The Road to Economic Recovery: Pandemics and Innovation

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Abstract: In this paper, we investigate the economic consequences of pandemics from an idea-based theory of economic growth. We assume that pandemics pose a threat to research productivity and analyse the long-term consequences of pandemic shocks to innovation output. We demonstrate that following a pandemic, innovation output is disrupted for approximately seven years. The effect of pandemic shocks on innovation output varies between countries, and sector to sector regarding economic activity. Pandemic shocks lead to a short-term drop in the number of patent applications. Crucially, the duration of a pandemic has a strong effect on innovation output. Overall, the effects of this most recent pandemic on future innovation output, and subsequently on growth, are expected to be felt long into the future. This paper supports the policies designed to reduce the effect of the "Great Lockdown" on research productivity. Policies that target the more innovative firms are moving in the right direction in terms of reducing the time it will take for innovation to recover from the effects of COVID19.

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1. Introduction

"At such difficult times, the importance of innovation comes to the fore. When we emerge from this challenging time, we will need the UK's entrepreneurial spirit to be stronger than ever."

Tej Parikh (Institute of Directors) responding to the announcement of the Future Fund

On 20 April 2020, in response to the COVID-19 pandemic, the UK government announced the Future Fund, a billion pound support package for innovative firms.[2] The objective of this policy is very clear: to support the road to economic recovery by increasing the intensity of innovation. The link between innovation and GDP growth is undisputed: Kogan et al. (2017) demonstrate that innovation waves are followed by an acceleration in per capita GDP and productivity. Hasan and Tucci (2010) show that countries hosting more innovative firms also have higher economic growth. Importantly, Kogan et al. (2017) and Acemoglu et al. (2018) show that increases in aggregate innovation dominate creative destruction, leading to real increases in output. Acemoglu et al. (2018) demonstrate that such increases can be achieved more efficiently via a targeted policy response to encourage innovation within the more innovative firms.

Schumpeterian growth theory, as outlined above, depends on the ability of researchers to produce ideas. However, Bloom et al. (2020) show that during the decades preceeding the explosion of the COV-19 pandemic, research productivity declined sharply in the US. The slowdown in research ideas caused by "Great Lockdown" (Gopinath, 2020) is only going to

[2] Along similar lines, on 27 March 2020, the US President, Donald Trump, signed into law the Coronavirus Aid, Relief, and Economic Security Act with an aim to support individuals and businesses affected by the impact of COVID-19.

exacerbate the problem of the fall in research productivity (Gorlick, 2020) as the social environment that affects the intensity of creativity is affected (see Amabile et al., 1996).

In this paper, we investigate the effect of past pandemics on innovation output. To the best of our knowledge, this is the first attempt to provide evidence regarding the long-term effects of pandemics on research productivity, thereby shedding light on the ways in which pandemic episodes impact economic growth.

We use patent data from the European Patent Office's PATSTAT database and select data from 1900 to 2012. We focus on the set of G7 countries (Canada, France, Germany, Italy, Japan, the United Kingdom and the United States) and pandemic episodes with at least reported 100,000 deaths. Our measure of innovation output is the number of successful applications per country per year. We use a set of model-free or local projection estimators that allows us to estimate local projections sequentially *h* steps ahead into the future.

We show that following a pandemic, innovation output is disrupted for a period of approximately seven years, probably because of a drop in research productivity. This result is striking as it shows a much more long-term effect in innovation output that the one anticipated. Our model provides more reliable forecasts of the long-run rather than the short-run effects of pandemics on innovation output. We show that the main result of the effect of pandemic shocks on aggregate innovation output is driven mainly by a significant reduction in innovative activity in the Information and Communication technology sector. Furthermore, there are some notable differences in the magnitude of the pandemic shock across countries and the time to recovery. Pandemic shocks lead to a short-term drop in the number of patent applications. Finally, pandemic duration is strongly associated with a drop in patent applications. The results are robust to a number of robustness tests.

Our results have important policy implications. The paper supports the policies designed to reduce the effect of the "Great lockdown" on research productivity. Given the non-rival nature of innovation, the response to COVID19 needs therefore to have a global character as this will support economic growth. To this end, governments need to be prepared to support innovators in the immediate aftermath of the pandemic and patent offices may have to speedup the process of approving new patents. Finally, we recommend adopting policies that target the more innovative firms as this is expected to help reduce the time it will take for innovation to recover from the effects of COVID19.

In Section 2, we outline the Schumpeterian theory of economic growth and develop the hypothesis. In Section 3, we discuss our innovation data and develop our empirical strategy. In Section 4, we present the results of the empirical analysis and discuss policy implications. In Section 5, we present the results from our robustness checks and in Section 6 we conclude the paper.

2. The Schumpeterian theory of economic growth, shocks to innovation output and hypothesis

In this section, we discuss innovation as a mediating factor in achieving economic growth. Schumpeterian growth theory relies on the assumption that aggregate innovation dominates creative destruction. The economic consequences of pandemic shocks are felt for long into the future and macroeconomic and firm-specific shocks lead to smaller innovation output. In the following paragraphs, considering the link between pandemic shocks, economic growth and innovation, we suggest that pandemic shocks are likely to lead to a reduction in aggregate innovation output.

2.1. The Schumpeterian growth theory

Undoubtedly, Schumpeter's biggest contribution to economic thinking is the notion of "creative destruction" that characterises economic systems. According to Schumpeter, the process by which economies grow is a mostly evolutionary process, during which new innovations replace old innovations. This evolutionary process is endogenous, that is, it comes from within the economic system itself, it occurs discontinuously, at irregular intervals and with varying magnitudes, and brings fundamental changes, replacing old conditions with new equilibria (see Elliott, 1980).

Schumpeterian growth theory is effectively the "operational arm" of Schumpeter's idea of creative destruction.[3] Schumpeterian growth models assume that (i) firm and personal innovations (the innovators) affect the entire economy, (ii) innovators are motivated by the prospects of private wealth that come in the form of monopoly rents and (iii) new innovators have the capacity to eventually replace old innovators (creative destruction). The amount of

[3] For a detailed presentation of Schumpeterian growth theory, see Aghion et al. (2014).

research conducted by the innovators is a function of the prospects of monopoly rents and increases in higher wages for skilled workers over the next period (see Aghion and Howitt, 1992). In its basic form, therefore, the value of a new innovation is a positive function of the expected profit from this innovation minus the cost of creative destruction, that is the loss of monopoly rents from new innovations that replace old innovations (Aghion et al., 2014).

On aggregate, the effect of innovation on economic growth is positive when the increases in productivity achieved by new innovations are greater than the loss of monopoly rents of the previous innovator. Aghion and Howitt (1992) called the former effect "knowledge spillover effect" and the latter "business-stealing effect". Empirically, Acemoglu et al. (2018) have identified that holding other things constant, increases in aggregate innovation dominate creative destruction, leading to real increases in output. Kogan et al. (2017) show that, as suggested by theory, innovation comes in waves that are followed by acceleration in per capita GDP and productivity. Finally, Hasan and Tucci (2010) show that countries hosting more innovative firms also have higher economic growth.

2.2. Economic consequences of pandemic shocks and the role of innovation

The above demonstrates that according to the Schumpeterian growth theory, growth is primarily determined by the ability of people to create new ideas. How though, do pandemics affect economic growth?

In a neoclassical growth model, pandemic shocks threaten economic growth by disrupting both supply and demand in an economy. On the supply side, the effect of a pandemic shock is mostly felt by a loss in the number of hours worked. On the demand side, the loss relates to a fall in consumption. Empirical research on the effect of pandemic shocks to economic growth is limited but clearly growing. For the US, Meltzer et al. (1999) show that the estimated economic impact of another influenza pandemic would be between US$71.3 to $166.5 billion. However, the study assumes a closed economy and therefore ignores the costs related to disruptions in commerce. Jonung and Roeger (2006) show that under "reasonable scenarios", a pandemic shock is expected to lead to a loss in European Union GDP of between two and four percent. However, the latest growth forecast for the EU economy is that it is expected to contract by over seven percent in 2020 (see European Commission, 2020). More recently, Jordà et al. (2020) show that following a pandemic shock, the natural rate of interest declines for approximately two years, therefore demonstrating the very long-term effects of pandemics on economic growth.[4]

In an idea-based theory of economic growth, the ability of an economy to grow is the product of research productivity and the numbers of researchers:

$$\text{Economic growth} = \text{number of researchers} \times \text{research productivity}$$

To this end, Bloom et al. (2020) show that research productivity in the US halves every 13 years. Therefore maintaining constant growth requires a constant increase in the number of researchers (see also Kogan et al., 2017).

We assume that a pandemic poses a threat to both research productivity and the number of researchers. Pandemic shocks can first of all lead to a reduction in the number of researchers. This may be the outcome of a very high death toll, a shift of a large number of researchers to other activities, a large number of researchers losing their jobs or a combination of all three. Research productivity is also expected to fall as the social environment that affects the intensity of creativity is affected (see Amabile et al., 1996). In other words, innovation requires a

[4] A number of recent studies have attempted to quantify the effect of the COVID19 pandemic on economic growth (see Baker et al., 2020b and Leduc and Liu, 2020).

stimulating and supporting environment and pandemics threaten the nature of creativity that is essential for research productivity.

To summarise, in light of the above, we hypothesise that pandemic shocks pose a threat to research productivity, thereby reducing innovation output. In the main analysis below, we attempt to examine magnitude and the duration of the pandemic shock to aggregate innovation output.

2.3. Review of the empirical literature

In this subsection, we review the empirical literature on the effect of pandemics on the economy. We focus on the realised and forecasted economic impacts of COVID-19 and supplement it by research regarding previous pandemic episodes. To the best of our knowledge, there is no previous research on the effects of past pandemics on firm innovation output.

The economic crisis caused by COVID-19 has been regarded by the World Trade Organisation (WTO) and the Organisation of Economic Cooperation and Development (OECD) as the largest threat to the global economy since the 2007-08 financial crisis and has increased economic uncertainty, geopolitical risk and implied volatility of oil price (Sharif et al., 2020; OECD, 2020). Notably, Baker et al. (2020b) show that COVID-induced uncertainty is responcible for more than half of the contraction of real GDP in the US and Barro et al. (2020) demonstrate global real GDP per capita and real consumption per capita has decreased by approximately six and eight percent, respectively.

Jordà et al. (2020) focus on the long-term economic impact of past pandemics. They show that pandemics do not destroy physical capital (compared to war); instead, they decrease labour supply and increase real wages for survivors. Carlsson-Szlezak et al. (2020a) and Carlsson-Szlezak et al. (2020b) suggest three main transmission channels through which the COVID-19 pandemic has a negative effect on the economy. The first is the decreased consumption of goods and services. The second is the indirect influence working through the shock of financial markets. The third is the impact on the supply-side, which consists of supply chains, labour demand and employment. We provide empirical evidence for each one of these transmission channels below.

Household consumption dramatically increased at the beginning of the COVID-19 outbreak, followed by a sharp decline in the overall spending when the virus spread and a growing number of people stayed at home (Baker et al., 2020c). Goolsbee and Syverson (2020) show that while consumer traffic is reduced by 60 percent following COVID-19 outbreak, only seven percent of that decrease is explained by the introduction of legal restrictions.

Baker et al. (2020a) show that no previous pandemic has had such an impact on financial markets as the COVID-19 pandemic. They show that this effect is mainly attributed to the fact that government restrictions and voluntary social distancing has had a powerful effect service-orientated economies. Barro et al. (2020) show a dramatically short-term decrease in realised real returns on stocks and short-term government bills following the growth of flu death rates. Ding et al. (2020) investigate the connection between firm characteristics and stock price reactions to COVID-19 cases. They show that the impact of the pandemic was fiercer on firms with weaker financing pre-COVIV-19, more exposure to COVID-19 via supply chain activities, fewer Corporate Social Responsibility (CSR) activities, more entrenched executives and greater hedge fund ownership.

Finally, Bonadio et al. (2020) show that one-quarter of the decline in average real GDP is explained by disruptions in global supply chains. Importantly, because of the spillover effects via supply chains, this negative effect is more severe for countries that are highly dependent on international trade (Fernandes, 2020). Bloom et al. (2020) analyse the impact of COVID-19 on

UK total factor productivity (TFP). They show that TFP in the private sector is reduced by 5% in 2020. In the long term, TFP is likely to increase at a smaller rate due to a reduction in R&D expenditure.

3. Data, variables and methods

In this section we explain our data sources, variable measurements and estimation methods.

3.1. Sample selection and variables

We use patent data from the European Patent Office's PATSTAT database (2016 Autumn Edition). We select data from 1900 to 2012 (approximately 21.5 million successful patent applications) as we drop the final four years to ensure that the data is relatively free of truncation bias (Dass et al., 2017). We focus on the set of G7 countries (Canada, France, Germany, Italy, Japan, the United Kingdom and the United States). The bulk of global innovative activity is concentrated in those seven countries (see also Section 4 and Guloglu et al., 2012). We measure innovation as the number of successful patent applications per country.[5] As a robustness test, we also reproduce the results using a sample of the top ten most innovative countries over the sample period (France, Germany, Korea, Japan, the United Kingdom, the United States, China, Switzerland, Austria, and Russia, hereafter T10).

[5] In line with studies in the innovation literature (see Levine et al., 2017), we (i) identify the first time an invention is patented and call it the "original patent", (ii) date patents using the application year of the original patent as the application date is closer to the actual date of innovation and (iii) focus on utility patents only. We record the country of the invention using the Patent Authority that accepts the application of the original patent, See also the Robustness tests section.

In Figure 1, Panel 1, we present the time series of the average number of applications granted for the G7 countries and the applications granted for the G7 as a proportion of total patenting activity. Equally, in Figure 1, Panel 2, we estimate the same time series for the T10 countries. Innovation output is rather volatile but remained at relatively similar levels until the beginning of the 1970s when Japan and China increased their innovation output. Interestingly, the slump in innovation activity in the 1970s and 1980s is related to innovation activity conducted by the former Soviet Union.

Figure 1

The World Health Organisation (WHO) defines a pandemic as “the worldwide spread of a new disease” (WHO, 2020). However, it makes no mention of a minimum number of cases/deaths that have to be reported in order to call an outbreak a pandemic. As such, we follow the recent paper by Jordà et al. (2020) and select pandemic episodes with at least 100,000 deaths reported (see also Cirillo and Taleb, 2020). The list of pandemics is reported in Table 1. On 15 May 2020, the death toll due to the COVID-19 pandemic was 307,000, a figure much higher than the minimum threshold used in this study.

Table 1

3.2. Estimation methods

We use a local projection estimator model introduced by Jordà (2005) to estimate the impulse response functions of pandemic shocks to innovation output. Local projection estimators are shown to produce more reliable forecasts over Vector Autoregression (VAR) models at medium to longer forecast horizons.

In particular, Pope (1990) shows that the bias in the estimation of the autoregressive parameters increases as impulses are at longer forecast horizons. Additionally, VAR estimators require large lag length to produce reliable impulse responses (Kapetanios et al., 2007). Local projection estimators are more robust to misspecification errors introduced by the data generation process by regressing the dependent variable vector at $t+h$ on the information set at time t. Hence, a new forecast is created by each impulse horizon as compared to the use of iterant forecasting based on the same coefficient estimates from one VAR estimation. The loss of efficiency from estimating local projection impulse responses as opposed to using correctly-estimated VARs, is low at medium to long-term forecast horizons (Haug and Smith, 2012). Furthermore, unlike VAR estimators, the nonlinear transformations of the estimated slope parameter are not required by impulse responses based on local projections. As a result, this approach can be better approximated by Gaussian distributions and thereby increase the coverage accuracy of impulse response confidence intervals.

Our objective is to estimate the impulse response functions for innovation following a pandemic episode. We use a model-free or local projection estimator that allows us to estimate local projections sequentially h steps ahead (see Jordà, 2005 and Jordà and Taylor, 2016) as follows:

$$\Delta Innov_{i,t+h} = \alpha_i^h + \beta^h P_t + \sum_{l=1}^{L} \beta_l^h \, Innov_{i,t-l} + C_i^h + e_{i,t+h}^h; \tag{1}$$

for $h = 1, \ldots, 15,$ and $L = 3$

Where $Innov_{i,t-l}$ is the natural logarithm of one plus the number of successful patent applications per year and for each country i. $\Delta Innov_{i,t+h}$ denotes the innovation's growth rate and is the difference of the natural logarithm of the innovation variable from time t to $t+h$; P_t denotes the dummy variable that is 1 if there is a pandemic start, 0 otherwise; *Ci* denotes country fixed-effects. Three lags of innovation indicator are adopted as control variables.[6]

Furthermore, we access the effect of pandemic shocks by sector of economic activity by estimating the following set of regressions:

$$\Delta Innov_{i,t+h,z} = \alpha_i^h + \beta_z^h P_t + \sum_{l=1}^{L} \beta_l^h \, Innov_{i,t-l} + \, C_i^h + e_{i,t+h,z}^h \qquad (2)$$

In Equation (2) we estimate separate regressions by sector of economic activity, *z*. To this end, we use the existing statistical classification of economic activities for the European Union, NACE Rev.2, in order to categorise patents into three sectors: (1) manufacturing, (2) construction and (3) information and communication. NACE Rev. 2 is developed on the basis of the United Nations' International Standard Industrial Classification of All Economic Activities (ISIC Rev. 4). The first application recorded with NACE Rev.2 in the PATSTAT was submitted in 1845. It shows the weight of the association between an application and different technical fields. By using this, we are able to classify patents to one or more sectors based on their degree of association. Approximately, only 6.7% of patent applications (1.46 million applications) do not have a sector classification.

Finally, we investigate the effect of pandemic shocks to the number of patent applications. In particular, on PATSTAT, (i) we identify the first application of each invention, (ii) record the country of residence of its primary assignee (i.e., owner) as the country of the invention and (iii) focus on utility patents only.

[6] We choose the pandemic start date as we expect that the pandemic period is the most disruptive period for innovation. The choice of number of lags does not affect the results. See also the Robustness tests section.

We examine (1) the next year effect of the end of a pandemic to the number of submitted applications and (2) the effect of the pandemic duration on next year's number of submitted applications. To this end, we estimate the following regressions:

$$Innov_{i,t+1} = \alpha_i \ + \beta P_t^{End/Dur} + C_i \ + e_{i,t+1} \qquad (3)$$

where $Innov_{i,t+1}$ denotes the natural logarithm of 1 plus the number of submitted patent applications at year *t+1* for each country *i*. $P_t^{End/Dur}$ refers to the dummy variables of pandemic (P^{End} and P^{Dur}) at time *t*. P^{End} is 1 if there is a pandemic end, 0 otherwise. P^{End} is 1 if there is a pandemic, 0 otherwise. *Ci* denotes country fixed-effects.

4. Empirical Results

In this section, we provide the main results of this study and discuss policy implications. We start by investigating the effect of pandemic shocks on aggregate innovation output. Next, we classify patents by sector of economic activity and show the effect of pandemics separately for the manufacturing, construction and information and communication sectors. In the third subsection, we show the effect of pandemic shocks by country of award and in the final section, we demonstrate the effect of pandemic shocks on patent applications.

4.1. Pandemic shocks and aggregate innovation

In Table 2, we present our main results. The dependent variable is the change in innovation output. Each row refers to a separate local projection model with country-fixed effects. Three lags of innovation output are included in each regression (not reproduced here).

The results presented in Table 2 show that pandemic shocks disrupt research productivity with effects being felt long into the future. Innovation remains relatively stable for approximately four years after the pandemic start. This result however is not surprising. R&D investments take several years to materialise, so the relatively stable trend of applications four years after the pandemic start most likely reflects R&D investments that started before the pandemic had any effect on R&D projects. Subsequent innovation output is reduced for three years and, overall, it takes approximately seven years for innovation output to return to pre-pandemic levels. Clearly, the model provides more reliable forecasts of the long-run rather than the short-run effects of pandemics on innovation output.

Table 2

In Figure 2, we produce the impulse responses of innovation output to a pandemic. The solid line refers to the pandemic coefficient value for h = 1,...,15 and the light and dark shaded areas refer to 70% and 95% error bands, respectively.

The impulse response plots are striking. In a recent interview, Professor Bloom, Senior Fellow at Stanford's Institute for Economic Policy Research, summarised the fears for a "slump in innovation" as follows: *"The new ideas we are losing today could show up as fewer new products in 2021 and beyond, lowering long-run growth"* (Gorlick, 2020). In line with this prediction, Figure 2 demonstrates that the effects of past pandemics on research productivity – and therefore on innovation output – are felt for approximately seven years from the onset of the pandemic. This result, whilst in line with the current expectations of the impact of COVID19 on economic growth, they show a much longer-term effect on innovation output that the one anticipated.

Figure 2

4.2. Pandemic shocks by Sector of Economic Activity

In this subsection, we present the results of the effect of pandemic shocks to innovation output by sector of economic activity (NACE Rev.2).[7] We present the impulse response results in Figure 3.

Figure 3

In line with the main result, following a pandemic shock, innovation output remains unchanged for approximately four years, probably due to the lag between R&D investments and patent applications. Overall, the manufacturing and the construction sectors are immune to the pandemic shock. Importantly, our main result regarding the effect of pandemic shocks on aggregate innovation output is driven mainly by a significant reduction in the Information and Communication technology sector, a sector that depends more on research productivity than the construction and manufacturing sectors do.

Overall, the results by sector of economic activity demonstrate that one-size-fits-all government policies that support innovation output may be inefficient as more research-intensive sectors receive a disproportionately large pandemic shock. An allocation of resources to sectors that historically have a greater exposure to pandemics is likely to lead to a faster economic recovery.

4.3. Results by country of award

In this subsection we investigate the effect of pandemic shocks on innovation output by country of award. In the first part of the analysis, we establish that following a pandemic shock, global

[7] We do not report the regression results of the set of local projection estimator models by country in order to conserve space. The results are available upon request. We provide an interpretation of the impulse response plots with respect to the pandemic coefficient values in Section 4.1.

innovation outlook takes approximately seven years to recover. We present the results by country in Figure 4.

Figure 4

There are some notable differences in the magnitude of the pandemic shock across countries and the time to recovery. The magnitude of the pandemic shock is small for Italy and for Japan considerably larger than the remaining G7 countries. Notably, innovation output in Canada is relatively more volatile than in the rest of G7. Whilst for the five of seven countries, the duration of the pandemic shock ie the time to recovery, is approximately seven years, for Italy, recovery is achieved after four years. On the other hand, innovation output in the UK remains at below pre-pandemic level for several years. Overall, the results by country underline the need for government initiatives that remedy the effect of the pandemic shock, especially with respect to the idiosyncrasies of the innovative sectors across countries.

4.4. Effect of pandemic shocks on patent applications

Finally, we investigate the effect of pandemic shocks and duration on patent applications. Even though the number of patent applications is likely to be affected by the applicant's ability to submit patent applications rather than just the ability to develop new ideas, this measure ultimately reflects the short-term effect of pandemic shocks to innovation. We focus on the pandemic end rather than the pandemic start as the first year of the pandemic will most likely reflect the research productivity of the previous year. Also, as the HIV/AIDS pandemic has a very long duration, we drop HIV/AIDS from the measurement of the pandemic duration dummy.

We present the results of the effect of pandemic shocks and duration on patent applications in Table 3. For robustness, we report the regression results for both the G7 and the T10 samples. Furthermore, we report the results with and without country-fixed effects.

As anticipated, pandemic shocks lead to a short-term drop in the number of patent applications. This result is statistically significant at 1% for the G7 countries. For the T10 countries, the effect of pandemic shocks to patent applications is negative but not significant. We conjecture that the insignificant result for the T10 countries reflects the fact that (i) the most significant pandemic episodes happened at the start of the twentieth century and (ii) the G7 (T10) countries have tended to capture an even smaller (larger) proportion of the total patenting activity since the 1990s. Figure 1, Panels 1 and 2 demonstrate that T10 traces more accurately global patenting activity towards the end rather than the start of the sample period. Equally, pandemic duration is strongly associated with a drop in patent applications. In contrast to the regression results for the P^{end} dummy, P^{dur} is negative and statistically significant at 1% level for both the G7 and T10 samples.

5. Robustness tests

To further support our main finding that pandemic shocks disrupt innovation output for long into the future, in this section we check the robustness of our results. Overall, we obtain qualitatively similar results that are robust to the model specifications. In each subsection below, we outline the specifications of each robustness test. We present all robustness test results in Table 4 and the corresponding impulse response functions in Figure 5.

Table 4

Figure 5

5.1. Using the pandemic end date

We first examine whether the effect of pandemic shocks on innovation output is robust to alternative pandemic date specifications. To this end, we re-run the baseline set of regressions and define P_t as the dummy variable that is 1 if there is a pandemic end, 0 otherwise. The results are presented in Table 4, Panel 1. In Figure 5, Panel 1, we present the impulse response function of the effect of pandemic shocks to innovation output.

5.2. Using the ten most innovative countries

One criticism may be that the G7 countries are not representative of global innovative activity. To respond to this criticism, we estimate Equation 1 using the top ten most innovative countries over the sample period (T10). Figure 1, Panel 2, shows the average number of successful patents per country and the percentage of global innovation activity that is awarded to the top ten most innovative countries over the sample period. We report the results of this set of regression models in Table 4, Panel 2. In Figure 5, Panel 2, we present the corresponding impulse response function.

5.3. Dropping the HIV pandemic

With the exception of HIV, most pandemics are short-lived. For robustness we drop HIV from the list of pandemics as it did not have a distinctive outbreak and estimate Equation 1 again. We present the re-estimation results in Table 4, Panel 3 and in Figure 5, Panel 3.

5.4. Use the patent owner's country of residence

Finally, approximately 31% of the successful patent applications do not mention the nationality of their applicants. In the main analysis, we used the country of the patenting office that is the first to accept the application of the original patent in order to classify patent applications per country. As a robustness test, in Table 4, Panel 4 and in Figure 5, Panel 4, we use the patent owner's residential country as the country of the invention.

Overall, the results in this section show that qualitatively the established relationship between pandemic shocks and innovation output remains the same, albeit statistical significance is not always consistent across samples and robustness tests. Nevertheless, the impulse response functions show that the main result still holds: following a pandemic, innovation output is disrupted for approximately seven years.

6. Policy implications

Finally, given the ongoing COVID19 pandemic, in this section, we discuss some very important policy implications that stem from our research.

First, given that the pandemic poses a clear threat to research productivity in the long-run, policies that may reduce the effect of the "Great Lockdown" on research productivity are needed. Second, whilst the pandemic shock has an effect on global innovation output, the results vary by country and sectors of economic activity. The response to COVID19 needs therefore to have a global character[8] but countries also need to introduce support schemes for the sectors that are more exposed to the pandemic shock. Overall, policies which target the more innovative firms are expected to remedy the effect of COV19 on future growth. Third,

[8] The "Next Generation EU" support fund with a total value of €750B is such an example. The fact that the European Commission has also recommended changes to the long-term European Union budget for 2021-2027 is in-line with the policy recommendation relating to the duration of the pandemic.

the pandemic shock is expected to have a strongly negative effect on patent applications.[9] Governments, need to be prepared to support innovators in the immediate aftermath of the pandemic. Patent offices may have to speedup the process of approving new patents. Bloom et al. (2020, p. 1139) show that "ideas are non-rival", meaning that "they can be used simultaneously by any number of people". Supporting inventors and expediting the patent application process is therefore key in supporting economic growth. Finally, innovation output is significantly and negatively affected by the duration of the pandemic and it is therefore important to implement support policies for the duration of the pandemic rather than as one-off expenditures only.

7. Conclusion

In this paper, we employ an idea-based theory of economic growth in which growth is a function of both research productivity and the number of researchers. Given that pandemics pose a threat to research productivity, we use a local projection estimator to model the effect of pandemic shocks on innovation output.

[9] Abi Younes et al. (2020) argue that R&D investment is pro-cyclical and tends to decrease when firms are faced with financial constraints. We therefore expect that the impact of the recent pandemic on R&D to be negative. We choose not to use R&D expenditure as a measure of innovation activity. Although R&D can represent innovative input during normal periods, it may not efficiently measure innovation performance during and after pandemic episodes. This is because R&D spending includes wages and salary of researchers. However, pandemics (increased infection and death toll) increase real wages for survivors in the long run (Jordà et al., 2020) but are less likely to improve their research productivity. Therefore, the increased R&D investment may not be able to represent an increased innovative ability during and after pandemic episodes.

We show that following a pandemic, innovation output is disrupted for a period of approximately seven years, probably because of a drop in research productivity. Given that COVID19 is expected to be a major obstacle to research productivity, especially during the lockdown, the effects of the pandemic on future innovation output and subsequently on growth are expected to be felt for long into the future. The main result in the effect of pandemic shocks on aggregate innovation output is driven primarily by a significant reduction in innovative activity in the Information and Communication technology sector. In addition, there are some notable differences in the magnitude of the pandemic shock across countries and the time to recovery. Pandemic shocks lead to a short-term drop in the number of patent applications. Finally, pandemic duration is strongly associated with a drop in patent applications.

This paper contributes to the recent debate on the economic consequences of COVID19. It supports policies designed to reduce the effect of the "Great Lockdown" on research productivity. We recommend policies that have a global character, support innovators, speed up the process of approving new patents and target the more innovative firms. However, further research should delve deeper into the exact effects of COVID19 and the "Great Lockdown" on research productivity. Finally, future research should investigate whether pandemic episodes result in structural breaks in innovation output across countries, but also very importantly, across industries.

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Table 1
Pandemic episodes since 1900 with at least 100,000 deaths

Event	Death toll	Location	Start /End date
Encephalitis lethargica pandemic	1.5 million	Worldwide	1915-26
Spanish flu	17-100 million	Worldwide	1918-20
Asian flu	1-4 million	Worldwide	1957–58
Hong Kong flu	1-4 million	Worldwide	1968–69
HIV/AIDS	32 million+	Worldwide	1981– present
H1N1/09 virus	203,000	Worldwide	2009-10

Note: source: https://en.wikipedia.org/wiki/List_of_epidemics

Table 2
Effect of a pandemic episode on innovation output

Dependent variable: *ΔInnovi, t+h*

h	*P*	*L*	*C*	*N*	R^2
1	0.05 (0.06)	3	Yes	625	0.07
2	0.12** (0.04)	3	Yes	622	0.11
3	0.06 (0.15)	3	Yes	620	0.12
4	0.28 (0.16)	3	Yes	615	0.13
5	0.15 (0.19)	3	Yes	608	0.18
6	-0.32 (0.26)	3	Yes	602	0.22
7	-0.6 (0.4)	3	Yes	594	0.26
8	0.42** (0.15)	3	Yes	586	0.27
9	0.42* (0.18)	3	Yes	578	0.29
10	0.18 (0.41)	3	Yes	570	0.32
11	0.50** (0.16)	3	Yes	562	0.38
12	0.51** (0.15)	3	Yes	554	0.41
13	0.58** (0.18)	3	Yes	546	0.44
14	0.66** (0.23)	3	Yes	538	0.47
15	0.68** (0.27)	3	Yes	530	0.50

Note: This table presents the results of the local projection model with country fixed effects and cluster-robust standard errors. *h* refers to the number of years in the future. *P* refers to the start of a pandemic. Country fixed effects (*C*) and three lags of innovation output (*L*) are included in each regression (not reproduced here). Standard errors are in parentheses. ***, ** and * indicates significance at 1%, 5% and 10% level, respectively.

Table 3
Effect of pandemic shocks on patent applications

Dependent variable:	**Ln(Innovation$_{i,t+1}$)**							
Sample	G7				T10			
	(1)		(2)		(3)		(4)	
P^{End}	-0.60***	-0.63***			-0.10	-0.09		
	(0.15)	(0.15)			(0.28)	(0.30)		
P^{Dur}			-2.24***	-2.34***			-2.24***	-2.24***
			(0.19)	(0.19)			(0.23)	(0.23)
N	712	712	712	712	859	859	859	859
Country FEs	No	Yes	No	Yes	No	Yes	No	Yes
R^2	0.002	0.114	0.074	0.193	0.001	0.102	0.060	0.166

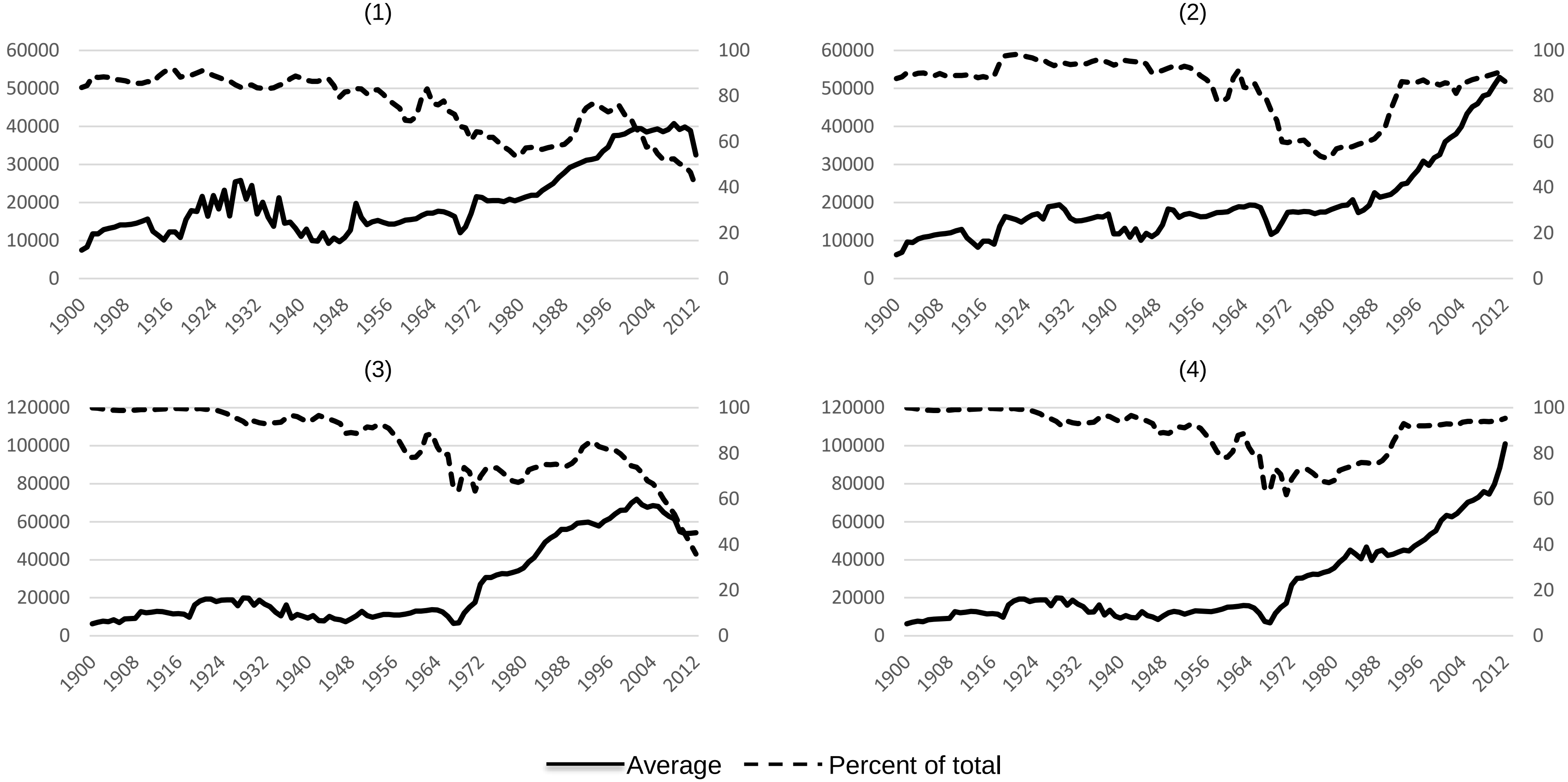
Note: This table presents the results of the effect of pandemic shocks on next year's innovation output. The dependent variable is the natural logarithm of one plus the number of submitted patent applications at year *t+1* for each country *i*. $P_t^{End/Dur}$ refers to the dummy variables of pandemic (P^{End} and P^{Dur}) at time *t*. P^{End} is 1 if there is a pandemic end, 0 otherwise. P^{End} is 1 if there is a pandemic, 0 otherwise. Standard errors are in parentheses. ***, ** and * indicates significance at 1%, 5% and 10% level, respectively.

Table 4
Robustness tests

	(1)		(2)		(3)		(4)	
h	*P*	R^2	*P*	R^2	*P*	R^2	*P*	R^2
1	0.03 (0.05)	0.07	0.06* (0.03)	0.10	0.05 (0.07)	0.07	-0.11 (0.11)	0.04
2	0.03 (0.05)	0.11	0.10** (0.04)	0.19	0.14* (0.06)	0.11	-0.28 (0.16)	0.04
3	0.21 (0.19)	0.12	0.14** (0.06)	0.12	0.04 (0.2)	0.12	-0.54** (0.2)	0.07
4	0.04 (0.19)	0.13	0.17* (0.09)	0.10	0.31 (0.17)	0.13	-0.39 (0.23)	0.08
5	-0.56* (0.27)	0.19	0.05 (0.11)	0.12	0.15 (0.21)	0.18	-0.58* (0.25)	0.08
6	-0.62 (0.5)	0.23	-0.45** (0.18)	0.15	-0.46 (0.29)	0.22	-1.32*** (0.23)	0.12
7	0.39* (0.17)	0.25	-1.01* (0.48)	0.20	-0.83 (0.54)	0.26	-1.50*** (0.38)	0.13
8	0.45* (0.19)	0.27	0.40*** (0.09)	0.20	0.50** (0.16)	0.27	-0.73 (0.4)	0.10
9	0.49** (0.18)	0.30	0.41*** (0.1)	0.20	0.53** (0.17)	0.29	-0.85** (0.29)	0.12
10	0.51** (0.2)	0.33	0.41*** (0.12)	0.22	0.19 (0.49)	0.32	-0.67* (0.3)	0.11
11	0.51* (0.23)	0.38	0.41*** (0.12)	0.25	0.61*** (0.16)	0.38	-0.36 (0.28)	0.12
12	0.58* (0.27)	0.41	0.41*** (0.12)	0.27	0.60*** (0.16)	0.41	-0.47 (0.31)	0.13
13	0.65 (0.34)	0.44	0.42*** (0.13)	0.29	0.68** (0.2)	0.44	-0.4 (0.23)	0.13
14	0.61 (0.38)	0.47	0.40** (0.13)	0.31	0.74** (0.25)	0.47	-0.33 (0.3)	0.14
15	0.57 (0.34)	0.50	0.40** (0.13)	0.32	0.74** (0.28)	0.50	-0.44 (0.29)	0.15

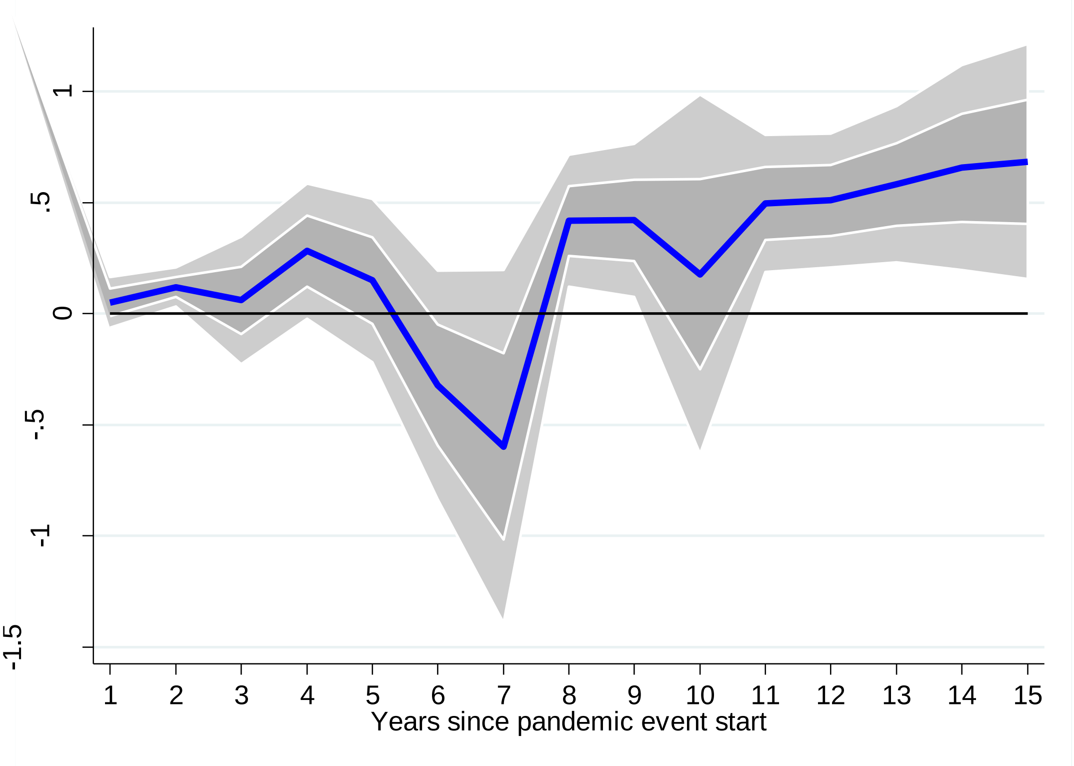
Note: This table presents the results of the robustness tests. We estimate a set of local projection models with country fixed effects and cluster-robust standard errors. *h* refers to the number of years in the future. Country fixed effects (*C*) and three lags of innovation output (*L*) are included in each regression (not reproduced here). In (1), *P* refers to the end of a pandemic period. In (2), (3) and (4), *P* refers to the start of a pandemic. In (2), we reproduce the results using the top 10 most innovative countries over the sample period. In (3), we do not account for the HIV pandemic. In (4), we use the patent owner's country of residence. Standard errors are in parentheses. ***, ** and * indicates significance at 1%, 5% and 10% level, respectively.

Figure 1
Time series of innovation from 1900 to 2012



Note: In (1), the solid line refers to the average number of applications granted for the G7. The dashed line refers to the proportion of successful applications granted in G7 countries as a percentage of total global activity. In (2), we replace G7 with T10. In (3), the solid line refers to the average number of applications submitted for the G7. The dashed line refers to the proportion of applications submitted in G7 countries as a percentage of total global activity. In (4), we replace G7 with T10.

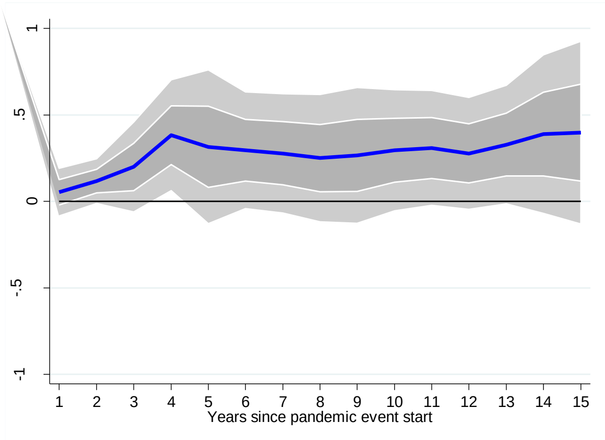
Figure 2
The impulse response of innovation output to a pandemic episode



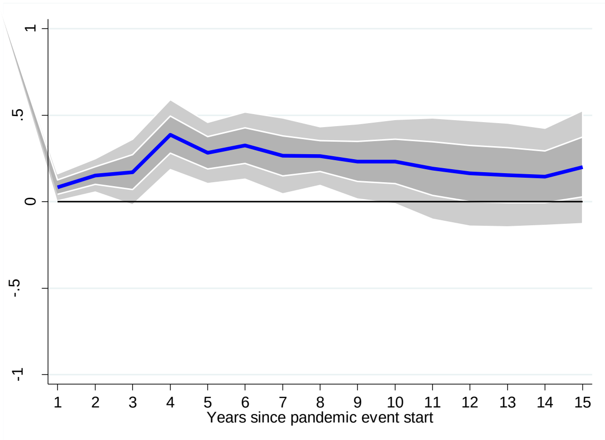
Note: The vertical axis refers to the percentage change to innovation following a pandemic episode. The shaded areas refer to 70% and 95% error bands.

Figure 3
The impulse response of innovation output to a pandemic episode by sector of economic activity

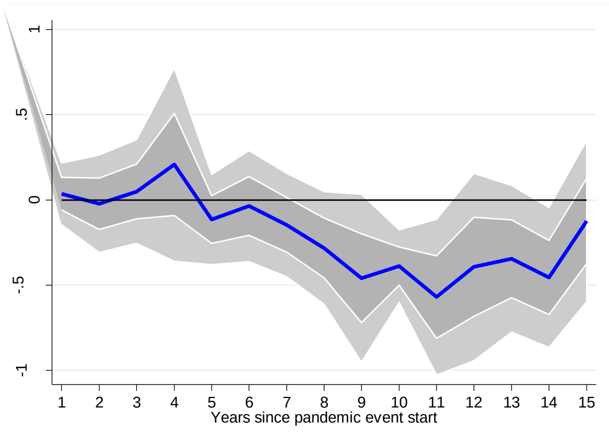
Manufacturing



Construction

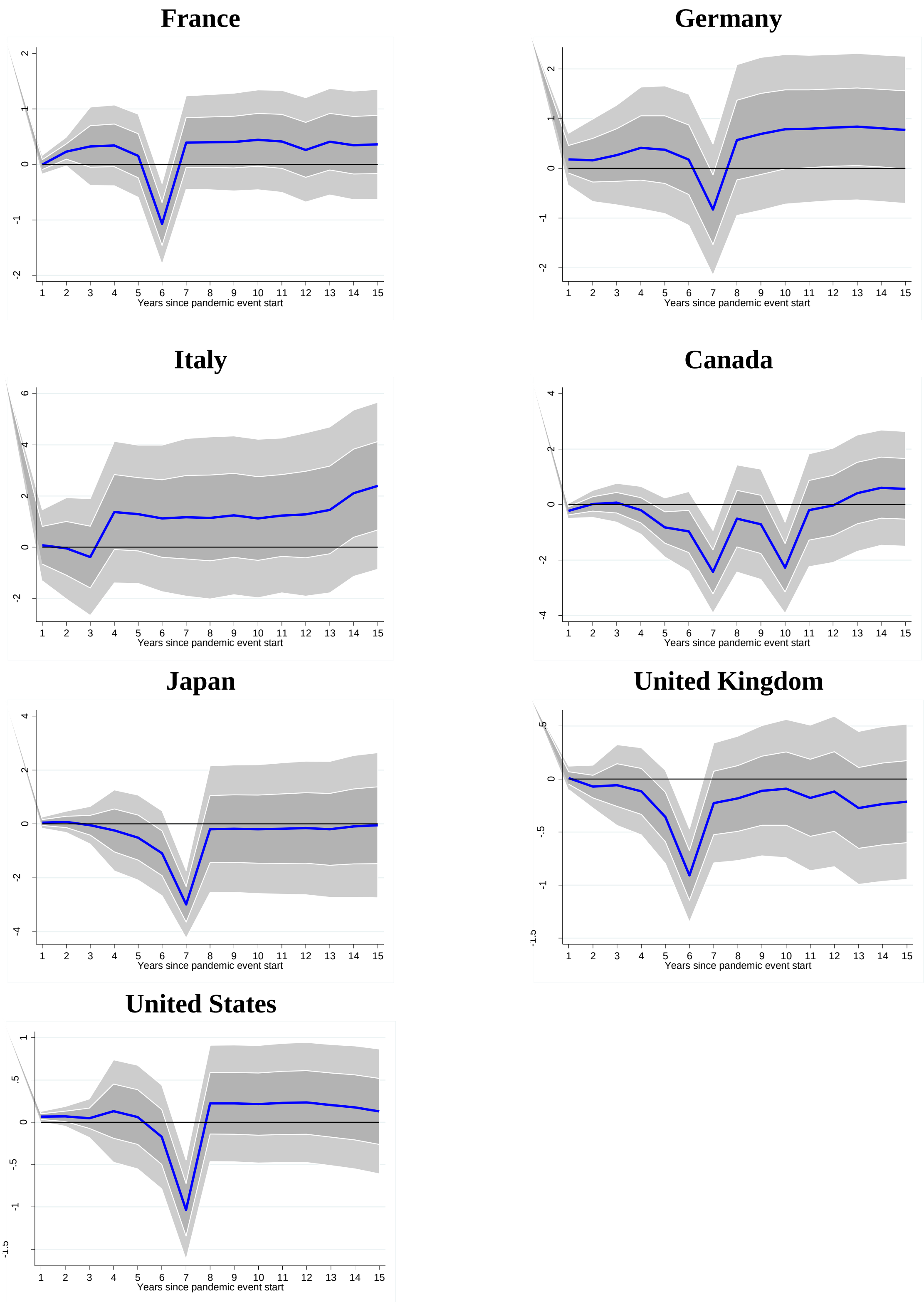


Information and communication



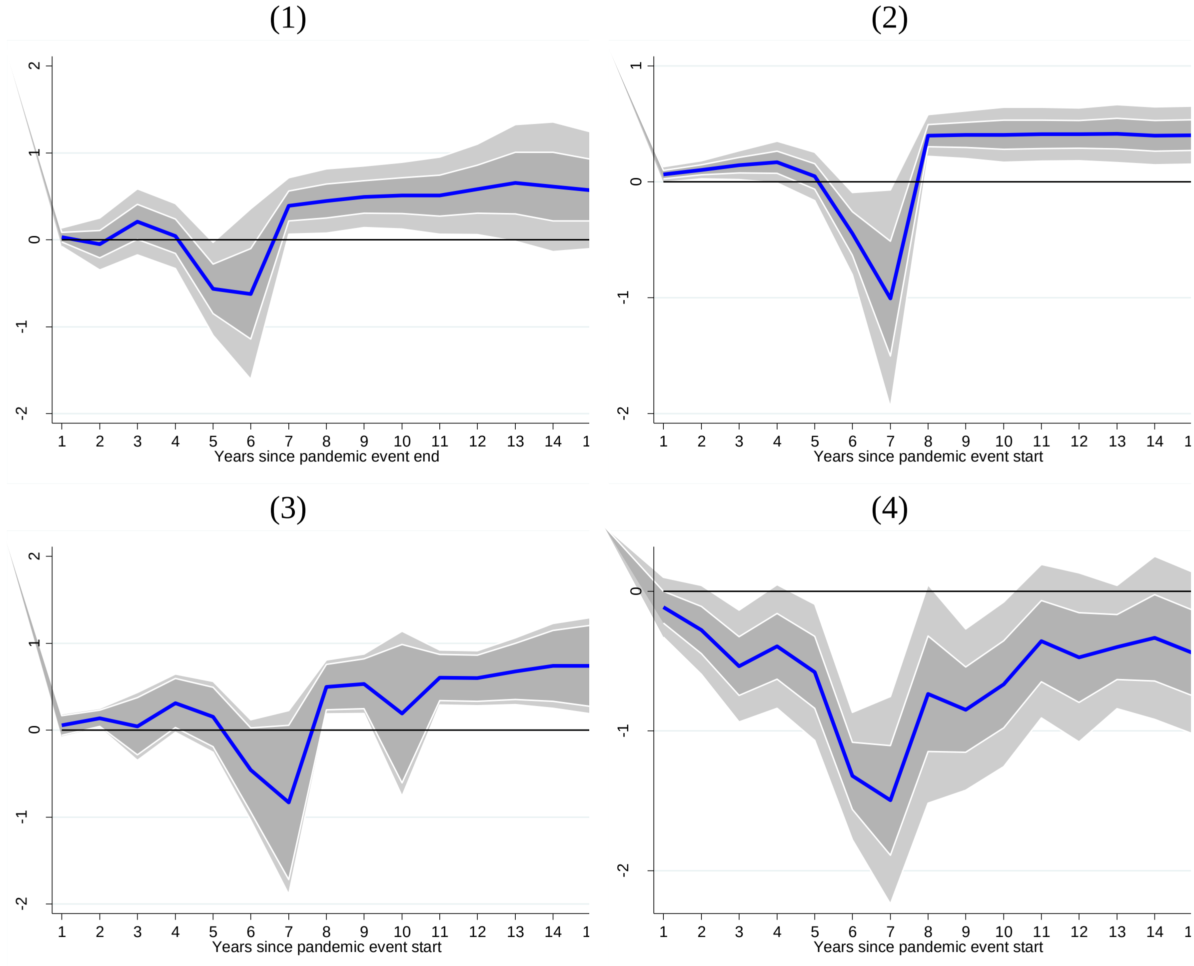
Note: The vertical axis refers to the percentage change to innovation following a pandemic episode. The shaded areas refer to 70% and 95% error bands.

Figure 4
The impulse response of innovation output to a pandemic episode by country



Note: The vertical axis refers to the percentage change to innovation following a pandemic episode. The shaded areas refer to 70% and 95% error bands.

Figure 5
Robustness tests: impulse responses of innovation output to a pandemic episode



Note: The vertical axis refers to the percentage change to innovation following a pandemic episode. The shaded areas refer to 70% and 95% error bands. In (1), we use the end of a pandemic period. In (2), we reproduce the results using the top 10 most innovative countries over the sample period. In (3), we do not account for the HIV pandemic. In (4), we use the patent owner's country of residence.