrease more than that of younger individuals during the local outbreak, and what are the potential welfare implications of this? Columns (1) and (2) in Panel B of Table 2

[13] According to Table 1, the mean of the generational gap in the online spending share between young and older people is 11.85 percentage points (i.e., 32.05%–20.20%).

show that local outbreaks in the DG area caused an 11.1% decrease in offline consumption per capita, leading to a 6.8% decrease in the total consumption per capita. This result implies that consumers substituted offline consumption with online consumption, which might have alleviated the negative impact of COVID-19 on total consumption. More importantly, column (3) shows that younger and older people experienced similar declines in offline consumption. However, column (4) shows that older people suffered from a larger decline in total consumption (i.e., offline and online consumption) than younger ones. Specifically, older people faced a 9.6% decline in total consumption. In contrast, the total consumption of younger people during the local outbreak changed little (relative to that of people in the other areas).

These findings indicate that the older generation's slower adaptation to new shopping technologies during the pandemic might have widened generational consumption gaps, leading to a welfare loss for the elderly. Furthermore, considering that older people's expenditures tend to focus on essential goods such as food and beverages (Figure A1, Table A2), this trend could signify an even more significant welfare loss for this demographic.

5.3 Medium-Run Analysis: Recovery Periods

[Table 3 about here]

In this section, we explore the recovery effects of COVID-19 from August 2020 to October 2020, a period that aligns with the easing of mobility restrictions in DG areas following the subsidence of the local outbreak. Table 3 outlines the results for this recovery phase, contrasting them with the pre-treatment period from October 2018 to January 2020. Column (3)-(4) of Panel A in Table 3 shows that during the recovery phase, the generational gap in online spending diminished to merely 3 percentage points. This suggests a substantial 40% decrease in the generational disparity observed at the height of the local COVID-19 outbreak (as shown in Columns (3)-(4) of Table 2, Panel A). This change occurred as the older population in DG areas reverted to their prior levels of online spending once mobility restrictions were lifted, while the younger population did not completely return to their pre-COVID online consumption levels (as indicated in Figure 2, Panel B). As a result, a significant part of this divergence in online shopping habits persisted even six months post the pandemic peak.

Conversely, in the DG region, offline consumption, which had initially decreased from February to March 2020 (Table 2, Panel B), almost returned to pre-pandemic levels in non-DG regions from August to October, as observed in Column (1) of Panel B in Table 3, without any notable generational differences (Column (3)). This rebound paralleled the decrease in the mobility gap between DG and non-DG regions, as illustrated in Figure 1, Panel B.

Integrating both online and offline consumption data from Columns (2) and (4) of Panel B, Table 3, the generational differences in consumption were found to be less significant than they were in the immediate aftermath of the outbreak, as demonstrated in Panel B of Table 2. What was initially a considerable disparity has now been reduced to about 3.4% (Column (4) of Table 3), marking a notable decrease in the previously observed divide. Nonetheless, the generational gap in total consumption continues to persist in the medium term, indicating that disparities between age groups are still present.

5.4 Further Analyses

We perform further analyses to evaluate the welfare effect of the widened generational online gap due to the local COVID-19 outbreak in DG areas. First, we measure the online spending shares based on the total amount of spending rather than the number of customers. The online gap due to the pandemic could be attributed to changes in the amount spent by existing online consumers rather than by the number of new online consumers. Following Einav et al. (2021), we decompose the online spending share (S) into the following three components:

$$S \equiv \frac{S_O}{S_T} = \underbrace{\frac{N_O}{N_T}}_{\text{Customer Margin}} \times \underbrace{\frac{V_O}{N_O}\frac{N_T}{V_T}}_{\text{Frequency Margin}} \times \underbrace{\frac{S_O}{V_O}\frac{V_T}{S_T}}_{\text{Transaction Margin}},$$

where the subscription indicates O for online and T for total. S_O and S_T are the amounts of online spending and total spending, respectively. N is the number of customers measured by the number of cardholders, and V is the number of transactions. The first term of the right-hand side of the equation is the customer margin, which indicates how many customers use online shopping. The second term represents intensive margins of the number of transactions (i.e., frequency margin), and the third term indicates the amount per transaction (i.e., transaction margin).

[Table 4 about here]

Panel A of Table 4 reports the COVID-19 pandemic effect on online consumption by each margin. Overall, the results show that the widened generational divide in online consumption was mainly attributed to the customer margin (columns (1) and (2)) rather than to the frequency (columns (3) and (4)) or transaction margins (columns (5) and (6)). Specifically, the percentage of young credit card holders using online shopping increased by 3.789 percentage points (around 25% of the mean of 14.87% according to Table A1), whereas the number of older credit card holders using e-commerce did not change much. This decomposition exercise indicates that the generational gap in online shopping was mainly due to the left-behind older people, who did not adapt to the new shopping technology.

5.5 Robustness Checks

In this section, we conduct a series of robustness checks to validate our findings. The first set of checks delves into detailed age group analyses and addresses potential issues related to the credit card data, as presented in Table 5. The second set focuses on issues related to identification, with findings reported in Table 6. Across all tests, our results remain qualitatively consistent.

[Table 5 about here]

First, we refine our analysis by segregating the older age group into middle-aged (45 to 59 years)[14] and old-aged groups (60 years and older). As expected, the results in column (5) of Table 5 indicate a more pronounced gap for the older group; the coefficients for the middle-aged and old-aged groups are -4.913 and -5.825, respectively. This suggests that the generational consumption gap begins to widen significantly at around age 45, intensifying further for older age groups.

Subsequently, we assess the reliability of our age-specific online spending shares derived from credit card data. Discrepancies in payment shares via credit and debit cards across different age groups could potentially bias our results. However, as shown in Appendix Figure A2, payment shares through credit cards remain relatively consistent across all age

[14] A 45-year-old in 2020 graduated from high school in 1995, the year the web-based internet first became commercially available in South Korea.

groups, with a noticeable divergence only for individuals aged 70 and older. To mitigate concerns related to low card usage in this demographic, we exclude individuals aged 70 and above from our sample and re-analyze the data.

Panel B of Table 5 details the impact of COVID-19 on online spending shares, excluding individuals aged 70 and older. Consistent with our initial findings in Table 2, columns (1) and (2) report the overall impact on the treated DG area, while columns (3) and (4) highlight the heterogeneous effects across different age groups. The results reinforce our initial conclusions, affirming that the observed lower online transition among the elderly is not attributable to their reduced credit card usage rates.

[Table 6 about here]

Further, our subgroup analysis in Panel A of Table 6 examines the differential responses between younger and older cohorts. The results underscore a notable disparity; the younger cohort in treated regions exhibits a more significant increase in online spending share (3.339 percentage points) compared to the older cohort (1.272 percentage points), aligning with our primary findings of expanding generational e-commerce usage gaps shown in Table 2.

Finally, we conduct tests to determine if generational trends in online spending shares are leading to spurious results. By incorporating age-specific trends and age-fixed effects in our regression analyses, we account for potential generational differences in online shopping trends. As depicted in Panel B of Table 6, the outcomes remain qualitatively consistent with those presented in Panel A of Table 2, reinforcing the validity of our findings.

6 Conclusion

This paper shows that older people's difficulty adapting to new shopping technologies widened generational consumption inequality in South Korea, where digital infrastructure is well-equipped. When mobility was restricted due to the pandemic, younger people could substitute their physical visits to shops for online shopping, which resulted in no changes in total consumption. However, the sudden transition to online shopping has been more difficult for older people, significantly decreasing their total consumption. Our findings imply that even if e-commerce reduced consumption inequality across spaces, the new shopping technology might have increased consumption inequality across different city populations.

This study is not without limitations. Above all, our estimates are based on the short window of time until the local outbreak of COVID-19 in the DG areas subdued in South Korea. However, this locally occurred temporal shock created an exogenous quasi-experimental setting that allowed us to mimic a longer-run equilibrium with the departure of offline stores due to the rise of e-commerce and, therefore, limited physical accessibility to stores.

Given that the speed of digital transformation has been unprecedented, understanding how the gains from e-commerce are spatially and demographically distributed is a crucial policy concern. The findings from this paper raise a new challenge that e-commerce could exacerbate generational consumption inequality within cities, even when the spatial disparity in digital infrastructure is absent. The real challenges will arise if the accessibility to offline stores decreases significantly due to the "apocalypse" of offline stores (Chun et al., 2023; Gupta et al., 2022; Van Nieuwerburgh, 2023), as the proportion of online shopping increases. We leave this debate as our future research.

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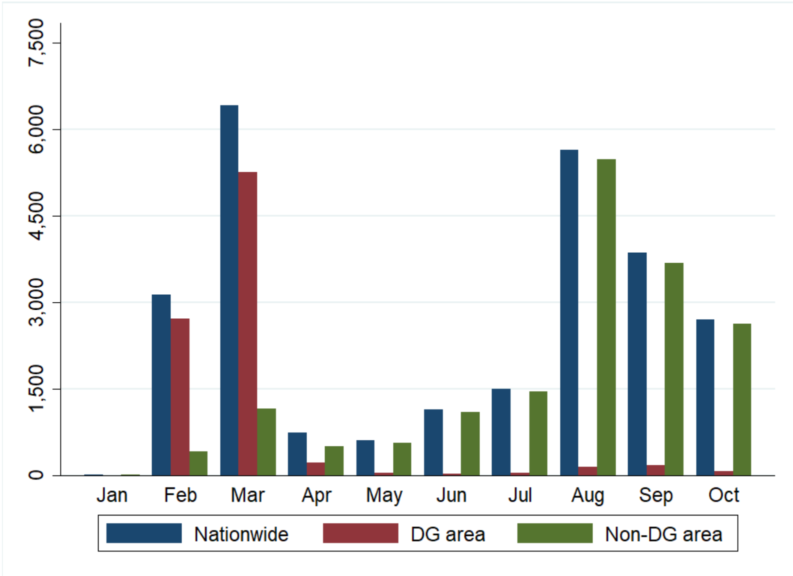
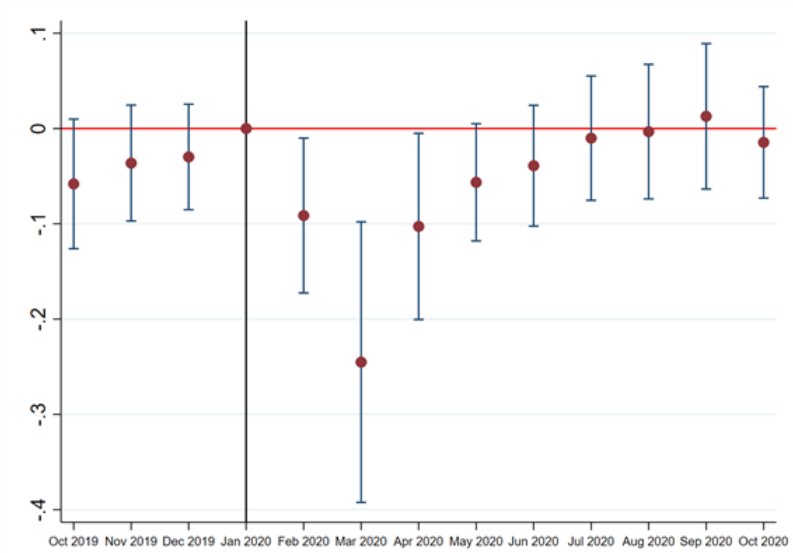
Figures and Tables



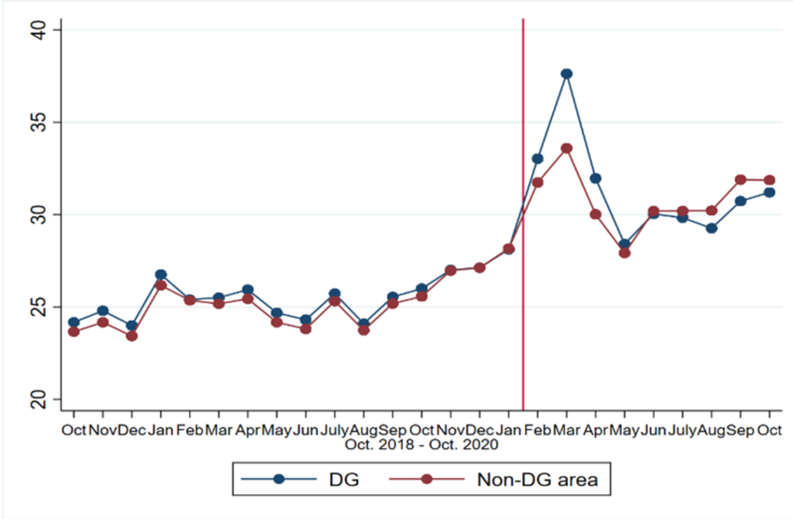
(a) COVID-19 Cases: DG Areas vs. Non-DG Areas (Jan 2020–Jun 2020)



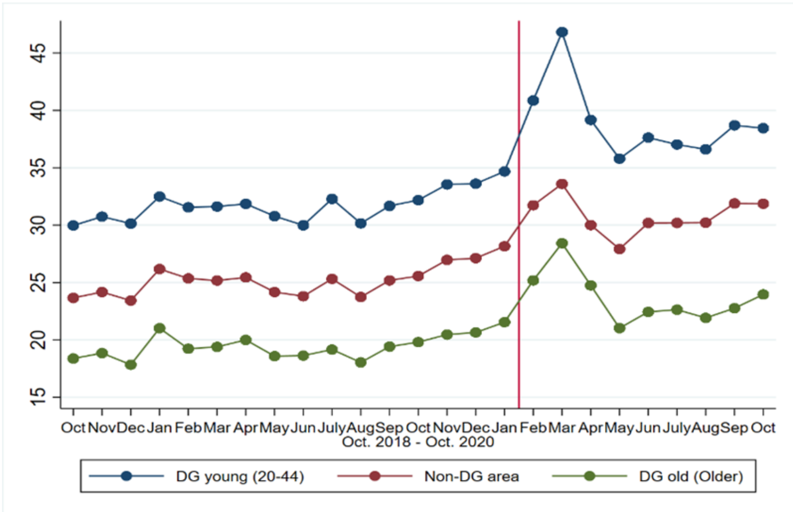
(b) Mobility: DG Areas vs. Non-DG Areas (before and after COVID-19)

Figure 1: COVID-19 Cases and Mobility

Notes: In Panel (a), the bars indicate monthly confirmed cases of COVID-19 for DG and non-DG areas from January to October 2020 (source: Korea Disease Control and Prevention Agency). Panel (b) plots the differences in mobility counts, between DG and non-DG areas, from October 2019 to October 2020 (source: SK Telecom). The mobility of a district is defined as a count of users located outside their residential districts. The January 2020 coefficient is normalized to zero, serving as a baseline, and is presented with 95% confidence intervals. Standard errors are clustered at the county level.



(a) Online Spending Share: DG vs. Non-DG Areas



(b) Online Spending Share: Younger vs. Older Group

Figure 2: Online Spending Share before and after COVID-19

Notes: Panel (a) shows online spending shares for DG and non-DG areas from October 2018 to October 2020. Panel (b) shows online spending shares for younger (20–44) and older (45 and older) groups in the DG area from October 2018 to October 2020.

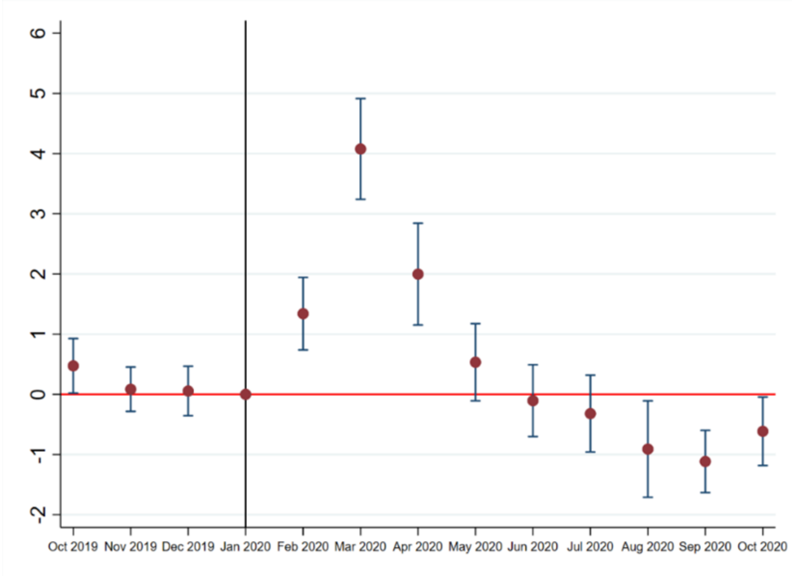


Figure 3: Online Spending Share: Event Study

Notes: The event study graph illustrates the differences in online spending share between DG and non-DG areas from October 2019 to October 2020. The January 2020 coefficient is normalized to zero, serving as a baseline, and is presented with 95% confidence intervals. Standard errors are clustered at the county level.

Table 1: Descriptive Statistics

	Mean	Median	S.D.	p25	p75
Panel A. Dependent Variables					
Online spending share (%)	26.13	24.80	10.64	18.17	33.01
By age group					
Younger (20-44)	32.05	31.28	9.81	24.70	38.82
Middle-aged and Older (45 +)	20.20	19.36	7.7	14.82	24.89
By treatment area					
Treatment area (DG)	26.66	24.84	11.62	18.12	33.73
Control area (non-DG)	26.04	24.79	10.48	18.18	32.90
Panel B. Key Independent Variables					
By treatment area and period					
DG (Daegu or Gyeongbuk)	0.14	0	0.34	0	0
Post (Feb. 2020 - Mar. 2020)	0.11	0	0.31	0	0
By age group					
Younger (20-44)	0.5	0.5	0.5	0	1
Middle-aged and Older (45 +)	0.5	0	0.5	0	1
Panel C. Control Variables					
Population density (pop/km^2)	3,885.4	498.9	6,116.6	92.2	5,651.1
Log county income per capita	10.37	10.36	0.10	10.32	10.42
Log county income per capita (age $\times$ sex)	10.39	10.36	0.26	10.20	10.58

Notes: The sample includes 82,437 observations (county $\times$ age $\times$ sex cells) from October 2018 to March 2020.

Table 2: Effects of COVID-19

Panel A. Online Spending Share by Age

	(1)	(2)	(3)	(4)
		Online Share (%)		
Post×DG	2.304***	2.299***	4.943***	4.843***
	(0.337)	(0.337)	(0.642)	(0.649)
Post×DG×Older (45+)			-5.278***	-5.090***
			(0.871)	(0.871)
Controls	N	Y	N	Y
Fixed effects	Y	Y	Y	Y
Adj. R^2	0.797	0.806	0.798	0.807
Obs.	82,437	82,437	82,437	82,437

Panel B. Offline and Total Consumption by Age

	(1) Offline	(2) Off + Online	(3) Offline	(4) Off + Online
Post × DG	-0.111***	-0.068***	-0.122***	-0.020
	(0.011)	(0.006)	(0.021)	(0.013)
Post × DG × Older (45+)			0.021	-0.096***
			(0.030)	(0.022)
Controls	Y	Y	Y	Y
Fixed effects	Y	Y	Y	Y
Adj. R^2	0.915	0.921	0.915	0.921
Obs.	82,437	82,437	82,437	82,437

Notes: The sample period is October 2018 to January 2020 (pre-treatment) and February 2020 to March 2020 (post-treatment). In Panel A, the dependent variable is online spending share (%). In Panel B, the dependent variable is the log of offline spending per capita and the log of the sum of offline and online spending per capita, respectively. Both Panel A's and Panel B's samples include county × age × sex cells from October 2018 to March 2020. All regressions include age, sex, county, and year-month fixed effects. Controls include population density, log of county income per capita, and log of county income per capita by (age × sex) cell. Numbers in parentheses are county-clustered standard errors. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 3: Effects of Recovery

Panel A. Online Spending Share by Age

	(1)	(2)	(3)	(4)
		Online Share (%)		
Recovery × DG	-1.284***	-1.257***	0.230	0.156
	(0.235)	(0.217)	(0.405)	(0.395)
Recovery × DG × Older (45+)			-3.027***	-2.826***
			(0.692)	(0.682)
Controls	N	Y	N	Y
Fixed effects	Y	Y	Y	Y
Adj. R^2	0.799	0.808	0.799	0.808
Obs.	87,017	87,017	87,017	87,017

Panel B. Offline and Total Consumption by Age

	(1)	(2)	(3)	(4)
	Offline	Off + Online	Offline	Off + Online
Recovery × DG	0.014	-0.006	0.004	0.012
	(0.009)	(0.008)	(0.016)	(0.013)
Recovery × DG × Older (45+)			0.020	-0.034*
			(0.023)	(0.020)
Controls	Y	Y	Y	Y
Fixed effects	Y	Y	Y	Y
Adj. R^2	0.899	0.908	0.899	0.908
Obs.	87,017	87,017	87,017	87,017

Notes: The sample period is October 2018 to January 2020 (pre-treatment) and August 2020 to October 2020 (recovery). In Panel A, the dependent variable is online spending share (%). In Panel B, the dependent variable is the log of offline spending per capita and the log of the sum of offline and online spending per capita, respectively. Both Panel A's and Panel B's samples include county × age × sex cells. All regressions include age, sex, county, and year-month fixed effects. Controls include population density, log of county income per capita, and log of county income per capita by (age × sex) cell. Numbers in parentheses are county-clustered standard errors. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 4: Further Analysis: Decomposition of Online Spending Share

	(1)	(2)	(3)	(4)	(5)	(6)
	Customer		Frequency		Amount per Trans.	
Post × DG	1.680***	3.789***	-0.020***	-0.025**	-0.015	-0.031
	(0.190)	(0.356)	(0.007)	(0.011)	(0.013)	(0.024)
Post × DG× Older (45+)		-4.217***		0.009		0.031
		(0.418)		(0.014)		(0.038)
Controls	Y	Y	Y	Y	Y	Y
Fixed effects	Y	Y	Y	Y	Y	Y
$Adj.R^2$	0.866	0.868	0.251	0.251	0.378	0.378
Obs.	82,437	82,437	82,437	82,437	82,437	82,437

Notes: The sample period is October 2018 to January 2020 (pre-treatment) and February 2020 to March 2020 (post-treatment). In Panel A, online spending share (%) is decomposed into three dependent variables of the customer (columns (1) and (2)), frequency (columns (3) and (4)), and amount per transaction margins (columns (5) and (6)). The sample includes county × age × sex cells from October 2018 to March 2020. All regressions include age, sex, county, and year-month fixed effects. Controls include population density, log of county income per capita, and log of county income per capita by (age × sex) cell. Numbers in parentheses are county-clustered standard errors. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 5: Robustness Checks 1

Panel A. Online Spending Share by Age

	(1)	(2)	(3)	(4)
	Online Share (%)			
Post × DG	2.304***	2.299***	4.943***	4.843***
	(0.337)	(0.337)	(0.642)	(0.649)
Post × DG × Mid (45-59)			-4.913***	-4.718***
			(0.805)	(0.795)
Post × DG × Old (60+)			-5.825***	-5.639***
			(1.053)	(1.064)
Controls	N	Y	N	Y
Fixed effects	Y	Y	Y	Y
Adj. R^2	0.797	0.806	0.798	0.807
Obs.	82,437	82,437	82,437	82,437

Panel B. Excluding People Aged 70 and Older

	(1)	(2)	(3)	(4)
	Online Share (%)			
Post × DG	2.307***	2.300***	4.951***	4.848***
	(0.344)	(0.344)	(0.648)	(0.655)
Post × DG × Older (45+)			-5.286***	-5.097***
			(0.871)	(0.870)
Controls	N	Y	N	Y
Fixed effects	Y	Y	Y	Y
$Adj.R^2$	0.799	0.808	0.800	0.809
Obs.	82,431	82,431	82,431	82,431

Notes: The sample period is October 2018 to January 2020 (pre-treatment) and February 2020 to March 2020 (post-treatment). The dependent variables are online spending shares (%). Panel A and Panel B's sample includes county × age × sex cells from October 2018 to March 2020. All regressions include age, sex, county, and year-month fixed effects. Controls include population density, log of county income per capita, and log of county income per capita by (age × sex) cell. Numbers in parentheses are county-clustered standard errors. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 6: Robustness Checks 2

Panel A. Subgroup Analysis

	(1)	(2)	(3)
		Online Share (%)	
Sample	All	Younger (below 45)	Older (45 and older)
Post × DG	2.304***	3.339***	1.272***
	(0.014)	(0.462)	(0.297)
Fixed effects	Y	Y	Y
Adj. R^2	0.797	0.809	0.697
Obs.	82,437	41,220	41,217

Panel B. Including Age-Specific Trends

	(1)	(2)	(3)	(4)
		Online Share (%)		
Post × DG	2.304***	2.299***	3.776***	3.680***
	(0.337)	(0.337)	(0.678)	(0.686)
Post × DG × Older (45+)			-2.945***	-2.762***
			(0.958)	(0.957)
Controls	N	Y	N	Y
Fixed effects	Y	Y	Y	Y
$Adj.R^2$	0.801	0.810	0.801	0.810
Obs.	82,437	82,437	82,437	82,437

Notes: The sample period is October 2018 to January 2020 (pre-treatment) and February 2020 to March 2020 (post-treatment). The dependent variables are online spending share (%). The sample includes county × age × sex cells from October 2018 to March 2020. All regressions include age, sex, county, and year-month fixed effects. Controls include population density, log of county income per capita, and log of county income per capita by (age × sex) cell. Numbers in parentheses are county-clustered standard errors. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Online Appendixes

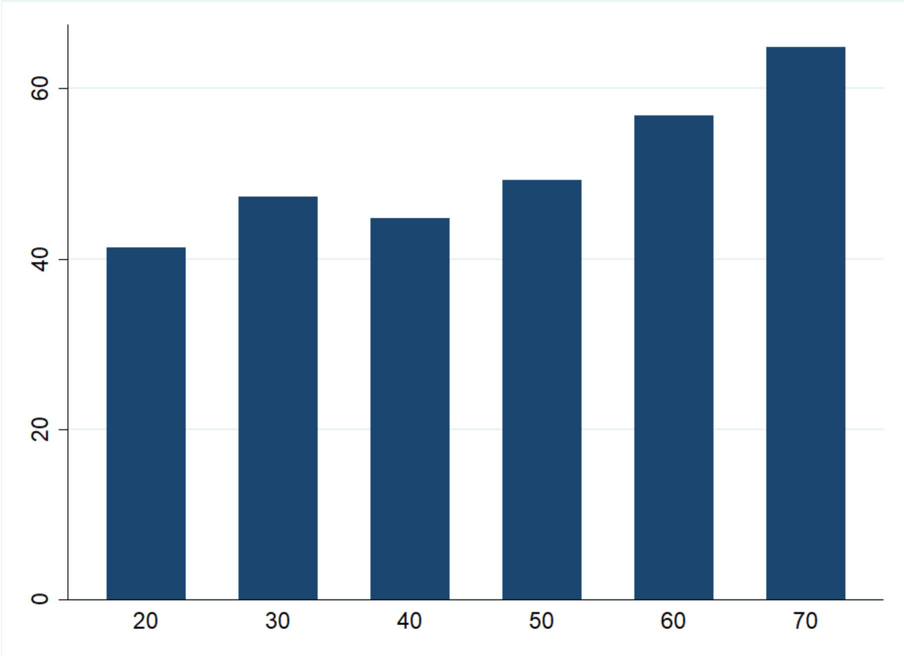


Figure A1: Share of Essential Good Consumption by Age Group

Notes: Each bar is the share of essential good consumption for an age group (20–29, . . . , 60–69, and 70 and older) in 2019. We classified essential goods following the New York State Department of Economic Development's guidance on essential retail in response to COVID-19. Data are obtained from the 2019 Survey on the Usage Behavior of Payment Methods and Mobile Payment Services published by the Bank of Korea.

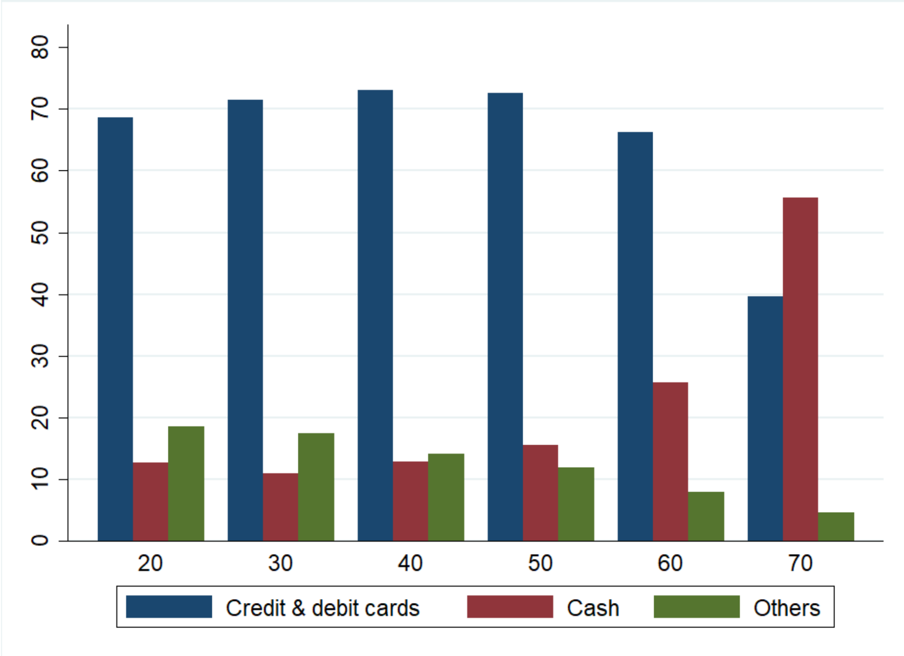


Figure A2: Share of Payment Methods by Age Group

Notes: Each bar is the share of the total payments that used a particular method for an age group (20–29, . . . , 60–69, and 70 and older) in 2019. Bars in blue, red, and green denote the shares paid by credit and debit cards, cash, and other methods, respectively. Data are obtained from the 2019 Survey on the Usage Behavior of Payment Methods and Mobile Payment Services published by the Bank of Korea.

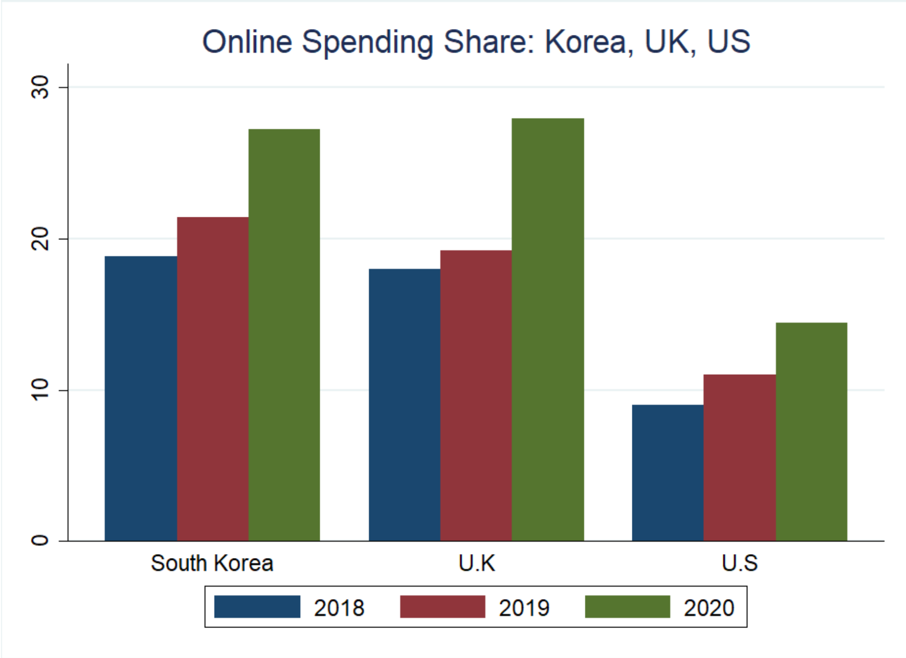


Figure A3: Cross-Country Comparisons of Online Spending Shares

Notes: Each bar represents countries' share of online spending in 2018, 2019, and 2020. The data source is Online Shopping Trend Survey (Statistics Korea), Retail Sales Index time series (Office for National Statistics), and Quarterly Retail E-Commerce Sales (US Census Bureau) for South Korea, UK, and US statistics, respectively.

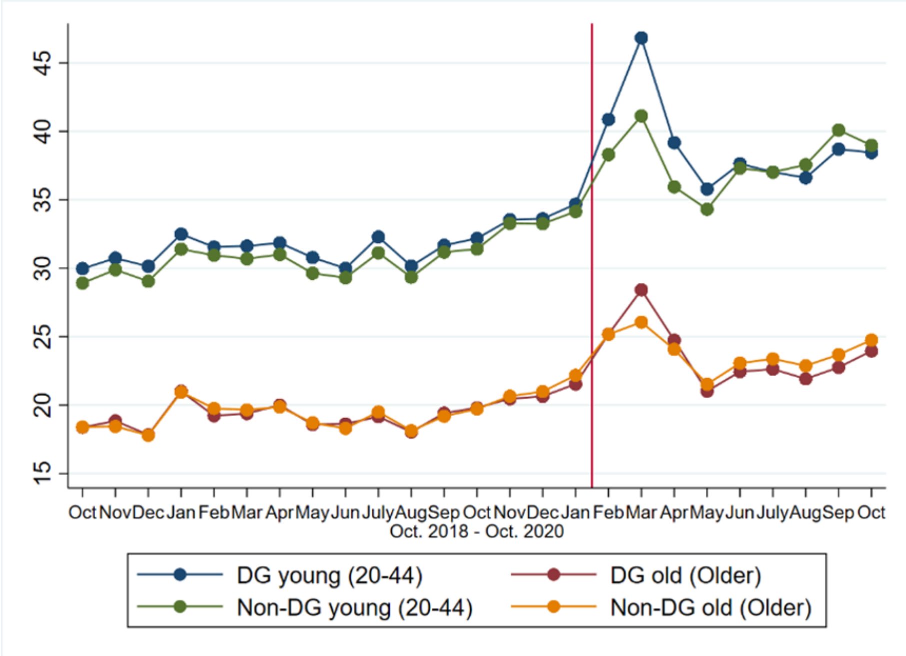
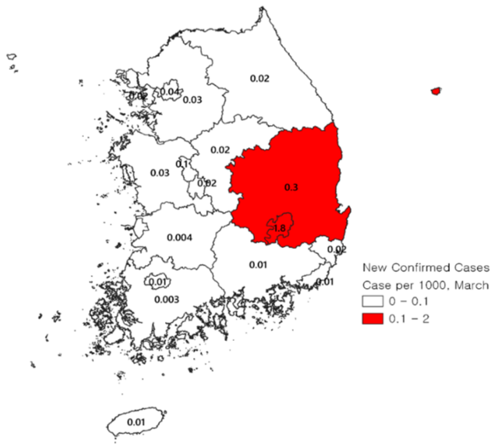
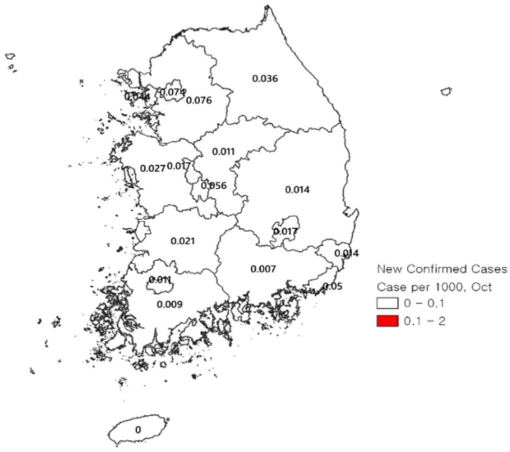


Figure A4: Cross-Country Comparisons of Online Spending Shares

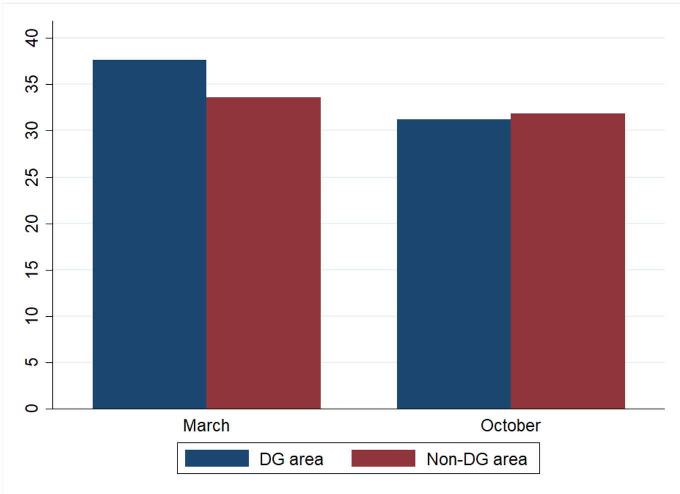
Notes: Figure shows online spending shares for younger (20–44) and older (45 and older) groups in the DG area and non-DG area from October 2018 to October 2020.



(a) COVID-19 Cases: Mar. 2020



(b) COVID-19 Cases: Oct. 2020



(c) Online Shopping Share: Mar. 2020 vs. Oct. 2020

Figure A5: Online Spending Share after Slowdown in COVID-19

Notes: The upper panels present newly confirmed cases per 1,000 people in March (Panel (a)) and October 2020 (Panel (b)) (source: Korea Disease Control and Prevention Agency). DG area in the map is in red in Panel (a). In Panel (c), the bar charts show online spending shares for the DG and non-DG areas from March to October 2020.

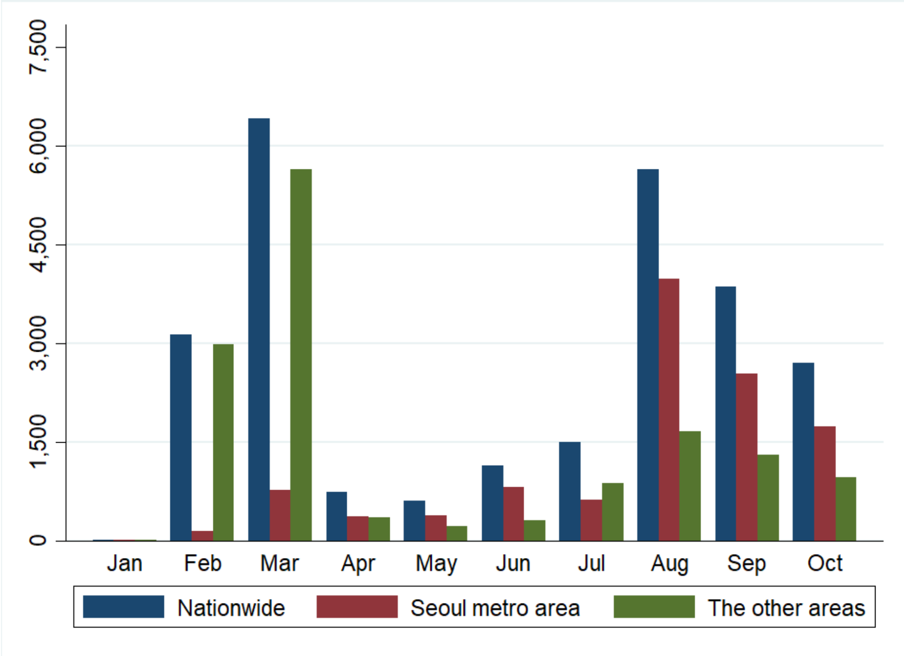


Figure A6: New Confirmed Cases: Seoul Metro Area vs. The Other Areas

Notes: A bar represents COVID-19 cases from January 2020 to October 2020. The red bar is for the Seoul Metropolitan area (Seoul and Gyeonggi), while the green bar is for the other areas. Nationwide cases are the sum of cases in the two areas. Source: Korea Disease Control and Prevention Agency.

Table A1: Descriptive Statistics

	Mean	Median	S.D.	p25	p75
Customer margin (%)	11.56	10.67	5.16	7.59	14.67
By age group					
Young (20-44)	14.87	14.17	4.68	11.15	17.87
Older (45 and older)	8.25	7.67	3.07	5.97	9.98
By treatment area					
Treatment area (DG)	12.09	10.82	5.99	7.63	15.45
Control area (non-DG)	11.48	10.64	5.01	7.59	14.58
Frequency margin	1.13	1.12	0.19	1.03	1.21
By age group					
Young (20-44)	1.18	1.18	0.14	1.10	1.24
Older (45 and older)	1.08	1.06	0.22	0.98	1.15
By treatment area					
Treatment area (DG)	1.16	1.14	0.31	1.04	1.24
Control area (non-DG)	1.12	1.12	0.16	1.02	1.21
Amount per transaction margin by age group	2.10	1.99	0.56	1.76	2.35
By age group					
Young (20-44)	1.86	1.83	0.30	1.69	2.00
Older (45 and older)	2.35	2.28	0.66	1.97	2.63
By treatment area					
Treatment area (DG)	2.04	1.91	0.63	1.68	2.27
Control area (non-DG)	2.11	2.00	0.55	1.77	2.27
Offline spending per capita (mil. KRW)	0.86	0.67	0.90	0.42	1.03
By age group					
Young (20-44)	0.93	0.72	0.97	0.47	1.09
Older (45 and older)	0.80	0.63	0.82	0.38	0.96
By treatment area					
Treatment area (DG)	0.75	0.56	0.73	0.34	0.96
Control area (non-DG)	0.88	0.69	0.93	0.44	1.04
Total credit card spending per capita (mil. KRW)	1.22	0.93	1.37	0.57	1.44
By age group					
Young (20-44)	1.41	1.06	1.55	0.69	1.62
Older (45 and older)	1.03	0.80	1.13	0.47	1.24
By treatment area					
Treatment area (DG)	1.06	0.76	1.08	0.47	1.31
Control area (non-DG)	1.24	0.95	1.41	0.60	1.45

Notes: The sample includes 82,437 observations (county $\times$ age $\times$ sex cells) from October 2018 to March 2020.

Table A2: Online Shopping Exposure by Age Group

Panel A. Consumption Basket (i.e., Spending Share) by Product Category (2019)

	(1) Young (20-44)	(2) Older (45+)	(3) Older (60+)
Furniture and interior	6.35%	4.30%	3.26%
Electronics and appliances	7.38%	6.35%	5.63%
Food and beverage	49.38%	63.61%	71.47%
Clothing and clothing access.	28.51%	21.38%	15.89%
Hobbies (e.g., sports, music)	8.38%	4.35%	3.76%

Panel B. Online Consumption Intensity by Product Category (2019, 2021)

	(1)	(2)	(3)	(4)
	Korea		U.S.	
	2019	2021	2019	2021
Furniture and interior	40.42%	45.87%	36.27%	47.30%
Electronics and appliances	47.52%	40.59%	35.99%	47.56%
Food and beverage	9.27%	13.80%	3.21%	6.95%
Clothing and access.	28.69%	36.11%	26.32%	34.07%
Hobbies (e.g., sports, music)	33.58%	35.26%	32.78%	39.03%

Panel C. Changes in Online Exposure

	(1) Young (20-44)	(2) Older (45+)	(3) Older (60+)
$\sum_{j:category} Intensity_{j,t} \times \text{SpendingShare}_j$			
$t = 2019$	21.64%	18.25%	16.44%
$t = 2021$	22.93%	22.58%	20.71%
Δ Online Exposure (2021-2019)	1.28%	4.34%	4.27%

Note: Panel A utilizes data from the Household Income and Expenditure Survey 2019 in Korea. Panel B sources data from the Service Industry Survey 2019 and Online Shopping Survey 2019 in Korea, as well as the Annual Retail Trade Survey 2020 in the U.S. Panel C derives its '$Intensity_{j,t}$' metric from the data of 2019 and 2021 found in Columns (1) and (2) of Panel A, by each category j. The '$SpendingShare_j$' in Panel C is based on the spending shares by category presented in Panel B, indicating the proportion of income spent in various sectors.