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The Role of Face-to-face Contact in Innovation: The Evidence from the Spanish Flu Pandemic in Japan[1]

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Abstract

This study empirically investigates the role of face-to-face contact in innovation, by exploiting the Spanish flu pandemic in Japan from 1918 to 1921, which prohibitively increased the cost of face-to-face contact between inventors. By using unique patent bibliographic data for this period, we estimate the pandemic's impact on innovation for face-to-face contact-intensive technologies using the Difference-in-Differences (DID) approach. The estimation results show that during the pandemic, patent applications for face-to-face contact-intensive technologies significantly decreased, and did not fully recover even after the pandemic ended. We also find that the negative impact is driven by a decrease in new entries into patent applications, that is, patent applications by the inventors who applied for patents for the first time. We further find that productive inventors had experienced incidences of co-invention during their early careers. These results suggest that the decrease in face-to-face contacts with colleagues and seniors in the preliminary stages of inventors' careers reduced the opportunity to nurture new inventors.

Keywords: Innovation, Knowledge spillovers
JEL classification: O30

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1 Introduction

Exchange of ideas with others is the key for knowledge growth (Lucas and Moll, 2014), and collaborative work is an effective way for idea exchange (Azoulay et al., 2010). Indeed, collaboration in scientific research and invention has been increasing and the average quality of collaborative work is higher than that of solo work (Wuchty et al., 2007). Based on these observations, this study explores the channel of idea exchange in collaborative work, focusing on the role of face-to-face communication. This is because the knowledge exchanged in collaborative work may often be tacit one, which could be efficiently transmitted only through face-to-face communication (Saxenian, 1996).

For this purpose, we study the patenting activities in Japan during the Spanish Influenza pandemic from 1918 to 1921. The Spanish Influenza was the most serious pandemic in the modern world, which caused 20–40 million deaths. Japan was also seriously affected, with the number of deaths being 390,000. In addition, it is notable that in Japan, the mortality rate of the Spanish Influenza was higher for the age group of 20–40 years, that is, the prime aged workers (Hayami, 2006). According to Ministry of Home Affairs (1922), it is estimated that more than 240,000 employed people lost their lives due to the pandemic in Japan. The damage to the prime aged workers would reduce the opportunity for knowledge exchange through face-to-face communication among them, and thereby, affect innovation to the extent that face-to-face communication was essential.

To identify the effect of face-to-face communication on innovation, we exploit the difference in the intensity of face-to-face communication across technology fields. That is, we categorize patent technology fields into the communication-intensive fields and the communication non-intensive fields, by the share of co-inventions in the total patents before the pandemic. More specifically, we compare the percentages of co-inventions in the total patents before the pandemic, across technology fields. Following this, we categorize the fields with the percentages higher than the 75 percentile as the collaboration intensive fields that require more face-to-face communications for innovation, and the other fields as the non-collaboration intensive fields. Then, using the former as the treatment group and the latter as the control group, we estimate how the decline in face-to-face communication due to the pandemic reduced innovations by Difference-in-Differences (DID) approach.

The estimation results show that the number of patent applications declined by 19% during the pandemic in the collaboration intensive fields. In addition, the decline in the patent applications in the collaboration intensive fields was larger in the regions where the infection was more serious. We further find that the decrease in patent applications in the collaboration intensive fields during the pandemic was mainly driven by the decrease in new entries into patent applications, that is, patent applications by the inventors who applied patents for the first time. In other words, even in the collaboration intensive fields, the number of patent applications by incumbent investors, who had applied for patent before the pandemic, did not decline significantly, and had just shifted from co-inventions to sole inventions in the pandemic. These findings suggest that face-to-face communication indeed contributed to innovation by collaborative work, and that opportunities of technical guidance, communication, and knowledge exchange with seniors and colleagues in the early career of an inventor was especially important.

This paper is related to several strands of the literature. First, it contributes to the literature on the peer effects in innovation. Azoulay et al. (2010) show that the collaborative research with highly competent researchers enhances creativity of life scientists through knowledge spillovers, using the data on co-authorship with academic "superstars" who died prematurely and unexpectedly. Moser et al. (2014) show that the German Jewish chemists, who immigrated to the US from the Nazi Germany, improved the US inventions in the chemistry fields. They also show that the positive impact was driven by new entries of American scholars to those fields by collaborating with the immigrating German Jewish chemists. This shows the importance of co-invention experience with the productive inventors in the early career. Similarly, Waldinger (2010, 2012) find that star scientists have positive impact on Ph.D. students, but not on the established researchers, by exploiting the expulsion of Jewish professors from universities in Nazi Germany. Jaravel et al. (2018) show the importance of team specific capital in the context of invention, instead of scientific research. This paper is consistent with the literature in the sense that it reveals the positive impact of collaborative work on innovation, especially by early career inventors. In contrast, our study covers inventions in Japan at a time when the country was still in the process of industrialization and the level of technology was still low. Our contribution to this strand of literature is to show that knowledge spillover played a significant role in inventions in the contexts other than the cutting-edge science and technology that have been the subject of previous studies.

Second, this paper is related to the literature on the implication of spatial distance in knowledge spillovers. Starting with Jaffe et al. (1993), many articles have studied geographical barriers of knowledge spillovers (e.g., Murata et al., 2014; Inoue et al., 2019; Griffith et al., 2011). They find that the main driver of the geographic frictions in knowledge spillovers is the cost of communication between remote inventors, especially by face-to-face contacts, which requires trip costs. Inoue et al. (2019) show that co-invention relationship is geographically concentrated. In addition, it reveals that the pattern of concentration is unchanged from 1986 to 2006, although information technologies for remote communication were vastly developed, suggesting the importance of face-to-face contacts. Our paper contributes to this strand of literature by showing the importance of face-to-face contacts on innovation in causal sense, using Spanish Influenza Pandemic as a plausible natural experiment.

Finally, this paper is related to the literature on the economic impact of Spanish Influenza. In the previous literature, there has been a body of studies examining the fatal origin hypothesis that the characteristics of the fetal period have a persistent impact in later life, as exemplified by the study by Almond (2006). In the context of Japan, Ogasawara (2017, 2018) examines the hypothesis. However, studies examining Spanish Influenza's direct impact on the economy are scarce. As an exemption, Barro et al. (2020) showed that Spanish Influenza had a significant negative macroeconomic impact using cross country data. In Japan, Noy et al. (2020) showed that the high mortality rate of Spanish influenza negatively affected production in the textile industry, which was the largest industrial sector at that period in Japan. Contrasting those papers, our paper contributes the literature by showing the pandemic's impact on innovation activities in line with Berkes et al. (2020), which shows the impact on NPCs on innovation activity in US city level panel data. Our findings are consistent with Berkes et al. (2020), who estimate the impact of Non-Pharmaceutical Interventions (NPIs) on innovation in the Spanish flu pandemic in the U.S. They find that the number of patent applications do not decrease in cities with stronger NPIs. This is possibly because the NPIs prevented the increase in inventor deaths and did not result in the loss of human interactions. Given that strong NPIs were not implemented in Japan, the reason for the decrease in the number of patent applications in collaboration intensive technology in this study is consistent with Berkes et al. (2020)'s interpretation. That is, the decrease in human interaction is due to the death of inventors.

The remainder of this paper is organized as follows. In the next section, we overview the Spanish Influenza pandemic in Japan. Section 3 describes the dataset, especially our novel historical patent database in Japan. Section 4 explains our empirical strategy, exploiting the pandemic period and characteristics of the patent technology classes. Section 5 presents the results and discusses possible mechanisms. Finally, Section 6 concludes the paper.

2 Historical backgrounds

The Spanish Influenza pandemic in Japan had three waves. The first wave was from October 1918 to March 1919, the second wave from December 1919 to March 1920, and the third wave from December 1920 to March 1921. According to the Ministry of Health Bureau, 23.8 million people were infected and 0.39 million people died against the total population of 55 million in Japan (Ministry of Home Affairs, 1922, pp.85-91). Figure 1 shows the number of excess deaths which can be attributable to the Spanish flu in the period of the pandemic following Hayami (2006)[1]. The first and second waves caused a substantial number of deaths, and the third wave was much lower.

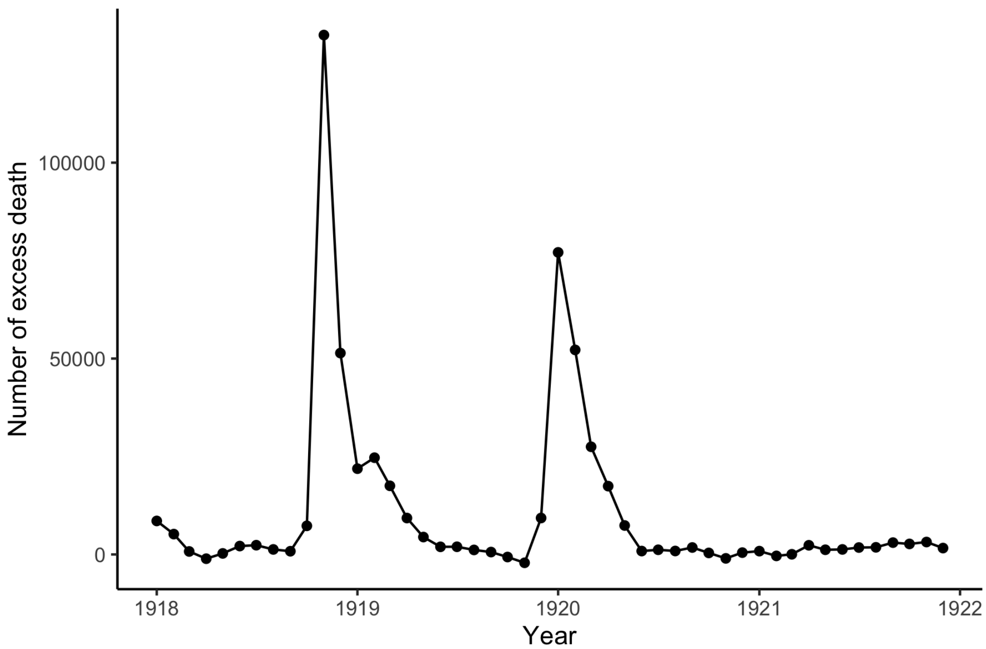
The pandemic had a substantial impact on economic activities and lifestyles. For instance, the number of trains and buses was reduced because of the rise in infection rate among employees of railroad and bus companies, making it difficult for citizens to travel within a city. (Hayami, 2006; Ministry of Home Affairs, 1922). Even though the government did not officially order the closure of factories, many factories had to shut down due to the spread of the flu among their employees. Given this situation, the government instructed that if any worker of a factory had the influenza infection or was suspected to have it, they were required to be absent from work for a certain period of time. Reduction of the trains and buses would be an impediment to face-to-face communication between inventors. Factory closures would also be an impediment to the R&D activities conducted there.

A notable feature of the Spanish Influenza in Japan was that the mortality rate was highest for working age people from 20 to 49 years old. More precisely, the mortality rate by the Spanish Influenza, that is, the number of influenza deaths per total population in each age group, was the highest for the 30-34 age group for males and for the 25-29 age group for females. This suggests that many workers in various occupations were lost. In fact, Ministry of Home Affairs (1922) states that among the total deaths by the Spanish Influenza, 62.6% were employed, which means more than 240,000 employed people were lost due to the Spanish Influenza.

So many deaths of employed people could have a significant impact on innovation activities. Deaths

[1] Excess deaths are defined as the number of influenza-related deaths minus the number of influenza-related deaths in a normal year. We use the years before the pandemic, 1916 and 1917, as normal years. Influenza-related death is defined using the following medium categories of causes of death in the data: influenza, pulmonary tuberculosis, acute bronchitis, chronic bronchitis, pneumonia and bronchopneumonia, other respiratory diseases, and unknown cause.

Figure 1: Number of excess deaths in the pandemic in Japan



Note: Following to Hayami (2006), excess death is calculated based on the average number of deaths in 1916 and 1917.

of colleagues had the opportunities of knowledge diffusion through face-to-face contacts lose. Especially deaths of senior colleagues would negatively affect the future of early career inventors Waldinger (2010). Unlike the "star scientists," whom Waldinger (2010) focus on, it is difficult to obtain the information on detailed careers of each engineer or on the exact number of engineers who died by the pandemic. For a certain group of companies, however, we can obtain the information on the deaths of engineers. Each issue of the Internal Newsletter of Mitsubishi (*Mitsubishi Shashi*) (Mitsubishi Corporate History Publishing Association, 1981) lists the names and dates of retirements from each company in the Mitsubishi Group, along with the reason for retirement and the job title at the time of retirement. Table 1 shows the annual number of cases where the reason for retirement was death and the job title at the time of retirement was an engineer (*gishi* or *gishi-ho* in Japanese). It is observed that the number of deaths of engineers increased between 1918 and 1920. Of course, not all deaths during this period were because of the Spanish Influenza, but the increase in deaths during the pandemic period (excess deaths) can be attributed to the Spanish Influenza. Two of the engineers who died during this pandemic period had registered patents, according to our patent database explained in the next section. Both of them had a tenure of about 10 years, and were presumably young. One of them had applied for a patent in 1918 with three colleagues, and the loss productive colleague who could produce a patent must have had a significant negative impact to the remaining colleagues.

Table 1: Number of engineer deaths in Mitsubishi Group during the pandemic

Year	Number of engineer deaths
1917	4
1918	9
1919	13
1920	11
1921	5

3 Data

We use a novel historical patent database in Japan developed by Inoue et al. (2020). The database covers all the Japanese patent information from 1887, when the modern patent system was established in Japan to 1950. The database provides the information on the inventor's name and address, the assigner's name and address, and the technology classifications for all the patents registered in those periods. We restrict the sample to patents applied from 1911 to 1930.[2]

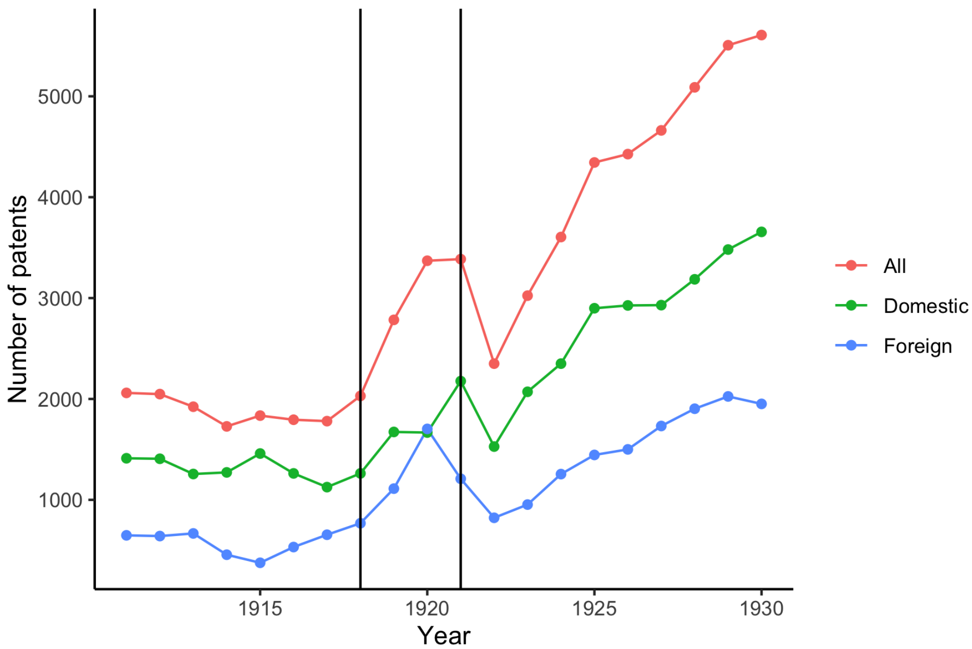
The official technology classification system was revised in our sample period. To make the technology classification consistent throughout the sample period, we use the Catalogue of Patents by Technology Classification published in 1958 (Japan Patent Office, 1958). This is the list of all the patents registered to that time, which reassigned a technology class to each patent according to the technology classification system at that time. The reassigned technology class in the Catalogue is a so-called Japan Patent Classification established in 1952, which has 132 classes. We use the Japan Patent Classifications as the main technology classification measure. Additionally, to capture broad industry classifications (agriculture, chemistry, electricity, machinery, textile, and necessities), we use the patent classification system in 1915 as a supplement. By combining Japan Patent Classification and the patent classification in 1915, we have a patent classification system with 182 classes.

Figure 2 shows the number of patents applied in the sample period. The sample period covers the period when Japanese industries started to upgrade by adopting foreign technologies. Around 2,000 patents were applied each year in the 1910s. Out of them, almost one third were held by inventors with foreign addresses. The majority of these foreign patents were by German inventors. Since Germany became Japan's enemy in World War I from 1914 to 1918, the number of foreign patent applications decreased during the war. Meanwhile, the number of patents applied by inventors with domestic addresses steadily increased throughout the sample period.

We aggregate the patent data to technology $\times$ year level. Table 2 reports the summary statistics of the samples for selective three years: pre-pandemic (1916), during-pandemic (1921), and after-pandemic (1926). We can identify co-inventions by the information of inventor's name. If multiple inventors are

[2]As Inoue et al. (2020) write, the Japan Patent Office in Tokyo was destroyed by the Great Kanto Earthquake in 1923, and all the documents until that time were lost. The patent information available today for the years before 1923 was organized by re-collecting documents that were scattered outside Tokyo, such as at the regional branch offices. Therefore, for a considerable number of patents before 1911, bibliographic information are incomplete.

Figure 2: Number of patents applied



registered for a patent, we regard that patent as a co-invention by the registered inventors. As shown in Table 2, the share of patents by co-inventions gradually increased overtime. In 1916, the share of patents by co-invention is 9.6%, which became 13.4% in 1926.

4 Hypothesis and empirical strategy

As described above, the Spanish Influenza pandemic led to the closure of factories, restrictions on movement, and the deaths of workers. This resulted in a significant loss of opportunities for face-to-face contact between workers. This would significantly impede knowledge diffusion across workers and consequently decline innovation. However, the pandemic's impact would not be uniform across technology fields. The impact would be greater for technologies that required more knowledge diffusion through face-to-face communication. Thus, we propose the testable hypothesis that Spanish Influenza pandemic hindered innovation activities in the technology fields that required intensive face-to-face communications.

We use Difference-in-Differences approach to identify the impact of pandemic on innovation activities. We categorize patent technology classes into the face-to-face communication intensive classes and the face-to-face communication non-intensive classes. To do so, we use the role of collaborative innovation activities in each patent technology class before the pandemic. The patent technology classes, where knowledge exchange through face-to-face communication was important, are likely to have a greater fraction of collaborative patents. However, the patent technology classes, where knowledge exchange through face-to-face communication is less important are likely to have a smaller fraction of collaborative patents because it is easier for one person to invent. We consider a patent a collaborative patent if multiple

Table 2: Summary statistics

	Mean	SD	Min	Median	Max
(A) 1916					
Number of Patent (All)	14.339	12.42	1	11	80
Number of Patent (Domestic)	10.137	8.727	0	8	41
Share of Co-invented Patent (All)	0.096	0.112	0	0.074	0.667
Share of Co-invented Patent (Domestic)	0.111	0.199	0	0.025	1
(B) 1921					
Number of Patent (All)	26.903	18.697	2	21.5	78
Number of Patent (Domestic)	17.548	14.082	0	13.5	68
Share of Co-invented Patent (All)	0.115	0.104	0	0.099	0.625
Share of Co-invented Patent (Domestic)	0.088	0.101	0	0.071	0.5
(C) 1926					
Number of Patent (All)	34.702	33.18	2	24	169
Number of Patent (Domestic)	25.524	24.692	0	18	149
Share of Co-invented Patent (All)	0.134	0.131	0	0.106	0.667
Share of Co-invented Patent (Domestic)	0.126	0.141	0	0.085	0.667

inventors are registered. We then calculate the fraction of collaborative patents for all the patents in each technology class, for the period from 1911 to 1917. We define the patent technology classes with the fraction of collaborative patents greater than the 75 percentile as collaboration intensive technology that is considered to require intensive face-to-face communication for invention. We use the collaboration intensive technology as the treatment group, and other technology classes as the control group.

Table 3 shows the mean value of the fraction of co-invention in the pre-pandemic period by technology. For the all-patent applications, including those from both of domestic and foreign inventors, Chemistry and Textile have larger mean values. However, if we focus on the patent applications by domestic inventors, Electricity and Textile have larger mean values, whereas Machinery and Necessities have smaller mean values. According to Nakaoka (2006), there are two types of inventors in Japan during this period: traditional inventors who invented in the field of traditional industries, and the so-called engineers who invented in the field of modern industries. Traditional inventors mainly belonged to the necessity sector.

Table 3: Share of co-invented patent by technology

Technology	Share of Co-invented Patent (All)	Share of Co-invented Patent (Domestic)
Agriculture	0.11	0.10
Chemistry	0.14	0.11
Electric	0.11	0.13
Machinery	0.11	0.08
Necessities	0.09	0.08
Textile	0.14	0.13

Table 4 shows the summary statistics of the main variables in the pre-pandemic periods. We aggregate each variable in each technology class by summing all the pre-pandemic periods, and calculate mean and standard deviations by collaboration intensive and non-collaboration intensive technology classes. Main outcome variables, number of patents by all inventors, and number of patents by domestic inventors are not significantly different between the collaboration intensive and the non-collaboration intensive technology classes. For both variables, the mean values are slightly larger for collaboration the intensive technology class, but the difference is not significant.

Table 4: Summary statistics in the pre-pandemic periods

	Collaboration intensive technology		Other technology		
	No. Obs	mean (sd)	No. Obs	mean (sd)	p-value
Number of Patent (All)	33	109.97 (124.521)	99	96.212 (70.005)	0.431
Number of Patent (Domestic)	33	74.182 (87.784)	99	68.071 (54.741)	0.638
Share of Co-invented Patent (All)	33	695.606 (806.124)	99	605.414 (442.912)	0.42
Share of Co-invented Patent (Domestic)	33	0.14 (0.072)	99	0.083 (0.074)	0 ***

The estimation equation is as follows,

$$\begin{aligned}\text{Number of patents}_{it} =& \beta_1(\text{Collaboration Intensive Dummy}_i \times I[1919 \leq t \leq 1921]) \\ &+ \beta_2(\text{Collaboration Intensive Dummy}_i \times I[1922 \leq t]) + \eta_i + \zeta_t + \varepsilon_{it},\end{aligned}$$

where $\text{Number of patents}_{it}$ is the number of patent applications in technology class i in year t. $\text{Collaboration Intensive Dummy}_i$ is the dummy variable that equals to one, if technology class i belongs to the collaboration intensive technology class, and zero otherwise. $I[1918 \leq t \leq 1922]$ is the dummy variable that equals to one, if year t is the during pandemic period (1918-1922). $I[1923 \leq t]$ is the dummy variable that equals to one, if year t is after the pandemic period (1923-). η_i is technology class fixed effect, ζ_t is year fixed effect, and ε_{it} is the error term.

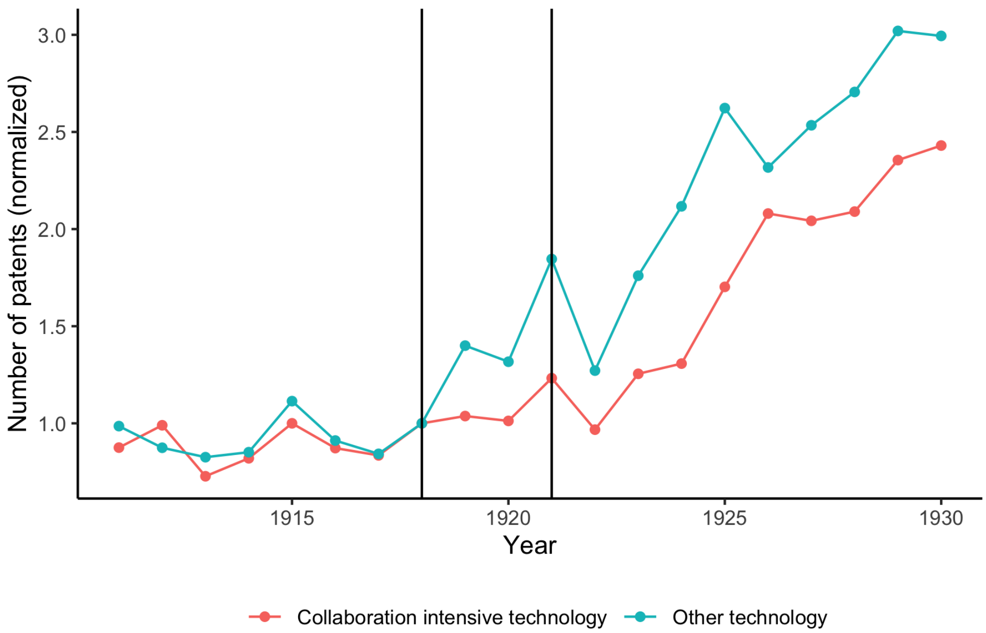
As shown in Table 2, some technology classes had no patent application during certain years. To address this zero-application problem, we conduct the estimation by Pseudo Poisson Maximum Likelihood method proposed by Silva and Tenreyro (2006).

5 Results

5.1 Baseline results

Figure 3 shows the average number of patents by matched treatment and control groups. Those variables are standardized in 1917 by dividing the number of patents in 1917. The number of patent applications was similar for the treatment and control groups, before the pandemic. However, when the pandemic broke out in 1918, patent applications of the two groups sharply diverged. That is, patent applications in the treated group decreased relative to those in the control group. Furthermore, although the pandemic was over by the end of 1921, the gap between the two groups did not narrow until the late 1920s. The plot shows that the Spanish Influenza pandemic had a significant and persistent impact on the innovation activities in collaboration intensive technology.

Figure 3: Number of patents (Collaboration intensive technology vs. other technology)



Note: The number of patents are standardized by dividing by those in 1917. Two vertical lines show 1918 and 1921, the start and end of the pandemic respectively.

The baseline results of the DID estimation are reported in Table 5. Column (1) is the result of using the patent samples by both foreign and domestic inventors. First, the coefficient on the interaction of the collaboration intensive dummy and the pandemic dummy is negative and statistically significant. The number of patent applications in the collaboration intensive technology classes declined by 18% during the pandemic period. Second, the coefficient on the interaction of the collaboration-intensive and the after-pandemic dummies are negative, but not significant. These results suggest that patent applications in collaboration intensive technology fields declined during the pandemic period, but it recovered after it. Third, Column (2) shows the result for the case where we the use number of patents by domestic inventors as the outcome variable. The result is qualitatively the same as Column (1). That is, during the pandemic period, invention by domestic inventors significantly declined in the collaboration intensive technology classes. To control for the heterogeneity across technology classes, we conduct the same exercise using matched sample. Column (3) shows the result. The result is qualitatively the same, but the magnitude increases. Especially, even if it is not significant, the decline in the number of patent application is larger after the pandemic than during the pandemic. This suggests that the pandemic's negative impact on the innovation activities, in collaboration intensive technology, sustains after the pandemic.

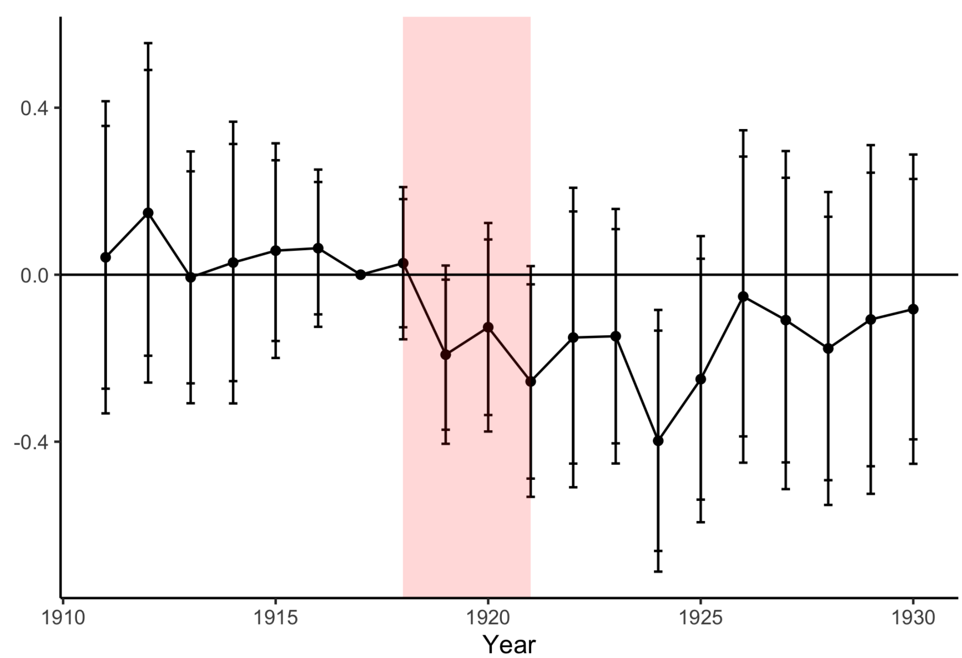
Figure 4 shows the event study plots. The outcome variable is the number of patent applications by domestic inventors. We use the matched sample and set 1917 as the base year. The red shaded areas represent the pandemic period. Bars show that the 90% and 95% confidence intervals. It clearly shows that before the pandemic, the trends of the patent applications are not different between the treatment

Table 5: Baseline result

Dependent Variables:	Number of patents (All)	Number of patents (Domestic)	
Model:	(1)	(2)	(3)
Variables			
Collaboration Intensive Dummy × During Pandemic	-0.177***	-0.159**	-0.193**
	(0.060)	(0.065)	(0.094)
Collaboration Intensive Dummy × After Pandemic	-0.108	-0.067	-0.218
	(0.134)	(0.114)	(0.134)
Sample	All	All	Matched
Fixed-effects			
Technology class	Yes	Yes	Yes
Year of Submission	Yes	Yes	Yes
Fit statistics			
Pseudo R^2	0.66172	0.61077	0.65518
Log-Likelihood	-11,215.7	-9,434.3	-4,764.4
Observations	2,640	2,640	1,320

Note: * p<0.10, ** p<0.05, *** p<0.01. Standard errors are clustered by technology-class level.

Figure 4: Event study plot on number of patent applications by domestic inventors



Note: Dots show the point estimates of the coefficient for Collaboration Intensive Dummy$_i$ times year dummies. Bars show that the 95% and 90% confidence intervals. We set 1917 as the baseline year. Red shaded area shows the treatment period (1919–1921). Sample for the estimation is matched by the pre-treatment characteristics.

group and the control group. During the pandemic period, however, the number of patent applications in collaboration intensive technology declined. Even after the pandemic, the downward trend continues until 1925. This shows that the Spanish Influenza pandemic negatively affected innovation activities in the collaboration intensive technology classes during the pandemic period, and this negative effect continued for a few years. This persistency suggests that the decline of innovation activities in collaboration intensive technologies caused by the persistent decline of human interactions due to the death of the inventors by the pandemic.

The number of technology classes is not so large, and the results may be sensitive to the threshold to define treatment group. Hence, instead of using a binary variable on the treatment group or the control group, we conduct the same DID exercise using the share of co-invented patent in the patent applications before the pandemic as the treatment variable. The results are shown in Table 6. Results are qualitatively

Table 6: Results using continuous treatment variable

Dependent Variables:	Number of patents (All)	Number of patents (Domestic)	
Model:	(1)	(2)	(3)
Variables			
Share of Patents by Collaboration × During Pandemic	-1.23**	-1.37**	-1.86**
	(0.504)	(0.629)	(0.841)
Share of Patents by Collaboration × After Pandemic	-0.763	0.602	-1.01
	(1.47)	(1.10)	(1.35)
Sample	All	All	Matched
Fixed-effects			
Technology class	Yes	Yes	Yes
Year of Submission	Yes	Yes	Yes
Fit statistics			
Pseudo R^2	0.66139	0.61092	0.65391
Log-Likelihood	-11,226.5	-9,430.6	-4,782.0
Observations	2,640	2,640	1,320

Note: * $p<0.10$, ** $p<0.05$, *** $p<0.01$. Standard errors are clustered by technology-class level.

similar to the baseline results. During the pandemic period, the number of patent applications declined in the collaboration intensive technology.

In summary, the number of patent applications in the collaboration-intensive technology decreased during the pandemic period. This can be observed even if patent applications by foreign inventors are excluded, which means that the number of inventions by domestic inventors in the collaboration-intensive technology classes decreased during the period. In addition, this negative impact of the pandemic on inventions was observed even after the pandemic period. These results indicate that the pandemic affected the inventions in the collaboration-intensive technology not only during the pandemic, but also for years after the pandemic ended.

5.2 Other nature of the technologies

5.2.1 Technologies related modern vs. traditional industries

It is possible that the nature of inventors differed by technology, and the difference in the development paths of technologies drive the baseline results. As mentioned above, Nakaoka (2006) classifies pre-war Japanese inventors into two groups. The first is craftsman in the traditional sector who created inventions related to the improvement of incumbent technologies. The second are the so-called engineers with higher education who belonged to modern industries and engaged in development of technologies as professional engineers. Most collaboration intensive technologies might be modern technologies, and they would be developing along with Japan's industrialization. To control for the difference between traditional and modern technologies, we exclude traditional technologies from our samples.

To identify traditional technologies, we use the broader class information of the patent classification. As mentioned above, the patent classification system in 1915 classifies six broad technology categories (Table 3), and most of the traditional technologies are classified into the necessities class. Hence, we consider the technology classes categorized into necessities as traditional technologies. Then, we run the regressions excluding the technologies of the necessities. As shown in Table 3, the share of co-invented patents in the necessities class is smaller than the other classes.

The estimation results are reported in Table 7. Column (1) shows the results using

Table 7: Results excluding technologies in Necessity

Dependent Variable:	Number of patents (Domestic)			
Model:	(1)	(2)	(3)	(4)
Variables				
Collaboration Intensive Dummy × During Pandemic	-0.169**	-0.193**		
	(0.070)	(0.094)		
Collaboration Intensive Dummy × After Pandemic	-0.117	-0.218		
	(0.119)	(0.134)		
Share of Patents by Collaboration × During Pandemic			-1.67**	-1.86**
			(0.698)	(0.841)
Share of Patents by Collaboration × After Pandemic			-0.121	-1.01
			(1.21)	(1.35)
Sample	All	Matched	All	Matched
Fixed-effects				
Technology class	Yes	Yes	Yes	Yes
Year of Submission	Yes	Yes	Yes	Yes
Fit statistics				
Pseudo R^2	0.61457	0.65518	0.61427	0.65391
Log-Likelihood	-7,773.3	-4,764.4	-7,779.2	-4,782.0
Observations	2,140	1,320	2,140	1,320

Note: * $p<0.10$, ** $p<0.05$, *** $p<0.01$. Standard errors are clustered by technology-class level.

Collaboration Intensive Dummy$_i$ as the treatment variable, and Column (2) shows the results restricting to matched samples. In both specifications, even if we exclude technologies belonging to necessities related to traditional industries, the results are mostly unchanged. The number of patent applications by domestic inventors in the collaboration-intensive technologies decreased during the pandemic period. Similarly, if we use the share of patents by collaboration as the treatment variable, the results remain qualitatively unchanged (Columns 3 and 4).

5.2.2 Impact of WWI

The Spanish Influenza began during WWI (1914-1918), and the pandemic's inception in Japan was just after WWI. Therefore, it is possible that the effect of the end of WWI drives our baseline results. In this section, we discuss this possibility.

First of all, although Japan participated in WWI as an Allied country, it did not suffer direct damage to its land, because it was far away from Europe, the main battleground. Therefore, we need not to consider the direct damage caused by the war. WWI affected Japan through the channel of international trades. In particular, the disruption of European exports to Japan due to WWI had a substantial impact on the Japanese economy. During that time, Japan was in the process of industrialization and relied on imports from Europe for a variety of materials and products. In particular, it depended on imports of dyes and pharmaceuticals from Germany. Disruption of import from Europe provided an opportunity for Japan to substitute domestic production for import (Oishi, ed, 1985; Nakaoka, 2006). In addition, Japanese government enforced compulsory licensing of the patents registered German applicants by the enemy act to promote those industries and technologies. Moser and Voena (2012) revealed that the compulsory licensing of German patents in the U.S. led to a 20% increase in patent production in the U.S., and a similar phenomenon may have occurred in Japan.[3]

To exclude the impact of the compulsory licensing, we conduct the DID exercise excluding technologies related to dyes and pharmaceuticals (Japan Patent Office, 1985; Nakaoka, 2006). The results are reported in Table 8. The results are mostly the same as the baseline results.

5.3 Mechanism

We have established that the number of patent applications by domestic inventors decline during the pandemic period. Then, the next question is, why did this occur? This subsection tackles this question.

5.3.1 Entrant vs. incumbent inventors

To do that, we divide patent applications into those by entrant inventors and incumbent inventors. The entrant inventors here are the inventors who applied patents for the first time in their careers. Using the number of patents applied by the entrant inventors, we conduct the same DID exercise. The results are reported in Table 9. Column (1) shows the results using the number of patents applications by domestic entrant inventors as the outcome variable. The number of patent applications by domestic entrant inventors declined significantly during the pandemic period. Column (2) shows the result using the share of

[3]Moser and Voena (2012) also show that the positive impact of compulsory licensing mainly arises from patents registered in 1931, ten years after the licensing. This is because it takes take time to understand the advanced technology through experience and learning. Since Japan, during those periods, was relatively less developed than the US, it was expected to take more time to catch up with the latest technologies. Thus, even if the compulsory licensing positively affects domestic invention in technologies that have licensed patents, it would be ignorable in our study periods till 1928.

Table 8: Results excluding WWI related technology

Dependent Variable:	Number of patents (Domestic)			
Model:	(1)	(2)	(3)	(4)
Variables				
Collaboration Intensive Dummy × During Pandemic	-0.143**	-0.187*		
	(0.067)	(0.097)		
Collaboration Intensive Dummy × After Pandemic	-0.072	-0.202		
	(0.115)	(0.134)		
Share of Patents by Collaboration × During Pandemic			-1.20*	-1.77**
			(0.666)	(0.896)
Share of Patents by Collaboration × After Pandemic			0.672	-0.859
			(1.18)	(1.47)
Sample	All	Matched	All	Matched
Fixed-effects				
Technology class	Yes	Yes	Yes	Yes
Year of Submission	Yes	Yes	Yes	Yes
Fit statistics				
Pseudo R^2	0.60517	0.64854	0.60529	0.64730
Log-Likelihood	-9,108.0	-4,465.9	-9,105.4	-4,481.6
Observations	2,580	1,260	2,580	1,260

Note: * $p<0.10$, ** $p<0.05$, *** $p<0.01$. Standard errors are clustered by technology-class level.

collaborative patents before the pandemic as the treatment variable. Columns 3 and 4 restrict the samples to the matched ones. The results are qualitatively the same. The number of patents applied by domestic entrant inventors declined for collaboration intensive technology classes during the pandemic period.

We can conduct the same exercise using the number of patents by incumbent inventors as the outcome variable. The results are reported in Table 10. Contrasting the case of the entrant inventors, the number of patents by incumbent inventors in the collaboration intensive technology classes did not change during the pandemic period in any specifications. These results suggest that the decline in the number of patents in collaboration intensive technology is driven by the decline in the entries of new inventors, not by the decline in inventions by incumbent inventors.

5.3.2 Incumbent inventors' response to the pandemic

To explore why incumbent inventors in the collaboration intensive technology were not affected by the pandemic, and how they react to the pandemic, we conduct the inventor level analysis. First, we restrict the data to the incumbent inventors, that is, the inventors who applied at least one patent before the pandemic. Then, we aggregate the number of patent applications by inventor and by year. Using these data, we analyze how invention activities differed between the inventors who had many collaborations before the pandemic and those who did not during the pandemic. Specifically, we estimate the following equation.

$$\begin{aligned}\text{Number of patents}_{it} =&\beta_1(\text{Share of co-invention}_i \times I[1919 \leq t \leq 1921]) \\ &+ \beta_2(\text{Share of co-invention}_i \times I[1922 \leq t]) + \eta_i + \zeta_t + \varepsilon_{it}\end{aligned}$$

Table 9: Entrant inventors

Dependent Variable:	Number of Patents (Domestic)			
Model:	(1)	(2)	(3)	(4)
Variables				
Collaboration Intensive Dummy × During Pandemic	-0.232***		-0.267***	
	(0.053)		(0.089)	
Collaboration Intensive Dummy × After Pandemic	-0.144		-0.333***	
	(0.108)		(0.125)	
Share of Patents by Collaboration × During Pandemic		-2.25***		-2.82***
		(0.591)		(0.847)
Share of Patents by Collaboration × After Pandemic		-0.413		-2.09*
		(0.965)		(1.14)
Sample	All	All	Matched	Matched
Fixed-effects				
Technology class	Yes	Yes	Yes	Yes
Year of Submission	Yes	Yes	Yes	Yes
Fit statistics				
Pseudo R^2	0.54008	0.53970	0.59186	0.58965
Log-Likelihood	-9,294.9	-9,302.5	-4,761.5	-4,787.3
Observations	2,640	2,640	1,320	1,320

Note: * p<0.10, ** p<0.05, *** p<0.01. Standard errors are clustered by technology-class level.

Table 10: Incumbent inventors

Dependent Variable:	Number of Patents (Domestic)			
Model:	(1)	(2)	(3)	(4)
Variables				
Collaboration Intensive Dummy × During Pandemic	-0.101		-0.175	
	(0.145)		(0.177)	
Collaboration Intensive Dummy × After Pandemic	0.111		-0.021	
	(0.198)		(0.234)	
Share of Patents by Collaboration × During Pandemic		0.963		0.594
		(1.24)		(1.50)
Share of Patents by Collaboration × After Pandemic		2.62		0.582
		(1.96)		(2.46)
Sample	All	All	Matched	Matched
Fixed-effects				
Technology class	Yes	Yes	Yes	Yes
Year of Submission	Yes	Yes	Yes	Yes
Fit statistics				
Pseudo R^2	0.57757	0.57832	0.60753	0.60732
Log-Likelihood	-5,953.3	-5,942.8	-3,184.0	-3,185.7
Observations	2,640	2,640	1,320	1,320

Note: * p<0.10, ** p<0.05, *** p<0.01. Standard errors are clustered by technology-class level.

where Number of patents$_{it}$ is number of patent applications by inventor i in the year t. Share of co-invention$_i$ is the share of co-invented patents of inventor i before the pandemic.

The estimation results are reported in Table 11. Column (1) shows the results when we use the sum of the numbers of the patents by solo-invention and by co-invention, as the outcome variable. During and after the pandemic, the number of patents by the collaboration intensive inventors declined. Column (2) shows the results when number of patents by co-invention as the outcome variable. During and after the pandemic, the number of co-invented patents by the collaboration intensive inventors declined. Column (3) shows the results when number of patents by solo-invention as the outcome variable. During and after the pandemic, the number of solo-invented patents by the collaboration intensive inventors increased. Taken together, the results suggest that incumbent co-invention intensive inventors shifted their invention activities from co-invention to solo-invention during and after the pandemic. At the same time, the number of patents declined overall, which suggests that the shift does not completely compensate the decline in co-inventions.

Table 11: Invention by incumbent inventors who applied at least one patent both before and after the pandemic

Dependent Variables:	Number of patents (All)	Number of patents (Co-invented)	Number of patents (Solely-invented)
Model:	(1)	(2)	(3)
Variables			
Share of Co-invention (pre pandemic) × During Pandemic	-0.402***	-2.98***	0.817***
	(0.155)	(0.362)	(0.206)
Share of Co-invention (pre pandemic) × After Pandemic	-0.303**	-4.21***	2.20***
	(0.138)	(0.255)	(0.178)
Sample	All	All	Matched
Fixed-effects			
Inventor	Yes	Yes	Yes
Year of Submission	Yes	Yes	Yes
Fit statistics			
Pseudo R^2	0.25839	0.23459	0.25807
Log-Likelihood	-59,669.9	-12,798.6	-48,137.2
Observations	239,084	65,164	194,860

Note: * p<0.10, ** p<0.05, *** p<0.01. Standard errors are clustered by technology-class level.

Several inventors might quit their innovation activities because of illness and mortality by the flu. The above results might include such a direct impact of the flu. We conduct the same analysis restricting the samples to the inventors who applied at least one patent both before and after the pandemic period. The results are reported in Table 12. They are qualitatively the same as Table 11. However, in Column (1), the negative impact on the number of patent applications by co-inventions and solo-inventions are not significant. This suggests that the pandemic made collaboration intensive inventors shift their invention activities from co-invention to solo-invention. Furthermore, collaboration intensive inventors who continuously invented after the pandemic did not reduce their total invention activity.

In summary, the results suggest that for the inventors who continued inventing after the pandemic, the total number of inventions did not decrease, although they shifted from co-invention to solo-invention.

Table 12: Invention by incumbent inventors who applied at least one patent both before and after the pandemic

Dependent Variables:	Number of patents (All)	Number of patents (Co-invented)	Number of patents (Solely-invented)
Model:	(1)	(2)	(3)
Variables			
Share of Co-invention (pre pandemic) × During Pandemic	-0.143	-1.70***	0.486**
	(0.165)	(0.329)	(0.205)
Share of Co-invention (pre pandemic) × After Pandemic	0.066	-2.82***	1.44***
	(0.142)	(0.240)	(0.171)
Sample	All	All	Matched
Fixed-effects			
Inventor	Yes	Yes	Yes
Year of Submission	Yes	Yes	Yes
Fit statistics			
Pseudo R^2	0.20507	0.22295	0.21535
Log-Likelihood	-28,677.0	-6,141.9	-24,510.3
Observations	50,154	20,526	48,194

Note: * p<0.10, ** p<0.05, *** p<0.01. Standard errors are clustered by technology-class level.

5.3.3 Early career of inventors

Moser et al. (2014) revealed that co-invention with productive inventors in the initial stages of their career leaves a long-term positive impact on the productivity of inventors. The pandemic may have negatively affected inventions in the collaboration intensive technologies classes by depriving potential inventors of the opportunities to collaborate with their senior colleagues earlier in their careers, and thereby, it prevented these potential inventors from being productive inventors. Especially as the level of technology becomes more advanced, it will be difficult to conduct research and development alone from the beginning, and it is likely that an inventor's career begins from learning from their seniors and gradually becoming an independent inventor. In this case, reduction of learning opportunities in the workplace due to pandemics would have a negative impact on the inventors' development in that area, and the effect is expected to be more serious in collaboration-intensive technology classes.

As stated in Section 2, deaths by the Spanish Influenza were serious for the age group between 20 to 49 years old, which includes the so-called prime aged workers. Also, according to Ministry of Home Affairs (1922), who reported detailed analysis of pandemic in a large glass producing factory (Asahi Glass, Co.). 14.6% of the employees in this factory were infected by influenza. Furthermore, among them, a high percentage (16.2%) of young employees within the first year of employment were infected, and the incidence rate decreased as the year since employment increased. This suggests that the Spanish flu may have a greater impact on younger people, and may prevent them from co-working with each other.

To see whether such a career path really existed, we conduct an analysis using the inventor-year level data, used in the previous section. We count the number of patent applications by inventor and by year, for both of solo-invention and co-invention. Then, analyze the relationship between the number of patent applications and the inventors' career. Specifically, we focus on the relationship between the number of co-inventions and the inventor's inventions in the first year of their career. The estimation equation is:

$$\text{Number of co-invented patents}_{it} = \beta \text{First application year dummy}_{it} + \gamma \text{Number of patents}_{it} + \eta_i + \zeta_t + \varepsilon_{it}$$

where Number of co-invented patents$_{it}$ is number of co-invention patent applications by inventor i in the year t. Number of patents$_{it}$ is the total number of patent applications by inventor i in the year t. First application year dummy$_{it}$ is a dummy variable if year t is inventor i's first year of patent submissions.

The results are reported in Table 13. Columns (1) and (2) show the results using the samples of the inventors who applied for a patent at least more than one year. Column (1) shows the result using number of solely invented patents as the outcome variable. The coefficient on the first submission year dummy is negative but not significant. In contrast, Column (2) shows the results using the number of co-invented patents as the outcome variable. The coefficient on the first submission year dummy is positive but not significant. For inventors, including less productive ones who may have invented for just two years, the pattern of collaborating and solo inventions are not significantly different between the first year of invention and the rest of the years of the inventor's career. To focus on more productive inventors, we restrict the

Table 13: Inventor's first year of invention and collaboration

Dependent Variables:	Number of Solo-invented Patents	Number of Co-invented Patents	Number of Solo-invented Patents	Number of Co-invented Patents
Model:	(1)	(2)	(3)	(4)
Variables				
First Application Year Dummy	-0.057	0.091***	-0.113	0.119**
	(0.064)	(0.031)	(0.074)	(0.049)
Log (Number of Total Patents)	2.20***	0.346***	2.10***	0.304***
	(0.269)	(0.050)	(0.133)	(0.058)
Sample	Patenting more than 1 year	Patenting more than 1 year	Patenting more than 3 years	Patenting more than 3 years
Fixed-effects				
Inventor	Yes	Yes	Yes	Yes
Year of Submission	Yes	Yes	Yes	Yes
Fit statistics				
Pseudo R^2	0.49427	0.88118	0.55087	0.66601
Log-Likelihood	-3,032.1	-383.86	-1,241.2	-531.77
Observations	3,648	3,648	1,620	1,620

Note: * p<0.10, ** p<0.05, *** p<0.01. Standard errors are clustered by technology-class level.

samples to the inventors who applied for a patent at least more than three years. Column (3) shows the result including the number of solely invented patents as the outcome variable. The coefficient on the first submission year dummy is negative and significant. Even though we control for the number of total patents on the first year of invention, the number of solo-invented patents are significantly fewer than the rest of the inventor's career. Column (4) shows the results using number of co-invented patents as the outcome variable. The coefficient on the first submission year dummy is positive and significant. Contrasting the solo-invented patents on the first year of invention, the number of co-invented patents are significantly more than the rest of the inventor's career. The results suggest that inventors tend to start their career by collaborating with other inventors. Then, they increase their solo inventions. Spanish Influenza pandemic impeded the opportunity of collaborating with the early career inventors and declined the number of inventions, especially in the technologies that needed more collaboration and face-to-face communications.

5.3.4 Summary of the possible mechanism

In summary, the results suggest the following mechanism. First, the incumbent inventors who had applied for patents before the pandemic shifted from co-inventions to sole inventions during the pandemic. However, the total number of patents did not decrease significantly. Meanwhile, the number of patents by entrant inventors, who had not applied for patents before the pandemic, decreased in collaboration intensive technology classes during the pandemic, and the baseline result is driven by this decrease in new inventors. Regarding the decrease in new inventors, we analyzed the careers of inventors to find that the inventors who continued inventing for a certain period of years made more collaborative inventions early in their careers. This suggests that the pandemic made it difficult for new inventors to invent technologies that required intensive contact and collaboration.

As indicated by Hayami (2006), the pandemic caused a higher mortality rate for the so-called prime age group between 20 to 49 years old. This may have resulted in a decrease in patents by newcomers in the collaboration intensive technology classes, which requires more technical guidance, communication, and knowledge exchange.

6 Conclusion

This study investigates the role of face-to-face communication on innovation using the case of Spanish Influenza pandemic in Japan as an event, which prohibitively increased the cost for face-to-face contact. The results show that the number of patent applications declined by 19% during the pandemic in the collaboration intensive fields. We further find that the decrease in patent applications in the collaboration intensive fields during the pandemic was mainly driven by the decrease in new entries into patent applications. These findings suggest that face-to-face communication indeed contributed to innovation by collaborative work. In addition, they also reveal that opportunities of technical guidance, communication, and knowledge exchange with seniors and colleagues in the early career of an inventor were especially important.

The subject of this study is inventions in Japan at a time when the country was still in the process of industrialization and the level of technology was low. Our results show that knowledge spillovers played a significant role in the inventive activities of such a developing economy and have important implications for development policy.

Under the COVID-19 pandemic, many cities were locked down and social distancing policies were implemented. Many people worked from home and their former communications with colleagues based on face-to-face were replaced by online meetings. Even though online communication technologies can complement the lack of face-to-face communication, the decline of face-to-face communication may affect innovation activities in the medium term.

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