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How Does COVID-19 Affect Digital Innovation and Transformation?

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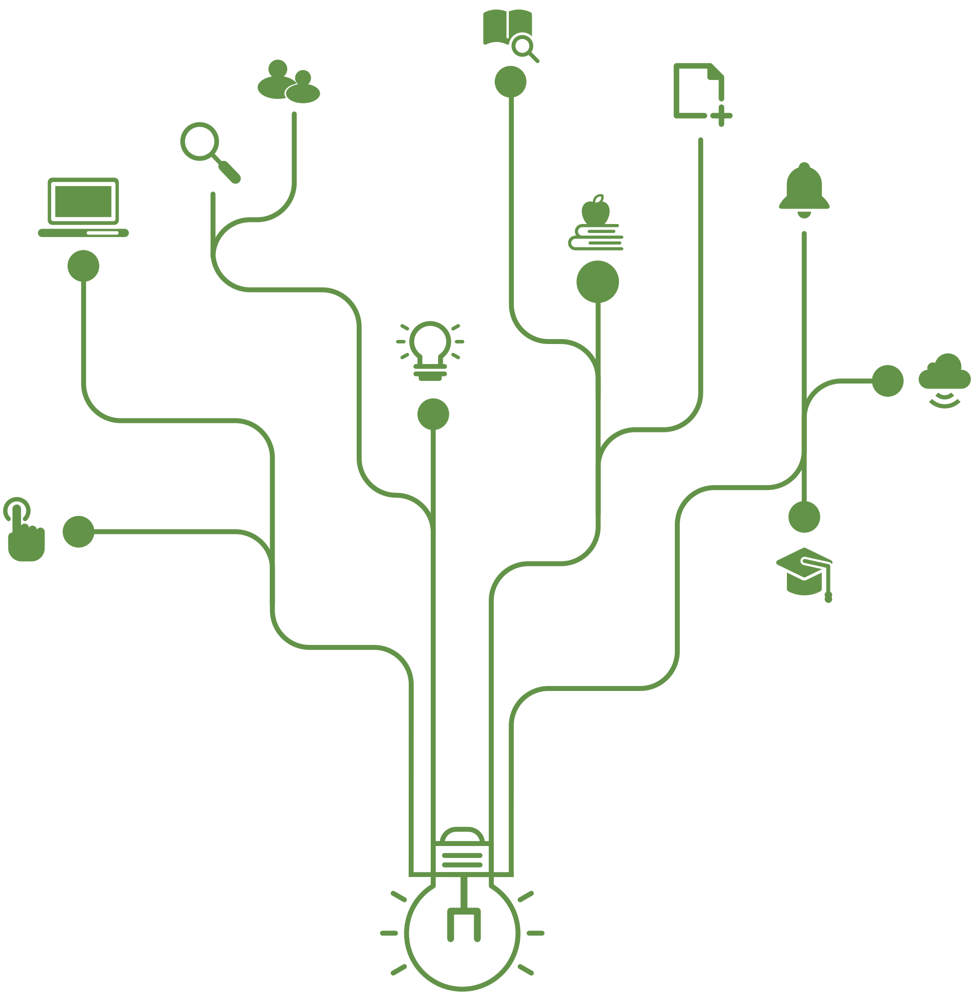

KDI SCHOOL
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Chungeun Yoon*

Abstract

I investigate how the COVID-19 crisis affects innovation activity. I measure the effect of digital resilience on innovation activity in response to the unexpected COVID-19 pandemic that caused the severe lockdown. I find that the total patent applications of industries and firms with digital resilience were not affected by the crisis. However, digital innovation measured by patents related to non-face-to-face and 'untact' significantly increased. Workforce did not change for firms with digital resilience before the crisis. Furthermore, the increase in card transactions online provides evidence on digital transformation in economies. The results are driven by small firms, suggesting that small innovative firms found opportunities in times of the crisis. Investing in digital resilience for start-up innovative firms could generate significant economic benefits during the crisis.

JEL classification: J24, J61, L25

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1 Introduction

Does a crisis hamper innovation or spur innovation? Unsurprisingly, COVID-19 has imposed significant challenges on business and corporate. The crisis is likely to have a negative effect on the overall innovation activity. For example, innovation activity shrunk in responding to the 2008 financial crisis (Archibugi et al., 2013) or natural crises caused by earthquakes or tsunamies (Filippetti and Archibugi, 2011). To mitigate the detrimental effects and minimize risks during the crisis, business and corporate are reluctant to invest R&D and innovation. However, some firms and corporate executives believe that opportunities are found in times of crisis, thus investing more in innovation activity to overcome the crisis and create a new market (Azoulay and Jones, 2020; Ebersberger and Kuckertz, 2021; Abi Younes et al., 2020). Therefore, it is ambiguous that the crisis has a negative effect on innovation or a positive effect on innovation activity in economies.

Previous studies find that firms with higher digital resilience and digital platforms performed significantly better during the pandemic (Raj et al., 2021; Bai et al., 2021). To be specific, Raj et al. (2021) show that restaurants which already adopted Uber Eats and delivery system before the COVID-19 crisis experienced substantial increases in orders and sales during the pandemic. Bai et al. (2021) find that firms prone to work-from-home before COVID-19 had higher sales and incomes during the crisis. Few studies provide empirical evidence about digital innovation and transformation from measures of patent activity in response to the COVID-19 crisis.

I investigate the effect of the COVID-19 crisis on innovation, measured by untact-related patent applications. In the age of COVID-19, non-face-to-face methods called untact become a new norm. For example, contact-free methods such as online shopping, food delivery, online meeting, webinar, and online class are becoming more mainstream during COVID-19. I also examine how the pandemic changes consumption patterns that affect untact-related innovation activity of business and firms. Specifically, I investigate whether people increased untact-related expenditure such as online shopping and food delivery using card transaction data.

I collect patent data from Korea Intellectual Property Rights Information Service (KIPRIS) that covers all patent applications in Korea from 1983 to the present. Using text analysis and patent classification (Cooperative Patent Classification; CPC), I identify untact-related patent applications. To examine consumption pattern analysis during COVID-19, I use card transaction data from the BC card company that is the biggest payment processing company in Korea and in alliances with other card companies. Categories of the data allow me to create monthly expenditures depending on categories such as restaurant, clothing, and online shopping.

I find that the industry that already had patents related to non-face-to-face methods before the pandemic experienced a significant increase in untact-related patent applications during the COVID-19 crisis. Though the overall innovation activity does not differ from other industries, the proportion of untact-related patents significantly surged in response to the crisis. I also find that firms with pre-pandemic untact-related patents increased untact-related patents during COVID-19. Furthermore, I find that the proportion of untact-related consumption substantially increased during the crisis from card transaction data. The results suggest that the change in consumption patterns triggered digital innovation and transformation in economies. Overall, these findings provide evidence how digital innovation and platforms can be a source of resilience for business and firms in response to the COVID-19 pandemic.

This paper contributes to several strands of literature. The paper fills the gap in a growing literature about COVID-19 to understand and overcome this unprecedented crisis by analyzing how digital innovation and transformation were triggered by the crisis. Al-Awadhi et al. (2020); Zhang et al. (2020) find an economic crisis on financial markets when many governments take the practices to manage the public health in response to the pandemic. To cope with the crisis, Raj et al. (2021) find that small restaurants used digital platforms such as UBER Eats thus increasing total activity and orders fulfilled per day. The digital platforms allow them to get access to customers during the crisis. Bai et al. (2021) find that public firms that had high work-from-home index values before COVID-19 experienced significantly higher sales, net incomes, and stock returns compared to their peers during the

COVID-19 crisis. In a similar vein, my paper provides evidence how firms and business are trying to get through the COVID-19 crisis by investing untact-related innovation.

Furthermore, my work provides the first empirical evidence on untact-related innovation activity during the COVID-19 crisis to my knowledge. As argued by many researchers (Azoulay and Jones, 2020; Abi Younes et al., 2020), innovation can help overcome the current crisis. Innovation and investment in terms of vaccine and treatment supported by many governments provides weapons to fight the pandemic. Abi Younes et al. (2020) argue that the COVID-19 crisis leads to a significant change in the rate, adoption, and direction of innovation activity. Historically, innovation during the crisis generates large positive spillovers. For example, the U.S. government created the National Defense Research Committee in 1940 to achieve innovations related to the WWII. This effort generated spillovers in numerous technologies including antimalarial and penicillin treatments (Azoulay and Jones, 2020). More specifically, Verma and Gustafsson (2020) investigate innovative technologies such as big data and digital healthcare using a bibliometric analysis in response to the COVID-19 crisis. Ebersberger and Kuckertz (2021) provide evidence that innovative start-ups quickly reacts to the COVID-19 pandemic. My paper contributes to this growing literature by investigating the causal effect of the COVID-19 crisis on innovation activity measured by patent applications.

The rest of this paper is organized as follows. Section 2 describes data and presents descriptive statistics. Section 3 outlines my empirical methods. Section 4 shows results and discusses their implications. Section 5 concludes and outlines next steps for further analysis.

2 Data

2.1 Patent data

I collect patent data from Korea Intellectual Property Rights Information Service (KIPRIS). All patent applications in Korea from 1983 to the present are open to the public. Specifically, I use 1,125,214 patent applications between 2015 and 2020 for empirical analysis in the paper. In each patent document, I can identify 1) application date, 2) patent classification (Cooperative Patent Classification; CPC), 3) applicants (corporate), 4) inventors, and 5) other pieces of information. I create two main data sets for empirical analysis using first three variables: application date, patent classification, and applicants.

The first data set is constructed as follows. I restrict CPC to 4-digit CPC scheme. I create patent data assigned to 670 4-digit CPC categories. Over 250,000 CPC schemes are available and CPC consists of section (one letter A to H and also Y)[1], class (two digits), subclass (one letter), group (one to three digits), and main group and subgroups (at least two digits). Four-digit CPC schemes use a combination of section, class, and subclass. For example, "A" is "human necessities", "A01" is "agriculture; forestry; animal husbandry; hunting; trapping; fishing", and "A01B" is "social working in agriculture or forestry; parts, details, or accessories of agricultural machines or implements, in general".[2] I define each 4-digit CPC scheme as a particular industry engaging in innovation activity in that CPC code. Using the application date, I finally create panel data where the unit of observation is industry(4-digit CPC) and year. Additionally, I create monthly patent applications in industry for robustness checks.

The second data set is panel data at the firm level. I first restrict data to patents applied by corporate applicants. Patents applied by a person are removed in the sample. KIPRIS provides 10-digit business registration number and corporate name thus allowing me to create

[1] A: Human Necessities, B: Operations and Transport, C: Chemistry and Metallurgy, D: Textiles, E: Fixed Constructions, F: Mechanical Engineering, G: Physics, H: Electricity, Y: Emerging Cross-Sectional Technologies

[2] https://www.cooperativepatentclassification.org/cpc/scheme/A/scheme-A01B.pdf

data on patent applications per firm and year. To be specific, a single firm is defined as a corporate applicant which has an unique combination of a business registration number and a corporate name in a patent document.

To identify untact-related patent application, I utilize the search terms: 'untact', "non-face-to-face", "non-facing", "contactless", "contact-free", "untact"(in Korean), and "Bidae-myeon"(in Korean). I identify 517 patent applications that contains these terms in a title or an abstract of a patent document. Table 1 describes a list of 4-digit CPC categories with untact-related patents and a proportion of untact-related patents. I find that 28 4-digit CPC schemes contains untact-related patents. For example, a 4-digit CPC code of 'G06F' that presents an industry related to 'recognition of data; presentation of data; record carriers; handling record carriers' had 0.49% untact patents in that category.

2.2 Employment

I collect employment data at the firm level from public data portal.[3] It is mandatory for employers with more than two employees in Korea to contribute to the cost of the national pension plan for employees. The number of employees who join the national pension plan, a corporate name, and a business registration number are open to the public provided by the National Pension Service (NPS). The data is released on a monthly basis in public data portal. Between 2015 and 2020, I identify 1,820,667 institutes that provide the number of employees. I consider the number of employees who are currently enrolled the plan as a proxy for the number of employees in a firm and create monthly employment data at the firm level.

I match the monthly employment data set with the monthly patent data set using a corporate name and a business registration number. Out of 50,703 firms in patent data, approximately 93 percent (47,343 firms) is exactly matched after cleaning some corporate names. For example, "Inc.", "Incorporated", "(Inc.)", parenthesis, and some types are removed in a

[3] www.data.go.kr

corporate name.

2.3 Card transaction data

To examine consumption pattern analysis during COVID-19, I use card transaction data from the BC card company over the past two years between November 2018 and October 2020. The company is the biggest payment processing company in Korea and in alliances with other card companies. The market share accounts for approximately 24 percent and the number of customers is about 36 million people out of 51 million total population in Korea. The data provides 236 categories of spending such as restaurant, clothing, and online shopping. I create panel data at the category level on a monthly basis.

To investigate how the COVID-19 crisis affects consumption pattern, I define the following categories as untact-related consumption: internet shopping mall, telemarketing, home shopping, and internet payment gateway.

2.4 Summary Statistics

Table 2 reports summary statistics of data used for analysis. The annual average of the proportion of untact-related patent applications between 2015 and 2020 is 0.057%. Shown in Figure 1, this proportion surged in the year 2020 when the COVID-19 pandemic rapidly spread.

In panel B, industry is defined as each 670 4-digit CPC scheme. I also find a small proportion of untact-related patents of 0.03% annually. Figure 2, Figure 3, and Table 3 report the results at the industry level using this data set.

In panel C, I restrict data to firms that have at least one patent application every year between 2015 and 2020. In general, patent applications are published 18 months after their earliest filing data. Considering that I collect patent data from the KIPRIS database on

October, 2021, patent applications by April, 2020 are published in general. It should be noted that the number of patent applications in the year 2020 is incomplete because of the 18-month delay in publishing patents. The annual average of total patent applications between 2015 and 2019 is 182,287, but the number of patent applications obtained from the database is 88,530. In addition, I exclude the top 1% of firms with patents or employees in order to avoid sensitivity to outliers. Figure 4, Figure 5, and Table 4 report the results at the firm level using this data set.

Table 1: PATENT CLASSIFICATION AND DESCRIPTION

Patent Classification (1)	Description (2)	Proportion of Untact Patents (%) (3)
A47G	household or table equipment	0.13
A47J	kitchen equipment; coffee mills; spice mills; apparatus for making beverages	0.00
A61B	diagnosis; surgery; identification	0.18
B23K	soldering or unsoldering; welding; cladding or plating by soldering or welding; cutting by applying heat locally	0.08
B32B	layered products	0.04
B65D	containers for storage or transport of articles or materials	0.00
B65G	transport or storage devices	0.12
E05F	devices for moving wings into open or closed position; checks for wings; wing fittings not otherwise provided for, concerned with the functioning of the wing	0.01
E06B	fixed or movable closures for openings in buildings, vehicles, fences or like enclosures	0.01
G01S	radio direction-finding; radio navigation; determining distance or velocity by use of radio waves; locating or presence-detecting by use of the reflection or reradiation of radio waves; analogous arrangements using other waves	0.06
G02F	devices or arrangements the optical operation of which is modified by changing the optical properties of the medium of the devices or arrangements for the control of the intensity colour phase polarisation or direction of light	0.00
G06F	electric digital data processing	0.09
G06K	recognition of data; presentation of data; record carriers; handling record carriers	0.49
G06N	computer systems based on specific computational models	0.09
G06Q	data processing systems or methods, specially adapted for administrative, commercial, financial, managerial, supervisory or forecasting purposes; systems or methods specially adapted for administrative, commercial, financial, managerial, supervi ¿ sory or forecasting purposes	0.43
G06T	image data processing or generation	0.07
G07C	time or attendance registers; registering or indicating the working of machines; generating random numbers; voting or lottery apparatus; arrangements, systems or apparatus for checking not provided for elsewhere	0.53
G07D	handling of coins or valuable papers	0.08
G07F	coin-freed or like apparatus	0.31
G08B	signalling or calling systems; order telegraphs; alarm systems	0.13
G09F	displaying; advertising; signs; labels or name-plates; seals	0.01
G10L	speech analysis or synthesis; speech recognition; speech or voice processing; speech or audio coding or decoding	0.14
H01M	processes or means	0.00
H01R	electrically-conductive connections; structural associations of a plurality of mutually-insulated electrical connecting elements; coupling devices; current collectors	0.06
H04L	transmission of digital information	0.13
H04M	telephonic communication	0.11
H04N	pictorial communication	0.06
H04W	wireless communication networks	0.08

Table 2: SUMMARY STATISTICS

	Mean (1)	Median (2)	SD (3)	Min. (4)	Max. (5)
A. All patents (2015-2020)					
Proportion of untact patents	0.057	0.049	0.029	0	0.114
B. Industry (2015-2020)					
Patents	239	61	631	0	9,917
Untact patents	0.123	0	0.906	0	25
Proportion of untact patents	0.030	0	0.241	0	12
Number of industry	670				
C. Firm (2015-2020)					
Patents	1	1	6	0	544
Untact patents	0.003	0	0.095	0	10
Proportion of untact patents	0.082	0	2.491	0	100
Employees	8	7	5	0	81
Employees hired	1	0	1	0	27
Employees laid off	0	0	0	0	29
Number of firm	7,772				

Notes: This table describes summary statistics. Panel A uses all patent applications between 2015 and 2020. In panel A, proportion of untact patents presents the annual average of untact patents divided by total patents. Panel B uses annual patent applications at the level of 4-digit CPC codes. Panel C reports statistics for patent applications and employees at the firm level. To avoid sensitivity to outliers, the top 1% of firms with patents or employees is excluded.

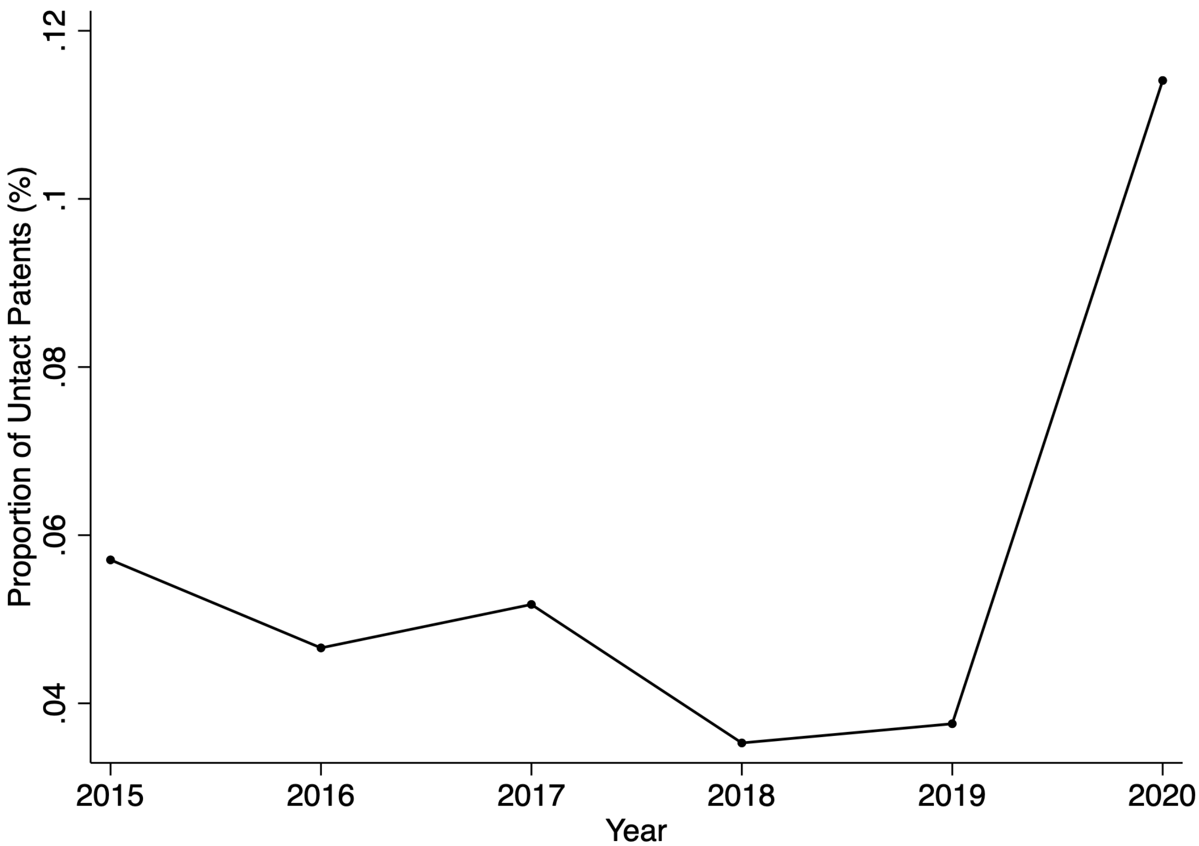


Figure 1: UNTACT PATENTS OVER TIME

Notes: The figure plots a proportion of untact patent applications in percentage terms over year.

3 Empirical Strategy

I investigate how digital innovations and channels can substitute for innovation activity in industry and firms when the COVID-19 pandemic and the subsequent economic lockdown hindered traditional channels in person. Specifically, I compare industries with pre-pandemic untact-related patents versus other industries with no such patents before COVID-19. The econometric model of a difference-in-differences framework is as follows.

$$Y_{it} = \beta(Treat_i \times Post_t) + \gamma_i + \tau_t + \epsilon_{it} \tag{1}$$

Y_{it} is the number of patent applications of industry i at year t, the number of untact-related patents, or the share of untact-related patents. $Treat_i$ takes one if industry i had untact-related patents between 2015 and 2019 before the COVID-19 pandemic. Table 1 presents 28 industries (4-digit CPC codes) with pre-pandemic untact-related patents. $Post_t$ takes one if year t is 2020 and zero otherwise. Industry fixed effects γ_i and year fixed effects τ_t are included in the model. Coefficient β measures the effect of the COVID-19 crisis on innovation activity of industries with digital resilience before the crisis. We report the results from this specification in Table 3.

The key identifying assumption is that outcomes of industries with pre-pandemic untact-related patents and those of other industries with no such patents would not change differently in the absence of the COVID-19 pandemic. I complement my empirical analysis with a difference-in-differences framework relative to a base year in an event study specification:

$$Y_{it} = \sum_t \beta_t(Treat_i \times YearDummy_t) + \gamma_i + \tau_t + \epsilon_{it} \tag{2}$$

where $YearDummy_t$ is a dummy variable corresponding to a particular year t. The coefficients β_t measure the effect of the COVID-19 pandemic on innovation relative to a base year 2019 before COVID-19. I plot the coefficients in Figure 3.

To investigate the effect on innovation of firms, I employ the same specifications in Equation 1 and Equation 2. The unit of observation is firm i at year t in replace of industry i at year t. In addition to that, I use another dependent variable of the number of employees in firm j at year t which I create from the National Pension Service.

Finally, I examine the effect of the COVID-19 crisis on consumption pattern using the similar specifications. The econometric model is as follows.

$$Y_{it} = \beta(Treat_i \times Post_t) + \gamma_i + \tau_t + \epsilon_{it} \tag{3}$$

Y_{it} is the amount of card transactions in category i at year-month t. $Treat_i$ takes one if industry i had untact-related patents between 2015 and 2019 before the COVID-19 pandemic. The independent variable, $Treat_i$, takes a value of one if category i belong to untact-related consumption: internet shopping mall, telemarketing, home shopping, and internet payment gateway. $Post_t$ takes one after January, 2020 when COVID-19 started spreading. Category fixed effects γ_i and year-month fixed effects τ_t are included in the model. Coefficient β measures the effect of COVID-19 on consumption pattern for categories with digital resilience before the crisis. We report the results from this specification in Table 6. I also employ the event study specification in the same method of equation 2.

4 Results

4.1 Industry

I report the empirical results for the effect of pre-COVID-19 digital resilience on innovation activity of industry. I first show the proportion of untact patents at the industry level by treatment status in Figure 2. Treatment industry which had untact patents before 2015 was considered as industry with the high digital resilience before COVID-19. In response to COVID-19 in the year 2020, the proportion of untact patents surged in treatment industry.

The results of regression analysis from equation eq:base at the industry level are reported in Table 3. The industry defined as each 4-digit CPC scheme that had already untact patents before 2015 did not change differently in overall patent applications from other industries that had no untact patents in column (1). However, columns (2) and (3) reports the coefficients on the effect on untact-related patents. Specifically, industries with pre-COVID-19 untact innovation experienced a significant increase in untact patents. Column (2) shows 28.1 percent increase in the number of untact-related patents and column (3) presents 0.24 percentage point increase in the proportion of untact-related patents. In sum, industries with pre-COVID-19 digital resilience were not severely affected in overall innovation activity, but in fact benefited from the COVID-19 crisis in terms of digital innovation.

The key identifying assumption of the difference-in-differences strategy is that industries with pre-COVID-19 untact patents and other industries with no such patents before COVID-19 would not change differently in the absence of the pandemic. Figure 3 shows the coefficients corresponding to a year relative to the base year of 2019 before the COVID-19 from equation 2. The coefficient in the year 2020 shows a substantial increase in the proportion of untact-related patents. Furthermore, there were no significant differences in coefficients before the base year of 2019. This provides evidence on the validity of the parallel pre-trends assumption underlying the difference-in-differences.

Table 3: THE EFFECT OF COVID-19 ON INNOVATION OF INDUSTRY

Dependent variable	Patents	Untact patents	Proportion of untact patents
	(1)	(2)	(3)
$Treatment \times Post$	-0.004	0.281***	0.241***
	(0.074)	(0.075)	(0.082)
Observations	4,020	4,020	4,020
R-squared	0.977	0.744	0.201

Notes: This table reports linear regression analysis of the effect of COVID-19 on patenting outcomes of industry. Industry is defined as 4-digit CPC codes. The dependent variables are: log(patent applications+1) in column (1), log(untact patent applications+1) in column (2), and untact patent applications divided by total patent applications in column (3). The independent variable, $Treatment$, indicates whether industry had untact patents before 2015. $Post$ takes a value of one in the year 2020 or later. All specifications include industry fixed effects and year fixed effects. Standard errors are clustered by industry.
$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

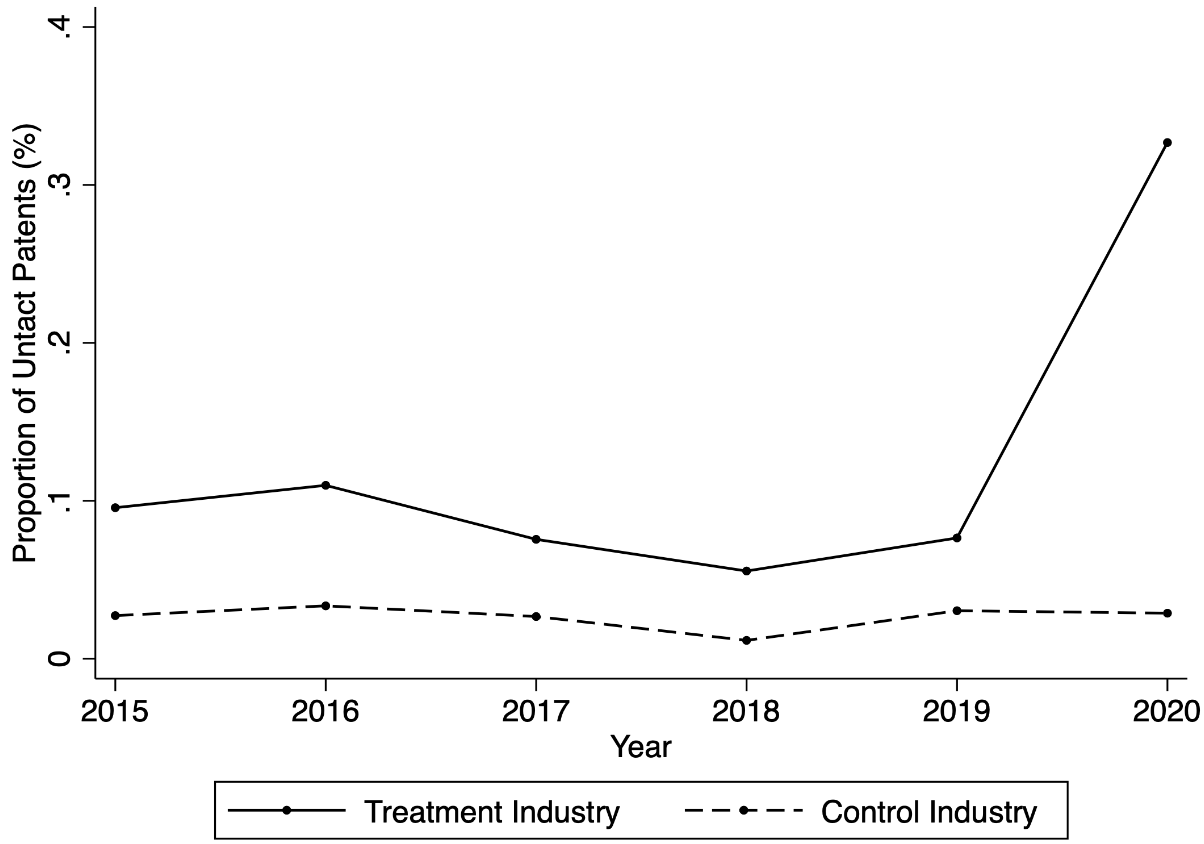


Figure 2: UNTACT PATENTS OF INDUSTRY BY STATUS

Notes: The figure plots an average proportion of untact patent applications given industry in percentage terms over year. Treatment industry is defined as 4-digit CPC schemes that had untact patents before 2015, while control industry consists of other 4-digit CPC schemes that had no such patents before 2015.

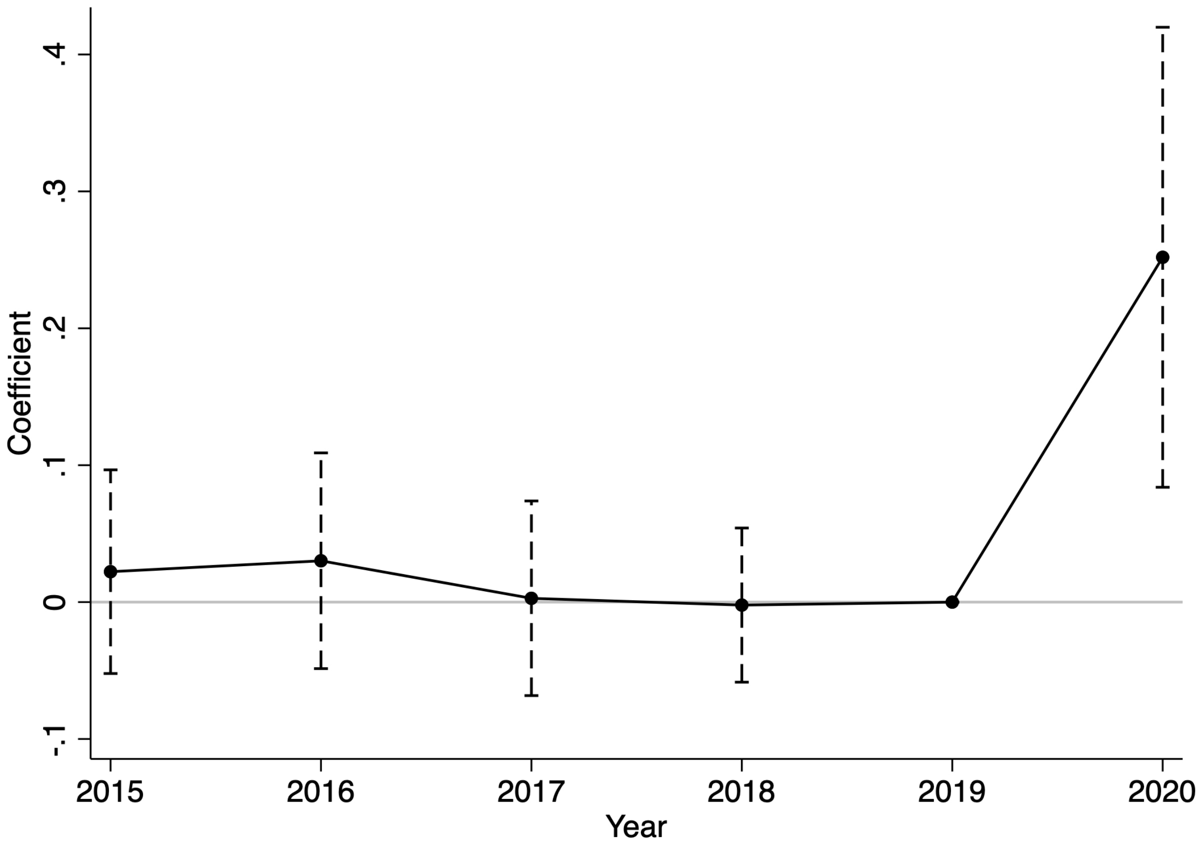


Figure 3: DIFFERENCE-IN-DIFFERENCES IN UNTACT PATENTS OF INDUSTRY

Notes: The figure shows regression coefficients and 95% confidence intervals relative to the base year 2019 obtained from linear regression analysis for patents of industry. The dependent variable is the proportion of untact patents. Standard errors are clustered by industry.

4.2 Firm

I investigate the effect of pre-COVID-19 digital resilience on innovation activity of firm. Similar to trends in patents at the industry level, Figure 4 shows that treatment firms that had untact patents before 2018 increased the proportion of untact patents compared to control firms that had no such pre-pandemic patents.

Table 4 shows the results at the firm level from the difference-in-differences analysis. Column (1) shows no significant difference in the total patents between firms with untact patents before 2015 and other firms with no pre-COVID-19 untact patents. Columns (2) and (3) shows a large increase in untact-related patent applications in response to the COVID-19 crisis. To be specific, I find that the number of untact patents increased by 32.9 percent in column (2) and the proportion of untact patents increased by 27 percentage points. Firms with pre-COVID-19 digital resilience did not increase in the overall patenting outcome, but significantly increased patenting activity related to digital innovation in response to the COVID-19 pandemic.

Panels B and C of Table 4 provides evidence that the results are driven by small firms rather than large firms. I restrict a sample of firms to small firms or large firms depending on the threshold of the firm's median employees. Small firms with 35 employees or below increased untact patents, but large firms with above 35 employees did not increase untact patents. The total patents of small firms increased, but patents of large firms decreased, though insignificant. This suggests that small firms are better able to adapt to changes in response to the crisis.

Figure 5 shows the coefficients corresponding to a year relative to the base year of 2019 before the COVID-19 from equation 2 at the firm level. Consistent with the results from the difference-in-differences regression analysis, untact patents surged in the year 2020. Insignificant coefficients before 2020 strengthens the identifying assumption of common pre-trends.

Furthermore, I investigate how the COVID-19 crisis affected another firm outcome measured by the number of employees. As shown in panel A of Table 5, I do not find any significant results for the number of employees in response to the COVID-19 pandemic. However, I find the number of new employees who were hired increased for small firms with pre-COVID-19 untact patents. Though insignificant, small firms were better able to hire new employees and keep the current workforce, while large firms did not hire new employees and tended to decrease in workforce. The results here are consistent with the increase in innovation activity of small firms. Overall, small start-up innovative firms found opportunities in times of crisis.

Table 4: THE EFFECT OF COVID-19 ON INNOVATION OF FIRM

Dependent variable	Patents	Untact patents	Proportion of untact patents
	(1)	(2)	(3)
A. All firms			
$Treatment \times Post$	0.041	0.329***	27.263***
	(0.128)	(0.085)	(7.950)
Observations	28,553	28,553	28,553
R-squared	0.549	0.668	0.395
B. Small firms			
$Treatment \times Post$	0.114	0.449***	33.175***
	(0.192)	(0.114)	(9.989)
Observations	13,711	13,711	13,711
R-squared	0.605	0.760	0.504
C. Large firms			
$Treatment \times Post$	-0.068	0.163	19.081
	(0.142)	(0.112)	(12.606)
Observations	14,842	14,842	14,842
R-squared	0.503	0.239	0.265

Notes: This table reports linear regression analysis of the effect of COVID-19 on patenting outcomes of firm. The dependent variables are: log(patent applications+1) in column (1), log(untact patent applications+1) in column (2), and untact patent applications divided by total patent applications in column (3). The independent variable, $Treatment$, indicates whether firm had untact patents before 2015. $Post$ takes a value of one in the year 2020 or later. Panel A incldues all firms regardless of firm size. Small firms in panel B are firms with a small number of employees on average (the median of the average number of employees, 35, or below). Large firms in panel C are firms with a large number of employees on average (above 35 employees). To avoid sensitivity to outliers, the top 1% of firms with patents or employees is excluded. All specifications include firm fixed effects and year fixed effects. Standard errors are clustered by firm.
$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

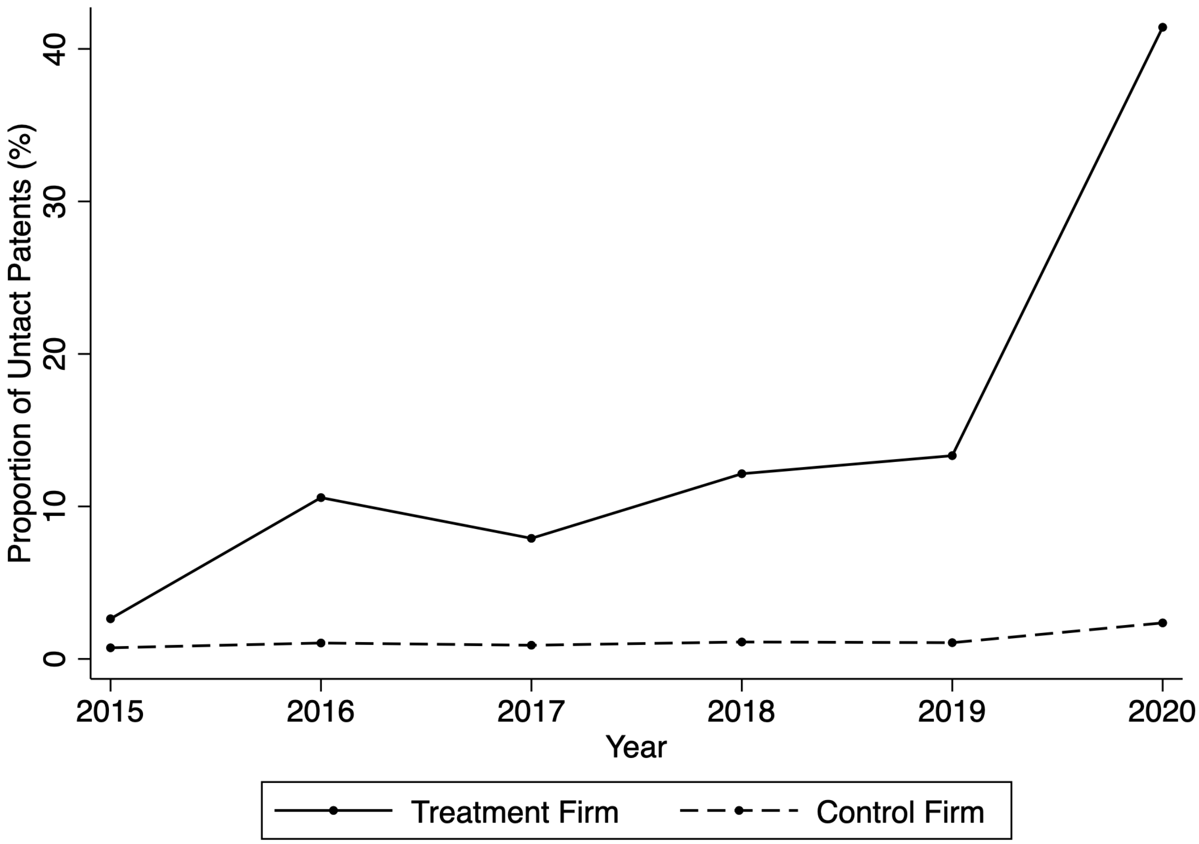


Figure 4: UNTACT PATENTS OF FIRM BY STATUS

Notes: The figure plots an average proportion of untact patent applications given firm in percentage terms over year. Treatment firm is defined as firm that had untact patents before 2015, while control firm consists of other firms that had no such patents before 2015.

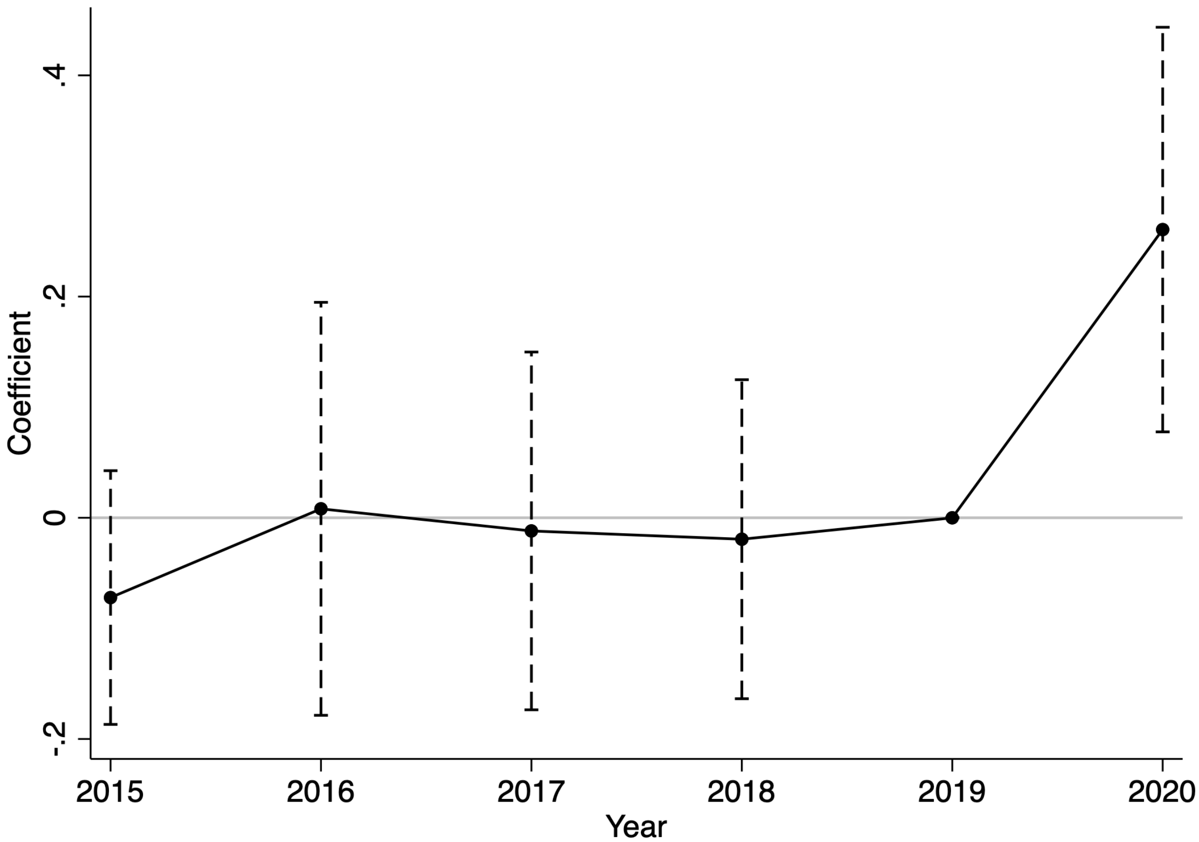


Figure 5: DIFFERENCE-IN-DIFFERENCES IN UNTACT PATENTS OF FIRM

Notes: The figure shows regression coefficients and 95% confidence intervals relative to the base year 2019 obtained from linear regression analysis for patents of firm. The dependent variable is the proportion of untact patents. Standard errors are clustered by firm.

Table 5: THE EFFECT OF COVID-19 ON EMPLOYEES OF FIRM

Dependent variable	Employees (1)	Employees hired (2)	Employees laid off (3)
A. All firms			
$Treatment \times Post$	-0.039	0.053	-0.016
	(0.481)	(0.085)	(0.048)
Mean of dependent variable	7.690	0.510	0.304
Observations	28,553	28,553	28,553
R-squared	0.721	0.449	0.463
B. Small firms			
$Treatment \times Post$	0.636	0.159*	0.046
	(0.523)	(0.089)	(0.062)
Mean of dependent variable	5.224	0.485	0.240
Observations	13,711	13,711	13,711
R-squared	0.700	0.477	0.486
C. Large firms			
$Treatment \times Post$	-0.956	-0.076	-0.104
	(0.862)	(0.160)	(0.073)
Mean of dependent variable	10.156	0.535	0.368
Observations	14,842	14,842	14,842
R-squared	0.581	0.435	0.435

Notes: This table reports linear regression analysis of the effect of COVID-19 on employees of firm. The dependent variables are: employees in column (1), new employees hired in column (2), and employees laid off in column (3). The independent variable, $Treatment$, indicates whether firm had untact patents before 2015. $Post$ takes a value of one in the year 2020 or later. Panel A incldues all firms regardless of firm size. Small firms in panel B are firms with a small number of employees on average (the median of the average number of employees, 35, or below). Large firms in panel C are firms with a large number of employees on average (above 35 employees). To avoid sensitivity to outliers, the top 1% of firms with patents or employees is excluded. All specifications include firm fixed effects and year fixed effects. Standard errors are clustered by firm.
$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

4.3 Consumption

I measure the effect of COVID-19 on consumption patterns using card transaction data. I compare the amount of card transactions offline such as restaurant and retail stores with the amount of card transactions online such as online shopping, home shopping and telemarketing. Figure 6 shows the amount and the proportion of card spending online over the past two years between November 2018 and October 2020. In response to the surge in COVID-19 cases in the early of 2020 in Korea, the proportion of consumption online substantially increased.

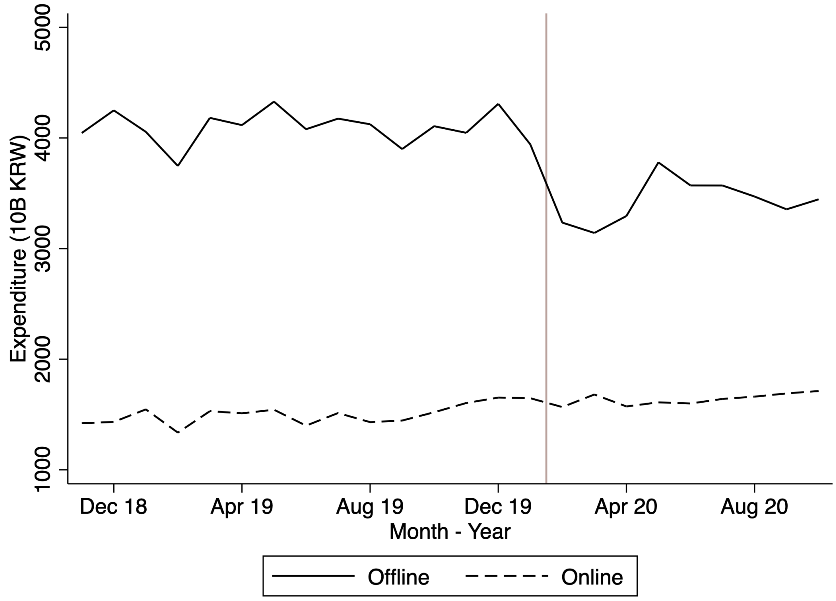
I find a significant increase in card spending online in response to the COVID-19 crisis using the regression analysis in Table 6. Categories with untact-related consumption experienced a large increase in the amount of card transactions by 30.7 percent in column (2) and the 17 percentage point increase in card transactions as a fraction of the average card transactions in 2019.

Figure 7 shows the coefficients relative to the starting time of the data set, November 2018. I find that the coefficients increased in response to the COVID-19 pandemic. In sum, the increase in card spending online provides evidence on digital transformation in consumption pattern. The results suggests that digital transformation in the market moves in the same direction as digital innovation of business and firm.

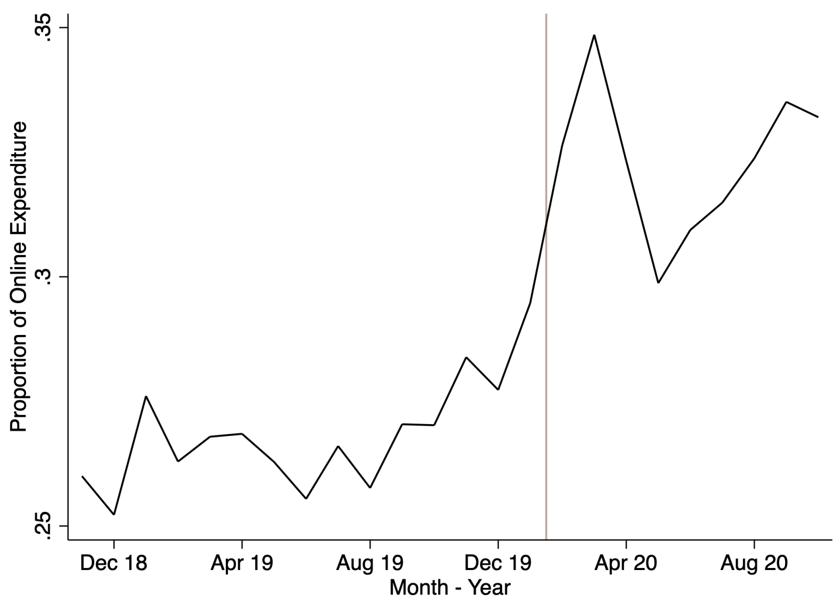
Table 6: THE EFFECT OF COVID-19 ON CONSUMPTION PATTERN

Dependent variable	Spending (1)	Normalized spending (2)
$Treatment \times Post$	0.307***	0.170**
	(0.082)	(0.075)
Observations	5,513	5,513
R-squared	0.967	0.176

Notes: This table reports linear regression analysis of the effect of COVID-19 on the amount of card transactions. The dependent variables are: log(monthly card spending+1) in column (1) and monthly card spending divided by the average monthly card spending in 2019 in column (2). The independent variable, $Treatment$, indicates whether category is related to untact. $Post$ takes a value of one in the year 2020 or later. All specifications include category fixed effects and year-month fixed effects. Standard errors are clustered by category.
$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.



(a) Amount of card spending online and offline



(b) Proportion of card spending online

Figure 6: CARD SPENDING ONLINE AND OFFLINE

Notes: Plot (a) shows card spending online and offline over time. A proportion of card spending online is shown in plot (b).

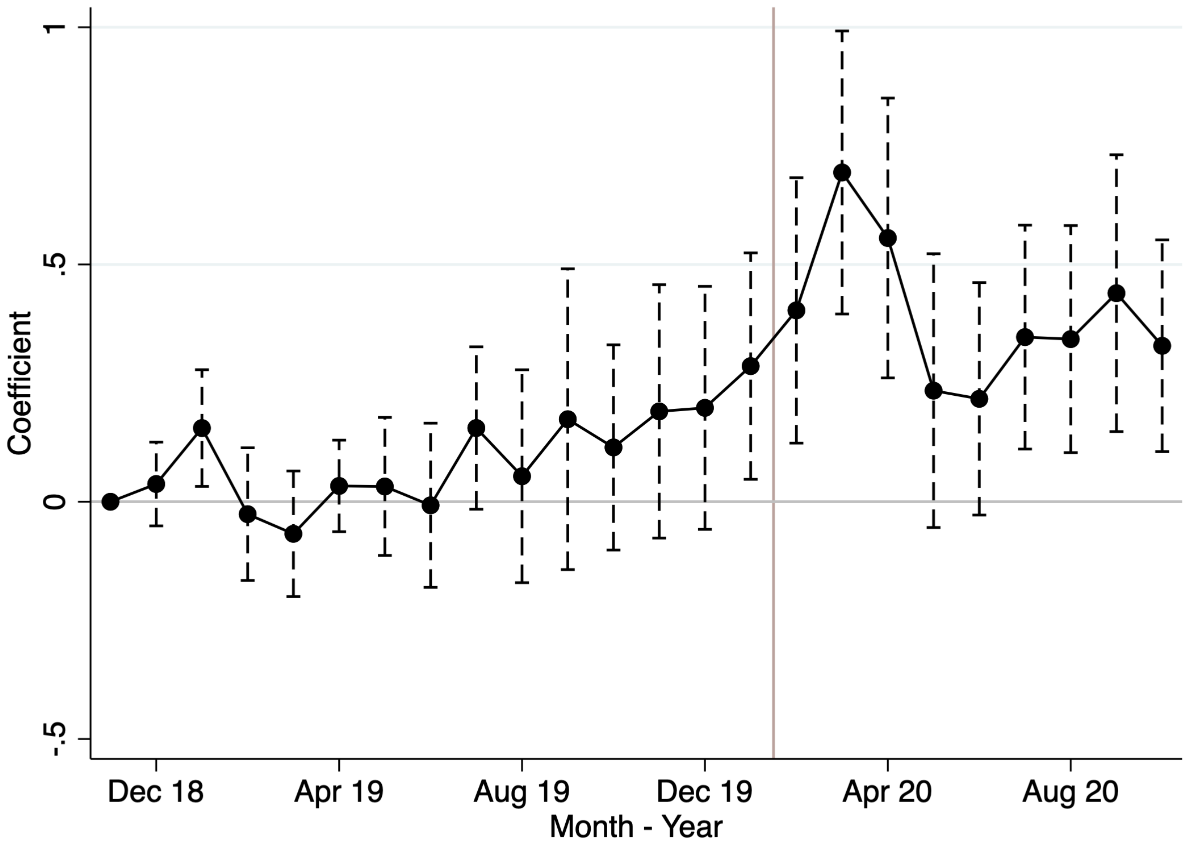


Figure 7: DIFFERENCE-IN-DIFFERENCES IN CARD SPENDING

Notes: The figure shows regression coefficients and 95% confidence intervals relative to the base time obtained from linear regression analysis for card spending. The dependent variable is log(monthly card spending+1). Standard errors are clustered by category.

5 Conclusion

I find that the overall innovation activity of industry and firm was not significantly affected by the COVID-19 crisis when industry and firm had digital resilience. Specifically, industries and firms with pre-COVID-19 digital innovation measured by untact-related patents before 2015 did not decrease the total patent applications compared to other industries and firms. Furthermore, they substantially increased untact-related patents in response to the COVID-19 crisis.

Workforce of firms also did not change when firms had digital resilience before the crisis. In fact, small firms benefited from the crisis. Small firms increased untact-related patents and new employees, but large firms did not increase any kind of patents. The results suggest that small firms found opportunities in times of crisis and they are better able to adapt to changes during the crisis.

Further research should be considered, particularly when complete patent applications are published 18 months later all patents were filed in the year 2020. The results highlight the important role of start-up innovative firms in explaining innovation activity of business during the crisis. Investing in digital resilience for start-up innovative firms could generate significant economic benefits.

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