The Consumption Response to Universal Payments: Evidence from a Natural Experiment*

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Abstract

We investigate the impact of the universal stimulus payments (100-350 thousand KRW per person) distributed by the largest Korean province of Gyeonggi under the COVID-19 pandemic on household consumption using large-scale credit and debit card data from the Korea Credit Bureau. As the neighboring Incheon metropolitan city did not distribute stimulus payments, we employ a difference-in-difference approach and find that the stimulus payments increased monthly consumption per person by approximately 30 thousand KRW within the first 20 days. The overall MPC of the payments was approximately 0.40 for single families. The MPC decreased from 0.58 to 0.36 as the transfer size increased from 100-150 to 300-350 thousand KRW. We also find that universal payments had a very heterogeneous effect on different groups of people. The MPC for liquidity-constrained households, which account for 8% of residents, was close to one, but the MPCs of the other household groups were not significantly different from zero. The unconditional quantile treatment effect estimates reveal that there was a positive and significant increase in monthly consumption only on the lower part of the distribution below the median. Our results show that a more targeted approach may more efficiently achieve the policy goal of boosting aggregate demand.

Keywords: COVID-19, Stimulus Payments, Consumption, Marginal Propensity to Consume, Difference-in-Difference

JEL Classification: D12, E21, E62, H24

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1 Introduction

Households' consumption response to a stimulus payment has long been an important subject for both economists and policy makers. However, the opportunity for an economy-wide empirical study has been rather limited because few governments can afford universal transfer payments. The serious economic downturn induced by the COVID-19 pandemic ironically provides an opportunity for an economy-wide empirical study this topic, as countries such as the United States, Hong Kong, Singapore, and South Korea distributed universal stimulus payments directly to all households (IMF, 2020). However, there are several challenges in studying the impact of stimulus payments on household consumption during the COVID-19 pandemic. First, it is difficult to set a distinct comparison group when the one-time payments were distributed to all households on a national basis. Second, the consumption response could be restricted by stay-at-home orders or the lockdown of businesses. We overcome these challenges by utilizing the ideal natural experiment setup in South Korea with novel microlevel data, which enables us to evaluate the policy effect more accurately.

We adopt the difference-in-difference (DiD) methodology to identify the causal effect of stimulus payments on household consumption by focusing on the universal payment distributed in the Gyeonggi Province of South Korea in April 2020. The policies and the regional aspect of Gyeonggi provide ideal natural experiment conditions. First, Gyeonggi is the only region that provided universal stimulus payments to all residents in April, which was before the central government's and any other local government's universal payment plans were implemented. Second, there was district-level variation in the size of transfers within Gyeonggi, ranging from 100 to 350 thousand KRW per person, which provides room for further analysis of policy implications. Third, Gyeonggi's experience can be considered representative in South Korea. It is included in the Seoul Capital Area (SCA), where 50.0% of the population and 52.0% of GDP (as of 2019) are concentrated. In fact, it is the largest province by population as well as by regional GDP in South Korea. We choose Incheon, which is another member of the SCA bordering Gyeonggi, as the comparison group. Another important fact is that there were no stay-at-home orders or lockdown of businesses in these regions in April because the COVID-19 pandemic in South Korea was restricted to the city of Daegu, which is far from the SCA.

We use individual-level monthly panel data that track a random sample of more than 200,000 households in Gyeonggi and Incheon from January 2019 to June 2020 provided by the Korea Credit Bureau (KCB). Compared to other datasets used in previous studies, such as the KDI (2020) or Chetty et al. (2020), our dataset is the most representative in terms of sample coverage and payment methods. It is selected from the entire population and covers all types of credit cards and debit cards used in Korea. Furthermore, total personal card spending amounts to 85% of household consumption in the 2019 GDP. This implies that our research can provide the most accurate picture available to us to better understand the consumption effects of COVID-19 emergency transfers.

Using household consumption data, rather than merchant sales data, is crucial for estimating the causal effect of stimulus payments on consumption, given that the use of stimulus payments was restricted to some industries and within three months. This is because households can substitute their income with transfers and adjust their consumption behavior to circumvent the restrictions. For example, households can save their income to spend in the future or to increase consumption in industries that are not allowed to use payments. In an extreme case, the marginal propensity to consume (MPC) can be zero for the payments. On the other extreme, the MPC can be as large as one if households do not adjust their original consumption plans and then additionally spend the entire transfer payment. Therefore, we cannot measure MPC or the effectiveness of stimulus payments precisely if we compare sales between allowed and disallowed industries or observe only where people use the stimulus payments. The panel data of household consumption allow us to overcome this problem by observing the evolution of total household consumption.

We exploit the spatial and temporal variation of the stimulus payments with the DiD identification strategy. Roughly speaking, we estimate the causal treatment effect by comparing monthly consumption in Gyeonggi (treatment group) and Incheon (comparison group) around April 2020, in which only the households in Gyeonggi received the stimulus payments. Considering that these two regions are located near each other and included in the SCA, they are subject to similar regulations and policies that could confound our estimation. We find that most policy actions by the central government to fight against COVID-19 and the economic downturn were commonly implemented in both regions. Nevertheless, we use various specifications to check the reliability of our empirical strategy and to reveal the heterogeneous impact of stimulus payments on different groups of households.

We begin by using the double-difference (DD) method to demonstrate how COVID-19 impacted consumption by comparing consumption between 2019 and 2020 in each region. We find that monthly consumption decreased by approximately 200 thousand KRW (approximately 200 USD) until April compared to 2019. When we compare the change in consumption from January to April 2020 in the two regions, monthly consumption per person was 27 thousand KRW higher in Gyeonggi than in Incheon. This difference indicates the impact of Gyeonggi's stimulus payments, as there was no significant difference in consumption between the two regions in 2019 when we did not have COVID-19. We then estimate the effect of stimulus payments using the triple-difference (DDD) method to remove possible confounding factors that affect the two regions differently. When we compare the change in consumption from January to April between 2019 and 2020 across the two regions, we find that the stimulus payments increased monthly household consumption by approximately 30 thousand KRW in Gyeonggi. The estimated MPC of stimulus payments is approximately 40%.

We also explore the transmission mechanism and heterogeneous effect of stimulus payments using quadruple difference (DDDD) in addition to DDD. We find that the MPC of the liquidity-constrained households, which account for 8% of residents, was close to one, but the MPCs of the other groups of households were not significantly different from zero. This implies that stimulus payments have an economic impact by easing the liquidity constraint. This result is consistent with previous studies, such as Baker et al. (2020). In addition, we find that MPC decreases from 0.58 to 0.36 as the size of stimulus payments increases from 100-150 to 300-350 thousand KRW. This implies that the cost-effectiveness decreases as the size of the stimulus payments increases by increasing the portion of savings among stimulus payments.

Furthermore, we investigate the distributional effects of the stimulus payments on consumption. Theoretical models with incomplete markets suggest that individuals who have received negative income shocks respond more strongly to transient stimulus payments (Deaton, 1991; Carroll and Kimball, 1996). There have been efforts to address this issue empirically (Jappelli and Pistaferri, 2014; Karger and Rajan, 2020). Unlike the previous literature, we investigate heterogeneity in households' responses to stimulus payments using the unconditional quantile regression (UQR) method (Koenker and Bassett, 1978). The UQR has gained increasing popularity, as it facilitates interpretation of a policy treatment effect in the presence of multiple control variables.

We complement our baseline analyses using the UQR method to estimate how the stimulus payments affected the expenditure distribution of exposed households. The estimated quantile treatment effects allow us to evaluate the impact of the stimulus payments on the lower, middle, and upper parts of the expenditure distribution. We find significant heterogeneity in the effects of the stimulus payments. While the payments had a significant mean impact on expenditures in line with our baseline results, the UQR estimates are highest in the lowest percentile and decline in the upper part of the distribution. The policy effects become close to 0 and insignificant above the 50th percentile. These estimates are consistent with those economic theories assuming that the level of expenditure is a good indicator of income or cash-on-hand; constrained households show excess sensitivity to a transient income shock. Our results show that a more targeted approach may be more efficient in achieving the policy goal of boosting the aggregate demand of the economy.

This paper relates to two strands of the literature. First, we add to the literature studying how one-time universal payments affect household consumption. For example, Johnson et al. (2006) and Parker et al. (2013) estimated the change in consumption expenditure caused by tax rebates in the United States in 2001 and in 2008, respectively. Johnson et al. (2006) showed that households spent 20 to 40 percent of their rebates, and responses were larger for low-income households. The estimated result of Parker et al. (2013) was slightly smaller (12 to 30 percent on average) using the 2008 tax rebates, and the authors noted that the difference might be due to sampling error or the differences in policy details and economic circumstances between 2008 and 2001.

Our estimation result is in line with previous works, but more importantly, we highlight that our analysis is based on detailed and comprehensive credit card spending data and financial information collected by credit rating agencies, whereas Johnson et al. (2006) and Parker et al. (2013) used consumption expenditure survey data. While Agarwal et al. (2007) analyzed the consumption response to the 2001 tax rebates using a panel data set of credit card accounts, its data source is one credit card issuer. Jappelli and Pistaferri (2014) estimated a Tobit model using survey data to study heterogeneity in the MPC. Karger and Rajan (2020) estimated separately for consumers who receive four different amounts of stimulus payments. Our paper is different from those in that we perform a UQR analysis using credit card data.

Second, our study directly contributes to the recent literature investigating the effects of COVID-19 stimulus payments. For instance, Baker et al. (2020), Chetty et al. (2020), Coibion et al. (2020), Karger and Rajan (2020), Carroll et al. (2020), Casado et al. (2020), Kim and Lee (2020), and Kim et al. (2020) estimate the spending impact of the U.S. CARES Act payments in 2020 and the Korea stimulus payments distributed considering the economic recession induced by COVID-19. We join this emerging literature by providing clean evidence using detailed individual-level panel data. Baker et al. (2020) investigated households' consumption responses using transaction data and found that households respond rapidly — during the first 10 days — to the receipt of stimulus payments. In line with their finding, we found that stimulus payments in Gyeonggi increased monthly consumption per person by 30 thousand KRW within the first 20 days. Additionally, we found that the effect of stimulus payments quickly disappeared in the following month. Additionally, as the authors highlighted the role of liquidity in spending responses, our study discusses it by providing empirical evidence. In particular, we focus on the responses of liquidity-constrained households, suggesting that the easing in the constraint is the main mechanism of the policy impact, which is consistent with evidence in Coibion et al. (2020). In addition to confirming and reinforcing the arguments in the related studies by exploring the case of South Korea, our paper estimates the pure effect of universal payments due to the ideal natural experiment setup of one representative metropolitan region of South Korea.

This paper is structured as follows. Section 2 provides background information regarding the stimulus payments in South Korea and our identification strategy. Section 3 describes the data used in this paper. Sections 4 and 5 present the empirical models and the main results. Section 6 discusses heterogeneity, and Section 7 shows the results from the distributional analysis. Finally, after presenting the robustness results in Section 8, Section 9 concludes the paper.

2 Background

This section provides an overview of the COVID-19 outbreak in South Korea, reviews the institutional background of the Korean government's response policies implemented in the form of stimulus payments and discusses the identification strategy based on them.

2.1 COVID-19 outbreak in South Korea and stimulus payments

The first case of COVID-19 in South Korea was detected on January 20, 2020. Figure 1 presents the spread of COVID-19 in South Korea from the date of the first confirmed case to the end of July 2020. This figure shows the number of newly confirmed cases on a daily basis and their accumulated number. The initial situation seemed to be under control, with fewer than 30 new cases of COVID-19 occurring daily, but in mid-February, an explosive outbreak started, especially in Daegu metropolitan city and its neighboring area.[1] In March 2020, there were more than 7,000 confirmed patients in this area. The peak of turmoil then passed, and the number of daily new cases reached fewer than 100 for four months in a row.[2] As of July 31, 2020, 14,311 confirmed total cases were reported in South Korea (27.6 confirmed cases per 100 thousand population in South

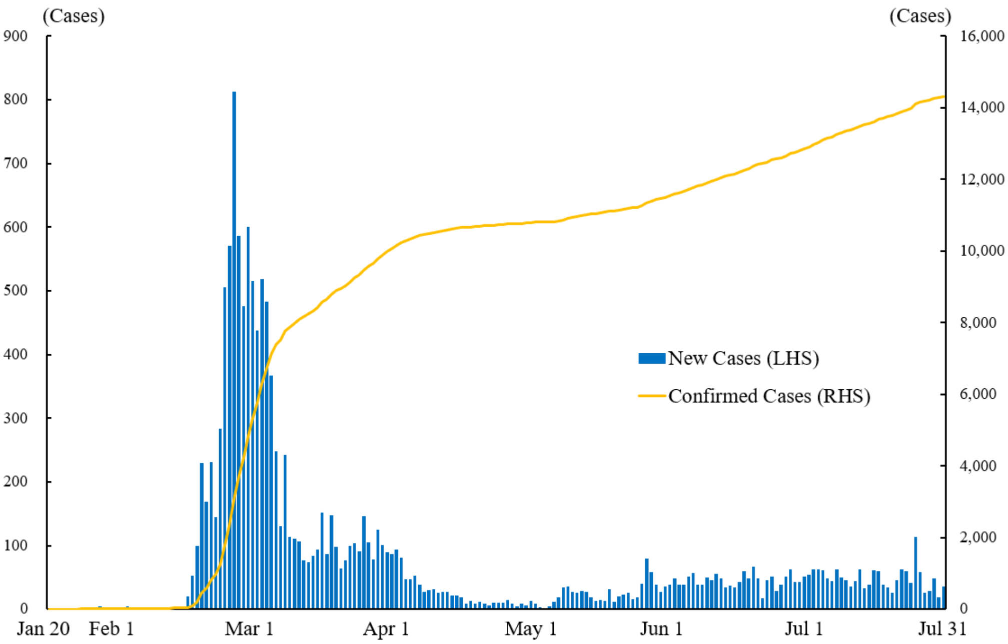


Figure 1: COVID-19 outbreak in South Korea (January - July, 2020)

[1] South Korea saw its first confirmed COVID-19 case on January 20, 2020.
[2] Sources: Korea Disease Control and Prevention Agency, Statistics Korea

Korea, as of July 31, 2020).

Although South Korea has not imposed a shut-down on either the national or the regional level, significant concern over the COVID-19 pandemic was sufficient to incur an economic downturn after the COVID-19 outbreak in South Korea (KDI (2020), BOK (2020), Aum et al. (2020), among them). Worrying over a COVID-19-induced economic recession, especially consumption shrinkage, the Korean government started to introduce various stimulus packages. We are particularly interested in the universal stimulus payments in Gyeonggi, which is the largest province by population, as well as regional GDP in South Korea. Gyeonggi provided a universal payment to all

[1]The explosion of confirmed cases around early March 2020 was the first wave in South Korea. There was a second wave around the end of August 2020 (the peak number of new cases was 441 on August 27) and a third wave between December 2020 and January 2021 (the peak number of new cases was 1,241 on December 25, 2020). This paper focuses on the post-first-wave period to analyze the effect of stimulus payments transferred in April 2020.

[2]There were 101 new cases on April 1, 2020, and the number of daily new cases did not exceed 100 from then until July 31, 2020 except for on July 25. On July 25, 113 new cases were detected, but most of the confirmed cases did not originate from regional infection (local transmission: 32 cases, imported cases: 81 cases). The monthly averages of the numbers of daily new cases were 32.6 for April, 22.7 for May, 44.5 for June, and 48.7 for July. (Sources: Korea Disease Control and Prevention Agency, Statistics Korea)

residents in an amount ranging from 100 thousand to 350 thousand KRW (approximately 100-350 USD) per person in the form of cash, direct deposit to credit or debit card accounts (hereafter, "credit card" denotes both credit and debit cards), or vouchers.[3] The payments were distributed starting in early April 2020 and had to be used in the recipient's neighborhoods before the end of August 2020. In this paper, we investigate how this universal payment affected household consumption by providing empirical evidence under the identification described in detail below.

2.2 Identification

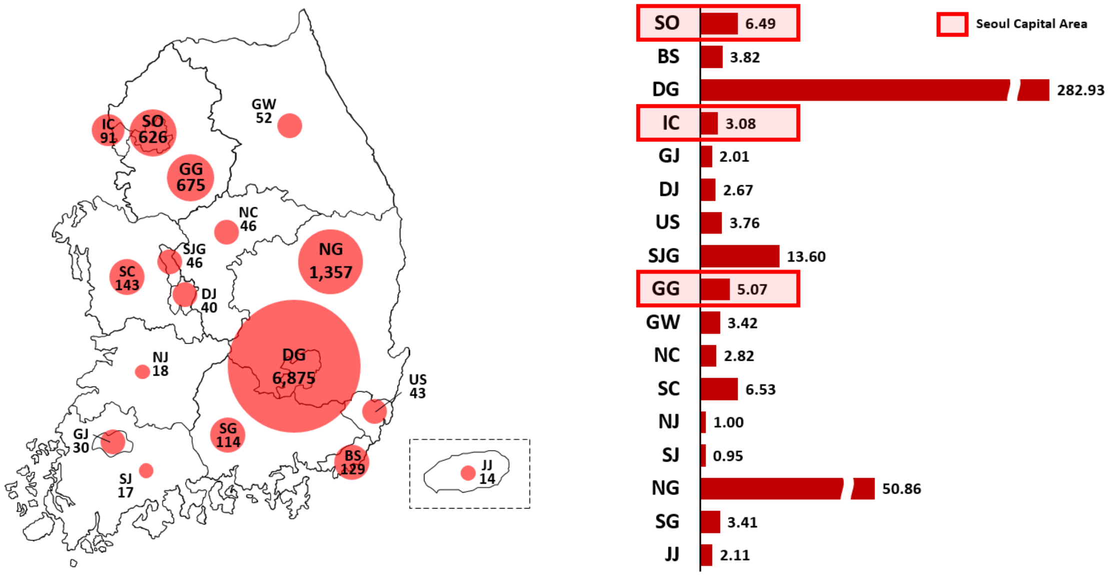
Starting with the initial outbreak of COVID-19, several local governments established individual emergency aid schemes for local residents based on each local economic situation.[4] Among them, Gyeonggi is the only region that provided universal stimulus payments to all residents in April 2020, before the central government's universal payment plan was implemented in May.[5] This is a crucial condition because it is difficult to set a distinct control group in the case of nationwide universal payments; first, the payments are paid to all households in South Korea; second, the amount of the payments is identical across households if their family size is the same. Therefore, this paper focuses on the period prior to May, and Gyeonggi is the only local government that introduced the universal payment scheme in that period.

To identify a group to compare to Gyeonggi, we focus on the SCA, which denotes the metropolitan area of Seoul, Incheon, and Gyeonggi and is located in northwestern South Korea. Covering only approximately 12% of the country's area, its population is 25.9 million (50.0% of total population, as of 2019), and its GDP is 1.0 quadrillion KRW (52.0 % of total GDP, as of

[3]This paper uses a terminology "vouchers" for the transfers distributed in the form of consumption vouchers, coupons, or local money cards. Here, a local money card is a type of gift card that a recipient can use in affiliate stores in the issuing region.

[4]South Korea is a unitary state in which governmental power is delegated by the central government to local governments.

[5]The central government announced a plan for universal stimulus payments to all households, which provoked academic and policy makers' interest in studying the impact of the transfer on household consumption (Kim and Lee (2020), Kim et al. (2020)). Specifically, households could apply and receive one-time stimulus payments from May 4 up to 1 million KRW according to the number of household members in the form of cash, direct deposits to credit card accounts, or vouchers. The payments could be used only at small-sized merchants in the recipient's neighborhoods before September 1.



(a) Cumulative Confirmed Cases

(b) Confirmed Cases per 100,000 Population

Figure 2: Regional Distribution of confirmed cases in South Korea

[1] The number of cumulative confirmed cases by each province at the end of April 2020 (Sources: Korea Disease Control and Prevention Agency, Statistics Korea)
[2] The rates of confirmed cases are calculated based on the regional population as collected by Statistic Korea as of 2019.
[3] SO: Seoul, BS: Busan, DG: Daegu, IC: Incheon, GJ: Gwangju, DJ: Daejeon, US: Ulsan, SJG: Sejong, GG: Gyeonggi, GW: Gangwon, NC: North Chungcheong, SC: South Chungcheong, NJ: North Jeolla, SJ: South Jeolla, NG: North Gyeongsang, SG: South Gyeongsang, JJ: Jeju

2019).[6] Therefore, we zoom in on Seoul and Incheon as candidates for the comparison group considering their geographical closeness and similarity, as they both fall within the SCA. In regard to the COVID-19 outbreak, the three regions of Seoul, Incheon, and Gyeonggi show similar patterns. Figure 2 presents the regional distribution of total confirmed cases at the end of April 2020. Except for the Daegu metropolitan city and its neighboring area of North Gyeongsang Province, where the explosive outbreak occurred in February and March, the other regions in South Korea were not significantly hit by the virus directly (especially considering the number of confirmed cases per 100 thousand population in Figure 2b). Taking the fear of transmission and its social and economic impacts into account, we argue that the three regions in the SCA shared similar circumstances in April 2020.

[6]As of 2019, the total population of South Korea was 51,779,203, and the regional population was 9,639,541

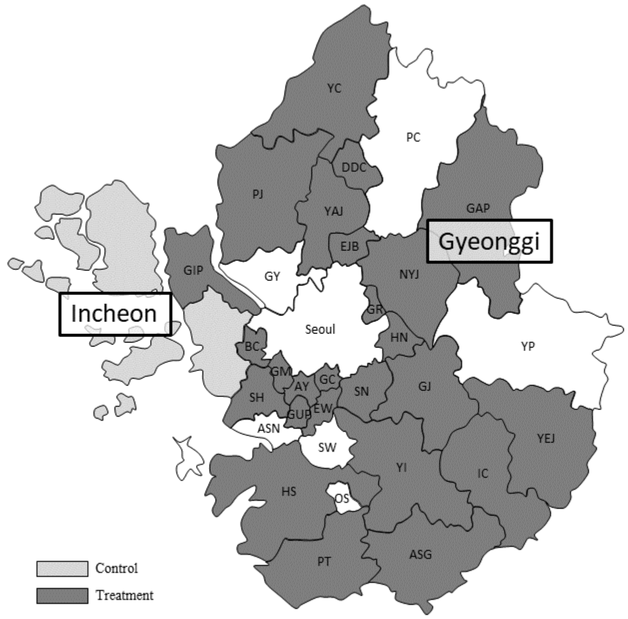


Figure 3: Treatment and control regions

[1] The SCA includes Seoul, Incheon, and Gyeonggi.
[2] PC, GY, YP, ASN and SW are excluded from the analysis because those cities provided stimulus payments in the form of cash transfer.
[3] SW: Suwon, BC: Bucheon, ASN: Ansan, SN: Seongnam, YI: Yongin, AY: Anyang, SH: Siheung, GY: Goyang, GIP: Gimpo, YC: Yeoncheon-gun, PC: Pocheon, DDC: Dongducheon, PJ: Paju, YAJ: Yangju, OS: Osan, UJB: Uijeongbu, NYJ: Namyangju, GR: Guri, HN: Hanam, YP: Yangpyeong-gun, GM: Gwangmyeong, GJ: Gwangju, GUP: Gunpo, UW: Uiwang, HS: Hwaseong, IC: Icheon, YEJ: Yeoju, PT: Pyeongtaek, ASG: Anseong, GAP: Gapyeong-gun, GC: Gwacheon

Among the regions in the SCA, Seoul, however, is excluded from our consideration since Seoul provided stimulus payments in April, which is the period of interest, only to low-income households in the form of cash or vouchers. Because these were not universal and consumption through cash or vouchers was not captured in our dataset of credit card spending, Seoul is not appropriate as the comparison group against Gyeonggi. Compared to Gyeonggi and Seoul, Incheon did not have large-scale own fiscal programs to support consumption. Incheon also provided transfers to specific groups in April, but the transfers were negligible in terms of the total amounts: 180 million KRW in Incheon and 2.1 trillion KRW in Gyeonggi.[7] There were also other types of selec-

(18.6%) for Seoul, 2,952,237 for Incheon (5.7%), and 13,300,900 for Gyeonggi (25.7%). The total GDP of South Korea is 1,924.0 trillion KRW, and the regional GDP is 433.5 trillion KRW (22.5%) for Seoul, 89.6 trillion KRW for Incheon (4.7%), and 478.3 trillion KRW for Gyeonggi (24.9%). Source: Statistics Korea

[7]Incheon provided a total of 180 million KRW to 600 low-income artists, 300 thousand KRW each, in April. The budget information of Incheon and Gyeonggi was publicly released to press by each local government office. Sources:

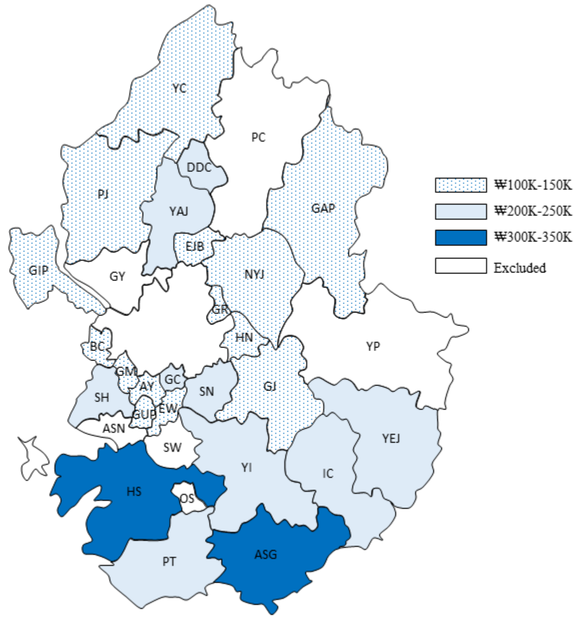


Figure 4: Stimulus payments in Gyeonggi (in credit card)

[1] Sources: Local municipal offices (as of April 2020)
[2] SW: Suwon, BC: Bucheon, ASN: Ansan, SN: Seongnam, YI: Yongin, AY: Anyang, SH: Siheung, GY: Goyang, GIP: Gimpo, YC: Yeoncheon-gun, PC: Pocheon, DDC: Dongducheon, PJ: Paju, YAJ: Yangju, OS: Osan, UJB: Uijeongbu, NYJ: Namyangju, GR: Guri, HN: Hanam, YP: Yangpyeong-gun, GM: Gwangmyeong, GJ: Gwangju, GUP: Gunpo, UW: Uiwang, HS: Hwaseong, IC: Icheon, YEJ: Yeoju, PT: Pyeongtaek, ASG: Anseong, GAP: Gapyeong-gun, GC: Gwacheon

tive payments to specific groups, such as freelancers, unpaid leavers, or low-income households, in the form of cash or vouchers. However, these transfers were paid on a national basis both in Gyeonggi and Incheon, so that their effects on consumption will be canceled out when we compare the two regions. Therefore, we adopt the DiD identification strategy with Gyeonggi as the treatment group (or groups of lower-level regions in Gyeonggi) and Incheon as the control group, as Figure 3 shows.[8]

Additionally, we can observe variation in the size of stimulus payments across the lower-level local governments in Gyeonggi.[9] Figure 4 presents 31 cities and counties in Gyeonggi, categorized

Incheon Metropolitan government, Gyeonggi Provincial government.

[8]The local government system in South Korea consists of two tiers: the upper level, which includes metropolitan cities (*teug-byeol-si* and *gwang-yeok-si*) and provinces (*do*), and the lower level, which includes cities (*si*), counties (*gun*), and districts (*gu*). For example, Seoul is an upper-level local government, and it supervises 25 districts that are lower-level local governments. Another example of an upper-level local government is Gyeonggi, which consists of 31 lower-level local governments (that are cities or counties).

into four groups by the size of payments in April. The amount of each region's stimulus payment covers the payment of 100 thousand KRW provided by the Gyeonggi local government as well as the additional payment distributed by the corresponding lower-level government. First, the 100-150 thousand KRW group includes 14 regions, in particular, 8 regions in this group fall into the 100 thousand KRW regions, which implies that these regions' lower-level local governments did not distribute their own stimulus payments in April.[10] Second, the 200-250 thousand KRW group includes 9 regions. Third, the 300-350 thousand KRW group includes 2 regions. Lastly, the remaining 6 regions are excluded from our analysis because their lower-level local governments provided their own payments in the form of cash or vouchers in April, so we cannot identify the pure effect of stimulus payments by the Gyeonggi local government. As a result, Gyeonggi provides the ideal natural experiment setup to investigate how the effect of stimulus payments on household consumption varies according to the size of payments.

3 Data

The primary data we use are Korea's consumer credit data provided by the KCB. The strength of this dataset is its coverage and accuracy. First, as the official credit rating agency, the KCB has credit data for South Korea's entire population, namely, all transactions made by credit cards and debit cards and loans and liabilities. The KCB keeps track of every individual with any credit history, and we use panel data containing 1.3 million individuals randomly sampled from the pop-

[9] To determine the existence of any structural cause of variation in the size of stimulus payments across the lower-level local governments, we regress the amount of stimulus payments on a measure of political inclination, a measure of local government financial status, and population one by one. For political inclination, we considered three variables: an indicator variable of which party a mayor is affiliated with, the Democratic (The Minjoo Party of Korea and others) or the Republican (People Power Party and others); an indicator variable of which party is a majority party in the region; and the proportion of Democratic members in the local council. For local government financial status, we considered two variables: financial independence ratio and revenue. We found that there was no variable that had a statistically significant effect on the amount of stimulus aid. The lowest p-value is observed for the financial independence ratio variable, with 0.12, and the second-lowest p-value is for the indicator variable of the majority party. The other regressors present high p-values from 0.51 to 0.98. Hence, we regard the variation in the size of payments as independent variation appropriate for natural experiments.

[10] The 8 regions distributed their own stimulus payments in May in the form of cash or vouchers, so they would not directly affect the credit card spending in April, which is our main focus.

Table 1: Household monthly card use and other characteristics, April 2020

	Gyeonggi + Incheon		Gyeonggi		Incheon	
Variable (in 1,000 KRW)	mean	std. dev.	mean	std. dev.	mean	std. dev.
monthly card use	1,933	(2,179)	1,977	(2,205)	1,753	(2,062)
annual income	53,376	(34,411)	54,028	(34,986)	50,694	(31,796)
housing asset	353,935	(376,083)	370,530	(394,194)	285,693	(279,791)
total debt	38,242	(78,782)	38,897	(80,094)	35,547	(73,077)
delinquent debt	58	(886)	56	(879)	65	(914)

ulation. Second, compared to other macroeconomic variables or survey data, the KCB provides high-quality, individual-level micro data. The KCB data are collected in almost real time for each person, directly from banks' and card companies' transaction records. This guarantees the highest accuracy compared to any survey-based data.[11] Its timeliness and detailedness are also superior to those of official macroeconomic statistics such as GDP, which is available only at a low frequency at a widely aggregated level.

As explained in the previous section, we focus on Gyeonggi and Incheon. In our sample, there are 173,976 households in Gyeonggi and 42,306 households in Incheon randomly selected from the population in April 2020. The household is defined as the individuals, up to six, living at the same address and is constructed from the individual credit record kept by the KCB.[12] Because households are the basic units of economic activity, such as consumption, we aggregate individual data to the household level for this research.

The key variable of interest is card use, which is the monthly total amount of credit card and debit card spending in the unit of thousand KRW. Household card use is constructed by summing the card uses of individual members of the household. In the Gyeonggi and Incheon areas, the average monthly household card use was 1,933 thousand KRW in April 2020. In South Korea, the vast majority of consumption is transacted through cards, allowing us to study consumption behavior with card payment data. Total personal card spending amounts to 85% of household

[11]The KCB compares the average values of all variables in the sample with those in the population and guarantees that the ratio for each variable is close to one for every district. One caveat is that the KCB does not have information about children below the age of eighteen due to legal constraints.

[12]When households move to other addresses and if this information is reported to financial institutions, the KCB can use this information to track these households.

consumption in the 2019 GDP.[13]

We also utilize many household-level control variables constructed from individual-level financial data provided by the KCB. The KCB estimates an individual's annual income every quarter using all financial records, and we define household income as the summation of each household member's estimated income. The average annual household income in our sample is 53,376 thousand KRW in the Gyeonggi and Incheon areas, estimated in April 2020. This sample average is close to the average household income from the national survey, which adds to the credibility of our data.[14]

The KCB also provides records of housing assets and total debt. The KCB does not collect individual-level total financial asset data, but the housing value should be relatively accurate due to mortgage contracts and can work as a good proxy for the total wealth of each household. The total debt data are the most accurate record available in Korea. It is the principal function of the KCB to keep track of every loan contract, as this is the essential input in constructing individual credit ratings. For the entire sample including both Gyeonggi and Incheon, the average housing assets are 353,935 thousand KRW, and the average debt is 38,242 thousand KRW in April 2020. We also use the outstanding delinquent debt amount as a control variable. Table 1 summarizes the descriptive statistics of the household variables we use for the analyses.

4 Econometric Models

The impact of the COVID-19 pandemic on household consumption was so great that many countries offered direct stimulus payments to households. Therefore, to understand the effect

[13]The total value of credit card and debit card transactions, except for corporate cards and cash advances (i.e., card loans) was 760.5 trillion KRW in 2019, while the nominal household consumption in the national accounts was 897.2 trillion KRW. Data source: Bank of Korea.

[14]The Survey of Household Finances and Living Conditions is the official national-level monthly survey conducted by Statistics Korea. When we combined labor income and business income from this survey, the average annual household income in 2019 was 56,040 thousand KRW and 50,490 thousand KRW in Gyeonggi and Incheon, respectively. When we also include capital income and transfer income, which may be more difficult to detect, the annual average of total household income from the survey is approximately 17% larger than the household income estimated by the KCB.

of stimulus payments on consumption, we first need to investigate the impact of the COVID-19 outbreak. We adopt the standard DiD model to investigate the consumption response to the outbreak of COVID-19 and the stimulus payments as

$$Y_{it} = \beta_0 + \beta_1 Post_t \cdot Treat_i + \beta_2 Post_t + \beta_3 Treat_i + \gamma X_{it} + \delta_i + \varepsilon_{it}, \tag{1}$$

where Y_{it}, the outcome variable, denotes the monthly consumption per person for household i at time t, $Post_t$ is an indicator for the post-treatment period, $Treat_i$ is an indicator for being in the treated group, X_{it} includes the time-varying controls, and δ_i is the household fixed effect. As consumption decisions are typically made at the household level, we include the fixed effect and time-varying controls at the household level for the benchmark model.[15] The controls include household income, wealth, total debt, delinquent debt, and the number of family members. The standard errors are clustered at the household level.[16]

First, we explore the impact of the COVID-19 outbreak on consumption. For this, we set $Treat_i = 1$ for households in 2020 and $Treat_i = 0$ for households in 2019. We then set $Post_t = 1$ for April and $Post_t = 0$ for January.[17] Given that the full-fledged spread of COVID-19 started in the middle of February in Korea, the monthly consumption in January becomes a good comparison target to investigate the effect of COVID-19 on consumption. This setup constructs the DD estimate comparing the consumption change between January and April in 2019 to that in 2020 for the given region. Here, we assume that consumption in each region would have moved similarly from January to April in both years if we did not have the COVID-19 outbreak. This DiD model will remove the effect of common factors affecting both years similarly, such as seasonal variation within a year, by comparing the change from January to April, but capture the effect of factors that change significantly between January and April and that exist only in 2020, such as the outbreak

[15]We also show the results with district fixed effects instead of household fixed effects. In this case, the standard errors are clustered at the district level.

[16]In all regressions, we exclude households if their minimum monthly card usage per person is below 50 thousand KRW (approximately 50 USD) and if their income per person is in the bottom 20%. The bottom income group is excluded because most of them received stimulus payments in the form of vouchers that are used to receive Basic Livelihood Security Program benefits.

[17]We drop observations in other months for this part of the analysis.

of COVID-19. We also investigate the evolution of consumption after January by adding the leads and lags of $Post_t$ for February, March, May, and June on top of April in the same regression for each region.

Next, we estimate the effect of stimulus payments on consumption using Equation (1). Specifically, we set $Treat_i = 1$ for households in Gyeonggi and $Treat_i = 0$ for households in Incheon in 2020. We then set $Post_t = 1$ for April and $Post_t = 0$ for January. This setup constructs the DD estimate comparing the consumption change from January to April in Gyeonggi and that in Incheon for the year 2020. If the two regions possess parallel trends, the DD estimate will capture the causal treatment effect of stimulus payments. Using this setup, we also examine the parallel trend assumption by comparing the two regions in 2019. Because there were no stimulus payments in 2019, we can conduct a placebo test by comparing Gyeonggi and Incheon in 2019. If the DD estimate for 2019 is significant, we reject the parallel trend hypothesis.

We try to estimate the treatment effect using Equation (1) with heterogeneous linear time trends and fixed effects for month and year. We set $Treat_i = 1$ for households in Gyeonggi and $Treat_i = 0$ for households in Incheon. In this setup, we use all data from January 2019 to June 2020 and set $Post_t = 1$ for April, May, and June in 2020. With this approach, we can control for the effect of economic growth that can be compounded in the above DD estimate. However, the estimates are sensitive to the specification of the time trends due to the large unexpected COVID-19 shock and relatively short time series in 2020. Therefore, we adopt the DDD approach to address this problem.

$$\begin{aligned} Y_{it} =& \beta_0 + \beta_1 Post_t \cdot Treat_i \cdot 2020_{it} + \beta_2 Post_t \cdot 2020_{it} + \beta_3 Treat_i \cdot 2020_{it} + \beta_4 Post_t \cdot Treat_i \\ & + \beta_5 2020_{it} + \beta_6 Post_t + \beta_7 Treat_i + \gamma X_{it} + \delta_i + \varepsilon_{it} \end{aligned} \tag{2}$$

where Y_{it} denotes the monthly consumption per person for household i at time t, $Post_t$ is an indicator for the post-treatment period, $Treat_i$ is an indicator for being in the treated group, 2020_{it} is an indicator for being in the year 2020, X_{it} includes the time-varying controls, and δ_i is the household (or subdistrict) fixed effect. The standard errors are clustered at the household (or subdistrict) level.

If we set $Treat_i = 1$ for Gyeonggi and $Treat_i = 0$ for Incheon, $Post_t = 1$ for April and $Post_t = 0$ for January, and $2020_{it} = 1$ for households observed in 2020 and $2020_{it} = 0$ for households observed in 2019, the DDD estimate compares the difference in the consumption change from January to April between Gyeonggi and Incheon for the year 2019 with that for the year 2020. This regression only includes data for January and April in years 2019 and 2020. As Equation (2) effectively includes every month and year dummy and compares consumption changes between a short period from January to April, there is little need to worry about time trends. Additionally, this setup can control for confounding factors that affect the two regions or two years differently. For example, the two regions might have different seasonal patterns from January to April. These types of confounding factors can bias the treatment effect from Equation (1). By using the DDD approach, we can remove the effect of these confounding factors.

We also estimate MPC by changing the Gyeonggi indicator in Equation (2) to the amount of stimulus payments (Baker et al., 2020). That is, we use the following specification:

$$\begin{aligned} Y_{it} = &\beta_0 + \beta_1 Post_t \cdot Amount_i \cdot 2020_{it} + \beta_2 Post_t \cdot 2020_{it} + \beta_3 Amount_i \cdot 2020_{it} + \beta_4 Post_t \cdot Amount_i \\ &+ \beta_5 2020_{it} + \beta_6 Post_t + \beta_7 Amount_i + \gamma X_{it} + \delta_i + \varepsilon_{it} \end{aligned} \tag{3}$$

where $Amount_i$ denotes the amount of the stimulus payment to household i. The other variables are specified in the same way as in the benchmark DDD model. The coefficient β_1 represents the portion of stimulus payments used to increase monthly consumption per person.

The theory of consumption predicts that the effect of stimulus payments should be stronger for households under liquidity constraints. By testing this prediction, we can understand the extent to which the mechanism of stimulus payments can be attributed to the easing of liquidity constraints.

We therefore use the DDDD equation as

$$
\begin{aligned}
Y_{it} = & \beta_0 + \beta_1 Post_t \cdot Treat_i \cdot 2020_{it} + \sum_{g=2}^{4} \beta_g Post_t \cdot Treat_i \cdot 2020_{it} \cdot LC_{git} \\
& + (Other\ Triple\ Interaction\ Terms) + (Double\ Interaction\ Terms) \\
& + (Linear\ Terms) + \gamma X_{it} + \delta_i + \varepsilon_{it}, \qquad (4)
\end{aligned}
$$

where LC_{2it}, LC_{3it}, and LC_{4it} are indicators for households with different amounts of liquidity. We define liquidity as monthly income minus consumption divided by family size. We split households into four groups based on the average amount of liquidity from January to March 2020: less than zero (the base group), from zero to 1 million KRW, from 1 to 2 million KRW, and more than 2 million KRW.[18] Baker et al. (2020) use account balances at the beginning of treatment as a measure of liquidity. Our measure gauges saving capacity before the treatment and is similar to theirs in the sense that unspent income is saved. The other variables are specified in the same way as in the DDD equation.

The treatment effect is measured as β_1 for the base group, $\beta_1 + \beta_2$ for the second group, $\beta_1 + \beta_3$ for the third group, and $\beta_1 + \beta_4$ for the fourth group. If the DDD estimate using equation (2) demonstrates the causal effect, we should expect to see a greater treatment effect for households with less liquidity.

5 Results

5.1 The impact of COVID-19

Table 2 shows the DD estimates for the impact of the COVID-19 outbreak. Panel A shows the impact of COVID-19 in Gyeonggi, where universal stimulus payments were distributed to all citizens in April 2020, while Panel B shows the impact of COVID-19 in Incheon, where there were no universal stimulus payments. Columns (1) and (2) show the results with district fixed effects,

[18] To avoid reverse causality, we exclude April from the calculation of the average liquidity.

Table 2: DD estimates for the impact of COVID-19

	Dependent variable: monthly consumption per person			
	(1)	(2)	(3)	(4)
Panel A. Treatment group = Gyeonggi, 2020				
Control group = Gyeonggi, 2019				
2020 × April	-225.88^{***}	-194.26^{***}	-190.02^{***}	-188.44^{***}
	(6.36)	(6.39)	(6.77)	(6.81)
2020	145.97^{***}	30.39^{***}	66.36^{***}	61.95^{***}
	(9.59)	(7.84)	(5.88)	(5.98)
April	0.11	-34.15^{***}	-14.33^{***}	-15.77^{***}
	(7.24)	(6.49)	(4.47)	(4.56)
Household controls	No	Yes	No	Yes
Household fixed effects	No	No	Yes	Yes
District fixed effects	Yes	Yes	No	No
# of observations	381,245	381,245	381,245	381,245
# of households	-	-	178,087	178,087
Panel B. Treatment group = Incheon, 2020				
Control group = Incheon, 2019				
2020 × April	-269.53^{***}	-226.79^{***}	-220.72^{***}	-217.20^{***}
	(8.32)	(6.81)	(11.67)	(11.78)
2020	127.88^{***}	1.45	34.11^{***}	28.43^{***}
	(19.06)	(14.07)	(10.64)	(10.82)
April	9.99	-31.94^{***}	-13.02	-16.36^{**}
	(9.50)	(8.91)	(8.01)	(8.18)
Household controls	No	Yes	No	Yes
Household fixed effects	No	No	Yes	Yes
District fixed effects	Yes	Yes	No	No
# of observations	121,246	121,246	121,246	121,246
# of households	-	-	57,436	57,436

Notes: The DD estimates compare the consumption change from January to April in 2020 to that in 2019 for the given region. The constant term is not displayed. The household controls include household income, housing assets, total debt, delinquent debt, and family size. Standard errors are clustered at the district level for columns (1) and (2), and at the household level for columns (3) and (4). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

column (1) without household controls and column (2) with household controls, such as income, wealth, total debt, delinquent debt, and the number of family members. Columns (3) and (4) show the results with household fixed effects, column (3) without household controls and column (4) with household controls. The estimated coefficients of the interaction term are quite robust to the changes in the specification, although their absolute values decrease with household fixed effects and household controls. We take regressions with the household fixed effects and controls as the benchmark model, i.e., column (4), and focus on the results from the benchmark specification.

The coefficients of the interaction term in Panels A and B demonstrate that the decrease in monthly consumption was larger in Incheon than in Gyeonggi after the COVID-19 outbreak. For example, Column (4) shows that monthly consumption per person decreased by 217,200 KRW in Gyeonggi and 188,440 KRW in Incheon. This large decrease is noteworthy since the infection rate was very low and there was no lockdown in the two regions.[19] The coefficient of the 2020 dummy shows that in January, before the proliferation of COVID-19, monthly consumption was higher than in January 2019, probably due to economic growth. The negative coefficient of the April dummy means that consumption was lower in April than in January 2019, probably for seasonal reasons. The DD regression removes these seasonal effects. Therefore, the estimates show that consumption was severely affected by COVID-19 in 2020, so monthly consumption decreased considerably even with economic growth and stimulus payments.

To further investigate the evolution of monthly consumption before and after the COVID-19 outbreak in 2020, we add both leads and lags running from February to June in the DD equation. Figure 5 depicts the coefficients of the interaction terms with the month dummies from February to June according to the benchmark specification in Table 2. Figure 5 demonstrates that there were few differences in the two regions in February and March even after the outbreak of COVID-19. Therefore, we can consider the large difference in April as representing the effect of stimulus payments in Gyeonggi.

5.2 The impact of universal stimulus payments

In Table 3, the change in consumption from January to April in Gyeonggi is compared to that in Incheon for the year 2020 in Panel A and for the year 2019 in Panel B. The interaction term in panel A shows the causal effect of stimulus payments on consumption. The estimates are robust to changes in the specification. Column (4), the benchmark model, shows that monthly consumption per person was 27,640 KRW higher in Gyeonggi than in the control group. This actually implies that the decrease in consumption from January to April was smaller in Gyeonggi than in Incheon. If this is truly the causal effect of stimulus payments, there should be no meaningful differences

[19]Only 5.1 and 3.1 confirmed cases per 100,000 population until April in Gyeonggi and Incheon, respectively. COVID-19 infections were limited to Daegu and North Gyeongsang until April, as explained in Section 2.1.

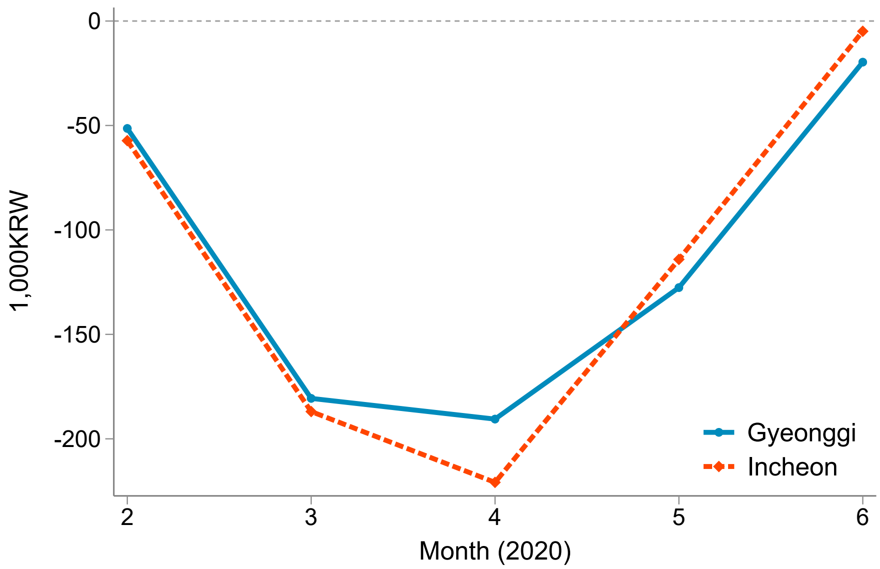


Figure 5: DD estimates for the impact of COVID-19

Notes: This figure shows the evolution of monthly consumption per person from January to the specified month in 2020 compared to that in 2019 for the given region. The estimation includes the household fixed effects and control variables, including household income, housing assets, total debt, delinquent debt, and family size.

between the two regions in 2019. Panel B provides the results of this placebo test. The coefficient of the interaction term is close to zero, with large standard errors, as expected. This result supports the parallel trends assumption before the treatment in the two regions.

In Panel A, the coefficient of the Gyeonggi dummy is not significant in the benchmark model. This implies that there is no significant difference in consumption in January between Gyeonggi and Inchoen before the COVID-19 pandemic. The large negative coefficient of the April dummy implies that consumption decreased considerably in Inchoen from January to April in 2020.

Although the results in Table 3 provide evidence for the causal treatment effect, it is still possible that there are some confounding factors that can affect time trends differently between the two regions. For example, the two regions could have different trends in economic growth. Therefore, we fully utilize the data from January 2019 to June 2020 and include heterogeneous time trends for each subdistrict on top of month and year fixed effects, as explained in Section 4. Additionally, we set $Post_t = 1$ for April, May, and June in 2020 and scale this indicator to obtain the effect on monthly consumption per person, which is consistent with previous results.

Table 3: DD estimates for the impact of universal stimulus payments

Dependent variable: monthly consumption per person	(1)	(2)	(3)	(4)
Panel A. Treatment group = Gyeonggi, 2020				
Control group = Incheon, 2020				
Gyeonggi × April	33.63***	32.70***	27.61***	27.64***
	(10.33)	(11.07)	(10.16)	(10.15)
Gyeonggi	−293.23***	−188.17***	−182.52	−183.86
	(5.37)	(6.03)	(169.37)	(169.30)
April	−259.47***	−262.48***	−230.71***	−231.10***
	(7.47)	(8.94)	(8.70)	(8.71)
Household controls	No	Yes	No	Yes
Household fixed effects	No	No	Yes	Yes
District fixed effects	Yes	Yes	No	No
# of observations	243,078	243,078	243,078	243,078
# of households	-	-	147,493	147,493
Panel B. Treatment group = Gyeonggi, 2019				
Control group = Incheon, 2019				
Gyeonggi × April	−10.21	3.48	0.01	0.37
	(11.73)	(8.48)	(9.20)	(9.19)
Gyeonggi	−195.28***	−132.94**	−57.04	−58.21
	(5.88)	(4.61)	(251.59)	(251.50)
April	10.35	−31.31***	−14.28*	−8.59
	(9.25)	(7.20)	(8.05)	(8.12)
Household controls	No	Yes	No	Yes
Household fixed effects	No	No	Yes	Yes
District fixed effects	Yes	Yes	No	No
# of observations	259,413	259,413	259,413	259,413
# of households	-	-	154,480	154,480

Notes: The DD estimates compare the consumption change from January to April in Gyeonggi to that in Incheon for the given year. The constant term is not displayed. The household controls include households' income, housing assets, total debt, delinquent debt, and family size. Standard errors are clustered at the district level for columns (1) and (2) and at the household level for columns (3) and (4). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Columns (1) and (2) in Table 4 present the estimation results using this standard DiD specification with heterogeneous linear trends across districts and fixed effects for districts and households, respectively. Different from previous results, the estimated effect of stimulus payments is negative. This is because the COVID-19 shock, which is not captured by the linear time trend from January 2019 to June 2020, biases the treatment effect. As we explored above, monthly consumption decreased considerably in 2020 after the COVID-19 outbreak. When we allow a structural break in the linear time trend between two years, the estimated treatment effect becomes similar to the results in Table 3 but only weakly significant even in the benchmark specification, Column (4),

Table 4: DD estimates with time trends

Dependent variable: monthly consumption per person				
Treatment group = Gyeonggi *Control group = Incheon*	(1)	(2)	(3)	(4)
Gyeonggi × Post	-69.89^{***}	-38.60^{**}	29.45	34.03^{*}
	(21.26)	(19.60)	(22.79)	(20.23)
Gyeonggi	-156.91^{***}	-119.22^{**}	-158.75^{***}	-137.68^{**}
	(2.46)	(56.51)	(1.45)	(56.61)
Post	-75.97^{***}	-73.58^{***}	-87.86^{***}	-101.21^{***}
	(19.25)	(18.16)	(27.55)	(24.77)
Household controls	Yes	Yes	Yes	Yes
Month and year fixed effects	Yes	Yes	Yes	Yes
District fixed effects	Yes	No	Yes	No
Household fixed effects	No	Yes	No	Yes
Het. linear trends (districts)	Yes	Yes	No	No
Het. linear trends (districts×years)	No	No	Yes	Yes
# of observations	2,244,028	2,244,028	2,244,028	2,244,028
# of households	-	291,587	-	291,587

Notes: The DD estimates are obtained from a regression with data from January 2019 to June 2020. The constant term is not displayed. Columns (1) and (2) include heterogeneous linear trends for each district over the whole period. Columns (3) and (4) include heterogeneous linear trends for each district and year. The household controls include household income, housing assets, total debt, delinquent debt, and family size. Standard errors are clustered at the district level for columns (1) and (2) and at the household level for columns (3) and (4). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

with household fixed effects.

Therefore, we use the DDD equation to avoid the need to include time trends and to control for other possible confounding factors, such as different seasonal consumption patterns in Incheon and Gyeonggi. Table 5 presents the DDD estimates. The coefficient of the triple interaction term in the benchmark model, Column (4), shows that the stimulus payments increased monthly consumption per person in Gyeonggi by 29,540 KRW. This is very similar to the DD results in Table 3.

The coefficients of the double-interaction and single variables are consistent with the DD results. For example, the large negative coefficient of the interaction between the dummies for the year 2020 and April shows the effect of COVID-19 in the two regions. The positive coefficient of the 2020 dummy implies that consumption increased in 2020, probably due to economic growth. The coefficient of the interaction between the dummies for the year 2020 and for Gyeonggi captures the different longer-term trends in the two regions from January 2019 to January 2020 and implies that consumption increased more in Gyeonggi than in Incheon.

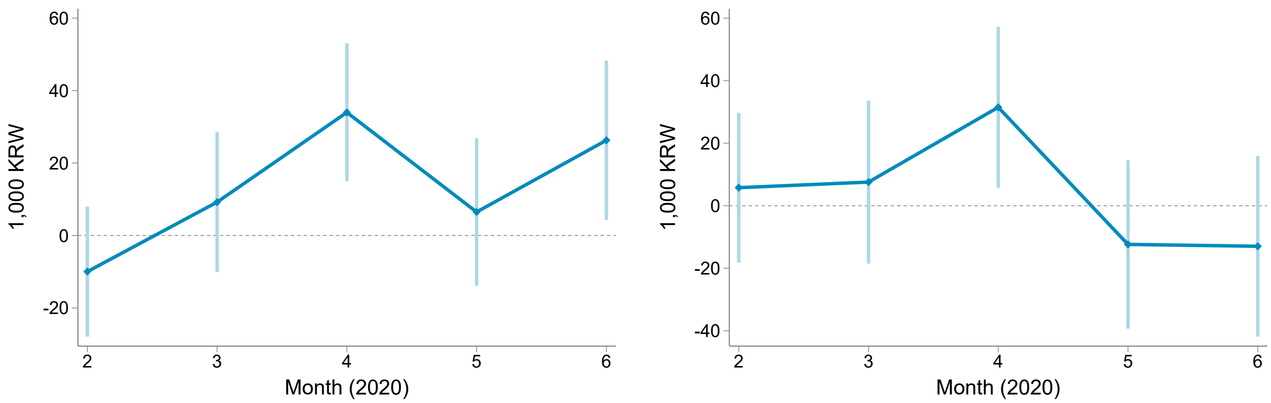
Table 5: DDD estimates for the impact of universal stimulus payments

	Dependent variable: monthly consumption per person			
Treatment group = Gyeonggi				
Control group = Incheon	(1)	(2)	(3)	(4)
2020 × April × Gyeonggi	43.65***	28.42***	30.76**	29.54**
	(10.20)	(10.03)	(13.50)	(13.49)
2020 × April	−269.53***	−223.66***	−220.77***	−217.83***
	(8.00)	(7.27)	(11.68)	(11.71)
2020 × Gyeonggi	18.09	39.62**	31.51**	32.87***
	(20.65)	(11.77)	(12.16)	(12.15)
April × Gyeonggi	−9.88	4.52	−1.79	−0.82
	(11.63)	(8.68)	(9.19)	(9.19)
2020	127.88***	−6.27	35.13***	29.25***
	(18.31)	(11.49)	(10.66)	(10.70)
April	9.99	−37.10***	−12.64	−15.24*
	(9.13)	(7.42)	(8.03)	(8.07)
Gyeonggi	−253.01***	−183.69***	−112.03	−107.74
	(13.82)	(8.01)	(109.07)	(108.77)
Household controls	No	Yes	No	Yes
Household fixed effects	No	No	Yes	Yes
District fixed effects	Yes	Yes	No	No
# of observations	502,491	502,491	502,491	502,491
# of households	-	-	235,225	235,225

Notes: The DDD estimates compare the difference in the consumption change from January to April between 2019 and 2020 in Gyeonggi to that in Incheon. The constant term is not displayed in the table. The household controls include households' income, housing assets, total debt, delinquent debt, and family size. Standard errors are clustered at the district level for columns (1) and (2) and at the household level for columns (3) and (4). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure 6 presents the treatment effects using DD and DDD equations as in Autor (2003). Panel A of Figure 6 extends the results in Column (4) in Table 3 by adding leads and lags, whereas panel B of Figure 6 adds leads and lags in the DDD specification of Column (4) in Table 5. Both panels of Figure 6 demonstrate the significant treatment effect in April. Before the treatment, the two regions did not show any significant differences in either panel. However, it seems that there is an increasing trend in panel A and consumption diverges again in June. This increasing trend disappears in panel B, which implies that the DDD effectively removes the effects of confounding factors that are not captured by the DD equation.

It is worth noting that the policy worked very quickly. Given that the application period for the stimulus payments started on April 9, the result implies that the payments significantly increased consumption within 20 days.



Panel A. Double difference

Panel B. Triple difference

Figure 6: DD and DDD estimates with leads and lags

Notes: This figure shows the effect of stimulus payments on monthly consumption per person. The left panel shows the result from the DD estimates, while the right panel shows the result from the DDD estimates. The vertical lines are 95% confidence intervals. Both include household fixed effects and control variables, including household income, housing assets, total debt, delinquent debt, and family size.

It is also worth noting that the treatment effect quickly disappeared starting in May. This suggests that the unused portion of payments in April were not saved for use within two or three months but saved from a longer-term perspective. In addition, given that the government started providing stimulus payments in May to all households in South Korea, the insignificant differences in May and June imply that our method effectively removes the effect of policy changes common to both the treatment and control groups.

6 Heterogeneity

In this section, we investigate the MPC to reveal the effectiveness of stimulus payments for different groups of people. Because our data do not have information about children below the age of eighteen, we include only single-person households for MPC calculation. It is less likely for these households to have children.

Table 6: DDD estimates for the MPC and transfer size

	Dependent variable: monthly consumption per person
Treatment group = Gyeonggi	
Control group = Incheon	
Panel A. Overall MPC	
	0.40^{***}
	(0.13)
Panel B. MPC by transfer size (unit: 1,000KRW)	
100-150	0.58^{**}
	(0.24)
200-250	0.45^{***}
	(0.16)
300-350	0.36^{**}
	(0.16)

Notes: One indicator variable for Gyeonggi is included in the regression for Panel A as the benchmark model, whereas two indicator variables for districts with different sizes of transfers are included for Panel B. The regressions include the household fixed effect and control variables, including household income, housing assets, total debt, and delinquent debt. Standard errors are clustered at the household level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

6.1 MPC and cost-effectiveness

When we earmark the stimulus payments, the earmarked money was almost completely spent, since there was a time limit for spending this money.[20] This, however, does not mean that monthly consumption increased by this amount because households could reduce consumption from their own income. Our MPC estimate from Equation (3) measures the net response of monthly consumption to the stimulus payments.

Panel A of Table 6 shows that the overall MPC is 0.40. This implies that 60% of payments were saved for future consumption or used to repay debt. We found no significant changes in the amount of household debt with the DDD equation in which the outcome variable is changed from consumption to debt. This suggests that 60% of payments were mostly saved for future consumption.

Panel B presents the MPC for different sizes of stimulus payments. The MPC decreases from 0.56 to 0.35 as the payment size increases from 100-150 to 300-350 thousand KRW. This implies

[20]The Korean Ministry of the Interior and Safety reported that approximately 82% of the stimulus payments provided by the central government in May were used within one month. It can be inferred that the pattern of using the stimulus payments provided by Gyeonggi in April would be similar to that of the central government because they used a similar online (and offline) system to provide these payments.

that stimulus payments were more cost-effective when the payment size was small. In other words, a higher portion of stimulus payments was saved in regions with larger stimulus payments even though the increase in the level of consumption was larger in these regions.

6.2 The role of liquidity

We further explore the heterogeneous effect of stimulus payments on households with different levels of liquidity using Equation (4). Table 7 shows the coefficients of the quadruple term in Equation (4).[21] The results suggest that the increase in consumption in response to the stimulus payments was mainly driven by households under liquidity constraints, which have expenditures greater than their income. The estimated MPC is 1.05 for households with liquidity below zero, but not significantly different from zero for other households that have an income greater than expenditures.[22]

This result has two important implications. First, it suggests that the easing of liquidity constraints is the main mechanism for the policy impact. Given that the portion of households with liquidity of less than zero is approximately 8%, the results imply that the stimulus payments were not effective in increasing net consumption for most households with sufficient income for their consumption. Second, the large difference in the estimated coefficients between constrained and unconstrained households implies that our results in the previous section using DDD are not confounded by omitted variables that may have differently affected consumption in Gyeonggi and Incheon. If we had an omitted variable bias, that would lead to a significant positive impact on both constrained and unconstrained households (Muralidharan and Prakash, 2017).

Panel B shows the MPC for recipients of different ages. The MPC is 85% for those in their 20s and 30s but not significantly different from zero for those who are older. It seems that this result

[21]We exclude households with extreme values for liquidity, which is defined as monthly income minus consumption divided by family size, below the 1st percentile (approximately -2 million KRW) or above the 99th percentile (approximately 4.3 million KRW) of the distribution.

[22]The estimated MPC is greater than one because several districts in Gyeonggi provided additional stimulus payments to targeted households, such as small business owners or low-income households below the median. Compared to the 1.4 trillion KRW used for the universal stimulus payments, these additional payments, ranging from 2.5 to 100 billion KRW, were small in scale.

Table 7: DDDD estimates for the MPC and liquidity

	Dependent variable: monthly consumption per person
Treatment group = Gyeonggi	
Control group = Incheon	
Panel A. MPC by liquidity (unit: million KRW)	
<0	1.05*
	(0.60)
0-1	0.23
	(0.40)
1-2	0.25
	(0.23)
≥2	0.07
	(0.29)
Panel B. MPC by age of recipients	
20-30	0.85***
	(0.19)
40-50	0.19
	(0.20)
60-70	−0.28
	(0.38)

Notes: This table shows the heterogeneous effects of stimulus payments using the DDDD estimates. The regression includes the household fixed effect and control variables including household income, housing assets, total debt, and delinquent debt. Standard errors are clustered at the household level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

is related to the fact that the young usually possesses less liquidity. The average liquidity level was the smallest for those in their 20s: 0.9 million KRW for those in their 20s, 1.3 million KRW for those in their 30s, 1.6 million KRW for those in their 40s, 50s, and 70s, and 1.4 million KRW for those in their 60s. Additionally, the method of application for stimulus payments could affect the result for older people. Applicants had to use an online application system to receive stimulus payments to their credit cards. The offline application was used only for other payment methods, such as cash or vouchers, which are not captured by our data. If older people preferred the offline application method, our estimates could underestimate the policy impact for older recipients.

7 Distributional Analysis

We next assess the impact of the stimulus payments on the lower, middle and upper parts of the consumption distribution. Economic theories (e.g., consumption in incomplete markets) suggest that the effect of the stimulus payments on consumption would be larger for lower income households. Hence, it would be interesting to see the differential effects of the policy on different groups of households.

One way to achieve this goal would be to estimate effects on each quantile conditional on the control variables (Koenker and Bassett, 1978). This conditional quantile regression method is used to assess the impact of a covariate on a quantile of a dependent variable conditional on specific values of the other covariates. In the presence of multiple covariates, however, the conditional quantile regression may generate results that are not interpretable in a policy context. To overcome this limitation, the UQR method can be used. Firpo et al. (2009) shows how to implement UQR with the recentered influence function (RIF) regression approach.

The recentering in the RIF approach involves adding the statistic to the influence function, IF, which measures the influence of a specific observation on a distributional statistic. For a quantile τ,we have $IF(y; q_\tau, f_y) = (\tau - 1\{y \leq q_\tau\}) / f_y(q_\tau)$, where q_τ denotes the τth quantile of the distribution of consumption, and f is the empirical density function evaluated at q_τ. Then we have $RIF(y; q_\tau, f_y) = IF(y; q_\tau, f_y) + q_\tau$. Then, the marginal effect of the unconditional quantile can be estimated by modelling the conditional expectation of $RIF(y; q_\tau, f_y)$ as a function of a set of explanatory variables X. As these estimates, which are in terms of probabilities, correspond to marginal effects on the cumulative distribution function of consumption, they need to be divided by a kernel estimate of the density of the consumption distribution at that point to arrive at the associated quantile treatment effects, which for consumption should be in monetary amounts.

We define the series of consumption cutoffs q_τ by every 10th quantile of the empirical consumption distribution. We follow the RIF-OLS approach of Firpo et al. (2009). The identifying assumption underlying the RIF estimator is that without treatment, the change in population shares around a given level of consumption would be the same in the treatment group as in the comparison group. The estimated distributional effects are presented graphically in terms of monetary amounts at each quantile. The treatment variable here is constructed as a three-element vector containing separate treatment indicators for different groups.

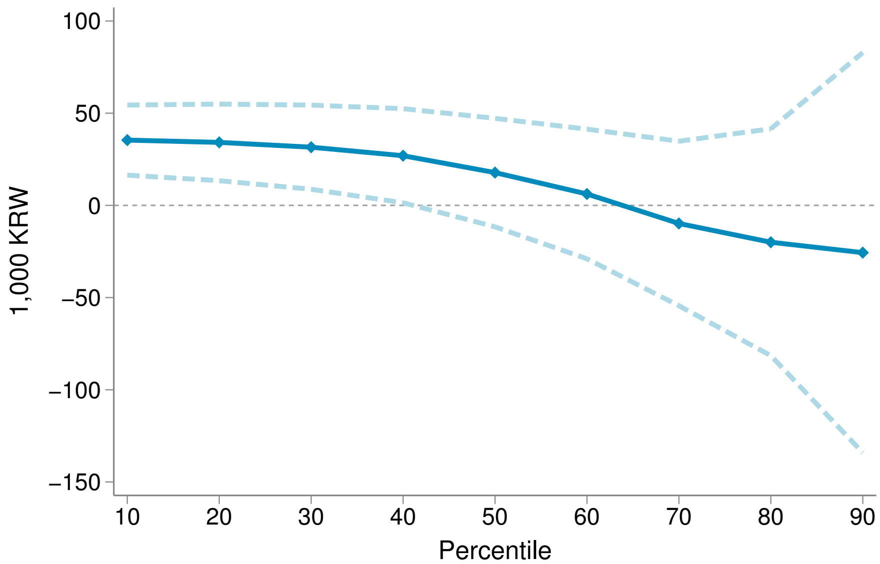


Figure 7: Quantile treatment effect estimates on expenditure.

Note: Treatment effect indicates triple-difference estimate ($2020 \times April \times Gyeonggi$). Treatment effect estimates at each tenth percentile. The dotted lines are 95% confidence intervals. The specification includes household control variables such as income, the total amount of debt, the amount in arrears, the asset value of housing, and family size.

Figure 7 shows the unconditional quantile treatment effect estimates on consumption. The effect of the stimulus payments is positive and significant only in the lower part of the consumption distribution at the 10th-40th percentiles. Households with low consumption tend to have a relatively low income, and the theory of consumption in incomplete markets suggests that the MPC of these households is likely to be high (e.g., borrowing constraint, precautionary savings). Hence, it is reasonable that the estimated effects will be larger at the lower end of the distribution.

Consistent with economic theories, the estimated effects decline in the upper part of the distribution. The treatment effect is highest at the 10th percentile, which is approximately 35,000 KRW. The estimated QTEs above the 50th percentile decline from 17,780 KRW to -25,620 KRW but are not significantly different from zero. The estimated QTEs imply that the government policy affects the spending of low-income households to some extent, but the policy may be ineffective in inducing middle-income and high-income households to spend more. Our results show that more targeted approach is more efficient in achieving the policy goal.

Table 8: MPC estimates in inner- and outer-ring districts

	Dependent variable: monthly consumption per person
Treatment group = Gyeonggi	
Control group = Incheon	
Inner-ring	0.42**
	(0.19)
Outer-ring	0.39***
	(0.14)

Notes: Indicator variables for inner-ring and outer-ring districts of Gyeonggi are included in the regression as the benchmark model. The regressions include the household fixed effect and control variables including household income, housing assets, total debt, and delinquent debt. Standard errors are clustered at the household level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

8 Robustness

8.1 Inner-ring and outer-ring districts

Gyeonggi is in the regional outskirts of Seoul, the capital city of South Korea, and we can decompose Gyeonggi into two subgroups according to geographical proximity to Seoul: inner-ring districts, most of which neighbor Seoul, and outer-ring districts.[23] Since the Seoul-neighboring districts may be different from the outer-ring districts in terms of consumption pattern, local industry, or urbanization—for example, a large portion of residents in the inner-ring districts commute to Seoul so most of the inner-ring districts are commuter towns—we investigate whether the baseline result is robust to subgroups or not.

Table 8 presents MPC for the inner- and outer-ring districts. Comparing the baseline result of 0.4, which was the estimated overall MPC in equation (3), we found that the MPC for both subgroups is robust. This result confirms that our results are robust to the possible differences between the inner- and outer-ring districts of Gyeonggi.

[23]Inner-ring districts of Gyeonggi include the districts bordering Seoul and the districts designated as overheated speculative zones: Seongnam, Uijeongbu, Anyang, Bucheon, Gwangmyeong, Gwacheon, Guri, Namyangju, Gunpo, Uiwang, Hanam, Yongin (Suji-gu, Giheung-gu) and Gimpo. Outer-ring districts include the districts of Gyeonggi other than the inner-ring districts: Pyeongtaek, Dongducheon, Siheung, Yongin (Cheoin-gu), Paju, Icheon, Anseong, Hwaseong, Gwangju, Yangju, Yeoju, Yeoncheon-gun and Gapyeong-gun. Note that Pocheon, Goyang, Yangpyeong-gun, Ansan and Suwon are excluded, as discussed in Section 2. For graphical understanding, please refer to Figure 3 or Figure 4 in Section 2.

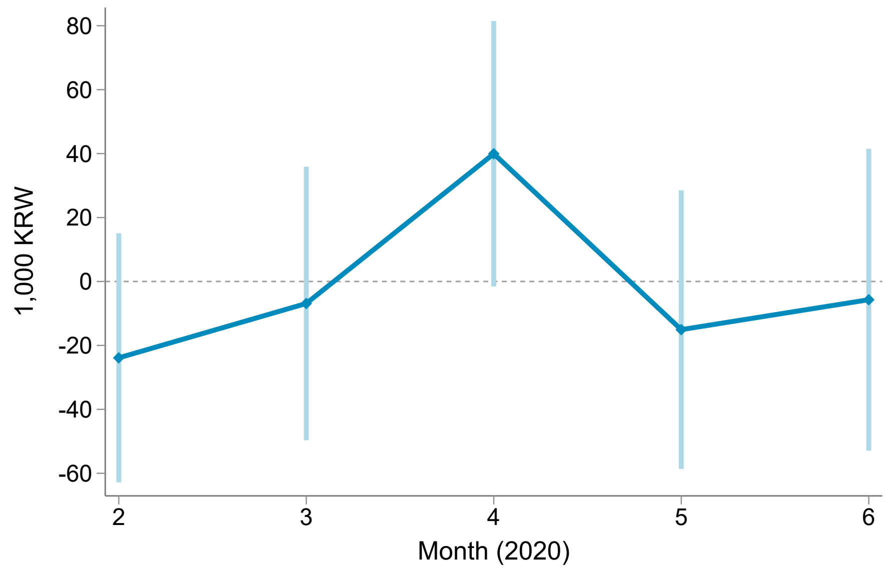


Figure 8: DDD estimates with nearby districts between Incheon and Gyeonggi

Notes: This figure shows the effect of stimulus payments on monthly consumption per person, using only nearby inland districts in Inchoen and Gyeonggi. The vertical lines are 95% confidence intervals. The estimation includes the household fixed effects and control variables, including household income, housing assets, total debt, delinquent debt, and family size.

8.2 Comparing districts near the border

Incheon is a gateway city to Seoul with the largest international airport in Korea and many harbors. Unlike this, Gyeonggi surrounds Seoul and has many satellite cities with residents commuting to Seoul, as mentioned above. Because of the differences in location and relationship with Seoul, Incheon and Gyeonggi have taken different paths in the process of industrial development. Our estimates could suffer from omitted variable bias if Incheon and Gyeonggi have different time-varying characteristics due to geopolitical differences. We examine this issue by comparing the eastern districts of Incheon bordering Gyeonggi to the western districts of Gyeonggi near Incheon. These districts are all inland and located near each other, sharing a border.[24]

Figure 8 shows a similar result from the benchmark model. The average treatment effect is approximately 40 thousand KRW, slightly higher than the benchmark result, but with wider con-

[24]Bucheon, Siheung, Gimpo, and Gwangmyeong are included for Gyeonggi, and Gyeyang-gu, Bupyeong-gu, and Namdong-gu are included for Incheon.

Table 9: DDD estimates to test parallel trends

Dependent variable: monthly consumption				
Treatment group = Gyeonggi grouped by the size of stimulus payments (unit: 1,000KRW)				
Control group = Incheon	All	100-150	200-250	300-350
2020 × Before × Gyeonggi	3.85	12.17	−5.11	−12.45
	(11.04)	(12.12)	(13.09)	(21.79)
HH controls	Yes	Yes	Yes	Yes
HH fixed effects	Yes	Yes	Yes	Yes
# of observations	748,694	479,948	393,336	236,514
# of households	235,225	151,467	124,021	75,078

The household control variables include household income, housing assets, total debt, delinquent debt, and family size. Standard errors are clustered at the household level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

fidence intervals due to the loss of observations. This result demonstrates that our results are not driven by the geopolitical differences between the two regions.

8.3 Endogenous policy change

While the results in the previous sections provide evidence of a positive causal impact of stimulus payments on consumption, there is still one further concern. If the size of stimulus payments was determined endogenously based on the conditions of districts, our DiD estimates could capture the different trends in different districts.[25] We address this concern by testing the parallel trend assumption using Equation (2). We include an indicator "Before" for February and March instead of an indicator for April. Then, we run the regression with different districts grouped by the size of stimulus payments as well as with all districts in Gyeonggi. If the coefficient of the DDD term is significant, we reject the parallel trend assumption.

Table 9 shows the results. The coefficient of the DDD term is not significantly different from zero for all districts in Gyeonggi or for the subgroups of Gyeonggi receiving different sizes of stimulus payments. Therefore, we cannot reject the parallel trend assumption for any of the groups of districts in Gyeonggi and conclude that our results in previous sections are not confounded by the conditions of districts.

[25]Note that regional characteristics that do not vary over time are removed by the household fixed effects.

9 Conclusion

This paper studies the impact of universal stimulus payments on household spending under the COVID-19 pandemic using large-scale panel data from the KCB. Specifically, we utilize the ideal natural experiment setup with a DiD approach to explore the effects of stimulus payments distributed by the largest Korean province, Gyeonggi, in April 2020. After investigating the effect of the COVID-19 outbreak on consumption, which is significantly negative, we find that the stimulus payments quickly increased monthly consumption per person by approximately 30 thousand KRW within the first 20 days. We estimate that the overall MPC of the payments was approximately 0.40. We show that the main mechanism driving this result is the role of liquidity-constrained households by finding that their MPC was close to one, while the MPCs of other groups of households were not significantly different from zero. Also, we show that heterogeneity matters. The MPC decreases from 0.58 to 0.36 as the transfer size increases from 100-150 to 300-350 thousand KRW, and the effect of stimulus payments is more significant in the younger age group. Lastly, the unconditional quantile treatment effect estimates reveal that there was a positive and significant increase in consumption only on the lower part of the distribution below the median.

Our empirical results suggest that a more targeted approach may more efficiently achieve the policy goal of boosting aggregate demand. However, a general equilibrium approach with a structural model could give different policy implications in terms of social welfare. Also, we focused here on the relatively short-run impact of the policy and the resulting implications. However, the policy could also have long-run effects if we consider the long-lasting and mixed effects of other policies, such as monetary policy, and expectations about future policies, such as additional stimulus payments. We leave these interesting and important questions for future research.

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