Bank of Japan Working Paper Series

How Do Floods Affect the Economy? An Empirical Analysis using Japanese Flood Data

Takuro Ashizawa*
takurou.ashizawa@boj.or.jp

Nao Sudo*
nao.sudou@boj.or.jp

Hiroki Yamamoto*
hiroki.yamamoto@boj.or.jp

No.22-E-6
June 2022

Bank of Japan
2-1-1 Nihonbashi-Hongokucho, Chuo-ku, Tokyo 103-0021, Japan

* Financial System and Bank Examination Department

How Do Floods Affect the Economy?
An Empirical Analysis using Japanese Flood Data*

Takuro Ashizawa† ・Nao Sudo‡ ・Hiroki Yamamoto§

June 2022

Abstract

The impact of natural disasters caused by increasing-scale climate change on economic activity has been the focus of global attention in recent years. Natural disasters primarily damage the assets owned by firms and households and public infrastructure, i.e., direct effects, but they may also affect the economic activity through the subsequent changes in production inputs, i.e., indirect effects. While there is already a large number of empirical analysis on the indirect effects, however, no consensus has been established not only on the scale and persistence, but even on the signs. In this paper, we estimate the indirect effects of past flood disasters in Japan on the real economy using *Prefectural Accounts* and *Flood Statistics*. There are three main findings. First, while floods have a negative effect on the GDP of the prefecture in which they occur, this effect may not persist over the long run as it loses statistical significance after the year following the year of occurrence. Second, floods have different effects across sectors. Floods generally have a negative effect on GDP of the manufacturing and the wholesale and retail sectors, while they tend to have a positive effect on GDP of the construction sector. Third, the magnitude of the indirect effect of floods differs for asset, facility, and equipment that incurs damage. Compared to damage to the assets owned by firms and households, damage to public infrastructure, such as roads, and to public service utilities, such as electric power facilities, tend to depress GDP more significantly, which may indicate the importance of public assets in the spillover effects of flood damage.

JEL Classification: C21, C23, O44, Q54

Keywords: Climate Change; Natural Disaster; Physical Risk; Floods

---

* The authors acknowledge the River Planning Division, the Water and Disaster Management Bureau, and the Ministry of Land, Infrastructure, Transport and Tourism for providing *Flood Statistics*. The authors are grateful to the Ministry of Land, Infrastructure, Transport and Tourism, S. Muto, J. Nakajima, Y. Sawada, C. Shimizu, J. Yoshida, and colleagues at the Bank of Japan especially K. Matsumura, I. Muto, K. Nakamura, K. Nishizaki, and K. Suzuki for comments and discussions. The views expressed in the paper are those of the authors and do not necessarily reflect those of the Bank of Japan.

† Financial System and Bank Examination Department (takurou.ashizawa@boj.or.jp)

‡ Financial System and Bank Examination Department (nao.sudou@boj.or.jp)

§ Financial System and Bank Examination Department (hiroki.yamamoto@boj.or.jp)

1 Introduction

In recent years, with the growing concern about climate change, the impact of natural disasters associated with climate change on economic activities has been the focus of global attention. The damage caused by natural disasters is considered to include not only direct consequences, such as loss of human lives and physical damage to assets owned by firms and households or to public infrastructure, i.e., direct effects, but also changes in economic activities, mainly disruptions to production activities and declines in households' income, i.e., indirect effects, that occur as an economic consequence of the direct effects on economic activities. In many countries, a large number of empirical analyses have already been conducted to measure the magnitude of direct and indirect effects or to identify the economic and social factors that affect the scale of these effects. However, as already pointed out in previous studies, for example, by Bayoumi (2021) and Cavallo et al. (2021), there is not necessarily a consensus on the scale, signs, and persistence of these effects, in particular indirect effects, nor on the determinants of the scale of the effects. This is considered partly because all natural disasters are heterogeneous by nature as physical phenomena and characteristics of affected countries or regions are also diverse.

In this paper, we empirically study the indirect effect caused by floods[1] damage in Japan. In Japan, in terms of the number of past natural disasters, flood-related disasters such as typhoons, floods, and landslides account for more than 70% of the total number of natural disasters and are considered to be non-negligible and important risks[2, 3]. Indeed, the Ministry of Education, Culture, Sports, Science and Technology (MEXT) and The Japan Meteorological Agency (JMA) have conducted simulations under the RCP2.6 scenario, a scenario in which needed measures are taken to achieve the Paris Agreement, an international agreement on greenhouse gas emissions, and the RCP8.5 scenario, a scenario in which no additional measures are taken, and reported that the number of heavy rainfall events may increase significantly in the future (MEXT and JMA [2020]), highlighting an increasing importance of considering flooding risk going forward. The Ministry of Land, Infrastructure, Transport and Tourism (MLIT) has also published projections showing that the frequency of flooding would increase by a factor of 2 to

---

1 The term "flood" in this paper indicates overall water-related disasters.

2 Flood risk is internationally recognized as an important risk. The Network for Greening the Financial System (NGFS) has identified flooding as a physical risk related to climate change, along with heat stress, in its NGFS Scenario (2021). This is because rising temperatures as a result of climate change are expected to cause changes in rainfall patterns against a background of increased water vapor retention in the atmosphere.

3 This article focuses on the analysis of "physical risks" among climate-related financial risks. For a discussion of the challenges and issues in the transition process to a decarbonized society, which are closely related to "transition risk" in climate-related financial risks, see Kurachi et al. (2022).

4 under these two scenarios (MLIT [2019]).

With the Prefectural Accounts and the Flood Statistics from 1998 to 2018 released from the Cabinet Office and the MLIT respectively, we conduct a time-series analysis on the relationship between the amount of flood damage to assets, equipment, and facilities that occurred in a specific year in each of the 48 prefectures in Japan (direct effects) and the changes in economic variables, including GDP at a prefecture-level, in that prefecture from the year of occurrence of flood event until two years later (indirect effects), using the local projection method. In the Prefectural Accounts, time series data are published not only GDP that captures economic activities in all sectors but also for sectoral GDP that captures value-added in a specific sector. In the Flood Statistics, not only the total amount of monetary damage due to floods but also the breakdown of damage, such as damage to assets owned by firms and households, damage to roads and other public infrastructure, and damage to power supplies and other public services are released. For this purpose of identifying the transmission channel of the indirect effects, we use these detailed data to examine not only the size of the indirect effects due to floods, but also the precise nature of the indirect effects of floods. We therefore study, for example, how the indirect effects on GDP in the manufacturing and construction sectors are different or how the indirect effects of flood damage to firms' assets differ from those of damage to roads and other public infrastructure.

The main results of the current paper are threefold. First, the occurrence of flood damage has a statistically significant negative effect on the level of GDP in the year of said damage. Quantitatively, when the flooding damage that amounts to 0.2% of GDP is considered, the associated indirect effect lowers the level of GDP by about -0.01% to -0.07% in the 90% confidence interval, compared to the level in the absence of flooding. This downward effect is not statistically significant after the subsequent year, suggesting that the indirect effect of flooding may not persist over a long period. Second, the effect of flood damage differs from sector to sector. Looking at the indirect effect on sectoral GDP, it is seen that the manufacturing and wholesale and retail sectors see a significant negative impact, although this depends on the type of assets, facilities, and equipment. Conversely, the construction sector is found to see a significantly positive effect. These differences in the responses among sectors to the flood damage can be attributed to the fact that there are both supply-side and demand-side factors in the transmission of flood damage and they exert impacts of different signs and magnitudes on each sector. For example, on the supply side, these could be a decrease in the input of production factors such as private capital stock and a decline in Total Factor Productivity (TFP) due to damage to public infrastructure work to depress economic activity. On the demand side, in addition to public recovery activities, these could be the role of insurance as pointed out in von Peter et al. (2012) and other studies, as well as private-sector repair and restoration activities based on the role of insurance work to push up economic activity. These differences among sectors have also been pointed out in previous studies overseas, such as Loayza et al. (2009). Third, the magnitude of indirect effects of flood damage differs for asset and facility that incurs flood-induced damage. Compared to damage to assets owned by firms and households, damage to public infrastructure, such as roads, and to public services, such as power supplies, tend to depress GDP more significantly, even if the amount of direct damage is the same.

The remainder of this paper proceeds as follows. In Section 2, we introduce previous studies on the empirical analysis of indirect effects of natural disasters, including floods, on the real economy and summarize representative results and differences from this analysis. Section 3 provides an overview of the data used in this analysis. Section 4 describes the estimation model used in the analysis. Section 5 discusses the estimation results and their implications. Section 6 concludes the paper.

2 Literature Review

It is not easy to pin down the nature of the indirect effects of natural disasters on the real economy, especially GDP, even theoretically. As argued, for example, by Bakkensen and Barrage (2019), there are multiple channels that indirect effects manifest themselves[4], both negative and positive. Consider the following standard production function

$$Y_t = A_t K_t^{\alpha} L_t^{1-\alpha},$$

where Y_t, A_t, K_t, and L_t are GDP, TFP, capital stock input, and labor input, respectively, and α is a parameter related to the production function. For labor input, the human capital stock can also be included if an endogenous growth model is considered. The first channel is the one in which natural disasters physically damage production inputs and consequently induce changes in supply-side economic conditions, such as shortages of specific production inputs or changes in allocation of production inputs, as described in Hsiang and Jina (2014) and others. For example, when a factory is flooded, there will be a decrease in the production capacity of production inputs, mainly capital stock K_t, and the subsequent decrease in GDP[5, 6]. If the

[4] A similar classification is presented in Hsiang and Jina (2014). In that paper, the authors categorize the following patterns of the real economy after a natural disaster takes place: (1) an immediate increase of GDP above the pre-disaster trend, which is referred to as creative destruction, (2) initial suffering and then an increase of GDP above the pre-disaster trend, which is referred to as build back better, (3) a decrease of GDP for some period and then a return to the pre-disaster trend, which is referred to as recovery to trend, and (4) a no-recovery path where the decline due to the disaster cannot be recovered, which is referred to as no recovery. As described below, the results of this paper are considered to fall under (3).

[5] When TFP is defined as in the above equation, a decline in TFP may take place in various situations including a situation where public infrastructure is damaged to the point where it is no longer able to provide the services it used to provide, as well as situations where the input volume of intermediate input goods declines.

[6] Even if there is no path related to the change in risk perception described below, the impact of natural disasters on GDP can

capital stock is frequently damaged by flooding, capital accumulation may be impeded and economic growth may be pushed down. Indeed, Hsiang and Jina (2014), using 6,700 cyclone cases and cross-country data, report a negative correlation between the rate of capital depletion due to cyclone occurrence and economic growth. Similarly, Bakkensen and Barrage (2019) report a negative correlation between TFP and cyclone size. Other empirical analyses reporting negative correlations between natural disasters and GDP include, for example, Noy (2009), Strobl (2011), von Peter et al. (2012), and Bello (2017). These analyses report that natural disasters not only depress GDP, but also that their depressing effects may be long-lasting. For example, Strobl (2011) reports that natural disasters depress income growth rates in the affected region in the year of occurrence and have no effect on growth rates thereafter; in other words, the level of economic size after the year of occurrence is depressed as a result of the occurrence of a natural disaster.

Existing studies that point out the importance of the demand side include von Peter et al. (2012), Sawada et al. (2017), and Tran and Wilson (2020). Even if the direct effect of a natural disaster reduces certain production inputs, if demand from residents or firms in the affected area is boosted by increased fiscal expenditures or insurance payments, the net production inputs and income may increase, boosting GDP. As an example, von Peter et al. (2012), using annual panel data for 203 countries from 1960 to 2011, report that although natural disasters permanently and statistically significantly depress GDP, this depressing effect almost disappears when the risk of loss is transferred through prior insurance contracts[7]. Noy (2009) also points out that the occurrence of natural disasters has a downward effect on GDP, and that such an effect is mitigated the larger the income and fiscal expenditure of the country in which the disaster occurs.

In addition, changes in saving and investment decisions through changes in the medium- to long-term risk perception of economic agents are also considered to be important. For example, if economic agents promote more investment in physical and human capital stock as a result of changes in their perception of the risk towards natural disasters, capital accumulation may increase over the medium- to long-term, leading to higher economic growth rates. Empirical papers that point to a positive effect of natural disasters include Skidmore and Toya (2002) and Tran and Wilson (2020). The former study, using data on the long-term growth rate of GDP and

---

be positive through this first channel, as pointed out in von Peter et al. (2012). This is because damage to the existing capital stock caused by a natural disaster is not recorded in GDP, while the restoration activity of the capital stock is recorded in GDP. For example, even if capital stock input decreases as a result of capital stock damage, if labor supply increases significantly due to restoration activities, the net effect on GDP could be positive.

7 As a case study, von Peter et al. (2012) report on the major earthquakes that occurred in Haiti and New Zealand in 2010. While the direct damage from the earthquakes was about the same in both countries, the GDP growth rate in Haiti declined significantly, while in New Zealand, the change in GDP growth rate may have been minor due to increased construction, inventory adjustment, and public spending. The study pointed out that the factor behind the difference is that earthquake insurance coverage was about 80% in the latter case, while it was less than 1% in the former case.

other economic variables as well as the frequency of natural disasters in 89 countries, reports that the frequency of natural disasters is positively correlated with the rate of accumulation of human capital, TFP, and GDP growth in these countries. Authors then argue that this result may be due to a mechanism whereby an increase in the risk of natural disasters reduces the expected rate of return on physical capital, thereby encouraging investment in human capital. Figure 1 is a summary of these previous studies' findings on indirect effects using the length of horizons considered in those studies as well as the signs of effects on the real economy.

On the other hand, there are some empirical studies that do not necessarily coincide with these channels. For example, Cavallo et al. (2013) report that, with the exception of extremely large-scale disasters, natural disasters basically have no statistically significant impact on the real economy. In addition, even for the extreme disasters, it is the political instability following a natural disaster that pushes the real economy down; removing this factor, the report shows that the real economy is not significantly affected by natural disasters.

The analysis in this paper shares similarities with these previous studies, in that it estimates the indirect effects of natural disasters. The difference, however, is that these studies often analyze medium- to long-term GDP growth rates, whereas this paper focuses on the short-term dynamics of the effects of natural disasters by using annual data and local projections. In addition, this study uses prefecture-by-prefecture data, which implies that the sample areas are relatively consistent in terms of economic and social institutions as compared to cross-country data, and uses relatively high granular measures of natural disasters, such as the amount of damage to each damaged facility, rather than dummy variables such as whether or not a natural disaster has occurred. This is a distinctive feature of this paper[8].

3 Data

The analysis in this paper estimates the impact of flood damage on the real economy using prefecture-by-prefecture flood damage data from the Flood Statistics (MLIT) and prefecture-by-prefecture GDP from the Prefectural Accounts (Cabinet Office), as well as other economic data. As mentioned in Yamamoto and Naka (2021), the smallest unit of flood damage recorded by Flood Statistics is the municipality, but since data on the economic activities at the municipality level are limited, this paper constructs and analyzes panel data using prefecture data, for which relatively rich economic data is available.

[8] Studies using higher granularity data than national data include Tran and Wilson (2020), who analyze the impact of natural disaster damage on employment and income by county in the United States, and Blickle et al. (2021), who analyze the impact on banks' financial conditions.

3.1 Flood damage

Data on flood damage in each prefecture are obtained from the Flood Statistics. Flood Statistics are calendar year statistics that have been conducted annually since 1961, recording damage caused by floods comprehensively and for the details of all sizes for the purpose of obtaining the basic data necessary for implementing administrative measures for flood control. The survey covers three categories: (1) general assets such as households, firms, and farmland; (2) public infrastructure such as roads, bridges, and river and coastal levees; and (3) public services such as railroads, water supplies, and power supplies, and is based on reports from local governments and business entities. The recorded damage includes quantitative information such as the number of damaged offices and buildings, as well as the amount of damage estimated under certain assumptions. For example, looking at the per capita total damage due to flooding during the sample period 1998-2018 by prefecture, the average per capita damage due to flooding during this period was approximately 13,000 yen; however, the maximum value was approximately 750,000 yen, which is not a small amount. In addition, looking at the amount of damage to general assets per capita by municipality for the 23-year period from 1996 to 2018, for which data are available, the maximum value was approximately 4.1 million yen, which may exceed annual income in some municipality.

3.2 Prefectural Accounts

Prefectural Accounts are used as the main real economic data for each prefecture. Prefectural Accounts are prepared by each prefecture and record the prefectural economy based on the definition and methodology of national accounts. In recording the Prefectural Accounts, the Cabinet Office has published the Standardized Method for Prefectural Accounts and the Guidelines for Prefectural Accounts Methodology (Cabinet Office), which take into account inter-prefectural comparisons. However, as indicated in the guidelines, due to the lack of statistical data as the basis for calculation, some primary statistics used for compiling the Prefectural Accounts use the data with frequency lower than the Flood Statistics, such as the Economic Census Survey that is conducted every five years. Therefore, there are some series in which the impact of annual flood damage may not be well represented in the figures, or only to a limited degree[9]. Such series are dropped from the scope of the analysis for the purpose of this paper.

Note that the Flood Statistics are on a calendar year basis, whereas the Prefectural Accounts are on a fiscal year basis. However, as shown in Hashimoto and Sudo (2022), floods rarely

[9] For example, consumption per household in the prefectural accounts includes a value calculated as "consumption per household" times "number of households." Of these, consumption per household is based on the National Survey of Family Income and Expenditure conducted every five years by the Ministry of Internal Affairs and Communications.

occur between January and March. In addition, if there is a lag in the effects of flood damage that occurs between October and December, the fiscal year statistics include January through March of the following year may reflect the impact of such flood damage.

4 Models and methodologies

4.1 Baseline model: Model A

The estimation methodology is a fixed-effects model that includes fixed effects for each prefecture and time. Such fixed-effects model formulations are frequently used in empirical analyses of the impact of natural disasters on economic activity, including Tran and Wilson (2020) and Yamamoto and Naka (2021), as described in Botzen et al. (2019). In this article, we use the following formulation:

$$\begin{aligned} &\log Y_{i,t+h} - \log Y_{i,t-1} \\ &= \sum_{\tau=-3}^{0} \beta_{\tau,h} D_{i,t+\tau}^{0} + \mu_h \left(\log F_{i,t} - \log F_{i,t-1}\right) \\ &\quad + \delta_{i,h} + \delta_{t,h} + E_{i,t+h} + C_h + \varepsilon_{i,t,h}. \end{aligned} \tag{1}$$

Here, the first index i in each variable denotes the prefecture and the second index t denotes the time. $Y_{i,t+h}$ represents the real economic variable in year t+h. The specification that the logarithmic difference between $Y_{i,t+h}$ and $Y_{i,t-1}$ is included as the dependent variable is equivalent to analyzing the cumulative sum of the response of the variable $Y_{i,t}$ up to h years after the flood event. The first term on the right-hand side, $D_{i,t}^{0}$, is the amount of damage caused by flooding and is normalized by dividing by GDP of the year prior to the year of flooding. $D_{i,t-1}^{0}$, $D_{i,t-2}^{0}$, and $D_{i,t-3}^{0}$ are the amounts of flood damage in each year from three years before the flood event to the year before the flood event, following the specification used in Tran and Wilson (2020). These variables control for the impact on GDP of flood damage occurring before time t on $Y_{i,t}$ at time t.

When a flood occurs, the real economy in the affected area may be affected by fiscal expenditures spent by the government or public and private insurance payments from the areas outside, which we hereafter refer to as "financial factor". Existing analyses, including Tran and Wilson (2020), often consider the effects that are driven by such a financial factor as part of the indirect effects of flood damage, including the direct effect of the government transfer on residents' income or fiscal multiplier effects that should theoretically increase the output from the demand side. However, there are the government expenditure or the receipt of insurance in normal times as well and these financial factors are unrelated to the flooding that occurred in year t, the year under analysis. From this perspective, we control for the effects of financial factors by including deposits $F_{i,t}$ by prefecture in the explanatory variables.[10,11] δ_i and δ_t represent prefecture fixed effects and time fixed effects, respectively. $E_{i,t}$ is an earthquake dummy that controls for the heterogeneous effects of significant earthquakes that cannot be controlled by δ_t -- this was 1 in FY 2011 in Iwate, Miyagi, and Fukushima, where the effects of the Great East Japan Earthquake were particularly large, and zero in all other cases. In this regard, the Great East Japan Earthquake was included in FY 2010, but as the date of occurrence was March 11, the impact on economic data was assumed to appear in the following year (FY 2011). Of the remaining terms, C_h is the constant term and $\varepsilon_{i,t,h}$ is the error term.

4.2 Alternative model: Model B

From the perspective of ensuring the robustness of the results, in addition to the baseline model expressed in equation (1), we repeat the estimation using an alternative model, which we refer to as Model B[12]. Model B is based on equation (1) plus the lagged term of GDP, $\log Y_{i,t-1}$. Similar specification has been widely used in empirical studies on natural disasters using cross-country data, including Loayza et al. (2012) and Felbermayr and Gröschl (2014). As described in Mankiw et al. (1992) and Islam (1995), in the classical economic growth theory, such as the Solow model, the rate of economic growth in year t should be higher the larger the difference between the size of the economy at a steady state and the size of the economy $Y_{i,t}$ at that time. In other words, it reflects the idea that the pace of convergence of the economy to a steady state should vary with the level of economic size, and that this should be controlled in the estimation model. As shown below, each variable in equation (2) is the same as in equation (1) except for the lag term.

[10] Deposits by prefecture are based on the location of deposit-taking branches. The formulation that uses the amount of deposits to estimate the impact of natural disasters and takes into account the effects of financial factor is also adopted by Blicle et al. (2021). Consider that the scale of financial factor is the sum of the portion linked to the amount of flood damage and the portion determined independently from the amount of flood damage, then our estimation specification is considered to be able to control for the latter effect. On the other hand, the former part cannot be controlled.

[11] Previous studies, such as Skidmore and Toya (2002) and Felbermayr and Gröschl (2014), often use variables similar to deposits as variables representing economic size. In addition, these studies often include in their estimation model indicators related to political stability and trade openness. Since the analysis in our paper is about prefectures within the same country, these indicators are not included in the explanatory variables in the estimation model.

[12] With respect to estimation using dynamic panel data, Judson and Owen (1999) point out that the bias of the estimation results is small if the estimation sample is of a certain length in the time direction. In a previous study, Felbermayr and Gröschl (2014) take a similar approach to this paper. In addition, the estimation results did not change significantly when Model B was estimated using the generalized method of moments (GMM).

$$
\log Y_{i,t+h} - \log Y_{i,t-1} = \sum_{\tau=-3}^{0} \beta_{\tau,h} D^0_{i,t+\tau} + \rho_{t,h} \log Y_{i,t-1} + \mu_h \left(\log F_{i,t} - \log F_{i,t-1} \right) + \delta_{i,h} + \delta_{t,h} + E_{i,t,h} + C_h + \varepsilon_{i,t,h}. \tag{2}
$$

5 Estimation Results

5.1 Impacts of flood damage on GDP

Figure 4 shows the results of the estimation equation (1), where the dependent variable is growth rate of GDP by prefecture from the year of flood event (year 0) to two years later, and the explanatory variables are the total amount of flood damage, i.e., the sum of damage to general assets, damage to public infrastructure, and damage to public services. Solid vertical lines in the figure represent 90% confidence intervals and bars in the figure represent point estimates. A dark blue bar indicates that the corresponding estimate is of statistical significance at the 95% confidence level, while a light blue bar indicates statistical significance at the 90% confidence level[13]. Note also the same applies to subsequent figures.

First, in terms of the indirect effects of the total flood damage, the damage equivalent to 0.2%[14] relative to GDP in the previous year results in a statistically significant 0.04% point decline in GDP in the year of flood event. However, the statistical significance is only obtained in the year of occurrence. From the following year onward, the confidence interval gradually widens and statistically significance is lost. The same qualitative results are obtained when general assets damage, public infrastructure damage, and public services damage are instead included as an explanatory variable. In other words, in all cases, flood damage causes a statistically significant decline in GDP in the year of occurrence, while the statistical significance disappears in the following year. In terms of point estimates, the impact of general assets damage, public infrastructure damage, and public services damage on GDP is -0.05%, -0.13%, and -2.28%, respectively, suggesting that public infrastructure / public services damage

[13] The standard errors used to calculate confidence intervals are robust standard errors clustered by prefecture.

[14] The size of the total flood damage relative to the GDP in the year prior to the year of flood damage is, on average, about 0.2%. In the estimation exercises below, unless otherwise noted, we set the size of flood damage considered all equal to that of 0.2% of GDP in the year prior to the year of occurrence of flood event. It should be noted, however, that the 0.2% figure is a convenient setting simply to ensure comparability, and that for some assets, facilities, and equipment, the 0.2% loss relative to GDP may be larger than the total value of assets.

may have a larger indirect effect than damage to general assets. The confidence intervals for the impact of damage tends to be the narrowest in the year of occurrence, then expanding in the subsequent years. These estimates suggest that the indirect effects of flood damage may act as downward pressure on economic activity, that the effects may not persistent, and that they may differ depending on the type of asset, facility, and equipment that are damaged by a flood.

Next, in order to study the spillover channels of the indirect effects in detail, we further break down the damage into three categories: general assets damage, public infrastructure damage, and damage to the public services, and repeat the estimations. First, general assets damage is divided into the damage to households, i.e., damage to residential and business buildings and household goods, and damage to firms, i.e., machine tools, agricultural machinery, inventory assets, etc. Based on Flood Statistics during the sample period, damage to households and firms accounted for, on average, 70% and 20%[15] of the total general assets damage, respectively, with household damage being larger. Looking at household damage, the damage significantly depresses GDP in the year of flooding. However, after the following year, the statistical significance is lost and the point estimates turn positive. The point estimate for the firm damage in the year of occurrence shows a larger negative impact on GDP when compared to the amount of damage to households. However, in addition to the confidence interval not being statistically significant, the point estimates are positive from the following year and become statistically significant in the second year[16].

For damage to public infrastructure, the impact is divided into two categories: damage to roads and bridges and damage to other public infrastructure, such as river levees, steep-slope protection facilities, or parks. In the Flood Statistics for the sample period, the percentages of the former and the latter in total public infrastructure damage are about 30% and 70%, respectively. Damage to roads and bridges has a significant downward indirect effect in the year of occurrence. This is possibly because damage to the transportation network hinders the movement of labor and other production inputs and logistics, suppressing production and consumption activities. In terms of the point estimate, the downward effect is -0.4%, which is a deeper negative than damage to households and firms. The point estimates for the following year and the two following years also remain negative, though not statistically significantly. The point estimate for damage to other infrastructure is also consistently negative since the year

[15] Among damage to general assets, agricultural damage, emergency allowance costs for households and firms (e.g., cleaning costs associated with the disaster), and business shutdown losses are excluded from the analyses. In particular the latter two types of damage are considered indirect effects rather than direct effects.

[16] For damage to general assets, it is possible to create not only monetary indicators analyzed in the text, but also physical damage indicators such as the number of houses damaged (total number of buildings flooded under or above floor level, half destroyed, and totally destroyed) and the number of firm establishments damaged. Based on the estimates that use these indicators instead of monetary indicators used in our baseline estimation, the more firm establishment buildings are damaged, the more significantly GDP decreases in the year of flood damage. However, as with the other monetary indicators, no significant effect on GDP in the following year could be confirmed.

of occurrence. However, the negative effect is smaller than for roads and bridges, and the downward effect is not statistically significant in any year.

Lastly, the indirect effects of damage to public services are reviewed separately for power supply, transportation, water, and telecommunications[17]. In the Flood Statistics during the sample period, the respective damage as a percentage of total public services damage are, on average, about 44%, 38%, 12%, and 5%, respectively. Of these, only the damage to power supply facilities can be confirmed as statistically significantly dampening GDP. In terms of the point estimates, if flood damage equivalent to 0.2% of GDP in the previous year were to occur to power supply facilities, GDP would decline by 4.0 percentage points, and the extent of the negative effect is also relatively large compared to damage to general assets or public infrastructure. For other public service facilities, the confidence intervals are generally wide, reflecting the heterogeneous nature of these facilities and the damage, and although there are both positive and negative values in the point estimates, none of them are statistically significant.

In order to study the spillover channel of flood damage in more detail, Figure 5 shows the estimation result when estimating equation (1) using private gross fixed capital formation as the dependent variable[18]. First, for damage to general assets, even in the year of occurrence, no statistically significant indirect effect is obtained for both households and firms assets.

Regarding public infrastructure damage, both roads and bridges damage and other infrastructure damage significantly depress private gross fixed capital formation. In both cases, the effects are statistically significant until the year after the flood, indicating that the effects are reasonably persistent. Compared to the case of damage to general assets, this result may suggest the relative importance of public service provision through public infrastructure in private investment activities.

For damage to public services, it is seen that private gross fixed capital formation falls significantly in the year of occurrence and the year following the year when electric power supply facilities are damaged, and in the year following the year of occurrence when water

---

[17] For damage to public services, in addition to the items used in the analysis, the data on damage to gas supply utilities also exists, but the data is dropped from our estimation analysis due to the small sample size. Regarding damage to public services, damage to power supply is reported by 10 electric power companies; damage to transportation is reported by air, sea, and land transport companies, and damage to water supply is reported by water service companies, as stipulated in Article 3, Paragraphs 2-4 of the Waterworks Act; and telecommunications by companies based on reports from operators under Article 9 of the Telecommunications Business Act.

[18] As noted in footnote 8, among the GDP components, the private consumption is not studied in our estimation because the consumption of households, which accounts for the majority of the total GDP, is constructed from primary statistics that are not updated frequently. Specifically, according to the Guidelines for Estimation Methods of Prefectural Accounts, consumption of households is based on the National Survey of Family Income and Expenditure released from the Ministry of Internal Affairs and Communications, but this survey is conducted every five years. Therefore, for periods when no survey is conducted, the survey years are interpolated by the equal ratio (annual growth rate), and for each year since the most recent National Survey of Current Consumption, the same extrapolation by equal ratio is used to estimate final consumption expenditure. Therefore, the impact of that flood damage may not be well reflected, and dropped from our estimation.

facilities are damaged, indicating the relative importance of these services, as well as the results for damage to public infrastructure. For damage to transportation and telecommunication facilities, the results are not statistically significant, although the point estimates are all in the downward direction.

Figures 6 and 7 show the results of the same estimates as in Figures 4 and 5, using the estimation equation (2). The results are generally the same as those obtained using estimation equation (1). Specifically, the results are summarized in two points. First, flood damage has a depressive effect on GDP. For example, flood damage equivalent of 0.2% of the previous year's GDP, in terms of the size of flood damage, reduces GDP by 0.04% in the year of the flood event. However, a statistically significance is lost after the year following the year of occurrence. This observation is also seen when the flood damage is broken down into general assets, public infrastructure, and public services damage. Second, the depressing effect on GDP varies depending on which assets, facilities, and equipment are affected by a flood. Namely, while statistically significant negative effects can be seen for damage to general assets, damage to roads and bridges, and power supply facilities among public services in the year of flooding, no such statistical relationships are found for example regarding damage to other public infrastructure. Furthermore, when compared with assets, facilities, and equipment that have a statistically significant impact on GDP, damage to power supply facilities yields a relatively large negative impact on GDP.

5.2 Impacts of flood damage on sectoral GDP

As described in Section 2, there are likely to be multiple spillover channels for indirect effects of natural disasters, which may have different impacts on different sector. In the following, we estimate how the GDP of each sector responds to direct flood damage for the manufacturing sector, the electricity, gas, water, and waste management sector (hereafter referred to as "electricity."), the construction sector, and the wholesale and retail trade sector. In selecting sectors we analyze, we examine, in addition to the availability of long-term time series, the primary statistics used for compiling each sectoral GDP series including whether the statistics are updated at least as frequently as Flood Statistics, to see if the sectoral GDP series is suited to capture the effects of flood damage that occur in a specific year. Some series are therefore dropped from the analysis depending on the production method[19].

First, in terms of GDP in the manufacturing sector, as shown in Figure 8, both household and firm general assets damage have a negative effect in the year of the flood damage, with the

[19] For example, sectoral GDP of the real estate, professional, scientific and technical activities are not included in the analysis because they are estimated using national indices and are not considered to reflect annual economic dynamics of the corresponding sector in each prefecture.

effects of firms' general assets damage being statistically significant and the point estimate more deeply negative. However, the statistical significance is lost in the following year. For damage to public infrastructure and public services, the point estimates tend to be negative but the confidence intervals are wide and not significant.

The next set of estimates for GDP in the construction sector, as shown in Figure 9, differ significantly from those for GDP in the manufacturing GDP. The indirect effect of total flood damage on GDP in the construction sector increases with a statistically significant degree in the year of occurrence and in the following year. For general assets damage, both damage to households' and firms' general assets significantly boost the sectoral GDP in the year of occurrence, with damage to the former pushing up the GDP in the following year as well. In terms of point estimates, the estimate regarding firms' damage is larger. This positive effect may reflect a specific characteristic of the construction sector that the sector relative to other sectors tends to attract the restoration demand, in which households and firms repair and restore physical assets damaged by flooding, as pointed out in von Peter et al. (2012). Regarding damage to public infrastructure, the impacts of both roads and bridges and other infrastructure damage on construction GDP are not statistically significant. Within public services damage, damage to water supply facilities pushes up GDP in the year of occurrence.

The estimated results for GDP in the electricity sector are, as shown in Figure 10, similar to the results for GDP in the manufacturing sector and differ from those for GDP in the construction sector. Specifically, damage to general assets of households, damage to roads and bridges, damage to power supply, and damage to water supply facilities significantly depress GDP in the sector. In particular, damage to roads and bridges and that to power supply facilities continuously depresses GDP in the year following the year of occurrence, suggesting that public services using public facilities and utilities play an important role in the production activities of the sector. On the other hand, damage to transportation facilities statistically significantly increases GDP in the sector in the year following the year of flood damage.

Similar estimation results to those for GDP in manufacturing and electricity sectors are obtained for the impacts of flood damage on GDP in the wholesale and retail trade sector, as shown in Figure 11. Specifically, the results show that when flood damage occurs to roads and bridges or to power supply, the GDP of wholesale and retail trade sector in the year of flooding is statistically significantly depressed. Quantitatively, the impact of damage to power supplies is the largest. These observations contrast with what is observed for the effects on GDP in the construction sector. It is notable that the downward effect is more pronounced even when compared to the estimates for GDP in the manufacturing sector. These results also suggest that in the transmission of flood damage to GDP in the wholesale and retail trade sector, the production process and transportation process may play an important role.

Figures 12 through 15 show the estimation results for the indirect effects of flood damage on sectoral GDP when using the Model B instead of the Model A. There are some differences between the results under the two models, including a positive response of GDP in manufacturing sector to damage to telecommunications, a more pronounced boosting effect on GDP in the construction sector of general assets damage, and a non-significant response of GDP in wholesale and retail trade sector to public infrastructure damage. However, the results obtained under Model B are similar to those from Model A in that the impact of flood damage may differ across sectors, and the impacts of damage tend to be positive for the construction sector and not so for the manufacturing, electricity, and wholesale and retail trade sectors.

6 Conclusion

Although empirical analyses have been increasingly accumulated in various countries, there is yet no established view on the scale or persistency or even the signs of the indirect effects that natural disasters bring about to the economy. In this paper, we have quantitatively assessed how flood damage on various assets, infrastructure, or equipment, i.e., the direct effects, affect the real economy, i.e., indirect effects, using prefectural-level data of detailed flood events and the economic activity in Japan. To this end, we employ local projections to quantify both short-term and long-term dynamics of the indirect effects.

The main results obtained in this paper can be summarized as follows. First, flood damage has a statistically significant depressing effect on GDP in the year of flood damage. The magnitude of this indirect effect, when measuring by the size relative to the direct effect of flood damage, varies from about one-fiftieth to one-third. When measuring by the size relative to GDP in the year prior to the year of occurrence, a 1% level of flood damage has a depressing indirect effect of approximately -0.18% to -0.19% in the year of occurrence in terms of point estimates. The magnitude may further vary from -0.02% to -0.36% for the baseline and from -0.01% to -0.35% for Model B; based on the 95% confidence interval. In addition, the size of the indirect effect depends on the sectoral composition of the economy of the prefecture where the flood occurred or the type of assets, equipment, and facilities damaged by the flood. It is notable, however, that although there are some modest differences, in most of the cases, the indirect effect is no longer statistically significant after the year following the year of flooding, which may indicate that the effect is not persistent.

Second, the flood damage brings about indirect effects of different signs across sectors. It is seen that flood damage has a statistically significant negative impact on GDP in some sectors such as manufacturing and wholesale and retail trade sector, although the precise nature of the impact depends on the type of assets, equipment, and facilities. By contrast, it has a statistically significant positive impact on GDP in the construction sector. For example, flood damage to household assets of the size of 1% of GDP in the year before the flood event depresses GDP in the manufacturing sector by 1.2% and boosts GDP in the construction sector by 1.8% in the year of occurrence, based on point estimates. This suggests that while the indirect effects of flood damage are thought to have a depressing effect on the economy as a whole, there is also a push-up effect in some segments of the economy from restoration work on damaged houses, business establishments, and public infrastructure.

Third, the magnitude of the indirect effects of flood damage varies by the assets, equipment, and facilities that are damaged. Compared to damage to assets of households and firms, damage to public infrastructure such as roads and damage to public services such as power supplies tend to depress GDP greater. For example, in terms of point estimates, flood damage to household assets by 1% has reduces GDP by 0.32% in the year of occurrence, whereas the same size of flood damage to power supplies reduces GDP by 16.3%. These results may indicate the importance of public services and infrastructure in the spillover effects of flood damage.

There are three caveats in this study. First, there may be some issues regarding the fact that the analysis is conducted at the prefectural level. For example, the inputs for compiling prefectural GDP include statistics that collect national-level data rather than the corresponding prefectural data, or statistics that collect the prefectural data but only infrequently than the Flood Statistics. It is also possible that flood damage occurring in a particular municipality may have a greater impact on nearby prefectures than on other areas in the same prefecture.

Second, the size of indirect effects of flooding may change over time. As discussed in Hsiang and Jina (2014) and Bakkensen and Barrage (2019), the indirect effects of natural disasters are thought to be determined by various factors, including supply-side effects, such as lower inputs of production factors, demand-side effects, such as changes in earning of households and firms in the affected region due possibly to transfer associated with fiscal expenditures and insurance payments, and effects on physical and human investment behavior through changes in medium- to long-term risk perceptions of economic agents. Our estimation results net these factors and capture the average effects of these factors. Therefore, the results may change significantly depending on future developments in the economic structure and the awareness of economic agents, such as changes in the location selection of production facilities by firms on the supply side, the spread of insurance against natural disasters on the demand side, and growing interest in climate change on the risk perception side.

Third, the Flood Statistics used in our study is estimate of monetary damages based on damage reports, not on the physical intensity of the disaster, such as wind speed and rainfall. In this way, the direct and indirect effects caused by floods may be more precisely captured but it is possible the scale of monetary direct effects is also be affected by prior investments in flood control infrastructure and other factors[20]. The quantitative implications of our results therefore may also change depending on future disaster prevention-related measures and changes in the risk perception of households and firms. Addressing these issues and further improving the estimates of indirect and direct effects of natural disasters are left as our future research agenda.

[20] In this regard, in Appendix 2, we repeat the estimation exercise based on a specification in which flood control-related capital stock prior to the flood event is added as an explanatory variable and show that the qualitative implications are not largely different from those obtained from the baseline.

References

Bakkensen, L., Barrage, L. (2019) "Climate Shocks, Cyclones, and Economic Growth: Bridging the Micro-Macro Gap," NBER Working Paper Series, No.24893.

Bayoumi, T., Quayyum, S. N., Das, S. (2020) "Growth at Risk from Natural Disasters," IMF Working Paper, WP/21/234.

Bello, O. (2017) "Disasters, Economic Growth and Fiscal Response in the Countries of Latin America and the Caribbean, 1972-2010," CEPAL Review, No. 121.

Blickle, K., Hamerling, S. N., Morgan, D. P. (2021) "How Bad Are Weather Disasters for Banks?," Federal Reserve Bank of New York Staff Reports, no. 990.

Botzen, W. W., Deschenes, O., Sanders, M. (2019) "The Economic Impacts of Natural Disasters: A Review of Models and Empirical Studies," *Review of Environmental Economics and Policy*, 13(2), 167-188.

Cavallo, E. A., Becerra, O., Acevedo, L. (2021) "The Impact of Natural Disasters on Economic Growth," IDB working paper series, No. IBD-WP-1257.

Cavallo, E., Galiani, S., Noy, I., Pantano, J. (2013) "Catastrophic Natural Disasters and Economic Growth," *Review of Economics and Statistics*, 95 (5), 1549-1561.

Cavallo, E., Noy, I. (2011) "Natural Disasters and the Economy—A Survey," *International Review of Environmental and Resource Economics*, 5(1), 63-102.

Economic and Social Research Institute, Cabinet Office, Government of Japan (2018) "Standardized Method for Prefectural Accounts (2011 Standard Version)." (Available only in Japanese.)

Economic and Social Research Institute Cabinet Office, Government of Japan (2019) "Guidelines for Prefectural Accounts Methodology (2011 Standard Version)." (Available only in Japanese.)

Felbermayr, G., Gröschl, J. (2014) "Naturally Negative: The Growth Effects of Natural Disasters," *Journal of Development Economics*, 111, 92-106.

Fomby, T., Ikeda, Y., Loayza, N. V. (2013) "The Growth Aftermath of Natural Disasters," *Journal of Applied Economics*, 28(3), 412-434.

Hashimoto, R., Sudo, N. (2022) "Transmission of Flood Damage to the Real Economy and Financial Intermediation: Simulation Analysis using a DiGE Model," Bank of Japan Working Paper Series, No. 22-E-5.

Hsiang, S. M., Jina, A. S. (2014) "The Causal Effect of Environmental Catastrophe on Long-run Economic Growth: Evidence from 6,700 Cyclones," NBER Working Paper 20352.

Islam, N. (1995) "Growth Empirics: A Panel Data Approach," *The Quarterly Journal of Economics*, 110 (4), 1127–1170.

Jordà, Ò. (2005) "Estimation and Inference of Impulse Responses by Local Projections," *American Economic Review*, 95(1), 161-182.

Judson, R, Owen, A. (1999) "Estimating Dynamic Panel Data Models: A Guide for Macroeconomists," *Economics letters*, 65 (1), 9-15.

Klomp, J., Valckx, K. (2014) "Natural Disasters and Economic Growth: A Meta-analysis," *Global Environmental Change*, 26, 183-195.

Kurachi, Y., Morishima, H., Kawata, H., Shibata, A., Bunya, K., Moteki, J. (2022) "Challenges for Japan's Economy in the Transition to a Decarbonized Society: A Discussion Paper", Bank of Japan Research Paper. (Available only in Japanese.)

Loayza, N. V., Olaberria, E., Rigolini, J., Christiaensen, L. (2012) "Natural Disasters and Growth: Going Beyond the Averages," World Development, 40(7), 1317-1336.

Mankiw, N. G., Romer, D., Weil, D. N. (1992) "A Contribution to the Empirics of Economic Growth," *The Quarterly Journal of Economics*, 107 (2), 407-437.

Ministry of Education, Culture, Sports, Science and Technology of Japan and Japan Meteorological Agency (2020) "Climate Change in Japan 2020 - Report on Observations and Projections Assessment on Atmosphere, Land, and Oceans." (Available only in Japanese.)

Ministry of Land, Infrastructure, Transport and Tourism of Japan, Technical group for flood control plans considering the impacts of climate change (2019) "Recommendations on flood control plans considering the impacts of climate change." (Available only in Japanese.)

Ministry of Land, Infrastructure, Transport and Tourism (2020) "Flood Control Economic Study Manual (Draft)." (Available only in Japanese.)

Network for Greening the Financial System (2021) "NGFS Climate Scenarios for Central Banks and Supervisors."

Noy, I., (2009) "The Macroeconomic Consequences of Disasters," *Journal of Development Economics*, 88(2), 221-231.

Panwar, V., Sen, S. (2019) "Economic Impact of Natural Disasters: An Empirical Re-examination," *Journal of Applied Economic Research*, 13(1), 109-139.

Raddatz, C. (2009) "The Wrath of God: Macroeconomic Costs of Natural Disasters," World Bank Policy Research Working Paper, 5039.

Sawada, Y., Masaki, T., Nakata, H., Sekiguchi, K. (2017) "Natural Disasters: Financial Preparedness of Corporate Japan," RIETI Discussion Paper Series 17-E-014.

Skidmore, M., Toya, H. (2002) "Do Natural Disasters Promote Long-run Growth?," *Economic Inquiry*, 40(4), 664-687.

Strobl, E. (2011) "The Economic Growth Impact of Hurricanes: Evidence from US Coastal Counties," *The Review of Economics and Statistics*, 93(2), 575-589.

Strobl, E. (2012) "The Economic Growth Impact of Natural Disasters in Developing Countries: Evidence from Hurricane Strikes in the Central American and Caribbean Regions," *Journal of Development Economics*, 97(1), 130-141.

Tran, B. R., Wilson, D. J. (2020) “The Local Economic Impact of Natural Disasters,” Federal Reserve Bank of San Francisco, Working Paper 2020-34.

University of Tokyo Press (2018) “Productivity and Inequality by Region in Japan by Industry Analysis Using the R-JIP Database.” (Available only in Japanese.)

von Peter, G., von Dahlen, S., Saxena, S. C. (2012) “Unmitigated Disasters? New Evidence on the Macroeconomic Cost of Natural Catastrophes,” BIS Working Papers, No.394.

Yamamoto, H., Naka, T. (2021) “Quantitative Analysis of the Impact of Floods on Firms' Financial Conditions,” BOJ Working Paper Series, No.21-E-10.

Appendix–1. Model that controls the effects of damage to other assets, facilities, and equipment (Model C)

We show above the indirect effects of flood damage to specific assets, facilities, and equipment on real GDP and sectoral GDP using a specification which we refer to as Models A and B. In this appendix, we estimate the response of GDP to the flood damage by asset, facility, and equipment, using the following alternative specification which we refer to as Model C for the purpose of the robustness check of the results obtained in the main text.

$$\log Y_{i,t+h} - \log Y_{i,t-1}$$
$$= \sum_{\tau=-3}^{0} \beta_{\tau,h} D^{0}_{i,t+\tau} + \sum_{\tau=-3}^{0} \gamma_{\tau,h} D_{i,t+\tau} \tag{3}$$
$$+\mu_h\left(\log F_{i,t} - \log F_{i,t-1}\right) + \delta_{i,h} + \delta_{t,h} + E_{i,t+h} + C_h + \varepsilon_{i,t,h}.$$

Compared with Model A, Equation (3) includes as an explanatory variable the term $D_{i,t}$, which is the total flood damage less $D^0_{i,t}$. In words, this term is the sum of flood damage that occurred at assets, facilities, and equipment other than the amount of flood damage of interest, which is denoted as $D^0_{i,t}$. As with $D^0_{i,t}$, this variable $D_{i,t}$ is included as an explanatory variable from three years prior to the flood event to the year of the flood event, so that the associated effect of the flood damage that occurred prior to time t is controlled.

Figure A-1 shows the estimated indirect effects on GDP based on Equation (3). Compared to Figure 4, which shows the results under Model A, there are some differences, including a more positive shift in the indirect effects of general assets damage and its breakdown, and the persistence of the adverse effects of public infrastructure damage in the year following the flood. Admittedly, there are also similarities. In terms of the total indirect effects caused by flooding, the downward pressure is most pronounced in the year of flooding, and the impact diminishes in the following years. While not shown due to space limitations, the indirect effects on private gross fixed capital formation or on sectoral GDP are not changed qualitatively from the results under Model A.

Appendix─2. Model in which the effects of flood control-related social capital stock are taken into account (Model D)

The indirect effects of flood damage may vary depending on the size of flood control-related social capital stock before floods occur. From the perspective of checking the robustness of the estimation results obtained in the main text, this appendix uses the following estimation equation (4), which we refer to as Model D that includes the amount of flood control-related social capital stock as an explanatory variable.

$$\begin{aligned}
&\log Y_{i,t+h} - \log Y_{i,t-1} \\
&= \sum_{\tau=-3}^{0} \beta_{\tau,h} D_{i,t+\tau}^{0} + \omega_h \left(\frac{K_{i,t-1}^{chisui}}{K_{i,t-1}^{stot}}\right) \\
&\quad +\mu_h \left(\log F_{i,t} - \log F_{i,t-1}\right) + \delta_{i,h} + \delta_{t,h} + E_{i,t+h} + C_h + \varepsilon_{i,t,h}.
\end{aligned} \tag{4}$$

Here, $K_{i,t}^{chisui}$ represents the size of flood control-related social capital stock[21] and $K_{i,t}^{stot}$ represents the total social capital stock at time t in prefecture i, respectively. In the equation above, the ratio of flood control-related social capital stock to the social capital stock as of the year prior to the flood event is included. The data on the two types of social capital stock are taken from the R-JIP 2017 published by the Research Institute of Economy, Trade and Industry (RIETI). Because the data is available only up to 2012, the sample period of the analysis in this section differs from the main text.

Figure A-2 shows the estimated indirect effects of flood damage under the Model D. Compared to what is seen in Figure 4, there are some differences. For example, the impact of total flood damage on GDP in the year of the flood event is not significant and the impact of flood damage to power supply is statistically significant up to two years after the flood event. However, general pattern of the indirect effects of flood damage remains the same in the sense that flood damage dampens GDP, with the most pronounced effects in the year of flood event and limited effects in the following years, and that the scale of indirect effects varies by asset, facility, and equipment. Although not shown in the paper, the indirect effects on private gross fixed capital formation or on sectoral GDP also do not differ qualitatively from those under the baseline model[22].

---

[21] Flood control-related capital stock is defined as the sum of "flood control," "mountain control," and "coastal" of the social capital stock reported in the R-JIP 2017. The correlation coefficients between these flood control-related capital stocks (as of t-1) and the total amount of flood damage (as of t) over the sample period (1981-2012), after both series are converted into ratios relative to GDP, is about -0.4 on a national basis and ranges from -0.7 to +0.2 for each prefecture.

[22] The coefficient for the flood control-related capital stock itself is not significant under the formulation of estimation equation (4)

Figure 1: Impact of natural disasters on the real economy [23]

Impact on the real economy

	Short-term		Medium- to long-term
Positive	– Increased demand to restore damaged capital stock – Increased demand through insurance payments and other income transfers from outside the region – Reference : von Peter et al. (2012) , Sawada et al. (2017) etc.	Positive	– Increased productivity of capital stock due to replacement with more productive production equipment ($A_t\uparrow$) – Accumulation of capital stock in anticipation of future natural disasters ($K_t\uparrow$) – Reference : Skidmore and Toya (2002), Tran and Wilson (2020) etc.
Negative	– Decrease in capital input due to capital stock damage ($K_t\downarrow$) – Decrease in productivity through damage to public infrastructure, etc. ($A_t\downarrow$) – Reduced productivity through supply chain interruptions, etc. ($A_t\downarrow$) – Reference : Hsiang and Jina (2014), Bakkensen and Barrage (2019) etc.	Negative	– Migration to other areas in anticipation of future natural disasters ($L_t\downarrow$) – Investment to alternatives areas in anticipation of future natural disasters ($K_t\downarrow$)

[23] Prepared based on Tran and Wilson (2020) and other studies. A_t, K_t, and L_t in parentheses denote TFP, capital stock input, and labor input, respectively, when the production function is defined as shown in Section 2.

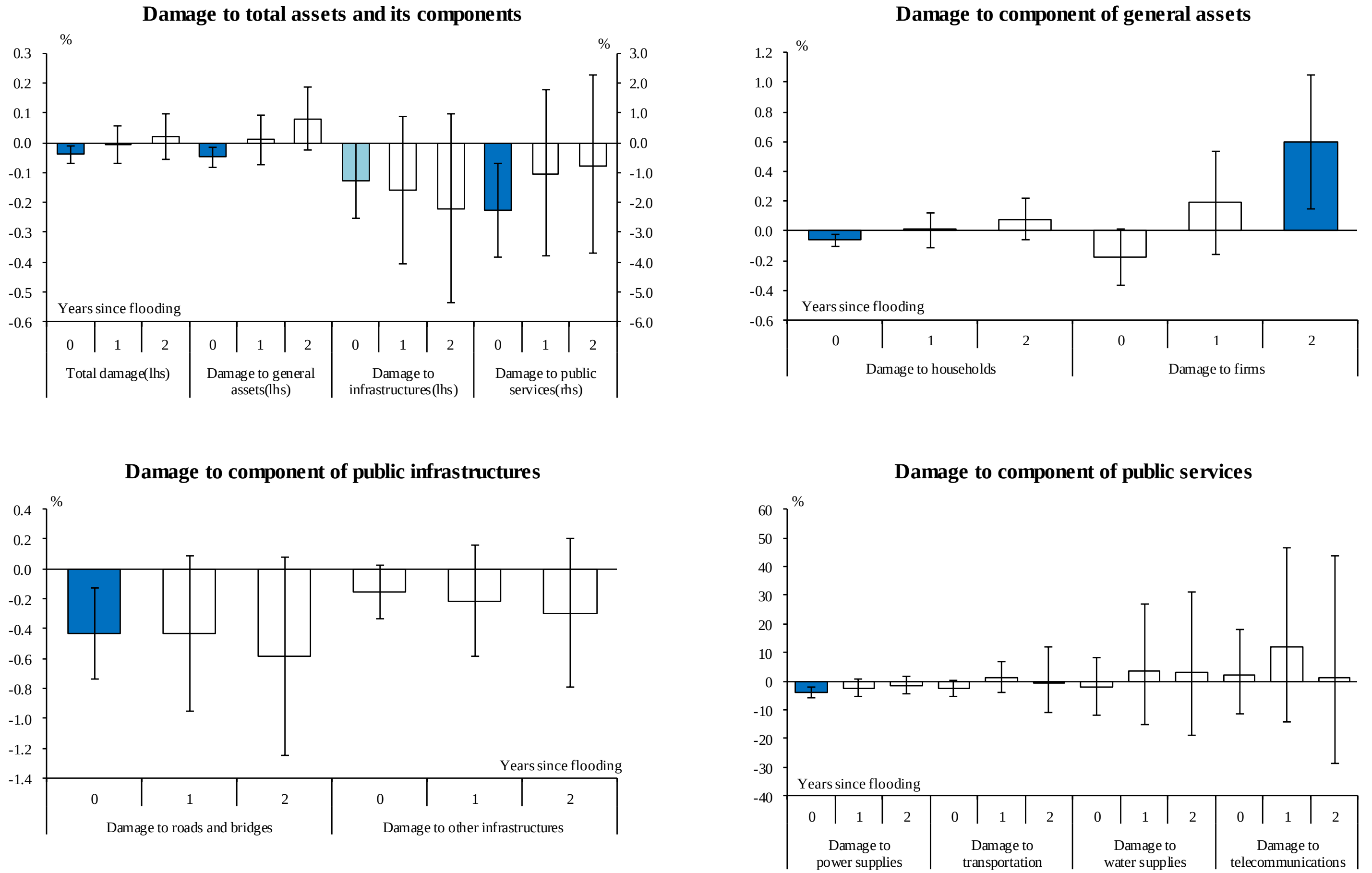
Figure 2: Descriptive statistics

		N	min	median	average	max	sd
Growth rate (%)	Y(t)/Y(t-1)	940	-10.24	0.95	0.78	8.71	2.62
	Y(t+1)/Y(t-1)	893	-15.11	1.72	1.54	12.05	3.72
	Y(t+2)/Y(t-1)	846	-14.53	2.30	2.11	18.52	4.29
Total flood damage	Japanese Yen	987	0	3,336	12,966	749,095	40,772
	per GDP (%)	940	0	0.05	0.19	6.91	0.55
Deposit (y/y chg. %)		940	-7.82	0.88	1.21	21.17	3.34

Figure 3: Correlation matrix

(obs = 987)	Total damage	Damage to general assets	Damage to infrastrucure	Damage to public services	Damage to roads, etc.	Damage to other infrastrucure	Damage to households	Damage to corporations	Damage to power supplies	Damage to transportation	Damage to water supplies	Damage to telecommunications
Total damage	1.00											
Damage to general assets	0.95	1.00										
Damage to infrastrucure	0.68	0.42	1.00									
Damage to public services	0.53	0.41	0.58	1.00								
Damage to roads, etc.	0.60	0.36	0.90	0.62	1.00							
Damage to other infrastrucure	0.67	0.43	0.98	0.53	0.80	1.00						
Damage to households	0.94	0.99	0.41	0.42	0.35	0.41	1.00					
Damage to corporations	0.62	0.62	0.34	0.31	0.35	0.31	0.51	1.00				
Damage to power supplies	0.37	0.28	0.42	0.91	0.50	0.35	0.28	0.23	1.00			
Damage to transportation	0.45	0.38	0.43	0.57	0.36	0.43	0.39	0.24	0.23	1.00		
Damage to water supplies	0.46	0.34	0.57	0.66	0.63	0.50	0.35	0.27	0.49	0.31	1.00	
Damage to telecommunications	0.39	0.28	0.47	0.38	0.39	0.48	0.28	0.18	0.23	0.20	0.34	1.00

Figure 4: Impact of flood damage on GDP (Model A)[24]



[24] Results of regression of prefectural GDP on the flood damage are shown on the horizontal axis using the estimation Model A. The colors of the bars indicate 95% statistical significance for dark blue, 90% statistical significance for light blue, and no statistical significance for white, and error bands indicate 90% confidence intervals. The vertical axis is the change from that in GDP in the year prior to the flood event in the case where flood damage equivalent to 0.2% of GDP in previous year occurred in the assets, facilities, and equipment on the horizontal axis. The 0-2 value on the horizontal axis indicates the year elapsed since the flood event when the year of the flood event is set to 0. The standard errors used to calculate confidence intervals are robust standard error clustered by prefecture. The same applies to Figure 5, Figure 8, Figure 9, Figure 10, and Figure 11.

Figure 5: Impact of flood damage on private gross fixed capital formation (Model A)

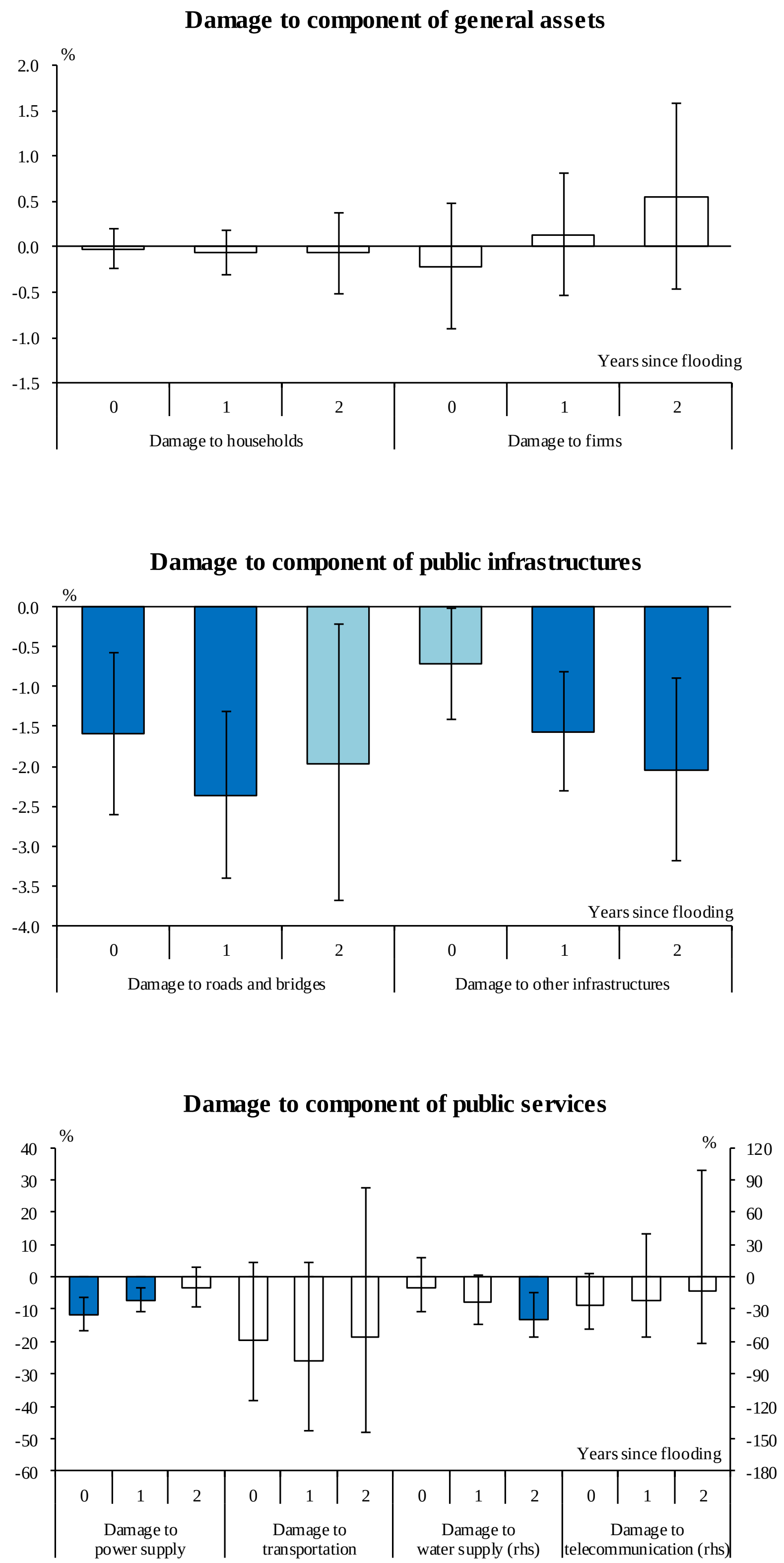
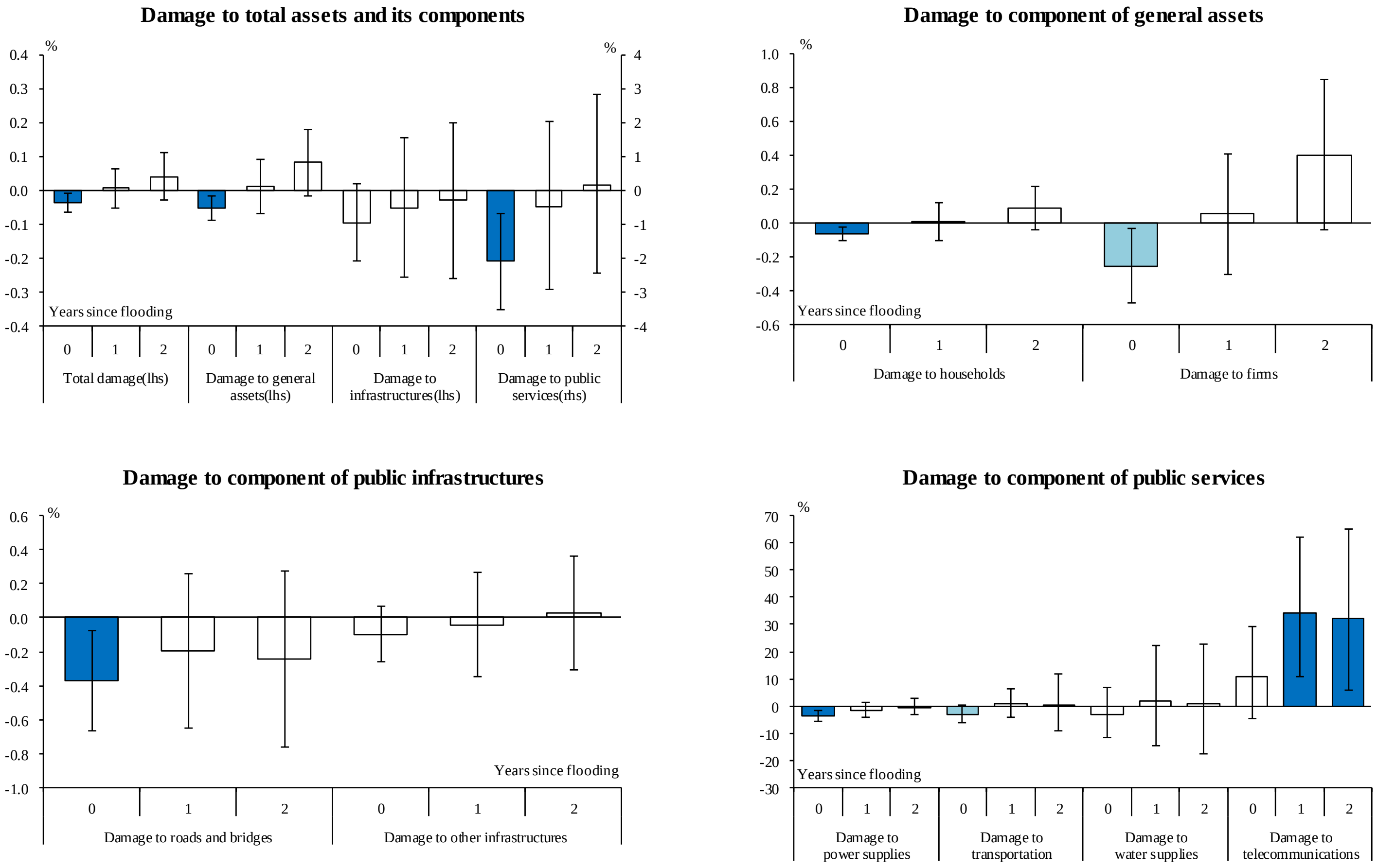


Figure 6: Impact of flood damage on GDP (Model B)[25]



[25] Results of regression of prefectural GDP on the flood damage are shown on the horizontal axis using the estimation Model B. The colors of the bars indicate 95% statistical significance for dark blue, 90% statistical significance for light blue, and no statistical significance for white, and error bands indicate 90% confidence intervals. The vertical axis is the change from that in GDP in the year prior to the flood event in the case where flood damage equivalent to 0.2% of GDP in previous year occurred in the assets, facilities, and equipment on the horizontal axis. The 0-2 value on the horizontal axis indicates the year elapsed since the flood event when the year of the flood event is set to 0. The standard errors used to calculate confidence intervals are robust standard error clustered by prefecture. The same applies to Figure 7, Figure 12, Figure 13, Figure 14, and Figure 15.

Figure 7: Impact of flood damage on private gross fixed capital formation (Model B)

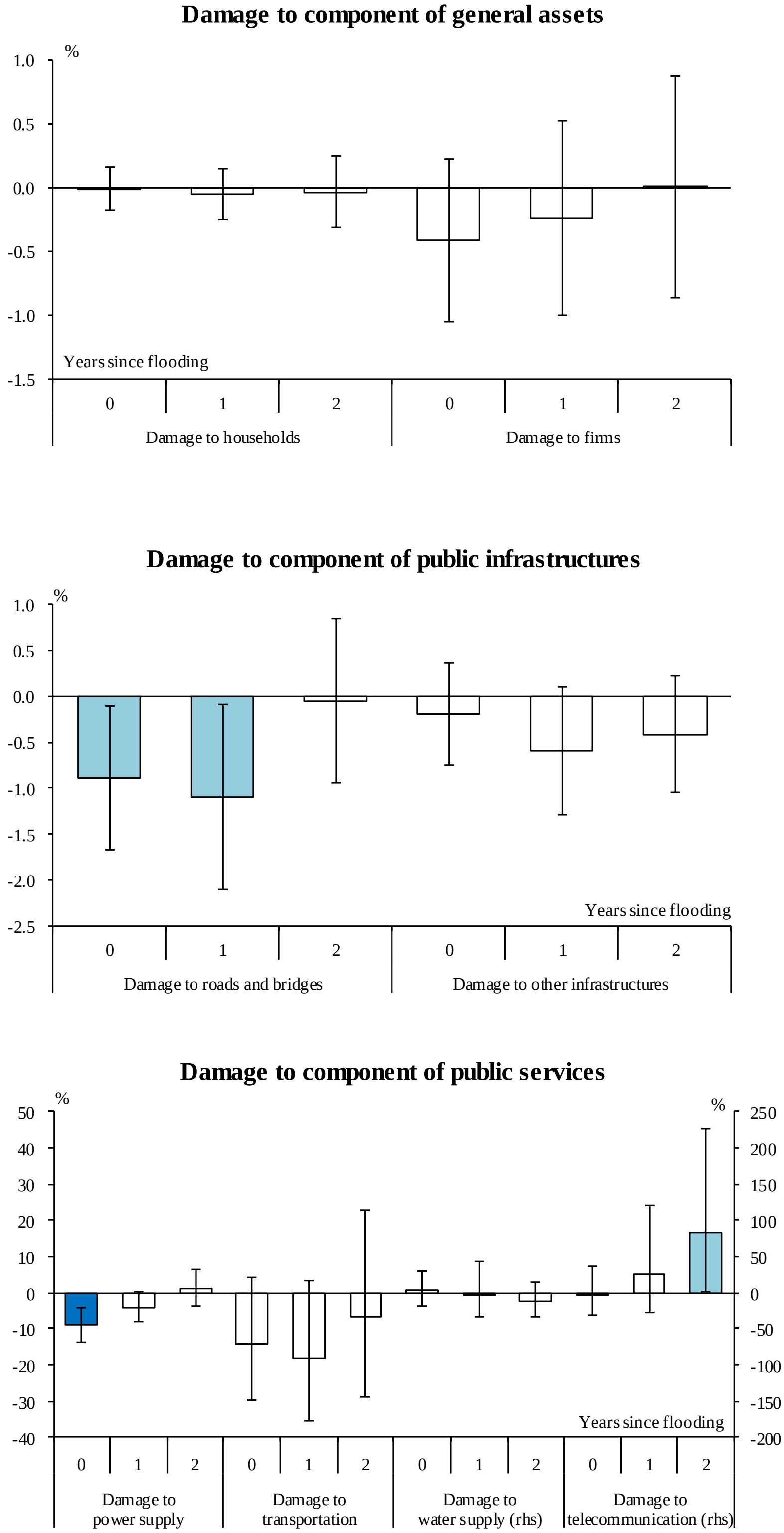


Figure 8: Impact of flood damage on manufacturing GDP (Model A)

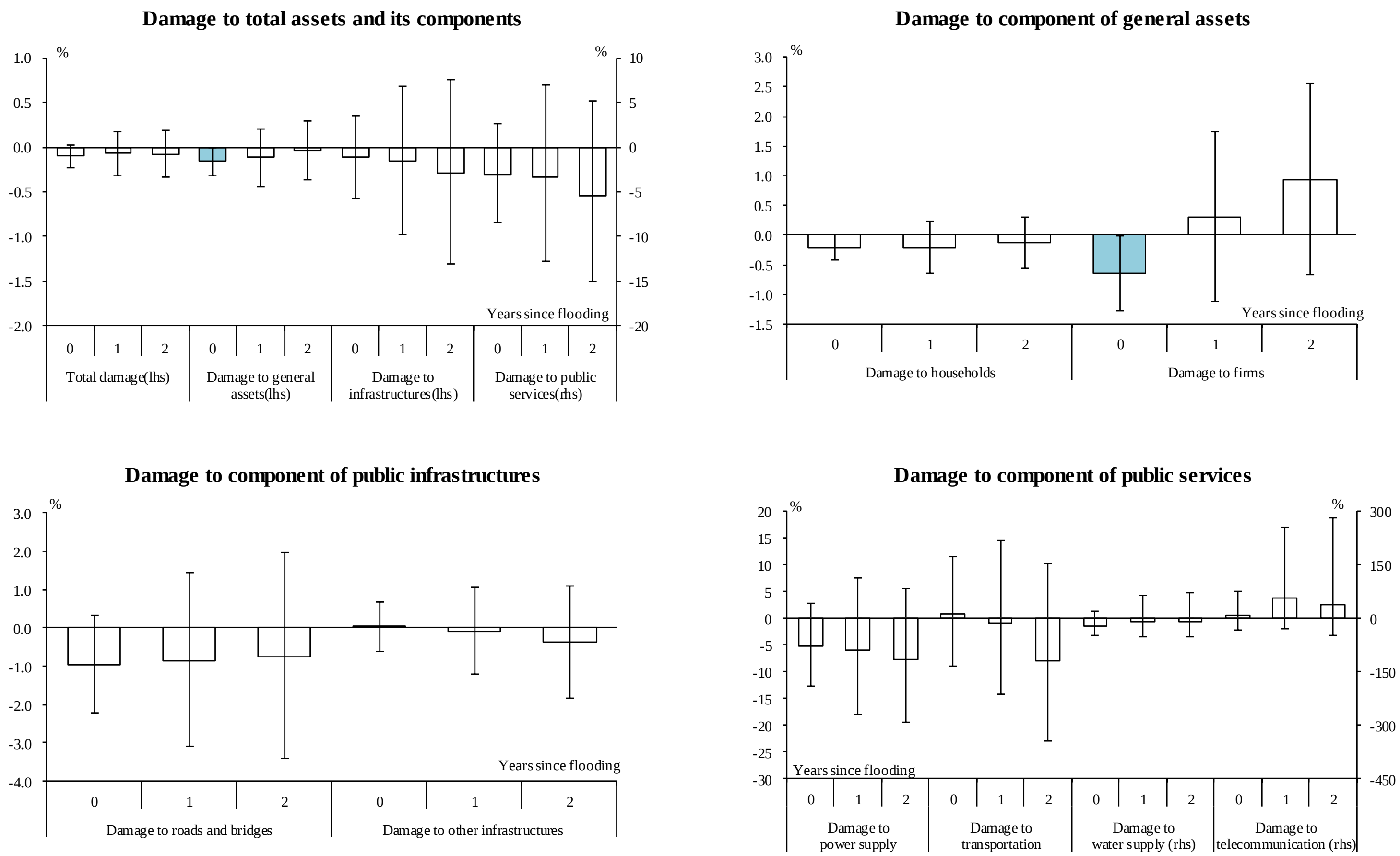


Figure 9: Impact of flood damage on construction GDP (Model A)

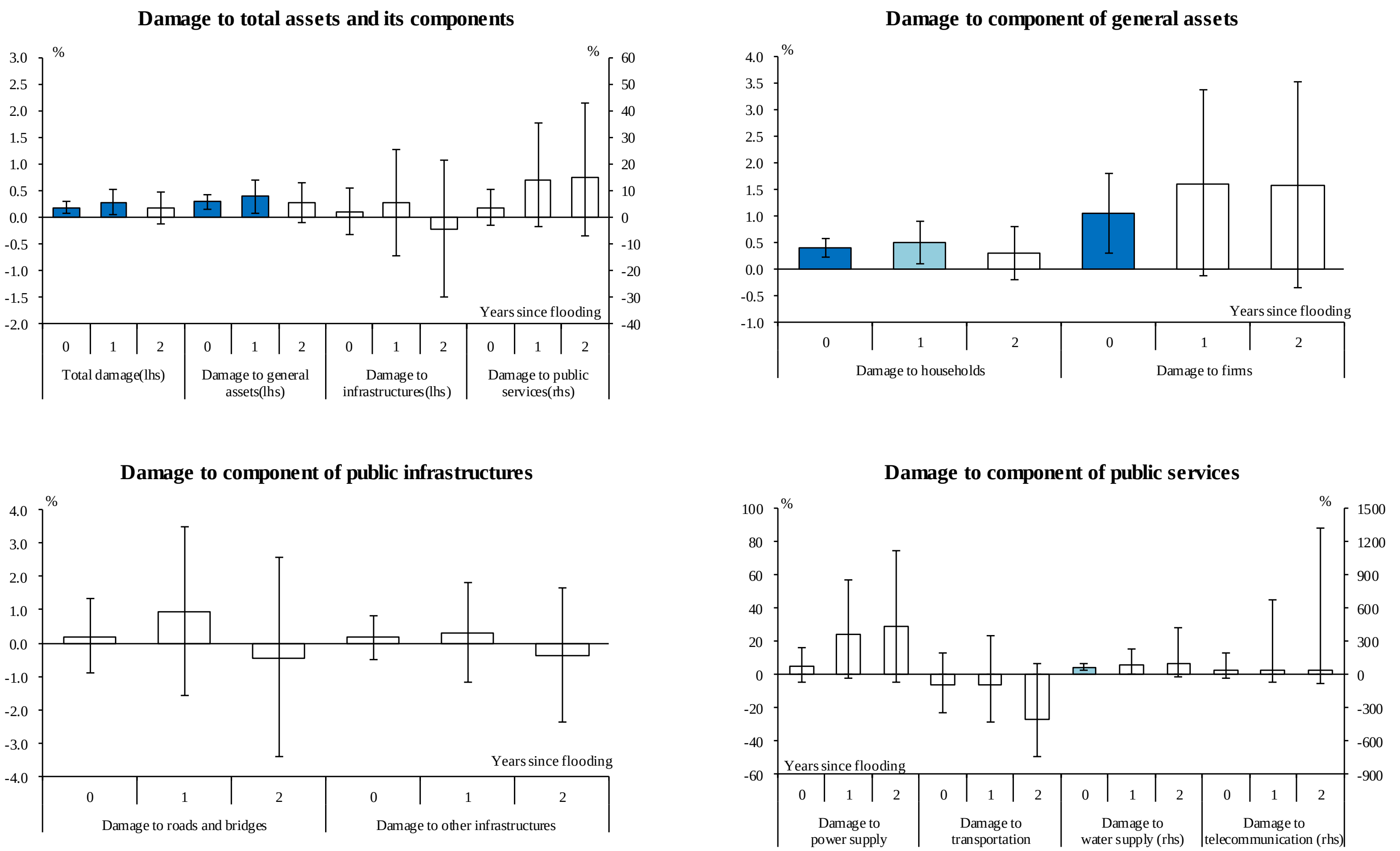


Figure 10: Impact of flood damage on electricity GDP (Model A)

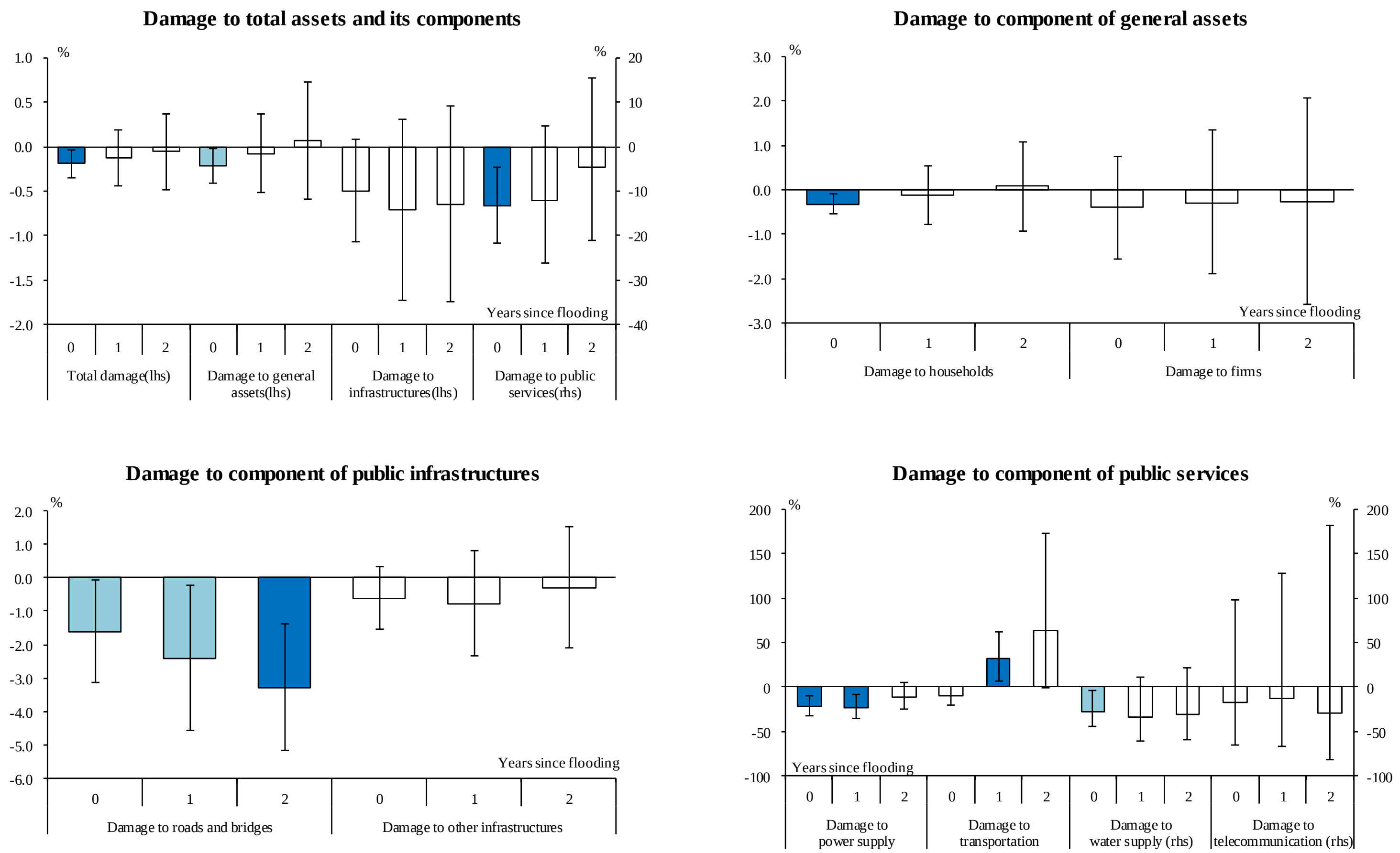


Figure 11: Impact of flood damage on wholesale and retail trade GDP (Model A)

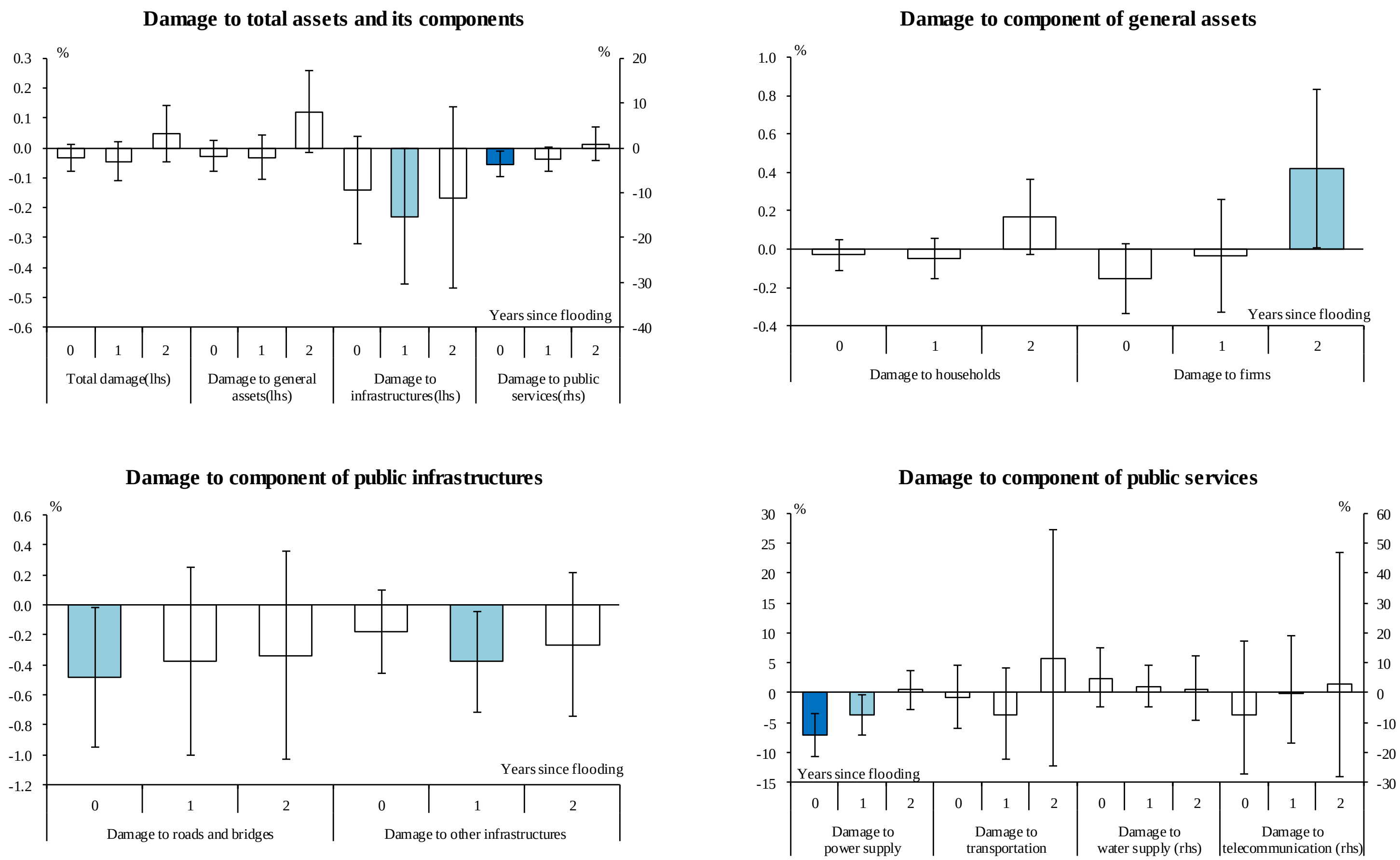


Figure 12: Impact of flood damage on manufacturing GDP (Model B)

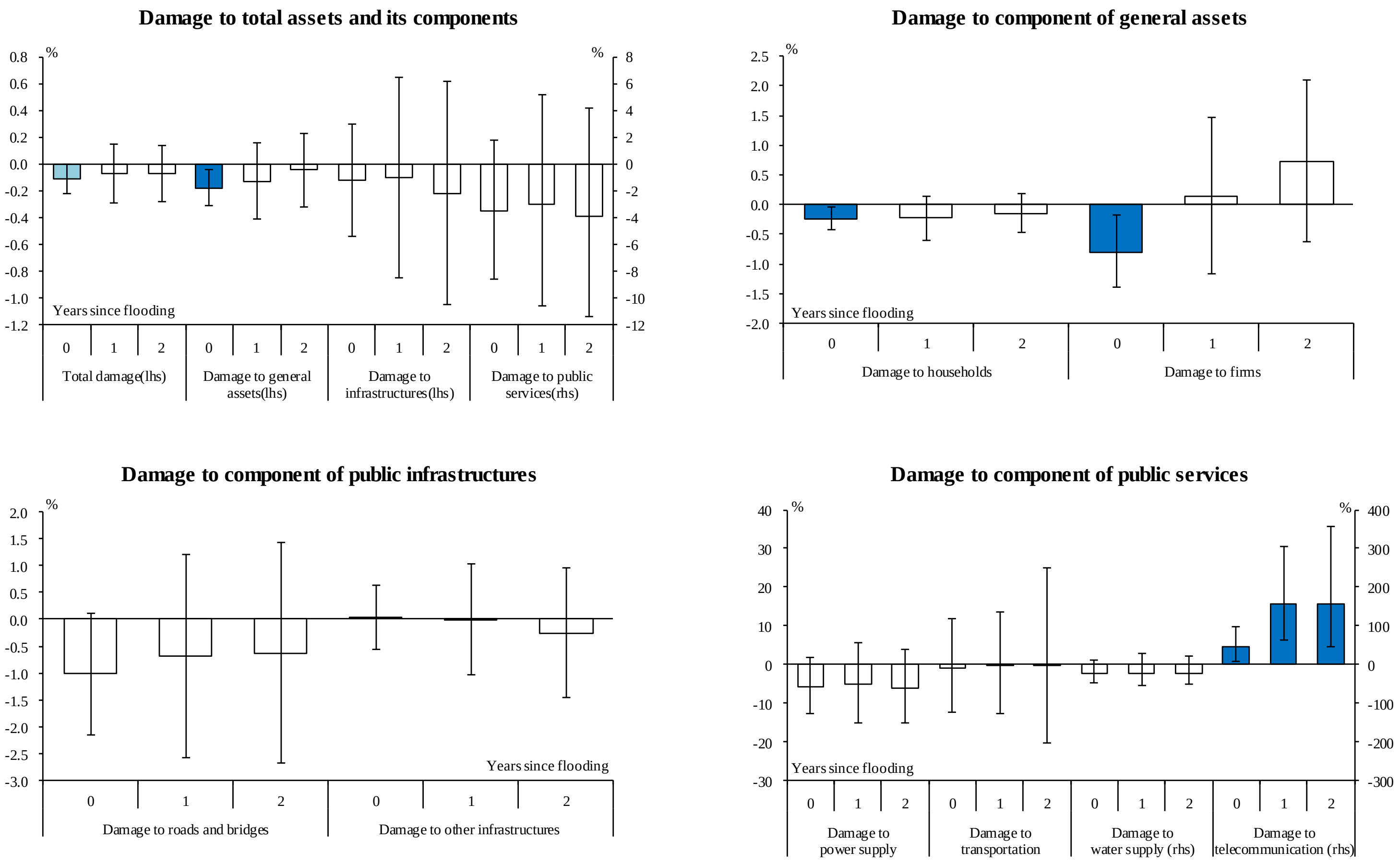


Figure 13: Impact of flood damage on construction GDP (Model B)

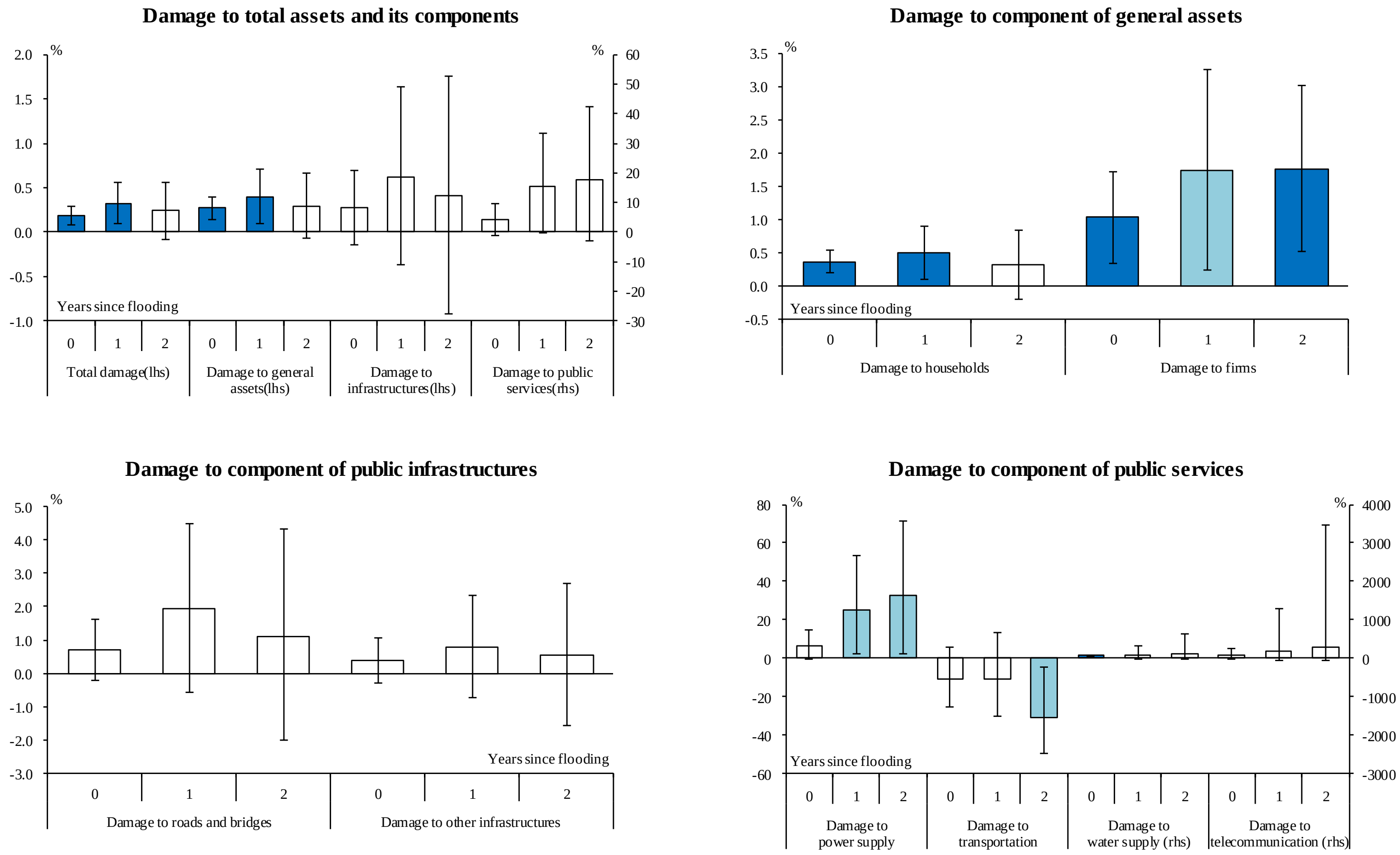


Figure 14: Impact of flood damage on electricity, etc. GDP (Model B)

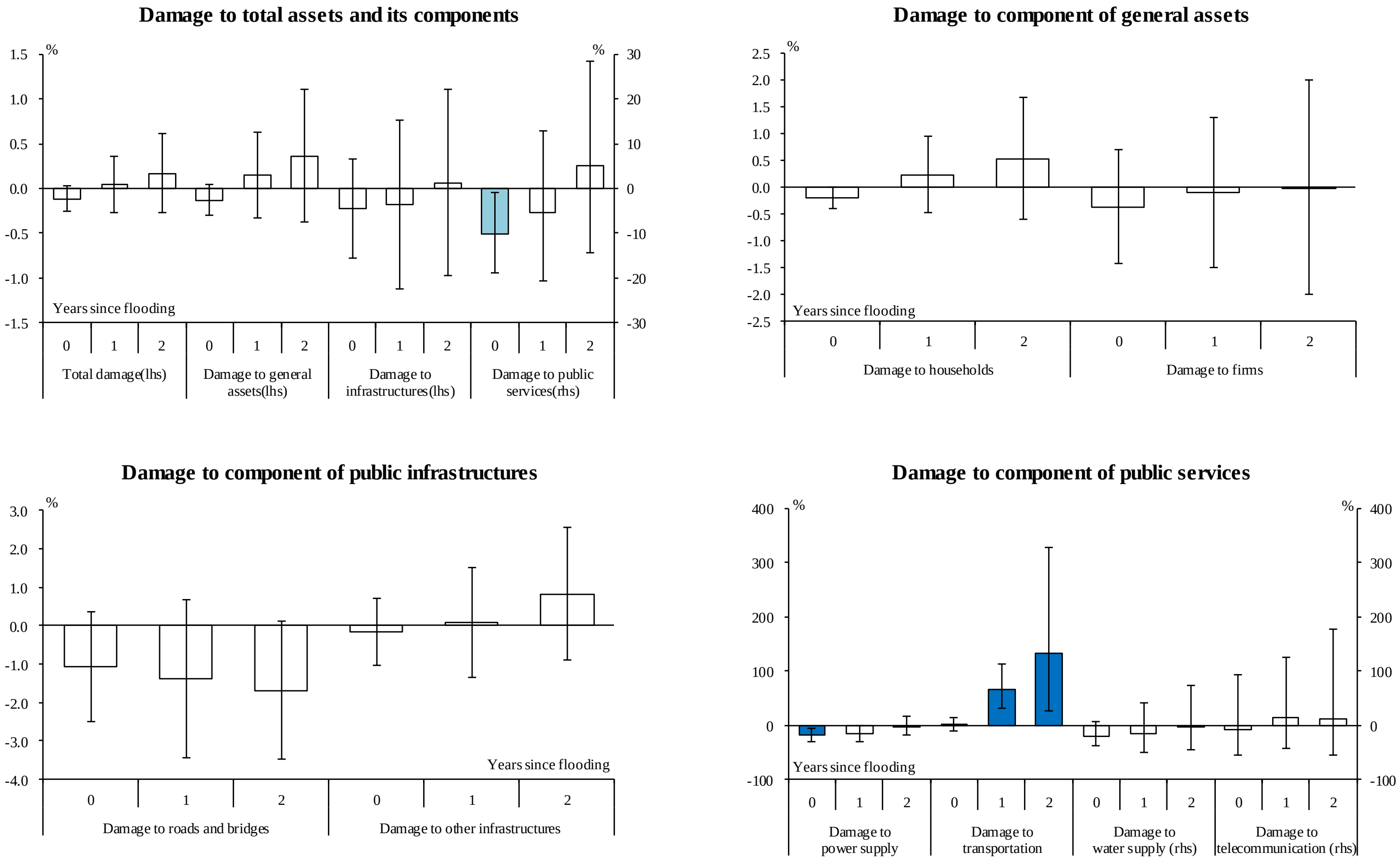


Figure 15: Impact of flood damage on wholesale and retail trade GDP (Model B)

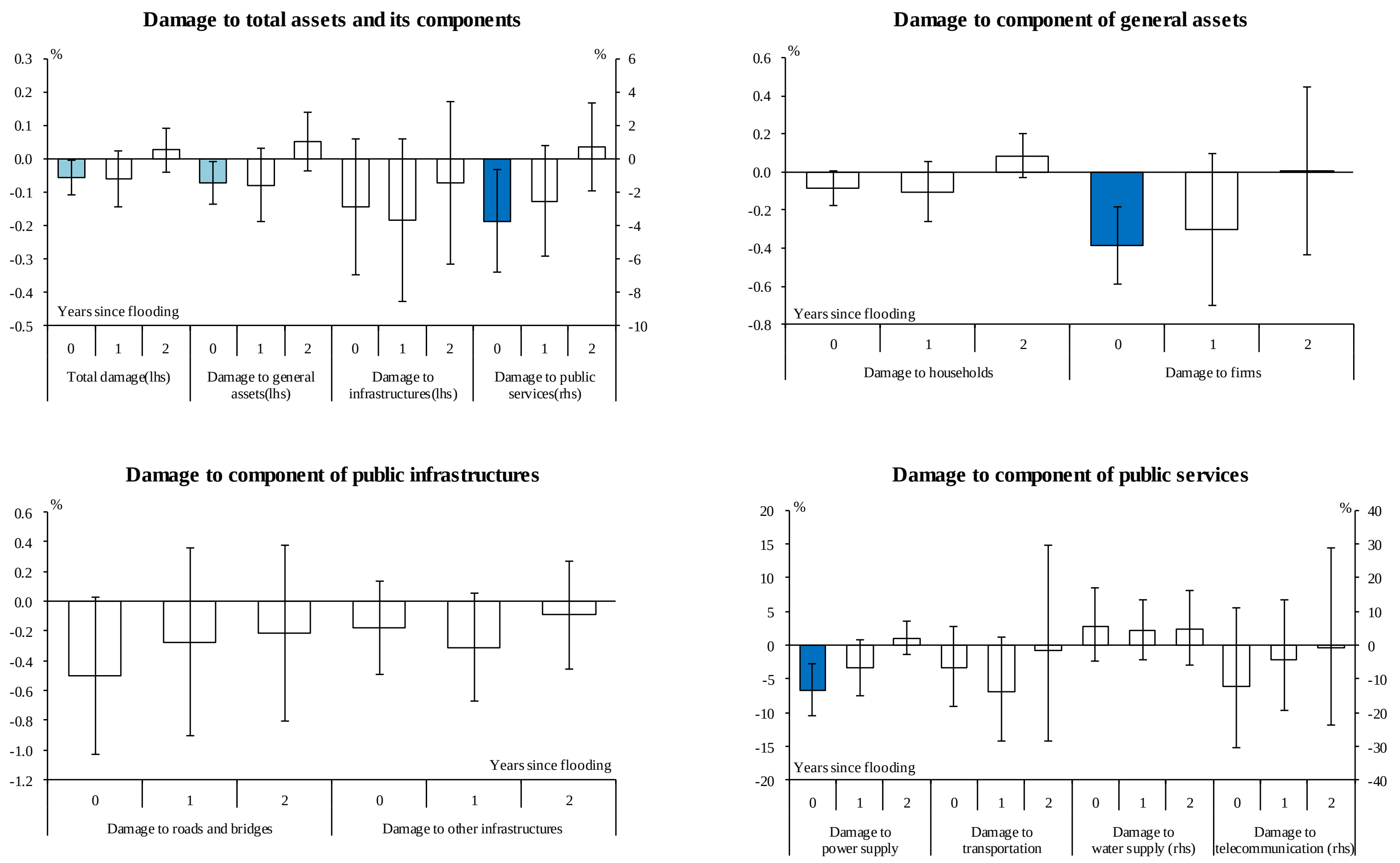
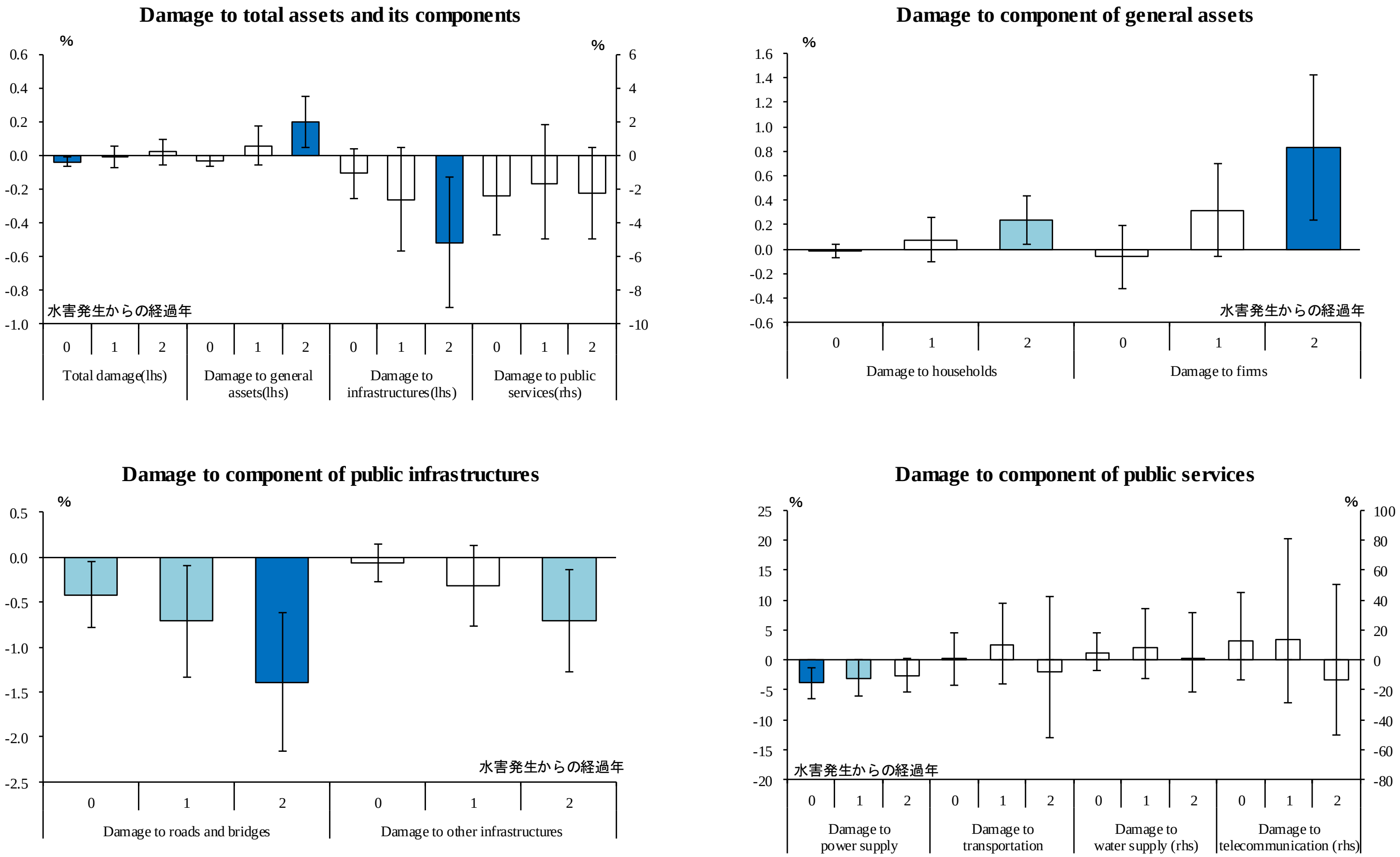
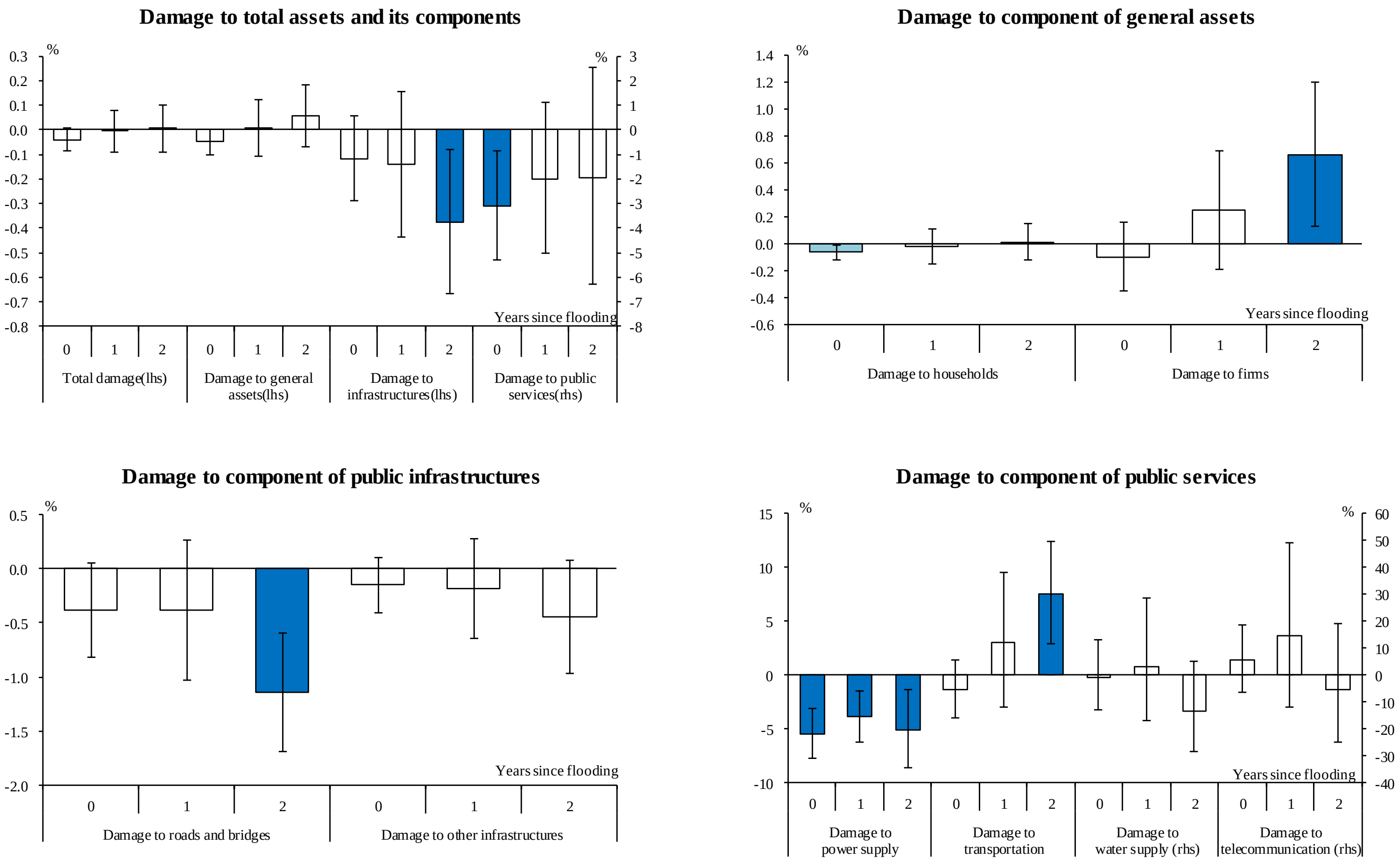


Figure A-1 Impact of flood damage on GDP (Model C)[26]



26 Results of regression of prefectural GDP on the flood damage are shown on the horizontal axis using the estimation Model C. The colors of the bars indicate 95% statistical significance for dark blue, 90% statistical significance for light blue, and no statistical significance for white, and error bands indicate 90% confidence intervals. The vertical axis is the change from that in GDP in the year prior to the flood event in the case where flood damage equivalent to 0.2% of GDP in previous year occurred in the assets, facilities, and equipment on the horizontal axis. The 0-2 value on the horizontal axis indicates the year elapsed since the flood event when the year of the flood event is set to 0. The standard errors used to calculate confidence intervals are robust standard error clustered by prefecture.

Figure A-2 Impact of flood damage on GDP (Model D)[27]



[27] Results of regression of prefectural GDP on the flood damage are shown on the horizontal axis using the estimation Model D. The colors of the bars indicate 95% statistical significance for dark blue, 90% statistical significance for light blue, and no statistical significance for white, and error bands indicate 90% confidence intervals. The vertical axis is the change from that in GDP in the year prior to the flood event in the case where flood damage equivalent to 0.2% of GDP in previous year occurred in the assets, facilities, and equipment on the horizontal axis. The 0-2 value on the horizontal axis indicates the year elapsed since the flood event when the year of the flood event is set to 0. The standard errors used to calculate confidence intervals are robust standard error clustered by prefecture.