Studying on Economic Recovery after Natural Disasters : Applying a Regional Input-Output Model

Yongjoon Kim, Donghwan An

Department of Agricultural Economics and Rural Development, College of Agriculture and Life Sciences, Seoul National University,
Gwanak-ro 1, Gwanak-gu, Seoul 151-921, Korea

Abstract. Climate change adaptation policy is essential, and the adaptation plan should be different depends on the region due to regional heterogeneity issues of climate change. However, the impact of flood disaster is not comparable since the empirical definition of flood is different according to the research papers. Furthermore, the indirect effects of the flood are rarely investigated, even though flood event could damage regional infrastructure, causing indirect damage by inter-regional relationship. This paper tries to build an integrated direct and indirect flood risk model to understand the impact of the flood and their effects on the entire economic system. First, we approximate the precipitation distribution to define flood disaster, and the non-linearity effects of a flood are demonstrated in the flood damage function. Second, in the simulation study using the estimated coefficient in damage function, the Gyeonggi-do, which is one of the highly developed city is forecasted as the most vulnerable region. Lastly, IRIO analysis indicates that the variance of the economic recovery path tends to increase according to the regional resilience level.

Key words: flood; damage function; IRIO; economic recovery path; simulation

Corresponding author
Donghwan An
Address: Department of Agricultural Economics and Rural Development / Institute of Agriculture and Life Sciences, College of Agriculture and life sciences, Seoul National University, Gwanak-ro 1, Gwanak-gu, Seoul 151-921, Korea
Tel and Fax +82-2-880-4729 & +82-2-873-3565
E-mail: dha@snu.ac.kr

1 Introduction

Adapting to climate change become essential, given that the increase in the magnitude of climate change and expanding the regional scope of its impact are expected. In particular, as disasters such as extreme events with low occurrence probability but significant influence tend to arise more frequently, the importance of effective adaptation policy targeting extreme events has been well recognized. However, guaranteeing the efficiency of adaptation policy under a limitation of a regional resource is not an easy task. The exact impacts and economic effects of climate change should be investigated thoroughly and interpreted with numerical values before establishing an adaptation policy. In reality, the economic assessment of climate change has been focused on the direct effects; the indirect effects are hardly considered, even though the impact of the disaster could spread on a full range of society through inter-industry effects. In addition to this, the impact of climate change or extreme events has not been evaluated thoroughly. For instance, the definition of flood in research paper represents several different forms, and the utilized model cannot fully capture the characteristics of the flood. Under these circumstances, an integrated direct and indirect flood risk model needs to be evaluated to capture extreme events-related issues and estimate the entire economic effects of a flood as resources for policymakers to look up.

The purpose of this paper is to evaluate the economic recovery path in the flooded region through inter-regional input-output model (IRIO Model) in terms of indirect effects of the flood events. The contents are as follows. First, we define flood as the random variable which belongs to 10% occurrence rate in the upper side of precipitation distribution (IPCC, 2007), which is approximated by a log-normal distribution. Along with the distributional assumption, the characteristics of flood such as rarity, severity, rapidity are reflected in the flood impact variable. Second, the flood damage function is estimated by using MVTOBIT Model (Multivariate Tobit Model) to reflect an error correlation issue between damage categories. Furthermore, the step function of flood impact variable reveals the non-linearity effects of extreme events while regional adaptive capacity is controlled. Third, this paper utilizes a regional input-output analysis to quantify the indirect economic impact of flood under imbalances of post-catastrophe economies (Steenge and Bočkarjova, 2007; Hallegatte, 2008; 2014, Koks et al., 2015; Shibusawa et al., 2017). In particular, the economic recovery path after a flood event is derived under the assumption of two bottleneck effects ((i) production activity interruption, (ii) transport network disruption). We simulate the most vulnerable city in the future (2020-2030), and evaluate time duration for recovering the regional economy entirely concerning recovery scenarios. Our efforts in estimating the indirect economic cost and dynamic aspects of economic recovery can be viewed as an empirical contribution of this paper.

This paper utilizes an inter-regional input-output table of the year 2013 (the bank of Korea), the table includes 16 regions of Korea, and the entire industry is divided into 161 sub-industries. The simulation results of damage function indicate that the most vulnerable city is found to be 'Gyeonggi-do' which is one of the highly developed cities in Korea. Moreover, the flooded region recovers its economy 16 periods after the extreme event under base recovery scenario. Furthermore, the recovery period has been expanded to 17 when the transport network bottleneck effects are assumed.

The structure of this paper is as follows. The next section develops models and discusses the data used for empirical analysis. In section 3, we provide the estimate results of the damage function as well as the simulation results under RCP 8.5 scenario. Section 4 presents the economic recovery period of 'Gyeonggi-do' as a flooded region, and sensitivity analysis is performed with bottleneck effects. The final section concludes with the policy implications obtained from the estimated results.

2 Model and Data

2.1 Flood Damage Function

The flood damage data has been collected at the regional level ('Sigun-gu'). The damage categories consist of death, flee, ship, agricultural land, crop, building, and infrastructure damage. Since our primary research purpose is investigating the indirect effects of flood due to production activity interruption and transport network malfunction; we exclude the death and flee damage. In addition, this paper estimates two damage functions based on two industries, (i) agricultural sector (ship, agricultural land, crop), (ii) manufacturing and construction sector (building and infrastructure).

Lavell at al. (2012) defines climate change risk as to the function of hazard, exposure, sensitivity, and capacity. This paper follows the definition of Lavell at al. (2012), and constitute the function with independent variable related to the above mentioned factors.

Below, equations (1) and (2) denote flood damage in agriculture, fa_{it}, and a flood damage in manufacturing and construction, fm_{it}, in county i in year t, respectively. The flood variable indicates a hazard, and also represents the consecutive days of flood weighted with frequency. The number, 30, 70, 110, 150 shows the threshold of the flood event, for instance, $flood\_30_{it}$ is a number of consecutive days of the flood when accumulated rain per two days belongs to the first category (30mm$\leq$ rain <70mm). $Flood\_70_{it}$, $Flood\_110_{it}$ are defined the consecutive flood day when the total rainfalls into 70mm to 110mm, 110mm to 150mm, respectively. Lastly, $flood\_150_{it}$ shows the most extreme flood case of rainfall is greater than 150mm. As a regional sensitivity, $Impervious_{it}$ is the sum of the impermeable area; the positive coefficient is expected to reflect the inundation tends to increase as an impermeable area increase. The local capacity variable to flood event is a $levee\_rp_{it}$ which represents the percentage of levee area over the total area. It is one of hardware-improving adaptation measures for protecting the asset from the flood damage. The yearly trend term, $trend_{it}$ formed a quadratic function; ϵ_{it} is an idiosyncratic error.

$$fa_{it} = \beta_0 + \beta_1 flood\_30_{it} + \beta_2 flood\_70_{it} + \beta_3 flood\_110_{it} + \beta_4 flood\_150_{it} + \beta_5 impervious_{it} + \beta_6 levee\_rp_{it} + \beta_7 trend_{it} + \beta_8 trend_{it}^2 + \epsilon_{it} \quad (1)$$

where i(=1, 2, …, 230), t(=1, 2, …, 7).

Below equation (2) is subtly different from equation (1) since it contains $grdp_{it}$ as another sensitivity variable. The flood damage in manufacturing and construction tends to increase when the urbanization proceeds and grdp (Gross Regional Domestic Product) variable is known to well represent the degree of urbanization. The u_{it} is an idiosyncratic error.

$$fm_{it} = \alpha_0 + \alpha_1 flood\_30_{it} + \alpha_2 flood\_70_{it} + \alpha_3 flood\_110_{it} + \alpha_4 flood\_150_{it} + \alpha_5 grdp_{it} + \alpha_6 impervious_{it} + \alpha_7 levee\_rp_{it} + \alpha_8 trend_{it} + \alpha_9 trend_{it}^2 + u_{it} \quad (2)$$

However, OLS (Ordinary Least Squares) estimation is not recommended in this case, since the decent portion of data is left-censored at 0; the Tobit model could be useful to estimate (Greene, 2011). The rate of left-censored data is 57.14% for fa_{it} and 48.57% for fm_{it} indicating that there is no flood at a specific location and time, or physical damage does not exceed specific thresholds. In addition to this, the error term in equation (1) and equation (2) shows contemporaneous correlation due to unobserved effects in each damage function. For instance, the geographical attribute or drainage conditions in the flooded agricultural region can cause flood damage on manufacturing facilities implying each flood damage category cannot be generated independently.

This paper utilizes an MVTOBIT (Multivariate Tobit) to control the error correlation between equations and censored data characteristics (Maddala, 1983; Cornick et al., 1994; Huang et al., 1987; Huang, 1999; Trivedi and Zimmer, 2005; Anastasopoulos et al., 2012). Below vector notation is referenced from Anastasopoulos et al. (2012) and Maddala (1983).

The Y_{ih}^{*} (NT$\times$ 1) is a latent variable presenting flood damage (one hundred million won) in i^th region in h^th damage category. X_{ih} (NT$\times$ K) is an independent variable for h^th damage category which is collected in the regional unit. β_h (K$\times$ 1) is a coefficient vector, ϵ_{ih} (NT$\times$1) is an error term vector. N is 230 regions (i=1,2, …, 230), T is 7 (the year 2010 – the year 2016), K is the number of independent variables, and h(=1, 2) is flood damage for agricultural industry and manufacturing industry, respectively.

$$Y_{ih}^{*} = X_{ih}\beta_h + \epsilon_{ih}, \quad \epsilon_{ih} \sim \mathrm{N}(0, \sigma_{ih}^{2}) \tag{3}$$

The relationship between a latent variable (Y_{ih}^{*}) and observed variable (Y_{ih}) is summarized in equation (4). 0 is the censored point.

$$Y_{ih} = \max\,(Y_{ih}^{*}, 0) \tag{4}$$

The damage function for agricultural sector (h=1) and manufacturing sector (h=2) constitute the equation system in equation (5).

$$\begin{bmatrix} Y_1 \\ Y_2 \end{bmatrix} = \begin{bmatrix} X_1 & 0 \\ 0 & X_2 \end{bmatrix} \begin{bmatrix} \beta_1 \\ \beta_2 \end{bmatrix} + \begin{bmatrix} \epsilon_1 \\ \epsilon_2 \end{bmatrix} = \mathrm{X}\beta + \epsilon \tag{5}$$

This paper deals two equations and assumes error terms (ϵ_1, ϵ_2) follow the bivariate normal distribution, which is summarized in equation (6). In the covariance matrix of an error term, σ is a standard deviation and ρ is a coefficient of correlation which indicates flood damage in each category tends to vary in the same direction when the sign is positive and vice versa.

$$\begin{pmatrix}\epsilon_1\\ \epsilon_2\end{pmatrix} \sim N\left(\begin{pmatrix}0\\ 0\end{pmatrix}, \begin{pmatrix}\sigma_1^2 & \rho\sigma_1\sigma_2\\ \rho\sigma_1\sigma_2 & \sigma_2^2\end{pmatrix}\right) \tag{6}$$

LR (Likelihood Ratio) test indicates the coefficient of correlation (ρ) is 0.4064, which is statistically significant with 1% significance level. The statistically significant ρ recommends MVTOBIT estimation, and a positive sign indicates increased damage in agriculture sector means more damage in manufacturing sector.

According to the Maddala (1983) the probability density function of error term ($\epsilon_1, \ \epsilon_2$) can be described in equation (7).

$$\mathrm{f}(\epsilon_1, \epsilon_2) = \ (2\pi)^{-1}|\Sigma^{-1}|^{\frac{1}{2}}\exp\{-\frac{1}{2}(y^* - X\beta)'\Sigma^{-1}(y^* - X\beta)\} \tag{7}$$

Finally, the likelihood function of bivariate model is summarized in equation (8).

$$\mathrm{L} = \prod_{A_1} f(\epsilon_1, \epsilon_2) \times \prod_{A_2} \int_{-\infty}^{-x_2\beta_2} f(\epsilon_1, \epsilon_2)\, d\epsilon_2 \times \prod_{A_3} \int_{-\infty}^{-x_1\beta_1} f(\epsilon_1, \epsilon_2)\, d\epsilon_1 \times \prod_{A_4} \int_{-\infty}^{-x_2\beta_2} \int_{-\infty}^{-x_1\beta_1} f(\epsilon_1, \epsilon_2)\, d\epsilon_1 d\epsilon_2 \tag{8}$$

2.2 IRIO (Inter-Regional Input-Output) for Post-Catastrophe Economies

This paper uses a non-competitive Inter-Regional Input-Output (IRIO) tables which allow imported goods. Table 1 shows the standard form of IRIO in Korea. We assume the toy model for intuitive understanding, the model has an economy consists of two regions, and each region has two industries. The total output always equals to the total outlay; the column-wise interpretation indicates the backward linkage, and the forward linkage can be understood in a row-wise manner.

This paper hypothesizes that flood events interrupt the production activity, and decrease in intermediate input flow has a negative impact on downstream industries (Shibusawa et al., 2018). The previous papers bring the concept of bottleneck effects to understand the production activity interruption by a flood. However, Shibusawa et al. (2018) expand the concept of bottleneck effects considering (i) production interruption and (ii) transport disruption by using IRIO. Moreover, the economic recovery path from the initial flood damage can be simulated in terms of regional recovery capacity.

{**Table 1.** A Non-Competitive Inter-Regional Input-Output Table *around here*}

The equation (9) shows the production interruption with survival rate (λ). The survival rate, {1 – (flood damage in value-added / total value-added)}, indicates decrease in production capacity due to damage on labor or capital. However, the input goods can be secured when the production activity stopped; this paper measures the survival rates only using value-added. Here, k (=r, s) is region, and j (= 1, 2) is industry, and t is a time period which 0 indicates normal time with no flood events. The X_j^k is the total outlay in region k in industry j. V_j^k is the value-added in region k in industry j. v_j^k is the value-added coefficient, V_j^k / X_j^k.

$$X_j^k(\mathrm{t}) = \lambda_j^k(t) X_j^k(0) = \frac{\lambda_j^k(t) V_j^k(0)}{v_j^k} \tag{9}$$

Where, $0 \leq \lambda_j^k(t) \leq 1$

The other bottleneck effect is the transport network disruption, which can be defined by the change in output coefficient in the forward linkage model. The below equation (10) shows the output coefficient matrix at a normal time (t=0). The output coefficient matrix (B^d) for regional input goods (z^d), $B^d = \left(\hat{X}\right)^{-1} z^d$, is an inter-industry relationship between regional input goods and total output. Here, the hat (^) sign represents a diagonal matrix.

$$
B^d(0) = \begin{bmatrix} b_{11}^{rr}(0) & b_{12}^{rr}(0) & b_{11}^{rs}(0) & b_{12}^{rs}(0) \\ b_{21}^{rr}(0) & b_{22}^{rr}(0) & b_{21}^{rs}(0) & b_{22}^{rs}(0) \\ b_{11}^{sr}(0) & b_{12}^{sr}(0) & b_{11}^{ss}(0) & b_{12}^{ss}(0) \\ b_{21}^{sr}(0) & b_{22}^{sr}(0) & b_{21}^{ss}(0) & b_{22}^{ss}(0) \end{bmatrix} \tag{10}
$$

However, if the transportation system came to a halt, the intermediate input cannot meet intermediate demand in relation to a decrease in output coefficient. Here, β_{ij}^{od} is the proportion of transport network disruption implying the rate of decline in output coefficient.

$$
B^d(t) = \begin{bmatrix} b_{11}^{rr}(0) & b_{12}^{rr}(0) & \beta_{11}^{rs}(t) b_{11}^{rs}(0) & \beta_{12}^{rs}(t) b_{12}^{rs}(0) \\ b_{21}^{rr}(0) & b_{22}^{rr}(0) & \beta_{21}^{rs}(t) b_{21}^{rs}(0) & \beta_{22}^{rs}(t) b_{22}^{rs}(0) \\ \beta_{11}^{sr}(t) b_{11}^{sr}(0) & \beta_{12}^{sr}(t) b_{12}^{sr}(0) & b_{11}^{ss}(0) & b_{12}^{ss}(0) \\ \beta_{21}^{sr}(t) b_{21}^{sr}(0) & \beta_{22}^{sr}(t) b_{22}^{sr}(0) & b_{21}^{ss}(0) & b_{22}^{ss}(0) \end{bmatrix} \tag{11}
$$

Where, $0 \le \beta_{ij}^{od}(t) \le 1$

Being consistent with above logit, total outlay after flood disaster in industry j in region r is summarized in equation (12). First term is the flow of input good within the region r; the survival rate at t period is applied, however output coefficient does not change since there is no transport disruption within region. Second term is a flow of the input goods between region r and region s; the transport network disruption is assumed as well as the survival rate. Third term is imported goods, and the import coefficient (b_{ij}^{mr}) can be decreased by the other transportation network disruption parameter (β_{ij}^{mr}). Last one is the amount of value added considering survival rate.

$$
\begin{aligned} X_j^r(t+1) = & \textstyle\sum_{i=1}^{2} [\lambda_i^r(t) X_i^r(0)] b_{ij}^{rr}(0) + \sum_{i=1}^{2} [\lambda_i^s(t) X_i^s(0)] [\beta_{ij}^{sr}(t) b_{ij}^{sr}(0)] \\ & + \textstyle\sum_{i=1}^{2} IM_i(0) [\beta_{ij}^{mr}(t) b_{ij}^{mr}(0)] + \lambda_j^r(t) V_j^r(0) \end{aligned} \tag{12}
$$

On the other hand, the community has the resilience to recover flood damage by fortifying revitalization of production activity and transportation system. In equation (13), we assume that labor and physical stock accumulates with the time given that the regional adaptive measure has been implemented in the flooded regions. The recovery rate, α, is assumed to be given exogenously; the survival rate tends to increase linearly with the lapse of time.

$$\lambda_j^k(t+1) = \lambda_j^k(1) + \alpha \cdot t \tag{13}$$

In addition, the flooded region can expect supply support from the surrounding regions. Import in t period rise by increasing the trade volume. The parameter θ indicates an amount of the additional supply from the gap between the imported amount in normal time and t period. If we assume the parameter θ equals to one, then the flood damage is fully recovered.

$$IM_j^k(t) = IM_j^k(0) + \theta\left(X_j^k(0) - X_j^k(t)\right) \tag{14}$$

Where, $0 \leq \theta \leq 1$

Lastly, the restoration process in the transport network disruption can be specified in equation (15). The other recovery rate, γ, is exogenously assumed, and the output coefficient increases linearly with the lapse of time.

$$\beta_{ij}^{od}(t+1) = \beta_{ij}^{od}(1) + \gamma \cdot t \tag{15}$$

The below equation (16) is derived after applying recovery scenario in equations (13-15). The subtle change was made from equation (12); the increase in survival rates and output coefficient is found as well as the shortage of total production value is partially fulfilled with additional imports.

$$X_j^r(t+1) = \sum_{i=1}^{2}[(\lambda_i^r(1)+\alpha\cdot(t-1))X_i^r(0)]b_{ij}^{rr}(0)$$
$$+\ \sum_{i=1}^{2}[(\lambda_i^s(1)+\alpha\cdot(t-1))X_i^s(0)][(\beta_{ij}^{sr}(1)+\gamma\cdot(t-1))b_{ij}^{sr}(0)]$$
$$+\ \sum_{i=1}^{2} IM_i(0)[(\beta_{ij}^{mr}(1)+\gamma\cdot(t-1))b_{ij}^{mr}(0)]\ +\ \theta\left(X_j^r(0)-X_j^r(t)\right)$$
$$+\ (\lambda_j^r(1)+\alpha\cdot(t-1))V_j^r(0) \tag{16}$$

2.3 Data for Empirical Analysis

In this paper, we utilized several data sets to include the effects of flood disaster under climate change and its indirect effects on the entire economic system. First, we collected daily precipitation data from synoptic weather observation operated by KMA (Korea Meteorological Administration) for flood impact variable estimation. We match the centroid of each region (Sigun-gu) with the nearest synoptic weather observation; it gives every region a corresponding precipitation data even if some of the regions do not have synoptic weather observation system. Second, flood damage data is obtained from WAMIS (Water Resources Management Information System) [1]. Flood damage data is collected by regional level in a yearly unit, and more than 48% of the samples are censored at zero given that flood has low occurrence rate and some damage category have not been recorded even though flood outbreak. Third, we use region-related sensitivity and capacity variables from KOSIS (Korean Statistical Information Service). Fourth, an inter-regional input-output table of the year 2013 (the bank of Korea) is used. The Original version of the IRIO contains 161 sub-industries, however, for the convenience of interpretation and the linkage between estimated results of damage function and IRIO data, 161 sub-industries are aggregated with three industries as a simple economic model. Lastly, RCP 8.5 scenario data is utilized from KMA to simulate the expected flood damage in each industry and region. The data for flood damage function estimation is summarized in Table 2.

[1] http://www.wamis.go.kr

{**Table 2.** List of Variables for Flood Damage Function Estimation *around here*}

3 The Flood Damage Function Estimation as a Direct Effects

3.1 MVTOBIT Flood Damage Function

In this paper, MVTOBIT is utilized to estimate flood damage on agriculture and manufacturing sector allowing the contemporaneous correlation across equations. The estimate results are described in Table 3. The hazard variables or flood impact variables are strongly significant with 1% p-value. According to IPCC (2007), the disaster is defined as two 10% extremes of the distribution of weather variables. This paper approximates the precipitation (accumulated rain during consecutive two days) distribution as a log-normal distribution, and upper 10% starts with 30mm. However, the results indicate that economic damage tends to dramatically increase after 110mm.

The non-linearity effects of flood showing extreme damage are demonstrated in manufacturing damage function. The gap among Flood-related variables are non-linearly increasing; the difference in coefficient between Flood_150 and Flood_110_150 is 13 times higher than the difference between Flood_30_70 and Flood_70_110.

This paper uses two sensitivity variables for urbanization index. As we expect, the signs of the coefficient are all positive and statistically significant at 1% significance level except GRDP variable. Here, the GRDP is the only variable to distinguish two damage functions, since the estimate results of the MVTOBIT with identical regressors equal to the equation by equation estimation. We assume GRDP only affects damage in manufacturing industry given that the economic value of facilities increases in the manufacturing sector as GRDP increases.

Lastly, the capacity variable shows strong negative sign to reduce the effects of the flood, implying the flood damage strictly depends on the regional capacity. However, in this paper, the focus is not on the adaptive capacity. The adaptation-related issues such as economic feasibility of adaptation policy or optimal adaptation level should be discussed in the further studies.

{**Table 3.** The Estimation Results of Flood Damage Function around here}

Furthermore, this paper estimates the marginal effects given that the coefficients in Table 3 indicate the linear increase of the latent variable for each unit increase in independent variable. The results show that one more flood day in Flood_30_70 causes economic damage to manufacturing as much as roughly 1 hundred million won. Its effect increase to 5.6 hundred million won when accumulated rain is greater than 150mm.

{**Table 4.** The Marginal Effects of the Flood Damage Function around here}

3.2 Simulation Analysis of Climate Change Effects on Flood Damage

The simulation of flood damage under RCP 8.5 scenario is performed with the estimated coefficients in the damage function. We assume that only flood impact variables affect on agriculture and manufacturing sectors; the sensitivity and capacity-related variables are not considered. It makes the simulation results under or over-estimated, which depends on the regional adaptive level; on the other hand, we can intuitively understand the simulated results in terms of the total effects of the flood.

Since the damage function is investigated by ‘Sigun-gu’ unit; we aggregate ‘Sigun-gu’ results into ‘Si-do’ scale. Moreover, we summed the forecasted flood damage during 10 years (year 2020 - year 2030), given that the flood is a probabilistic, which is rarely happened.

The simulated results are summarized in Table 5. The damage in manufacturing is always more significant than agricultural damage implying that more than half of the flood damage is located in the city or industrial area. We forecast the Gyeonggi-do is the most vulnerable place for flood, and the expected total damage reaches 3,390 one million won. The safest place is

Jeju-do, which is an island indicating the flood risk tends to expand in the inland area in the near future. The total damage in Jeju-do is under 313 one million won, which accounts for approximately 9% of damage in Gyeonggi-do. This paper utilizes the forecasted damage in Gyeonggi-do to figure out the economic recovery path under RCP 8.5 scenario.

{**Table 5.** The Simulation Results of the Flood Disaster around here}

4 An Analysis on Economic Recovery Path after Flood Disaster

This paper investigates the indirect effects of the flood disaster, given that the economy of the flooded region strongly depends on the surrounding region through input-output relationships. The economic damage in a flooded region affects the neighboring regions since the production activity in the neighboring region needs input goods from the flooded region. It indicates that production activity interruption caused by a flood can decrease the production of the entire economic system. Furthermore, the transportation system is not fully capable of functioning, implying the total production also decrease due to the limitation of the transaction amount.

We set three scenarios according to the level of regional resilience, and the results of the economic recovery path for each scenario is summarized in Figure 1. The base scenario shows that the economy in Gyeonggi-do is fully recovered after 16 periods when only production activity interruption is assumed. However, the recovery is completed after 17 periods when transportation network bottleneck is additionally assumed. Moreover, the agricultural sector is the most slowly recovered industry due to high flood damage rate. The manufacturing sector recovers relatively faster (12 periods) with no transportation bottleneck, given that flood damage is just the small portion of the total production of manufacturing. However, the recovery period of the manufacturing sector is severely expanded (17 periods) when the transportation network bottleneck is assumed. In particular, the transportation network bottleneck also affects service sector even though no flood damage is found in the service sector.

The effects of transportation bottleneck are sustained in other scenarios; however, according to the level of regional resilience, the recovery period can be shortened or further expanded. In the optimistic scenario, the economic recovery is completed after 6 periods under no transport bottleneck. However, in the pessimistic scenario, Gyeonggi-do is never recovered within 20 periods due to a decrease in recovery rate, supply support from surrounding regions, and more severe transport bottleneck effects.

{**Figure 1.** The Economic Recovery Path across Recovery Scenarios *around here*}

5 Summary and Concluding Remarks

This paper tries to understand the impact of a flood disaster and investigate their economic effects with direct and indirect aspects. The comprehensive procedure to evaluate the mechanism of climate change effect on our economy in a standard form is well known to be essential to establish effective adaptive policy. Being consistent with the above statement, our effort to build a comprehensive evaluating procedure can be viewed as a contribution.

In the estimation of damage function, the economic damage in the manufacturing sector is estimated with great importance, and the non-linearity effects of a flood can be demonstrated. In this paper, accumulated rain, which is more than 110mm induce economic damage dramatically.

In addition, we found the regional resilience level, which is able to recover the regional economy to normal time. In the base scenario, the economy in Gyeonggi-do is fully recovered after 16 periods with no transportation bottleneck. However, the recovery time tends to be delayed when we additionally consider transportation bottleneck effects (17 periods). It implies that transportation capacity has a critical role in revitalizing the regional economy, given that the enhancement of the inter-regional relationship is the key to survive. Furthermore, the variance of the recovery period tends to increase according to the regional resilience level, reflecting the effort to build regional resilience is compulsory in terms of adaptation.

However, this paper does not consider the economic feasibility of adaptation measure such as the regional capacity variable, levee_rp, even though the indirect effects of the regional resilience is quantified. In particular, the estimation of the economic feasibility of adaptation measure could provide more useful information for policymakers, since economic resilience is more like a concept. We leave these research subjects as a further study.

Acknowledgments: This work was supported by Korea Environmental Industry and Technology Institute (KEITI) through Climate Change Response Technology Project, funded by Korea Ministry of Environment (MOE) (201800131002).

References

Anastasopoulos, P. C., V. N. Shankar, J. E. Haddock and F. L. Mannering. 2012. "A Multivariate Tobit Analysis of Highway Accident-Injury-Severity Rates," *Accident Analysis and Prevention*. vol. 45, pp. 110-119.

Cornick, J., T. L, Cox and B. W. Gould. 1994. "Fluid Milk Purchases: A Multivariate Tobit Analysis," *American Journal of Agricultural Economics*. vol. 76, no. 1, pp. 74-82.

Greene, W. 2011. "Econometric Analysis," Nueva York.

Hallegatte, S. 2008. "An Adaptive Regional Input-Output Model and its Application to the Assessment of the Economic Cost of Katrina," *Risk Analysis: An International Journal*. vol. 28, no. 3, pp. 779-799.

Hallegatte, S. 2014. "Modeling the Role of Inventories and Heterogeneity in the Assessment of the Economic Costs of Natural Disasters," *Risk Analysis*. vol. 34, no. 1, pp. 152-167.

Huang, H. C., F. A. Sloan and K. W. Adamache. 1987. "Estimation of Seemingly Unrelated

Tobit Regressions via the EM Algorithm," *Journal of Business and Economic Statistics*. vol. 5, no. 4, pp. 425-430.

Huang, H. C. 1999. "Estimation of the SUR Tobit Model via the MCECM Algorithm," *Economics Letters*. vol. 64, no. 1, pp. 25-30.

Koks, E. E., M. Bočkarjova, H. de Moel and J. C. Aerts. 2015. "Integrated Direct and Indirect Flood Risk Modeling: Development and Sensitivity Analysis," *Risk Analysis*. vol. 35, no. 5, pp. 882-900.

Lavell, A., M. Oppenheimer, C. Diop, J. Hess, R. Lempert, J. Li, R. Muir-Wood and S. Myeong. 2012. "Climate Change: new Dimensions in Disaster Risk, Exposure, Vulnerability, and Resilience," In Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation: Special Report of the Intergovernmental Panel on Climate Change. pp. 25-64.

Maddala, G. S. 1983. "Limited-Dependent and Qualitative Variables in Econometrics," New York, Cambridge University Press.

Shibusawa, H., H. Irimoto, D. Sakamoto, R. Hanaoka and Y. Miyata. 2018. "Evaluating Spatial Economic Damage by Natural Disasters in Japan: A Dynamic Input-Output Approach," A Draft Paper for the 65th Annual North American Meetings of the RSAI November 7-10, 2018. San Antonio.

Steenge, A. E., and M. Bočkarjova. 2007. "Thinking about imbalances in post-catastrophe economies: an input-output based proposition," *Economic Systems Research*. vol. 19, no. 2, pp. 205-223.

Trivedi, P. K., and D. M. Zimmer. 2005. "Copula Modeling: and Introduction for Practitioners," *Foundations and Trends in Econometrics*. vol. 1, no. 1, pp. 1-111.

Table 1. A Non-Competitive Inter-Regional Input-Output Table

		Intermediate Demand				Final Demand			Total Output
		Region r		Region s		Domestic Demand		Export	
		Sector 1	Sector 2	Sector 1	Sector 2	Region r	Region s		
Region r	1	Z_{11}^{rr}	Z_{12}^{rr}	Z_{11}^{rs}	Z_{12}^{rs}	F_1^{rr}	F_1^{rs}	EX_1^r	X_1^r
	2	Z_{21}^{rr}	Z_{22}^{rr}	Z_{21}^{rs}	Z_{22}^{rs}	F_2^{rr}	F_2^{rs}	EX_2^r	X_2^r
Region s	1	Z_{11}^{sr}	Z_{12}^{sr}	Z_{11}^{ss}	Z_{12}^{ss}	F_1^{sr}	F_1^{ss}	EX_1^s	X_1^s
	2	Z_{21}^{sr}	Z_{22}^{sr}	Z_{21}^{ss}	Z_{22}^{ss}	F_2^{sr}	F_2^{ss}	EX_2^s	X_2^s
Import	1	Z_{11}^{mr}	Z_{12}^{mr}	Z_{11}^{ms}	Z_{12}^{ms}	F_1^{mr}	F_1^{ms}		
	2	Z_{21}^{mr}	Z_{22}^{mr}	Z_{21}^{ms}	Z_{22}^{ms}	F_2^{mr}	F_2^{ms}		
Value Added		V_1^r	V_2^r	V_1^s	V_2^s				
Total Outlay		X_1^r	X_2^r	X_1^s	X_2^s				

Table 2. List of Variables for Flood Damage Function

Variable		**Content**	**Sample Size**	**Mean**	**Standard Deviation**	**Range**
Dependent Variable	Agri[A)]	Flood damage in agriculture (one hundred million won)	1,610	3.73	19.79	[0, 378]
	Bu_Inf[A)]	Flood damage in manufacturing and construction (one hundred million won)	1,610	13.55	49.06	[0, 617.33]
Hazard	Flood_30_70[B)]	A consecutive days of flood weighted with frequency (30mm≤rain<70mm)	1,610	5.3	3.64	[0.06, 22]
	Flood_70_110[B)]	A consecutive days of flood weighted with frequency (70mm≤rain<110mm)	1,610	1.68	2.02	[0, 12]
	Flood_110_150[B)]	A consecutive days of flood weighted with frequency (110mm≤rain<150mm)	1,610	0.61	0.98	[0, 6.4]
	Flood_150[B)]	A consecutive days of flood weighted with frequency (150mm≤rain)	1,610	0.5	0.88	[0, 5.6]
Sensitivity	Grdp[C)]	Gross Regional Domestic Product (million won)	1,596	6,315,728	7,973,092	[211,695, 60,000,000]
	Impervious[C)]	A sum of impermeable area (m^2)	1,610	29,300,000	19,400,000	[0, 122,000,000]
Capacity	Levee_rp[C)]	A percentage of levee area over the total area (%)	1,610	0.27	0.29	[0, 2.11]

Note: A) is flood damage data (WAMIS, Water Resources Management Information System), B) is daily weather data from synoptic weather observation (Korea Meteorological Administration), C) a region-related sensitivity and capacity data (KOSIS, Korean Statistical Information Service).

Table 3. The Estimation Results of Flood Damage Function

Variable		Agricultural Damage	Manufacturing and Construction Damage
Hazard	Flood_30_70	1.4764244***(0.3038744)	3.1528233***(0.6192397)
	Flood_70_110	1.4070621***(0.4587791)	3.8444450***(1.4428574)
	Flood_110_150	5.9020248***(1.4391442)	9.3903191***(2.3493142)
	Flood_150	5.4136501***(1.8188002)	18.8338092***(2.7929135)
Sensitivity	Grdp	-	0.0000004*(0.0000002)
	Impervious	0.0000005***(0.0000001)	0.0000006***(0.0000001)
Capacity	Levee_rp	-10.5899042***(3.1121165)	-19.7933425***(5.7585075)
Trend		-5.7393382***(1.9568824)	-6.5679527(4.1930951)
Trend Squared		0.5827653**(0.2418445)	0.6203089(0.5602066)
Constant		-33.0705743***(5.8097245)	-60.4488858***(11.4433570)

Table 4. The Marginal Effects of the Flood Damage Function

Variable		Agricultural Damage	Manufacturing and Construction Damage
Hazard	Flood_30_70	0.3817064	0.9446867
	Flood_70_110	0.363774	1.151919
	Flood_110_150	1.525877	2.81364
	Flood_150	1.399615	5.643212
Sensitivity	Grdp	-	0.000000124
	Impervious	0.000000118	0.000000166
Capacity	Levee_rp	-2.737854	-5.930718
Trend		-1.483817	-1.967969
Trend Squared		0.1506649	0.1858644
Constant		-8.549881	-18.11242

Table 5. The Simulation Results of the Flood Disaster

Unit : one million won

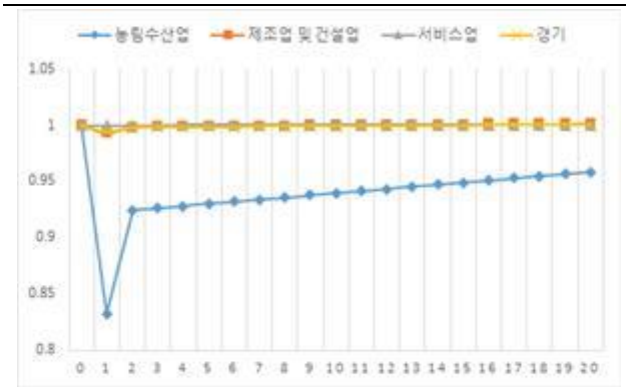
Region	Agricultural Damage	Manufacturing and Construction Damage	Total Damage
Gyeonggi-do	935	2,456	3,390
Jeollanam-do	885	2,288	3,173
Gyeongsangnam-do	830	2,145	2,975
Seoul	705	1,872	2,577
Gyeongsangbuk-do	675	1,749	2,423
Gangwon-do	624	1,652	2,276
Busan	559	1,448	2,008
Jeollabuk-do	529	1,354	1,883
Chungcheongnam-do	383	1,033	1,417
Chungcheongbuk-do	365	946	1,311
Incheon	239	632	870
Gwangju	240	620	861
Daegu	232	607	839
Ulsan	198	506	704
Daejeon	158	397	556
Jeju-do	87	226	313

Note: This paper rounds off the numbers to the first decimal place.

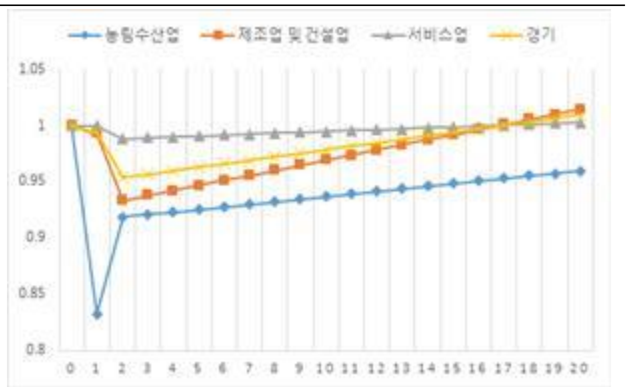
Figure 1. The Economic Recovery Path across Recovery Scenarios

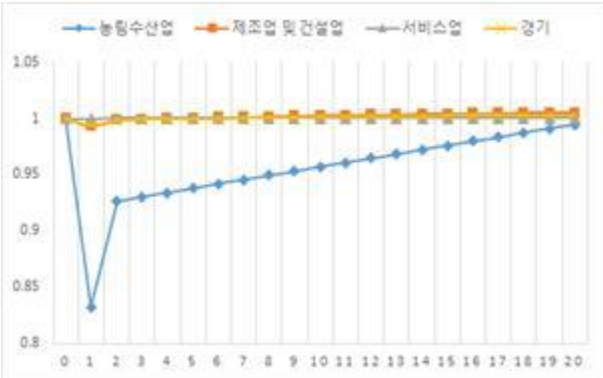
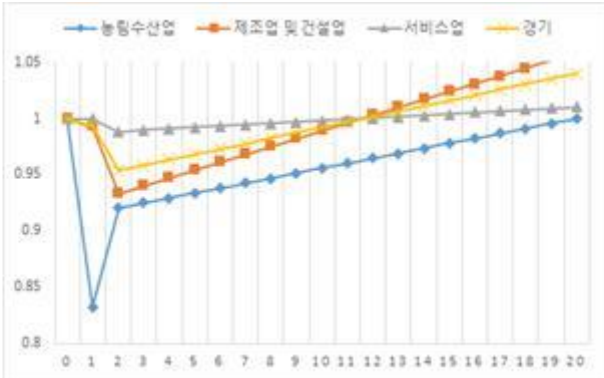
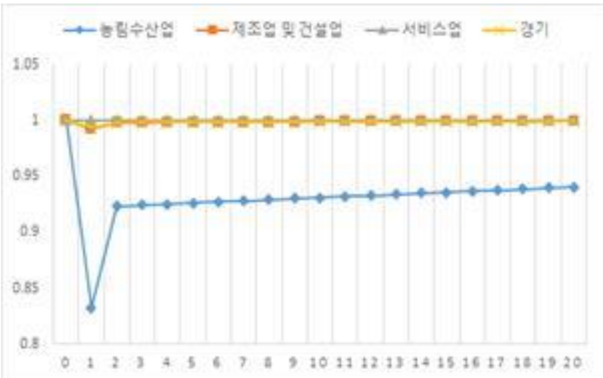
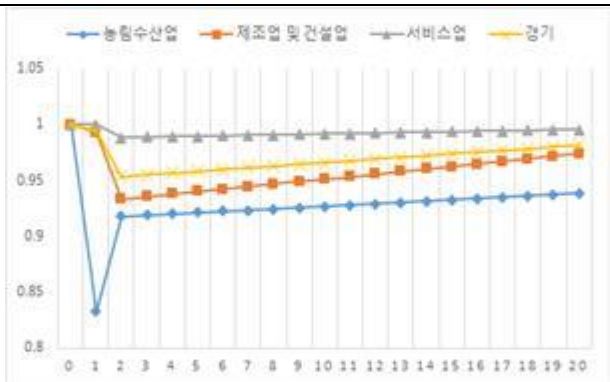
Base Scenario

α_1=0.004, α_2=0.00015, θ=0.1, β=1, γ=0



α_1=0.004, α_2=0.00015, θ=0.1, β=0.7, γ=0.02



<table>
<tr><th colspan="2">Optimistic Scenario</th></tr>
<tr><td>α_1=0.008, α_2=0.00035, θ=0.3, β=1, γ=0</td><td>α_1=0.008, α_2=0.00035, θ=0.3, β=0.7, γ=0.03</td></tr>
<tr><td>
</td><td>
</td></tr>
<tr><th colspan="2">Pessimistic Scenario</th></tr>
<tr><td>α_1=0.002, α_2=0.000075, θ=0.05, β=1, γ=0</td><td>α_1=0.002, α_2=0.000075, θ=0.05, β=0.7, γ=0.01</td></tr>
<tr><td>
</td><td>
</td></tr>
</table>