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The Growth Aftermath of Natural Disasters

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Abstract

This paper provides a description of the macroeconomic aftermath of natural disasters. It traces the yearly response of gross domestic product growth—both aggregated and disaggregated into its agricultural and non-agricultural components—to four types of natural disasters—droughts, floods, earthquakes, and storms. The paper uses a methodological approach based on pooling the experiences of various countries over time. It consists of vector auto-regressions in the presence of endogenous variables and exogenous shocks (VARX), applied to a panel of cross-country and time-series data. The analysis finds heterogeneous effects on a variety of dimensions. First, the effects of natural disasters are stronger, for better or worse, on developing than on rich countries. Second, while the impact of some natural disasters can be beneficial when they are of moderate intensity, severe disasters never have positive effects. Third, not all natural disasters are alike in terms of the growth response they induce, and, perhaps surprisingly, some can entail benefits regarding economic growth. Thus, droughts have a negative effect on both agricultural and non-agricultural growth. In contrast, floods tend to have a positive effect on economic growth in both major sectors. Earthquakes have a negative effect on agricultural growth but a positive one on non-agricultural growth. Storms tend to have a negative effect on gross domestic product growth but the effect is short-lived and small. Future research should concentrate on exploring the mechanisms behind these heterogeneous impacts.

This paper—a product of the Development Research Group and the Global Facility for Disaster Reduction and Recovery—is part of a larger effort in the department to study the main sources of vulnerability and to disseminate the emerging findings of the forthcoming joint World Bank-UN Assessment of the Economics of Disaster Risk Reduction. Policy Research Working Papers are also posted on the Web at http://econ.worldbank.org. The authors may be contacted at yikeda1@worldbank.org and nloayza@worldbank.org.

The Growth Aftermath of Natural Disasters*

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I. Introduction

This paper provides a description of the macroeconomic aftermath of natural disasters, specifically tracing the economic growth response in the wake of these events. Its purpose is to contribute to the analysis of the path of adjustment and recovery by tracing the yearly response of GDP growth --both aggregated and disaggregated into its agricultural and non-agricultural components-- to four types of natural disasters --droughts, floods, earthquakes, and storms. As has been shown in recent papers (see, for instance, Loayza, Olaberría, Rigolini, and Christiaensen 2009), the analysis by sector of economic activity and by type of natural disaster is crucial to measure and interpret its complex effects on the economy.

Apart from this disaggregated analysis, this paper has four other features that set it apart. First, it traces the growth response in every year of and after the event. This focus on the annual frequency is necessary to characterize the details of the adjustment path, rather than only explaining its net permanent effect. For instance, it is conceivable that, say, an earthquake has no long-run consequences on economic growth while having a growth path of decline followed by recovery, whose characterization would be of interest for the present analysis.

Second, the paper uses a methodological approach based on pooling the experiences of various countries over time to arrive at *mean* responses of growth to natural disasters. While losing country specificity, the methodology allows describing basic patterns in a sensible and robust manner. The econometric methodology consists of vector auto-regressions in the presence of endogenous variables and exogenous shocks, applied to panel, cross-country and time-series, data (for short, the methodology is described as panel VARX). The full sample consists of 87 countries representing all major regions of the world and 48 years covering the period 1960-2007.

Third, the paper considers the difference between advanced and developing countries. Some key papers in this literature have noted that although the impact of natural disasters is not the same across countries, it is not erratically heterogeneous either (see Skidmore and Toya 2007, and Noy 2009, among others). Rather the impact follows a more or less clear pattern, where poorer nations (in terms of economic, social, or institutional well-being) tend to experience stronger effects from natural disasters. In order to take this important insight into consideration, while preserving the panel nature of the analysis, the paper conducts the econometric study not only on the full sample of countries but also on two separate groups: poor or developing countries (62) and rich or advanced countries (25).

Fourth, the paper expands the analysis by considering the potentially different effect of severe vs. moderate natural disasters. Disasters of moderate magnitude are less difficult to handle than severe ones. Thus, in the presence of moderate natural disasters, governments and private organizations can deploy, redistribute, and relocate their physical and human resources to compensate for the losses and reactivate the economy. Under some conditions, moderate disasters may even bring about an increase in economic growth by raising land productivity (in the case of floods) or inducing capital transformation (in the case of earthquakes). However, if the disaster is of such magnitude that it overwhelms public and private responses, its effect is likely to be more detrimental.

At the end of this introduction, the paper offers a comprehensive review of the new and interesting literature dealing with the macroeconomic impact of natural disasters. Nevertheless, at this point, we highlight three papers that are most closely connected with this study. The first is the paper by Loayza, Olaberría, Rigolini, and Christiaensen (2009). In a sense, that paper and the present study can be regarded as companion papers. Produced almost concurrently, the two studies take advantage of disaggregation by type of disaster, sector of economic activity, and level of economic development in order to enrich the analysis and elucidate the interpretation of results. The focus of Loayza et al. (2009), however, is not on the path of adjustment and recovery but on the net effects in the medium to long terms, for whose analysis it uses period averages rather than annual data. Therefore, instead of employing a panel-VARX approach to trace yearly responses, Loayza et al. uses GMM-System estimator (designed for panels with large cross-section and short time-series dimensions) to obtain average net effects.

The second is the paper by Hochrainer and Mechler (2009). It assesses the macroeconomic consequences of natural disasters by comparing the gap between a counterfactual GDP and observed GDP. The counter factual is constructed using the projection of past GDP under the assumption of a no-disaster scenario. The paper finds that natural disasters on average lead to negative effects on GDP. Although Hochrainer and Mechler's paper differs from ours regarding the methodological approach, it is similar on the importance of separating natural disasters according to type and estimating their effects independently. Thus, it finds that typical (or median) storms, earthquakes, and droughts have a negative impact on GDP, while floods show a positive impact one. As shown below, these results are consistent with most of our findings.

The third paper is by Raddatz (2009). In this case, the methodological approach seems to be similar to ours regarding the use of an autoregressive model applied to panel data to assess the macroeconomic consequences of natural disasters. There are, however, some important differences. Raddatz concentrates on the effects of disasters on aggregate GDP growth, while we also analyze the effects on agricultural and non-agricultural sectors, finding differing effects on each of these sectors of the economy. Although Raddatz also recognizes the importance of disaggregating by type of disaster, he emphasizes a way of grouping them that, while popular in the literature, may mask contrasting effects. Such is the case of "climatic" natural disasters, which group together floods and droughts. We separate them and find that they have radically different impacts on economic growth. Another difference between Raddatz' analysis and ours is that we differentiate between relatively moderate disasters and extremely severe disasters to capture possible non-monotonic effects. On the other hand, Raddatz' contribution extends in dimensions that we do not explore. He finds that neither the inflow of foreign aid nor the initial level of indebtedness of the country significantly affects the growth impact of natural disasters. On the other hand, he finds that the level of economic development does influence the impact of natural disasters. It is this dimension of the heterogeneity across countries that we emphasize in this paper.

Before proceeding with the literature review, we now provide the outline of the paper. Section II presents the description of the data, including details on the sample regarding countries, periods, and frequency of observations; and on the variables used in the analysis concerning definitions, sources, and summary statistics, with special attention to the measures of moderate and severe natural disasters. Section III introduces the econometric methodology, including an exposition of the VARX method, and two important specification tests dealing with exogeneity assumptions and lag structures. Section IV presents the basic results, discussing and contrasting the effects of droughts, floods, earthquakes, and storms, focusing mostly on the sample of developing countries. Section V offers some concluding remarks.

Literature review

Economic research in this field is still in an early phase of development. In general, the results on the macroeconomic impact of natural disasters seem to be ambiguous. A close examination in recent studies further demonstrates that these effects may depend on economic, social, and institutional conditions, as well as on the type of natural disaster and sector of the economy.

Rasmussen (2004) assessed the impacts of natural disaster incidences using a cross-country sample for the period 1970 through 2002. The data were obtained from the EM-DAT database of the Centre for Research on the Epidemiology of Disasters (CRED), which is the major source of data on natural disasters used in most studies. According to CRED, a natural disaster is defined as a situation or event which overwhelms local capacity, necessitating a request for external assistance. The database consists of disaster events which fulfill at least one of the following criteria: ten or more people reported killed; 100 or more people reported affected; declaration of a state of emergency; or call for international assistance. These disasters include hydro-meteorological disasters such as floods, wave surges, storms, droughts, landslides and avalanches; geophysical disasters such as earthquakes, tsunamis and volcanic eruptions; and biological disasters such as epidemics and insect infestations. To provide a comprehensive picture, he compared the frequencies and impacts of disasters across countries by employing four measures, including the number of events divided by land area, the number of events divided by population, the number of affected persons divided by total population, and damage divided by GDP. He found that developing countries, particularly small island states in the Eastern Caribbean Currency Union (ECCU), face higher relative costs than advanced countries when measured in terms of the number of person affected and the value of the damage. The author also assessed the short-term impacts of 12 major disasters occurred in the ECCU and observed its negative effects on economic output as well as external and fiscal balances. The analysis showed that natural disasters led to a median reduction of 2.2% in the same-year real GDP growth. Moreover, a median increase in the current account deficit amounted to 10.8% of GDP in the disaster year. The median public debt was also observed to increase by a cumulative 6.5% over three years following disaster events.

Closely related to this approach, Heger, Julca, and Paddison (2008) investigated the macroeconomic impact of natural disasters with the specific focus on the Caribbean region. Their analysis was based on the annual dataset that included sixteen Caribbean states over the 1970-2006 period, drawn from the EM-DAT database. The authors first selected proxies for natural disasters through a simple OLS estimation. They identified the frequency of disasters, the estimated costs of disasters, and the number of total affected as the major explanatory variables for different macroeconomic outcomes. With those variables in the corresponding OLS regression analysis, the results illustrated that natural disasters negatively impact growth, fiscal balance, and external balance. These results coincide with those of Rasmussen’s presented above. Another significant finding was that when a country relies on export or import specialization, larger damages occur in response to disasters. The authors conclude that diversification of the economy can help mitigate the effects of natural disasters.

Using a panel vector auto-regression model, Raddatz (2007) examined the dynamic impacts of external shocks, including natural disasters, on the volatility of output. Focusing on low-income countries, he uses a sample of 40 countries over the period from 1965 to 1997. For the disaster measurement, the author employs the annual data on the number of disastrous events, compiled from the EM-DAT database. The analysis indicated that the effects of external shocks in general on per capita GDP are modest and contribute to only a small portion of its volatility, leading the author to conclude that output volatility is largely determined by internal causes rather than external shocks. However, shocks derived from some natural disasters did appear to have and important effect. In particular, it was observed that climatic disasters lead to a decrease of 2% in real per capita GDP one year after the disaster, while humanitarian disasters reduce it by 4%. On the other hand, geological disasters were found to be insignificant in terms of contribution to the variance of output.

A recent study by Noy (2009) investigated the short-run macroeconomic response to natural disasters using a panel dataset over the period 1970-2003. Taken from the EM-DAT database, three measures of disaster damages were employed: the number of people killed; the number of people affected; and the amount of direct damage. In light of potential factors that can influence the disaster impacts, the author took into account differences in population size, size of economy, and timing of incidences. The regression of annual GDP growth rate on the disaster measure and other control variables revealed that the impact of natural disaster is statistically significant when it is measured as the amount of property damage incurred. As other studies suggest, it was also found that the macroeconomic costs were much higher in developing countries than in developed countries. Noy further analyzed the determinants of these negative macroeconomic effects following disasters. He concluded that higher level of literacy, better institutional quality, higher per capita income, higher government spending, and more open economies along with better financial conditions are likely to contribute to countries' macroeconomic performance after natural disasters.

On a similar line, several studies have documented that economic development plays an important role in mitigating a countries' vulnerability to catastrophic incidences. Skidmore and Toya (2007) investigated the effects of the level of development on disaster impacts, using a dataset of natural disasters incurred in 151 countries over the period from 1960 to 2003. The analysis included two patterns of dataset obtained from the EM-DAT. One used the number of killed to assess the disaster impacts, while the other considered economic damages. The OLS regression analysis demonstrated that human and economic damages from natural disasters are generally reduced along with economic development. In particular, the results showed that deaths and damages were lower in countries with higher level of educational attainment, greater degree of openness, more developed financial sector, and smaller governments. The authors suggest that policymakers could consider further efforts in developing economic and social infrastructures, which can contribute to decreasing natural hazards.

Taking a different approach in exploring the impacts of capital and labor losses on short-term growth, Caselli and Malhotra (2004) tested the empirical validity of the predictions of the Solow growth theory. The theory suggests that a decline in the capital-labor ratio resulting from a natural disaster would lead to an increase in the country's growth rate, while an increase in the capital-labor ratio would curtail it. In their empirical analysis, the total number of people killed, injured, and affected by disasters were used to calculate the percentage loss in the labor force, while the immediate damage as a percentage of GDP was used as a proxy for the loss in capital stock. The data were compiled from the EM-DAT database for a sample of 172 countries for the period between 1975 and 1996. Using the real per capita GDP growth rate in the disaster year to estimate the Solow model, their empirical analysis found that sudden losses of capital and labor did not bring about a change in the economic growth as expected by the Solow growth model. The results, however, remain questionable given the proxies used to measure capital and labor destructions and the timing of the growth response.

Jaramillo (2007) presented a comprehensive analysis of the link between natural disasters and economic growth both in the short-run and long-run using a panel dataset of 113 countries over the period 1960-1996. However, disasters that develop through extended periods, such as droughts and famines, as well as insect infestations and epidemics are excluded from the analysis. The type of disasters examined by Jaramillo include earthquakes, floods, wild fires, wind storms, waves and surges, extreme temperatures, volcano episodes, and slides. Taking country and year fixed effects into account and controlling for trade openness and foreign aid, the author examined the short-run effects of disasters on economic growth, followed by an analysis of the long-run effects. For the short-run, Jaramillo assessed the impacts on GDP growth in the disaster year and the following year, whereas for the long-run, he tested for the cumulative disaster effects over the period 1960-1996 on the GDP per capital level in 1996. The regression results indicated that short- and long-term effects of disasters are determined by countries' income level, population, and the type of disaster. On the whole, it was found that the effects of disasters on GDP growth rate varied from 0.9% decrease to 0.6% increase depending on the disaster type.

Focusing specifically on the long-term macroeconomic impacts of natural disasters, the first comprehensive empirical research was done by Skidmore and Toya (2002). In their cross-country analysis, the authors use average per capita GDP growth over the period 1960-1990 and the total number of significant disaster events observed in respective countries during the same period. The disasters studied cover climatic and geologic disasters. The results revealed that climatic disasters have positive effects on the long-run economic growth as they induce higher capital accumulation and total factor productivity than before. It is argued that total factor productivity is the predominant factor in promoting growth after disasters. By contrast, geologic disasters were observed to affect growth negatively as it deteriorates physical capital and decreases human capital due to the initial loss of life.

Following Skidmore and Toya's findings, Cuaresma, Hlouskova, and Obersteiner (2008) examined the long-run effects of natural disasters by analyzing the direct relationship between foreign technology absorption and disaster incidences. Earlier studies argued that disasters can provide countries with opportunities to renew technologies, thereby promoting long-run growth. The authors assess this argument by using gravity model to analyze foreign knowledge spillovers between the G-5 countries and a sample of 49 developing countries. According to the regression results, natural catastrophic risk negatively affected knowledge transfers from the industrialized to developing countries. The authors further found that countries with higher levels of development are more likely to be better off than countries with lower levels of development through capital upgrading following natural disasters.

Hallegatte and Ghil (2007) added business cycle framework to the study of disaster impacts. They analyzed the effects of exogenous shocks, including natural disasters and stochastic productivity stocks, on economic behavior. Employing a Non-Equilibrium Dynamic model with endogenous business cycles, they found that total GDP losses resulting from natural disasters are higher when occurring during expansions than during recessions. The reason is that because pre-existing disequilibria are widened by exogenous shocks in the former phase, whereas the shocks are mitigated by the existence of unused resources in the latter case. The paper drew the conclusion that the phase of the business cycle during which a disaster occurs affects the degree of the macroeconomic response.

As discussed above, while some studies found common patters in the determinants of a country's vulnerability to catastrophic events, researchers have not come to a consensus on the impacts of natural disasters on economic growth. This paper attempts to help disentangle this ambiguity by using a better-grounded econometric methodology and a conceptually driven disaggregation by type of natural disaster and sector of economic activity.

II. Data

A. Periods, frequency, samples (groups of countries)

To perform our estimations, we use pooled cross-country and annual time-series data covering 87 countries over the period 1960-2007. The panel is unbalanced, with some countries having more observations than others. We refer to the data as “all countries”. Then we split the data into two groups: “rich countries” and “developing countries”. We classify 25 Arab and OECD countries into the first group and the other 62 counties into the second group. Table II.1 gives the list of countries of these groups.

B. Variables, definitions, sources

The main variables used in the paper are divided in three groups. First, to study the impact of natural disasters on the economy, we define three types of growth variables. The first is the growth rate of real per capita Gross Domestic Product (GDP). The others are the growth rates of real per capita value added in the two major sectors of the economy, the agricultural sector and the non-agricultural sector. All of them are measured as the log difference of per capita output (in 2000 US dollars), where per capita output is obtained by dividing the value added of each sector by the total population.

Second, as a variable which represents the role of external conditions that may affect the growth performance across countries, we use shocks to the Terms of Trade (TOT). Terms of trade shocks are measured by the growth rate of the terms of trade (export prices relative to import prices). The idea is to capture shifts in the demand for a country’s exports. Data for all the above variables were obtained from the World Bank (WDI, 2008).

The last set of variables represents the role of natural disasters on the growth performance across countries. Data for natural disasters were obtained from the Emergency Disasters Database (EM-DAT) maintained by the Center for Research on the Epidemiology of Disasters (CRED). EM-DAT provides the number of casualties (people confirmed dead, reported missing, and presumed dead), the number of people injured, and the number of people affected. People affected are those requiring immediate assistance during a period of emergency. Also, people reported injured or homeless are aggregated with those affected to produce the total number of people affected (we refer to this number as "total affected"). Throughout the paper, we assume that natural disaster variables are (block) exogenous with respect to the growth variables and shocks to the terms of trade.[1]

C. Moderate and severe natural disasters

As mentioned above, we divide natural disasters into four categories: droughts, floods, earthquakes, and storms. The measure of intensity of natural disasters, $ND_{t,i}^{k}$, is given by:

$$ND_{t,i}^{k} = \begin{array}{ll} drought_{t,i} & if\ k=1, \\ flood_{t,i} & if\ k=2, \\ earthquake_{t,i} & if\ k=3, \\ storm_{t,i} & if\ k=4, \end{array} \tag{1}$$

where

$$intensity_{t,i,j}^{k} = \frac{killed_{t,i,j}^{k} + 0.3 * total\ affected_{t,i,j}^{k}}{population_{t,i}}, \tag{2}$$

$$ND_{t,i,j}^{k} \quad \begin{array}{l} =1, \text{ if } intensity_{t,i,j}^{k} > 0.0001, \\ =0, \text{ otherwise,} \end{array} \tag{3}$$

[1] For the exogeneity of natural disaster variables, see section III.b.i.

$$ND_{t,i}^{k} = \sum_{j=1}^{J} ND_{t,i,j}^{k}, \tag{4}$$

and J describes the total number of type-k events (k = 1, 2, 3, and 4 correspond to drought, flood, earthquake, and storm, respectively) that took place in country i during year t. The following steps describe how to create the intensity measure. First, for each event of type-k disaster, we create a variable $intensity_{t,i,j}^{k}$ measuring the magnitude of the event relative to the size of the economy, that is, the sum of the number of casualties $\left(killed_{t,i,j}^{k}\right)$ and 30% of the total number of people affected $\left(total\ affected_{t,i,j}^{k}\right)$ divided by the population (equation (2)) [2]. Then we construct a dummy variable $ND_{t,i,j}^{k}$ which takes the value of 1 if $intensity_{t,i,j}^{k}$ is greater than 0.01% (equation (3)). Finally, for each type of disaster, the respective dummy variables $ND_{t,i,j}^{k}$, $j = 1, ..., J$ are summed up to obtain the indicator value $ND_{t,i}^{k}$ to assess the total magnitude of type-k disasters in country i during year t (equation (4)).

Many practitioners point out that the impact of moderate disasters and extremely severe disasters on the economic performance differ, not only in their magnitude, but also in their dynamic characteristics. To capture the particular effects of severe disasters, we construct a second measure of intensity, $sevND_{t,i}^{k}$, as follows:

$$sevND_{t,i}^{k} = \begin{matrix} sev.drought_{t,i} & if\ k = 1, \\ sev.\ flood_{t,i} & if\ k = 2, \\ sev.earthquake_{t,i} & if\ k = 3, \\ sev.storm_{t,i} & if\ k = 4, \end{matrix} \tag{5}$$

where

[2] This intensity measure is similar to the one established by the International Monetary Fund (IMF, 2003), and used by Becker and Mauro (2006).

$$intensity_{t,i,j}^{k} = \frac{killed_{t,i,j}^{k} + 0.3 * total\ affected_{t,i,j}^{k}}{population_{t,i}}, \tag{6}$$

$$sevND_{t,i,j}^{k} \begin{array}{l} = 1, \text{ if } intensity_{t,i,j}^{k} > 0.01, \\ = 0, \text{ otherwise,} \end{array} \tag{7}$$

$$sevND_{t,i}^{k} = \sum_{j=1}^{J} sevND_{t,i,j}^{k}. \tag{8}$$

Here, for the dummy variable for the intensity of individual *severe* disaster, $sevND_{t,i,j}^{k}$, we set the threshold at 1% of the population, while we applied the threshold of 0.01% for general or *moderate* disasters. In section IV, we show the results of two types of estimation, in which (i) only *moderate* disaster variables are included (the basic model), and (ii) both *moderate* and *severe* disaster variables are included.

D. Summary statistics

Regarding the growth variables introduced in the early part of this section, a few observations deserve some comments. First, we should point out that the growth performance of the different sectors varies widely in each country. As shown in Table II.2, during the period 1960-2007, the non-agricultural sector has had much higher average growth rate (1.7% in developing countries, 2.1% in rich countries) than the agricultural sector (0.31% in developing countries, 0.93% in rich countries). Also, Table II.3 shows that the correlation between the growth rates of non-agricultural sector with the agricultural sector is quite low (0.1095 in developing countries and 0.0173 in rich countries). The considerable disparities among the growth performances provide some grounds to suspect that natural disasters could have had diverse effects on the different sectors of the economy.

III. Methodology

A. Econometric method

The econometric model we adopt here is a fixed-effects Panel VARX model, namely,

$$\mathbf{y}_{t,i} = \boldsymbol{\alpha}_i + \boldsymbol{\Phi}_1 \mathbf{y}_{t-1,i} + \boldsymbol{\Phi}_2 \mathbf{y}_{t-2,i} + \boldsymbol{\Phi}_3 \mathbf{y}_{t-3,i} + \boldsymbol{\Theta}_0 \mathbf{x}_{ti} + \boldsymbol{\Theta}_1 \mathbf{x}_{t-1,i} + \boldsymbol{\Theta}_2 \mathbf{x}_{t-2,i} + \boldsymbol{\varepsilon}_{t,i}, \qquad (9)$$

where the country index is $i = 1, 2, \ldots, M$ and the time index for each country is $t = 1, 2, \ldots, T_i$. The fixed effect for each country is represented by $\boldsymbol{\alpha}_i$. Hereafter, the total number of observations for all countries in the panel is denoted by $T = \sum_{i=1}^{M} T_i$. The endogenous variables vector is denoted by the (2 × 1) vector $\mathbf{y}_{ti}$ while the (4 × 1) exogenous variables vector $\mathbf{x}_{ti}$ represents the occurrences at time t of the disasters, respectively, drought, flood, earthquake, and storm. In equation (9) we assume the homogenous error structure $E(\boldsymbol{\varepsilon}_{t,i}\boldsymbol{\varepsilon}'_{t,i}) = \boldsymbol{\Omega}$ for all t and i where $\boldsymbol{\varepsilon}_{t,i}$ is the (2 × 1) vector of errors of the system. Furthermore, we assume independence of the errors within equations, $E(\boldsymbol{\varepsilon}_{t,i}\boldsymbol{\varepsilon}'_{t,j}) = \mathbf{0}$, $i \neq j$, and across equations, $E(\boldsymbol{\varepsilon}_{t,i}\boldsymbol{\varepsilon}'_{s,j}) = \mathbf{0}$, for any t and s where $i \neq j$.

Model (9) is applied to three different groups of countries: All of the countries, Developing countries, and Developed Countries. We choose to estimate Model (9) by OLS to the demeaned series resulting in the so-called within-fixed-effects estimator. As pointed out by Nickell (1981), given that Model (9) is dynamic, if T is small and fixed, such an estimator is inconsistent as the number of countries, M, goes to infinity. However, in our case we consider the number of countries fixed and since in each grouping of the countries considered here the number of available observations, T, is at least 778.[3] In this case, the bias of the within-fixed-effects estimator should be negligible. Hereafter, we refer to the within-fixed-effects estimator simply as the OLS estimator, with the coefficient estimates being denoted by $\hat{\mathbf{\Phi}}_i$, i = 1, 2, 3, and $\hat{\mathbf{\Theta}}_i$, i = 0, 1, 2.

Model (9) can be written more compactly as

$$(\mathbf{I} - \mathbf{\Phi}_1 L - \mathbf{\Phi}_2 L^2 - \mathbf{\Phi}_3 L^3)\mathbf{y}_{t,i} = \boldsymbol{\alpha}_i + (\mathbf{\Theta}_0 + \mathbf{\Theta}_1 L + \mathbf{\Theta}_2 L^2)\mathbf{x}_{t,i} + \boldsymbol{\varepsilon}_{t,i},$$

or

$$\mathbf{\Phi}(L)\mathbf{y}_{t,i} = \boldsymbol{\alpha}_i + \mathbf{\Theta}(L)\boldsymbol{\varepsilon}_{t,i}, \qquad (9')$$

where L denotes the usual lag operator. To insure that (9') produces a steady state, we require that all of the roots of the determinant equation $\left|(\mathbf{I} - \mathbf{\Theta}_1 L - \mathbf{\Theta}_2 L^2 - \mathbf{\Theta}_3 L^3)\right| = 0$ lie outside of the unit circle. Inverting (9') produces the multiplier form of Model (9):

$$\mathbf{y}_{t,i} = \mathbf{\Phi}(L)^{-1}\mathbf{\Theta}(L)\mathbf{x}_{t,i} + \mathbf{\Phi}(L)^{-1}\boldsymbol{\varepsilon}_{t,i}. \qquad (10)$$

The mean responses from the occurrences of natural disasters are therefore captured by the lag polynomial

$$\mathbf{\Psi}(L) = \mathbf{\Phi}(L)^{-1}\mathbf{\Theta}(L). \qquad (11)$$

It follows that the coefficients of the lag polynomial $\mathbf{\Psi}(L)$ can be obtained by matching the coefficients in the expression

$$\mathbf{\Psi}(L)\mathbf{\Phi}(L) = \mathbf{\Theta}(L). \qquad (12)$$

This gives rise to the solutions

[3] The number of observations available in the sample of rich countries, with non-agricultural growth rate as an endogenous variable.

$$\boldsymbol{\Psi}_0 = \boldsymbol{\Theta}_0 \tag{13}$$

$$\boldsymbol{\Psi}_1 = \boldsymbol{\Theta}_1 + \boldsymbol{\Psi}_0\boldsymbol{\Phi}_1 \tag{14}$$

$$\boldsymbol{\Psi}_2 = \boldsymbol{\Theta}_2 + \boldsymbol{\Psi}_1\boldsymbol{\Phi}_2 + \boldsymbol{\Psi}_0\boldsymbol{\Phi}_2 \tag{15}$$

$$\boldsymbol{\Psi}_3 = \boldsymbol{\Psi}_2\boldsymbol{\Phi}_1 + \boldsymbol{\Psi}_1\boldsymbol{\Phi}_2 + \boldsymbol{\Psi}_0\boldsymbol{\Phi}_3 \tag{16}$$

$$\boldsymbol{\Psi}_s = \boldsymbol{\Psi}_{s-1}\boldsymbol{\Phi}_1 + \boldsymbol{\Psi}_{s-2}\boldsymbol{\Phi}_2 + \boldsymbol{\Psi}_{s-3}\boldsymbol{\Phi}_3 \qquad \text{for } s \geq 4\,. \tag{17}$$

Now let

$$\boldsymbol{\Pi} = \left[\boldsymbol{\Phi}_1\ \boldsymbol{\Phi}_2\ \boldsymbol{\Phi}_3\ \boldsymbol{\Theta}_0\ \boldsymbol{\Theta}_1\ \boldsymbol{\Theta}_2\right] \tag{18}$$

denote the coefficient matrix of (9). The coefficient matrix $\boldsymbol{\Phi}_i$ is 2 × 2 for i = 1, 2, 3 and $\boldsymbol{\Theta}_i$ is 2 × 4 for i = 0, 1, 2. Therefore, the coefficient matrix $\boldsymbol{\Pi}$ is (2 × (6 + 12)) = (2 × 18). Let $\boldsymbol{\pi} = vec(\boldsymbol{\Pi})$. Then $\boldsymbol{\pi}$ is a (2(18) × 1) vector with the first 18 elements being the autoregressive and current and lagged natural disaster coefficients from the first equation and the second 18 elements being the corresponding coefficients from the second equation.

Let $\boldsymbol{\psi}_s = vec(\boldsymbol{\Psi}_s)$ denote the (2(4) × 1) vector of the s-period delay mean responses due to natural disasters. The first 4 elements represent the s-period delay mean responses of the first endogenous variable to the natural disasters while the second 4 elements represent the s-period delay mean responses of the second endogenous variable to the natural disasters. Moreover, let $\hat{\boldsymbol{\pi}}$ denote the vector of the OLS estimates of equation (9). Then it can be shown under fairly general conditions that

$$\sqrt{T}(\hat{\boldsymbol{\pi}} - \boldsymbol{\pi}) \Rightarrow N(\mathbf{0}, (\boldsymbol{\Omega} \otimes \mathbf{Q}^{-1})) \tag{19}$$

where $\mathbf{\Omega} = E(\boldsymbol{\varepsilon}_{t,i}\boldsymbol{\varepsilon}'_{t,i})$ is the variance-covariance matrix of the error terms of (9) and $\mathbf{Q} = \text{plim}(\mathbf{X}'\mathbf{X}/T)$ where $\mathbf{X}$ is a (T × 18) design matrix of the form

$$\mathbf{X} = \begin{pmatrix} \mathbf{X}_1^{'} \\ \mathbf{X}_2^{'} \\ \vdots \\ \mathbf{X}_T^{'} \end{pmatrix} \tag{20}$$

where $\mathbf{X}_t^{'} = (\mathbf{y}_{t-1}^{'}\mathbf{y}_{t-2}^{'}\mathbf{y}_{t-3}^{'}\mathbf{x}_t^{'}\mathbf{x}_{t-1}^{'}\mathbf{x}_{t-2}^{'})$.

In implementing the result of equation (19), we need consistent estimates of $\mathbf{\Omega}$ and $\mathbf{Q}$. These estimates are obtained as follows:

$$\hat{\mathbf{\Omega}} = \frac{1}{T}\sum_{t=1}^{T}\hat{\boldsymbol{\varepsilon}}_t\hat{\boldsymbol{\varepsilon}}'_t \tag{21}$$

and

$$\hat{\mathbf{Q}} = \mathbf{X}'\mathbf{X}/T. \tag{22}$$

Let $\hat{\mathbf{\Psi}}_s(\hat{\boldsymbol{\pi}})$ denote the estimated s-period delay mean responses to the exogenous vector $\mathbf{x}_t$ where the dependence of these estimates on the coefficient estimates $\hat{\boldsymbol{\pi}}$ is made explicit. One way to obtain standard errors for these estimates is to use Monte Carlo methods. First, randomly draw a (36 × 1) vector from the distribution $N(\hat{\boldsymbol{\pi}}, \frac{1}{T}(\hat{\mathbf{\Omega}} \otimes \hat{\mathbf{Q}}^{-1}))$. Denote this vector by $\boldsymbol{\pi}^{(1)}$. Calculate $\hat{\mathbf{\Psi}}_s(\boldsymbol{\pi}^{(1)})$. Repeat this process for, say, a total of 10,000 times. Then to get, for example, the 90% confidence interval for the first element of $\mathbf{\Psi}_s$, say $\mathbf{\Psi}_{s1}$, we need the 5th percentile, $\underline{\mathbf{\Psi}}_{s1}$, and the 95th percentile, $\overline{\mathbf{\Psi}}_{s1}$, from the simulated values of $\mathbf{\Psi}_{s1}$ resulting in the 90% confidence interval for $\mathbf{\Psi}_{s1}$, namely, ($\underline{\mathbf{\Psi}}_{s1}$, $\overline{\mathbf{\Psi}}_{s1}$). The confidence intervals for the remaining elements of $\mathbf{\Psi}_s$ are similarly constructed.

B. Diagnostic tests

i. Individual and panel unit root tests

Before we can proceed to build a VARMAX panel model for analyzing the effects of natural disasters on various endogenous variables, we need to determine the stationary forms of the endogenous variables we are going to be using in our analysis. In this study we chose as the endogenous variables of interest (1) the log of real GDP per capita, (2) the log of real agricultural value added per capita, (3) the log of real non-agricultural value added per capita, and (4) the log of terms of trade. We chose to use the log transformation of the variables because of the variance stabilizing characteristics of the transformation and the fact that, if a unit root is contained in the logged variables, then differencing them yields a very straight-forward interpretation of the differenced data, namely percentage change.

We proceeded to pursue unit root testing in these variables in two ways: series-by-series unit root tests and panel unit root testing with individual country effects as in the Levin, Lin, and Chu (2002) and Im-Pesaran-Shin (2003) panel unit root testing frameworks. These unit root tests are, of course, dependent on the specification of the deterministic parts of the unit root test equations. That is, does the data contain a trend or not? Is the data without trend but has a non-zero mean as compared to a zero mean? To obtain consistent statistical hypothesis test results one must properly specify the deterministic parts of the data under the alternative hypothesis of stationarity. In this vein we tested the significance of the trend in the above four series by testing the significance of the intercept in the following AR(2) equation of the variable in question, country-by-country:

$$\Delta z_t = \alpha + \phi_1 \Delta z_{t-1} + \phi_2 z_{t-1} + \varepsilon_t . \tag{23}$$

In equation (23) z_t represents a particular country's variable in question and Δ represents the first differencing operator. We specified a second-order autoregression to ensure that the residuals of the equation would be white noise thus implying that OLS t-statistics involving the intercept α would be appropriate for testing for the presence or absence of trend. In the case that the null hypothesis $H_0 : \alpha = 0$ was supported, we concluded that the data does not have a trend in it. On the other hand, if the alternative hypothesis of $H_1 : \alpha \neq 0$ was supported, we concluded that the data has trend in it. With respect to the log of real GDP per capita and log of real non-agricultural value added per capita, the preponderance of tests indicate trend is present (52 of 87 null hypotheses rejected for the former and 47 of 87 null hypotheses rejected for the latter). In contrast, for the log of real agricultural value added per capita and the log of terms of trade, the preponderance of tests indicated that trend is absent (15 of 87 null hypotheses rejected for the former and 1 of 87 null hypotheses rejected for the latter). Thus, for the production run of unit root tests, we choose to treat all of the log of real GDP per capita and log of real non-agricultural value added per capita series as having trends in them while the log of real agricultural value added per capita and log of terms of trade series had no trend in them but non-zero means.[4]

As a result of these trend tests we chose to use an intercept and deterministic trend in testing for unit roots country-by-country in the log of real GDP per capita and log of real non-agricultural value added per capita series in the augmented Dickey-Fuller and Phillips-Perron unit root test equations while for the log of real agricultural value added per capita and the log of terms of trade, we chose to use only an intercept in the augmented Dickey-Fuller and Phillips-Perron unit root test equations. Of course, when testing for the sufficiency of the first difference in producing stationarity in a series, we checked the first difference of the series for unit roots using the appropriate deterministic terms implied by differencing. In particular, when testing for the stationarity of the first

[4] Detailed test results are available from the authors upon request.

difference of the log of real GDP per capita and the first difference of the log of real non-agricultural value added per capita we included only an intercept in the test equation. In contrast, when testing for the stationarity of the first difference of the log of real agricultural value added per capita and the log of terms of trade we set the intercept to zero in the test equation.

In contrast to the country-by-country unit root tests, the panel unit root tests of specific time series assume as the null hypothesis that a unit root exists for all of the countries, with country distinction coming only from having separate deterministic terms for each country (i.e. different intercept effects or different intercept effects as well as different trend effects for each country). The difference between the Levin, Lin, and Chu (2002) and Im-Pesaran-Shin (2003) panel unit root tests resides in the form of the alternative hypotheses assumed by the tests. In the Levin, Lin, and Chu test the alternative hypothesis takes the form of a common stationary first-order autoregressive coefficient across all of the countries whereas the Im-Pesaran-Shin test assumes all of the first-order autoregressive coefficients are stationary but that they can possibly take on different stationary values. Both tests are, of course, all-or-none tests in the sense that test results imply that either (1) all of the countries' given series have unit roots in them or (2) all of the countries' series are stationary of the same degree (as in the Levin, Lin, and Chu test) or different degrees (as in the Im-Pesaran-Shin) test. The benefit of the panel unit root tests are that, in the case of short time series in the panel, the power of the unit root tests are increased when one or more of the panel series are non-stationary as compared with country-by-country unit root tests.

The results of the above unit root tests applied to the four series are summarized in Table III.1.[5] The left half of the table pertains to unit root tests of the non-trending series (log of real agricultural value added per capita and log of terms of trade) while the right half of the table pertains to the unit root tests of the trending series (log of real GDP

[5] All of the results reported in Table III.1 were produced by EViews 6.0.

per capita and log of real non-agricultural value added per capita). In addition, the top half of the table (Section A) reports the unit root tests of the levels while the bottom half of the table (Section B) reports the unit root tests of the first differenced data. Furthermore, in each section the results of four unit root tests are reported, the first two tests being country-by-country unit root tests while the latter two tests are the panel unit root tests.[6]

The results reported in Table III.1 are summarized as follows:

- Log of real agricultural value added per capita. The preponderance of the individual unit root tests indicates the presence of a unit root. The panel unit root tests likewise indicate the presence of unit roots. After first differencing the series seems to be stationary.

- Log of Terms of Trade. The results for this series are similar to those of the previous non-trending series except for the significance of the Levin-Lin-Chu panel test where the p-value is less than 5% in the levels of the data. In contrast the Im-Pesaran-Shin panel test (with a flexible alternative hypothesis) indicates a unit root at the 10% level. Evidently, the log of terms of trade is "near" stationary. Despite this "split decision" on the existence of a unit root we decided to treat this series as having a unit root and to model its differences as being stationary.

- Log of Real GDP per capita. The preponderance of the individual unit root tests indicates the presence of a unit root. The panel unit root tests likewise indicate the presence of unit roots. After first differencing the series seems to be stationary.

[6] Note in the case of the first difference of the non-trending data, the Im-Peseran-Shin test is not reported as EViews does not accommodate the zero mean case.

- Log of real non-agricultural value added per capita. The same conclusions hold that hold for the log of real GDP per capita. Unit roots are present and the first differenced series appears to be stationary.

In summary, the test results of Table III.1 indicate that, when building meaningful VARMAX panel models to examine the impacts of various natural disasters on developing countries' GDP and agricultural, non-agricultural value added, and terms of trade, the growth rate forms of these endogenous variables should be used.

ii. Block exogeneity tests

The VARX model presented in the previous subsection is dependent on the assumption of exogeneity of the natural disaster variables. While all variables in the model are assumed to be endogenous in a simple VAR model, a VARX model allows some of the variables to be exogenous. In this section, we present the hypothesis testing method about the exogeneity of the disaster variables and its results.

Here, we are interested in the exogeneity of the disaster variables *as a group*, with respect to shocks to the terms of trade and one of the growth variables (GDP growth, agricultural growth, or non-agricultural growth). Without assuming the exogeneity of the disaster variables, we can rewrite Model (9) as a simple VAR of order p as follows:

$$\begin{aligned} \mathbf{x}_{t,i} &= \boldsymbol{\alpha}_i^1 + \sum_{h=1}^{p} \mathbf{A}_h \mathbf{x}_{t-h,i} + \sum_{h=1}^{p} \mathbf{B}_h \mathbf{y}_{t-h,i} + \mathbf{u}_{t,i}, \\ \mathbf{y}_{t,i} &= \boldsymbol{\alpha}_i^2 + \sum_{h=1}^{p} \mathbf{C}_h \mathbf{x}_{t-h,i} + \sum_{h=1}^{p} \mathbf{D}_h \mathbf{y}_{t-h,i} + \mathbf{v}_{t,i}, \end{aligned} \tag{24}$$

where

$$\mathbf{x}_{t,i} = \begin{bmatrix} drought_{t,i} \\ flood_{t,i} \\ earthquake_{t,i} \\ storm_{t,i} \end{bmatrix}, \qquad (25)$$

$$\mathbf{y}_{t,i} = \begin{bmatrix} TOT_{t,i} \\ GDP / Agr. / Non-agr.\, growth_{t,i} \end{bmatrix},$$

and $\boldsymbol{\alpha}_i^1$ and $\boldsymbol{\alpha}_i^2$ are the fixed effects for country *i*. In equation (24) we assume the homogenous error structures: $E(\mathbf{u}_{t,i}\mathbf{u}'_{t,i}) = \boldsymbol{\Omega}_{11}, E(\mathbf{u}_{t,i}\mathbf{v}'_{t,i}) = \boldsymbol{\Omega}_{12}, E(\mathbf{v}_{t,i}\mathbf{u}'_{t,i}) = \boldsymbol{\Omega}_{21}$, and $E(\mathbf{v}_{t,i}\mathbf{v}'_{t,i}) = \boldsymbol{\Omega}_{22}$ for all *t* and *i*, where $\mathbf{u}_{t,i}$ and $\mathbf{v}_{t,i}$ are the errors of the system. The group of variables represented by **x** is said to be *block-exogenous* with respect to the variables in **y** if $\mathbf{B}_h = \mathbf{0}$ for *h* = 1, …, *p*.

To check the exogeneity of the disaster variables, we can perform a likelihood ratio test with the null hypothesis, $H_0 : \mathbf{B}_h = \mathbf{0}$, *h* = 1, …, *p*. This test can be done with running OLS regressions of each of the disaster variables on *p* lags of all of them and *p* lags of all of the elements of **y**. Let denote $\hat{\mathbf{u}}_{t,i}$ the (4 × 1) vector of sample residuals from these regressions and $\hat{\boldsymbol{\Omega}}_{11}$ their variance-covariance matrix. Next, run OLS regressions of each of the disaster variables only on *p* lags of them, without lagged variables of **y**. Let denote $\hat{\mathbf{u}}_t(0)$ the (4 × 1) vector of sample residuals from the second set of regressions and $\hat{\boldsymbol{\Omega}}_{11}(0)$ their variance-covariance matrix. If

$$T * \{\log|\hat{\boldsymbol{\Omega}}_{11}(0)| - \log|\hat{\boldsymbol{\Omega}}_{11}|\}, \qquad (26)$$

where T is the number of observations, is greater than the critical value for a $\chi^2(4 \times 2p)$ variable, then the null hypothesis is rejected and the conclusion is that some of the disaster variables are helpful in forecasting **y**, i.e., the disaster variables are not block-exogenous with respect to the variables in **y**.

Table III.1 displays the results of the block exogeneity test. As it shows, the null hypothesis is not rejected in any of three samples, with any of growth variables, and with p = 1, 2, 3, at 5% of statistical significance. At 10% of significance, the null hypothesis is rejected only in 2 cases out of 27 cases, when we use the sample of rich countries and include the agricultural growth in **y**, with p = 1 and 3. These results strongly suggest the use of VARX model, over the use of VAR model in which all variables are treated as endogenous.

iii. Lag structure

Before estimating the panel VARX model, we need one crucial piece of information. That is the number of lags to include for each variable in the model. To identify the lag structure, some statistical criteria can be used.

A well-known criterion is Akaike's information criterion (AIC) (Akaike (1973)), given by

$$AIC = -2\left(\frac{l - K}{T}\right), \tag{27}$$

and an alternative is Schwarz's Bayesian information criterion (SBC) (Schwarz (1978)), which is given by

$$SBC = \frac{-2l + \log(T) \times K}{T}, \tag{28}$$

where T is the number of observations, K is the number of parameters in the model [7],

$$l = -T \times \left(1 + \log(2\pi) + \frac{1}{2}\log\left(\det\left(\frac{\hat{\boldsymbol{\varepsilon}}'\hat{\boldsymbol{\varepsilon}}}{T}\right)\right)\right), \tag{29}$$

[7] In our basic model, $K = 2(2p + 4(q + 1))$.

and $\hat{\boldsymbol{\varepsilon}}$ is the $(T \times 2)$ matrix of the error terms of Model (9). Models with a lower AIC or SBC are preferred. Both criteria add a penalty that increases with the number of regressors or lags.

Table III.2 shows the AIC and SBC statistics for the models with three different endogenous variables (GDP growth, agricultural growth, and non-agricultural growth) and three different groups of countries (all countries, developing countries, and rich countries). p and q represent the number of lags for the endogenous variables and the exogenous variables, respectively. In most cases, the results suggest either the models with $p = q = 1$, or the models with $p = q = 2$. Clearly, SBC tends to favor more parsimonious models than AIC, because the penalty for increasing the number of lags is larger for SBC.

Based on the information criteria values, we selected the lag length 2 as our basic lag structure. From a statistical point of view, there is little to choose between the lag length 1 and 2, since we have the mixed results from the information criteria. The latter one, however, provides much richer dynamics of the mean responses of the endogenous variables to exogenous shocks. As the goal of this paper is to study the dynamic effects of natural disasters, this is reason enough to select the lag length 2. We apply this lag structure to all of our models homogenously to simplify the interpretation.

IV. Results

We now report and discuss the main results on the growth consequences of natural disasters. We organize the presentation by type of disaster –droughts, floods, earthquakes, and storms. For each of them, we consider the effects on GDP per capita growth and its major components, agricultural and non-agricultural per capita value-added growth. We first estimate these effects using the sample of all countries (Table IV.1). Then, to gain further insight on the development angle of the issue, we divide the sample into developing countries (Table IV.2) and advanced countries (Table IV.3). Focusing on the sample of developing countries (for which the effects are stronger), we then consider the differing impact of moderate and severe natural disasters (Table IV.4).

The estimation of the VARX model renders a wealth of results, from which we choose those that are most pertinent to the main objective of the paper. Since we are interested in tracing out the dynamic path of adjustment in the aftermath of the disaster, the most relevant results are the mean response of growth to a given natural disaster for each year after the event. Since the effects are small and non-significant a few years after the event, we only report the mean responses for years 0, 1, 2, and 3 of the event (where year 0 is when the disaster occurred). We indicate whether these responses are statistically greater or smaller than zero, according to the Monte Carlo simulations explained in the methodological section of the paper. Furthermore, we report the cumulative effect of the event, which corresponds to the sum of mean responses for the 4 years after the event. We organize and present these results in several tables, as indicated above. In addition, we present a graphical representation of the mean responses for each natural disaster for the sample of developing countries, together with their corresponding confidence bands indicating 10% tails of the distribution of effects (Figures IV.1-4). The confidence bands are obtained through the Monte Carlo simulations mentioned above.

The majority of the discussion refers to the results obtained with the sample of developing countries. For comparison purposes, we also discuss the results from the sample of all countries (of which developing countries represent nearly 80%) and the sample of advanced countries.

Finally, we offer some robustness analysis regarding the lag structure of the VARX model (Appendix Tables A.1 and A.2, and Figures A.1-A.4). In particular, we use a more restrictive lag structure, $p = q = 1$, which, as mentioned in the previous section also received support from the information criteria tests. The results are broadly similar to those using the preferred longer lag structure. The main difference is that when only one lag is allowed, the mean responses corresponding to later years are smaller and less significant.

A. Droughts

Droughts have an overall negative effect on GDP growth. As expected, the effect is stronger for agricultural growth, but it is also negative for non-agricultural activities. For agricultural growth, the negative effect of droughts is larger on the year of the event. There is a significant recovery on the following year, but the cumulative effect remains significantly negative. For non-agricultural growth, the negative impact is felt on the year of the drought and also a couple of years afterwards, indicating the presence of delayed effects. In the sample of developing countries, the cumulative negative response to droughts is 1.7 percentage points (pp) for GDP growth and 1.6 pp for agricultural growth.

The pattern of results just described applies to the samples of all countries and of developing countries. For advanced countries, there is also a negative response on the year of the drought but it only applies to agricultural growth. Furthermore, in the subsequent years agricultural growth recovers so substantially that the cumulative effect of droughts for advanced countries is essentially zero.

Turning to the analysis of severe vs. moderate cases, the strongest negative effects (in size and statistical significance) come from severe droughts. The year of the event, severe droughts have twice the negative impact on GDP growth than moderate droughts. Furthermore, severe droughts induce larger volatility of growth, which means that they produce a larger drop the year of the event and a stronger recovery in the following year. In the case of GDP growth, this recovery is sufficiently strong so that the cumulative effect of severe droughts is comparable to that of moderate droughts (1.5-2.0 pp). However, in the case of agricultural growth, the recovery is insufficient and, then, the negative cumulative impact of severe droughts (2.0 pp) is twice as large as that of moderate ones. For non-agricultural growth, severe droughts also have the strongest impacts and the most volatile ones.

B. Floods

In contrast to droughts, floods tend to have a positive effect on economic growth. The mean response of GDP growth is positive and significant in years 2 and 3 after the event. This coincides with the mean response of non-agricultural growth, which indicates that the positive impact of floods for industry and services occurs with some delay. The timing of the effect highlights the importance of transmission mechanisms based on supply chain relationships (for instance, larger cotton production inducing a later expansion in textile production) and electricity generating capacity (as plentiful water supply facilitates electricity generation, leading to a future expansion of industry and services).

The response of agricultural growth is significantly positive one year earlier than non-agricultural growth, in year 1, but not the same year of the event. This may indicate that the potentially beneficial effects of floods on land productivity emerge in the subsequent harvesting cycle. For the sample of developing countries, the cumulative mean effect of floods on GDP growth is 0.5 pp and on agricultural growth, 0.6 pp.

This description of results applies to the samples of all countries and developing countries only. For advanced countries, only agricultural growth is significantly affected by floods. Although in year 3 after the event the mean response of agricultural growth is significantly negative, the previous mean response had been consistently positive so that the cumulative effect of floods is also positive and significant for advanced countries.

Regarding the comparison between moderate and severe floods, the annual mean responses indicate that the significantly positive effects observed above come only from moderate floods. Severe floods do not produce positive and significant mean responses of GDP growth or its two components. Regarding the cumulative effects, moderate floods induce an increase of 0.6 pp for GDP growth and 0.5 pp for agricultural growth. As something of an anomaly, the cumulative impact of severe floods is positive and significant, despite the fact that none of the annual mean responses is statistically significant.

C. Earthquakes

The results on the mean response of growth to earthquake shocks are weaker in terms of statistical significance than in the case of droughts and floods. Earthquakes do not seem to have a significant effect on GDP growth in any of the three samples of countries. However, there are some noteworthy results regarding sectoral growth, particularly for the sample of developing countries.

Focusing on the sample of developing countries, earthquakes appear to have a negative impact on agricultural growth, rendering a negative cumulative effect of about 1.4 pp. The fact that this effect is not due to a sharp response in any given year but, rather, to the accumulation of effects over some years may elucidate its likely channels. They may consist of, first, the disruption of transport and other infrastructure services that supports the distribution of agricultural inputs and outputs, and, second, a diversion of resources to reconstruction efforts in other sectors, particularly in urban areas.

In contrast, earthquakes elicit a positive mean response of non-agricultural growth in years 0 and 1 of the event. The latter one is statistically significant and amounts to an increase of 0.7 pp of value-added growth. This positive effect is consistent with the reconstruction activity that follows an earthquake in residential housing, public infrastructure, and production plants.

These results are further clarified when considering the effect of moderate vs. severe natural disasters. The negative cumulative impact of earthquakes on non-agricultural growth appears to occur with larger strength and significance for severe earthquakes. They produce a cumulated decrease in agricultural growth of almost 5 pp over the first years after the event. Similarly, the positive impact of earthquakes on non-agricultural activity seems to derive from moderate earthquakes only –severe earthquakes do not produce a significantly positive mean response of non-agricultural growth. In the case of severe earthquakes, the destruction of capital stock and labor force is large enough so as to cancel out the positive effect of reconstruction activity.

D. Storms

As in the case of earthquakes, the mean responses of growth to storms are weaker in statistical significance than those of droughts and floods. Nonetheless, some results do emerge from the data. Storms tend to have a negative effect on GDP growth and non-agricultural growth the same year of the event. This observation holds for the samples of all countries and developing countries. The effect is short-lived and small. In fact, for the sample of developing countries only, the negative impact of storms amounts to 0.3 pp of GDP growth and 0.4 pp of non-agricultural growth. In the following years, particularly for non-agricultural growth, there is a growth rebound representing most likely reconstruction efforts.

For the sample of rich countries, the effect of storms is minimal. There seems to be a negative response of agricultural growth in year 2 after the event, but in the surrounding years the mean response is positive, albeit non significant.

Turning to the comparison between moderate and severe storms, the main point to observe is that the negative growth effect noted above comes from the severe cases. For both GDP growth and non-agricultural growth, the cumulative effect of severe storms is negative and statistically significant, amounting to about 3 pp. For severe storms, the largest or most significant negative effects appear with some delay, in years 2 or 3 after the event. Conversely, for moderate storms, the mean response of growth and non-agricultural growth in those years is positive, reflecting in all likelihood the importance of reconstruction activities. How are these results consistent with those presented above? The negative and positive effects in later years of, respectively, severe and moderate storms would tend to cancel each other out when estimation does not differentiate by severity of the disaster.

Finally, regarding agricultural growth, moderate storms have a negative and significant effect in year 1 of the event. However, in the following year, the effect is positive, significant, and of about the same size, cancelling the previous one.

V. Concluding Remarks

This study has analyzed the path of macroeconomic adjustment and recovery in the aftermath of four types of natural disasters, namely, droughts, floods, earthquakes, and storms. Specifically, we have measured and examined the mean response of GDP per capita growth and its major components, agricultural and non-agricultural per capita value-added growth. Applying a VARX methodology on a panel of 87 countries and 48 years (1960-2007), we find heterogeneous effects on a variety of dimensions. First, the effects of natural disasters are stronger, for better or worse, on developing than on rich countries. Second, while the impact of some natural disasters can be beneficial when they are of moderate intensity, severe disasters do never have positive effects. Third, not all natural disasters are alike in terms of the growth response they induce, and, perhaps surprisingly, some can entail benefits regarding economic growth. Even within commonly used categories of natural disasters (e.g., climatic), different types of disasters can and do have different effects (e.g., droughts vs. floods).

Let’s focus the conclusion on the results for developing countries. Droughts have an overall negative effect on GDP growth. As expected, the effect is stronger for agricultural growth, but it is also negative for non-agricultural activities. For agricultural growth, the negative effect of droughts is immediate, while for non-agricultural growth, the negative impact is felt also with some delay. The cumulative negative response to droughts is 1.7 percentage points (pp) for GDP growth and 1.6 pp for agricultural growth.

In contrast to droughts, floods tend to have a positive effect on economic growth. The response of agricultural growth is significantly positive one year after but not on the same year of the event. The positive response of non-agricultural growth appears even later, which suggests the importance of transmission mechanisms based on supply chain relationships across sectors. The cumulative positive effect of floods on GDP growth is 0.5 pp and on agricultural growth, 0.6 pp.

Earthquakes do not seem to have a significant effect on GDP growth. However, there are some noteworthy results regarding sectoral growth. Earthquakes appear to have a negative impact on agricultural growth, rendering a negative cumulative effect of about 1.4 pp. In contrast, earthquakes elicit a positive mean response of non-agricultural growth one year after the event of 0.7 pp. This positive effect is consistent with the reconstruction activity that follows an earthquake in residential housing, public infrastructure, and production plants.

Storms tend to have a negative effect on GDP growth and non-agricultural growth the same year of the event. The effect is short-lived and small, however. In fact, the negative impact of storms amounts to 0.3 pp of GDP growth and 0.4 pp of non-agricultural growth. In the following years, particularly for non-agricultural growth, there is a growth rebound representing most likely reconstruction efforts.

In our opinion, future research should concentrate in exploring and clarifying the mechanisms through which the heterogeneous impacts of natural disasters on economic growth are produced. This paper has contributed to describing this heterogeneity, but much remains to be done in explaining it. For this purpose, both panel and individual country analysis should prove to be useful.

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Table II.1
List of countries

Country name	
All countries	87
Developing countries	62
Rich countries	25

*	Algeria		France	*	Pakistan
*	Argentina		Gabon	*	Panama
	Australia		Germany	*	Papua New Guinea
	Austria		Ghana	*	Paraguay
*	Bangladesh		Greece	*	Peru
*	Barbados		Guatemala	*	Philippines
	Belgium		Guinea-Bissau		Portugal
*	Belize		Guyana	*	Rwanda
*	Benin		Honduras		Saudi Arabia
*	Bolivia		Hungary	*	Senegal
*	Botswana		Iceland	*	Seychelles
*	Brazil	*	India	*	South Africa
*	Brunei Darussalam	*	Indonesia		Spain
*	Burkina Faso		Italy	*	Sri Lanka
*	Cameroon		Japan	*	St. Vincent and the Grenadines
	Canada	*	Jordan	*	Swaziland
*	Central African Republic	*	Kenya		Sweden
*	Chad	*	Korea, Rep.		Switzerland
*	Channel Islands	*	Lesotho	*	Syrian Arab Republic
*	Colombia		Luxembourg	*	Thailand
*	Congo, Dem. Rep.	*	Madagascar	*	Togo
*	Costa Rica	*	Malawi	*	Trinidad and Tobago
*	Cote d'Ivoire	*	Malaysia	*	Tunisia
	Denmark	*	Mexico		United Arab Emirates
*	Dominican Republic	*	Morocco		United Kingdom
*	Ecuador		Netherlands		United States
*	Egypt, Arab Rep.		New Zealand	*	Uruguay
*	El Salvador		Norway	*	Venezuela, RB
	Finland	*	Oman	*	Zambia

** indicates developing countries*

Table II.2
Descriptive Statistics

Sample: Developing countries

	Obs	Mean	Std. Dev.	Min	Max
Growth	2843	0.0167517	0.0546948	-0.4422607	0.4798489
Agr. Growth	2348	0.0031466	0.0826112	-0.4797475	0.4935743
Non-agr. Growth	2305	0.017093	0.0558703	-0.4585984	0.3568618

Sample: Rich countries

	Obs	Mean	Std. Dev.	Min	Max
Growth	1136	0.0236359	0.0330033	-0.2331791	0.1951103
Agr. Growth	858	0.0093051	0.0718126	-0.2801243	0.4300981
Non-agr. Growth	843	0.0211919	0.0358027	-0.2625033	0.1856347

Table II.3
Piecewise correlation among variables

Sample: Developing countries

	Growth	Agr. growth	Non-agr. growth	Droughts	Floods	Earthquakes	Storms
Growth	1						
Agr. growth	0.3878	1					
Non-agr. growth	0.7969	0.1095	1				
Droughts	-0.0735	-0.1048	-0.0294	1			
Floods	0.0377	0.0172	0.0386	0.0994	1		
Earthquakes	0.0098	0.0202	0.0071	-0.0169	0.1175	1	
Storms	-0.0124	-0.0116	-0.0057	0.0353	0.1747	0.0682	1

Sample: Rich countries

	Growth	Agr. growth	Non-agr. growth	Droughts	Floods	Earthquakes	Storms
Growth	1						
Agr. growth	0.0737	1					
Non-agr. growth	0.9684	0.0173	1				
Droughts	-0.0011	-0.0392	0.005	1			
Floods	-0.015	0.0271	-0.0037	0.0306	1		
Earthquakes	0.044	-0.0098	0.0582	-0.01	-0.026	1	
Storms	-0.0247	-0.0517	-0.005	0.037	0.0451	0.0249	1

Table III.1
Unit Root Tests

With coutnry-specific intercept	Agr. value added per capita	Terms of trade
A. Tests for Series in levels		
I. Fraction of countries that reject UR in ADFtest	2/75	11/76
II. Fraction of countries that reject UR in PP test	17/75	16/76
III. P-values of Levin-Lin-Chu test	0.123	0.0419
IV. P-values of Im-Pesaran-Shin test	0.969	0.101
B. Tests for Series in Differences		
I. Fraction of countries that reject UR in ADF test	46/75	63/76
II. Fraction of countries that reject UR in PP test	75/75	76/76
III. P-values of Levin-Lin-Chu test	0	0

With coutnry-specific intercept and country-specific trend	GDP per capita	Non-agr. value added per capita
A. Tests for Series in levels		
I. Fraction of countries that reject UR in ADF test	5/87	3/73
II. Fraction of countries that reject UR in PP test	5/87	4/73
III. P-values of Levin-Lin-Chu test	0.123	0.621
IV. P-values of Im-Pesaran-Shin test	1	1
B. Tests for Series in Differences		
I. Fraction of countries that reject UR in ADF test	59/87	49/73
II. Fraction of countries that reject UR in PP test	87/87	72/73
III. P-values of Levin-Lin-Chu test	0	0
IV. P-values of Im-Pesaran-Shin test	0	0

(i) The significance level is at 10 percent.
(ii) For all unit root tests, both individual and panel, the default settings of EViews 6.0 were used.

Table III.2
Block Exogeneity Tests for the Disaster Variables

		Significance level		
Sample		Lag 1	Lag 2	Lag 3
All countries	GDP growth	0.5112839	0.67821097	0.5277162
	Agr. growth	0.3291263	0.77459891	0.8643032
	Non-agr. growth	0.5947947	0.41047053	0.415458
Developing countries	GDP growth	0.6395072	0.82498702	0.7428414
	Agr. growth	0.3762702	0.84914854	0.9066644
	Non-agr. growth	0.6364801	0.53872097	0.5864839
Rich countries	GDP growth	0.1871027	0.29234087	0.1342733
	Agr. growth	0.056833*	0.11869545	0.0635466*
	Non-agr. growth	0.2488736	0.63553462	0.5321749

** denotes statistical significance at 10 percent level.*

Table III.3

Information Criteria Values

Sample			Number of lags		
			p = q = 1	p = q = 2	p = q = 3
All countries	GDP growth	AIC	-15.5853	**-15.5933**	-15.5777
		SBC	**-15.516**	-15.4855	-15.4314
	Agr. growth	AIC	-13.3562	**-13.3932**	-13.3752
		SBC	**-13.2769**	-13.2698	-13.2078
	Non-agr. growth	AIC	**-15.4666**	-15.4645	-15.4527
		SBC	**-15.3864**	-15.3396	-15.2832
Developing countries	GDP growth	AIC	**-14.5324**	-14.5318	-14.5089
		SBC	**-14.442**	-14.3911	-14.3179
	Agr. growth	AIC	-12.6936	**-12.72**	-12.6939
		SBC	**-12.591**	-12.5605	-12.4774
	Non-agr. growth	AIC	**-14.4328**	-14.4216	-14.4004
		SBC	**-14.3292**	-14.2603	-14.1815
Rich countries	GDP growth	AIC	-22.0632	**-22.1027**	-22.061
		SBC	**-21.865**	-21.7944	-21.6426
	Agr. growth	AIC	-17.6826	**-17.777**	-17.699
		SBC	**-17.4524**	-17.4189	-17.213
	Non-agr. growth	AIC	-22.1215	**-22.1395**	-22.0814
		SBC	**-21.8882**	-21.7766	-21.5889

Bold figures indicate the minimum AIC / SBC.

Table IV.1
Mean responses of the growth rates of each sector to natural disaster shocks
Sample: All countries

		Mean responses of					
		GDP growth		Agr. growth		Non-agr. growth	
AIC		-15.6239		-13.4292		-15.501	
SBC		-15.5623		-13.3587		-15.4297	
Droughts	Year 0	-0.013223	**	-0.031715	**	-0.004852	*
	Year 1	0.0023064		0.020766	**	-0.0001746	
	Year 2	-0.0044188	*	-0.0021294		-0.0053657	*
	Year 3	0.00028832		-0.0017919		-0.00056442	
	Cumulative effect	-0.015047	**	-0.014870	**	-0.010957	*
Earthquakes	Year 0	0.0017396		0.000020262		0.0019237	
	Year 1	0.002263		-0.0096375		0.0048984	
	Year 2	-0.0022208		-0.0047104		-0.0038522	
	Year 3	-0.0005828		0.0024555		-0.0012232	
	Cumulative effect	0.001199		-0.011872	*	0.0017467	
Floods	Year 0	0.0014053		0.001213		0.0006851	
	Year 1	-0.000036711		0.0050796	*	-0.0008682	
	Year 2	0.0026809	*	0.0013598		0.0025976	*
	Year 3	0.0006529	**	-0.0008888		0.0009695	**
	Cumulative effect	0.0047024	*	0.0067636	**	0.003384	
Storms	Year 0	-0.0031159	*	-0.0009415		-0.0037988	*
	Year 1	-0.0010362		-0.0030481		0.0011004	
	Year 2	0.00062423		0.0026836		-0.0002100	
	Year 3	0.000022213		-0.0005090		-0.0000592	
	Cumulative effect	-0.0035057		-0.001815		-0.0029677	

** (**) denotes statistical significance at one-tail 10 (5) percent level*

Table IV.2

Mean responses of the growth rates of each sector to natural disaster shocks

Sample: Developing countries

		Mean responses of					
		GDP growth		Agr. growth		Non-agr. growth	
AIC		-14.5741		-12.7693		-14.4715	
SBC		-14.4937		-12.6781		-14.3794	
Droughts	Year 0	-0.014091	**	-0.031021	**	-0.0052742	*
	Year 1	0.0022092		0.021654	**	-0.00025094	
	Year 2	-0.0050741	*	-0.0056886		-0.005939	*
	Year 3	0.00033704		-0.00059208		-0.00062653	
	Cumulative effect	-0.016619	**	-0.015648	**	-0.012091	*
Earthquakes	Year 0	0.0020709		- 0.001304800		0.0022349	
	Year 1	0.0032152		-0.0093886		0.0070503	
	Year 2	-0.0034535		-0.005758		-0.0049593	
	Year 3	-0.00084333		0.0026175		-0.0016999	
	Cumulative effect	0.00098927		-0.013834	*	0.002626	
Floods	Year 0	0.0014411		0.0011730		0.0005088	
	Year 1	-0.000070818		0.0049745	*	-0.0012603	
	Year 2	0.0029372	*	0.0004760		0.0030079	*
	Year 3	0.00067184	**	-0.0005522		0.0010942	**
	Cumulative effect	0.0049793	*	0.0060713	**	0.0033506	
Storms	Year 0	-0.0032138		-0.0002941		-0.0042957	*
	Year 1	-0.0008594		-0.0055736		0.0016841	
	Year 2	0.00083222		0.0053877		0.0000693	
	Year 3	-0.000072543		-0.0011998		-0.0001012	
	Cumulative effect	-0.0033135		-0.0016798		-0.0026434	

** (**) denotes statistical significance at one-tail 10 (5) percent level*

Table IV.3
Mean responses of the growth rates of each sector to natural disaster shocks
Sample: Rich countries

		Mean responses of				
		GDP growth	Agr. growth		Non-agr. growth	
AIC		-22.2151	-17.9134		-22.2782	
SBC		-22.0389	-17.7088		-22.0709	
Droughts	Year 0	0.007907	-0.060068	**	0.0018634	
	Year 1	-0.0063094	-0.020022		-0.0055474	
	Year 2	0.0093003	0.10835	**	0.0080284	
	Year 3	0.0047549	-0.0238	**	0.0041009	
	Cumulative effect	0.015653	0.00446		0.0084453	
Earthquakes	Year 0	0.00075515	0.0061523		0.0010407	
	Year 1	-0.0022573	-0.0075171		-0.0034712	
	Year 2	0.0021551	0.0006452		0.00021396	
	Year 3	0.0012077	0.0017494		0.00046867	
	Cumulative effect	0.0018607	0.0010298		-0.0017479	
Floods	Year 0	0.0021692	0.0044266		0.0030229	
	Year 1	-0.00021644	0.0049304		0.0019032	
	Year 2	0.00011382	0.011557		-0.0006401	
	Year 3	-0.000032614	-0.0037681	*	-0.0002934	
	Cumulative effect	0.0020340	0.017146	*	0.0039926	
Storms	Year 0	-0.0011873	-0.0067637		-0.0002764	
	Year 1	-0.0017083	0.010002		-0.0032889	
	Year 2	0.00014199	-0.015712	*	-0.0001117	
	Year 3	0.00052518	0.0026164		0.0005428	
	Cumulative effect	-0.0022284	-0.0098573		-0.0031342	

** (**) denotes statistical significance at one-tail 10 (5) percent level*

Table IV.4

Mean responses of the growth rates of each sector to moderate/severe natural disaster shocks

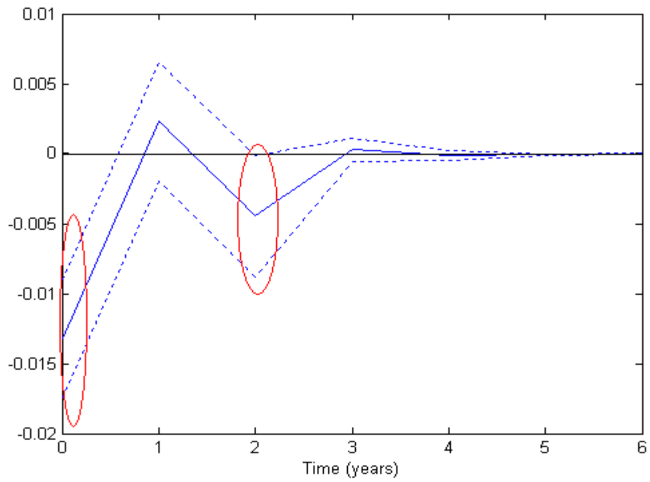
Sample: Developing countries

** (**) denotes statistical significance at one-tail 10 (5) percent level.*

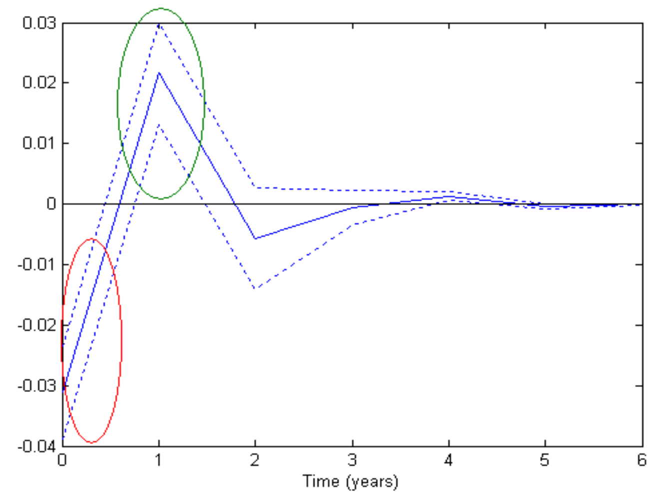
		Mean responses of					
		GDP growth		Agr. Growth		Non-agr. Growth	
		Moderate	Severe	Moderate	Severe	Moderate	Severe
AIC		-14.5476		-12.7444		-14.4379	
SBC		-14.4069		-12.5849		-14.2766	
Droughts	Year 0	-0.0085714 *	-0.018847 **	-0.011008	-0.046423 **	-0.0027887	-0.0078248 *
	Year 1	-0.0043316	0.006814 *	0.0014815	0.035768 **	-0.0044605	0.0028619
	Year 2	-0.006477	-0.0040597	-0.00044072	-0.0078779	-0.0040232	-0.0070282 *
	Year 3	-0.00040188	0.00092473	0.000025381	-0.0015406	-0.00066348	-0.0004734
	Cumulative effect	-0.019782 **	-0.015168 **	-0.0099418	-0.020074 **	-0.011936	-0.0124645
Floods	Year 0	0.0010823	0.0022661	0.0003944	0.007899	0.0005302	-0.00183
	Year 1	0.000602630	-0.0078984	0.0056914 *	0.0013757	-0.0010570	-0.0066199
	Year 2	0.0031417 *	-0.000058796	-0.00057858	0.0073623	0.0034817 *	-0.001819
	Year 3	0.000787 **	-0.00052586	-0.00028351	-0.0024108	0.0012580 **	-0.0004639
	Cumulative effect	0.0056136 *	-0.0062170	0.0052237 *	0.014226 *	0.0042129	-0.0107328
Earthquakes	Year 0	0.0013108	0.005904	0.0012498	-0.0080319	0.0010324	0.0051802
	Year 1	0.003685	0.0011218	-0.0083234	-0.025484	0.008449 *	0.0010412
	Year 2	-0.0048286	0.0043999	-0.0027261	-0.028254	-0.006611	0.0080918
	Year 3	-0.00093429	-0.00066329	0.0014124	0.012082 *	-0.0020765	0.00082313
	Cumulative effect	-0.00076709	0.010762	-0.0083873	-0.049688 **	0.0007939	0.015136
Storms	Year 0	-0.002562	-0.0061287	-0.00039477	0.0000557	-0.0037605	-0.0018873
	Year 1	-0.00030924	-0.0072597	-0.0062362 *	-0.0025188	0.0024532	-0.0054874
	Year 2	0.0021152	-0.014758 *	0.0065535 *	-0.010492	0.0018227	-0.018303 **
	Year 3	0.00010718	-0.0019053	-0.00152	0.0040787	0.0003248	-0.0043348 *
	Cumulative effect	-0.00064886	-0.030052 *	-0.0015975	-0.0088764	0.00084024	-0.0300125 *

Figure IV.1: Response to Drought Shock

Mean response of GDP growth



Mean response of agricultural growth



Mean response of non-agricultural growth

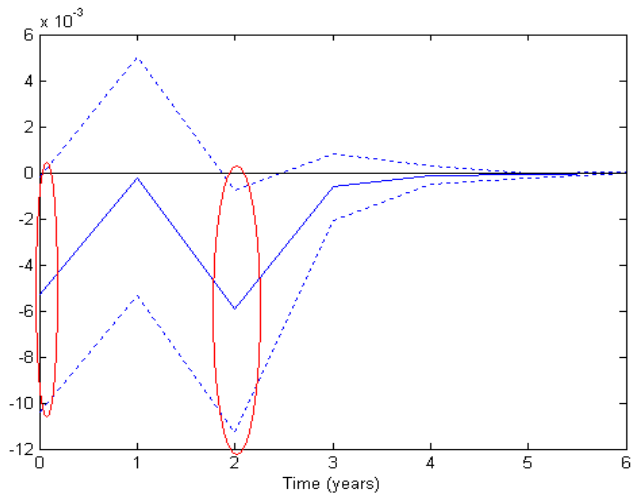
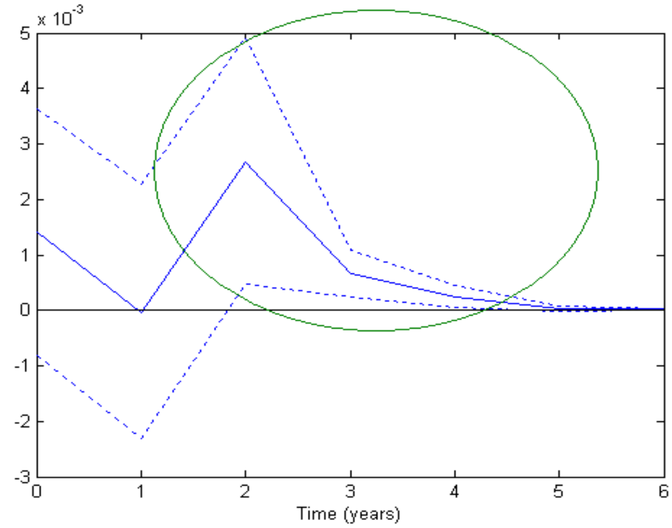
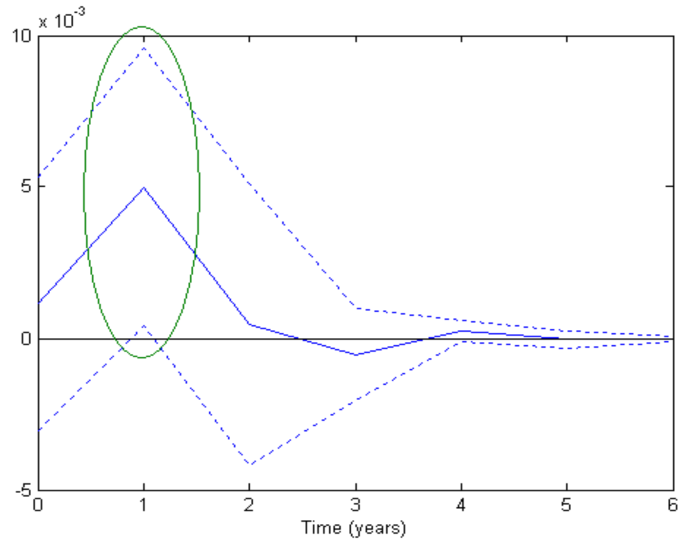


Figure IV.2: Response to Flood Shock

Mean response of GDP growth



Mean response of agricultural growth



Mean response of non-agricultural growth

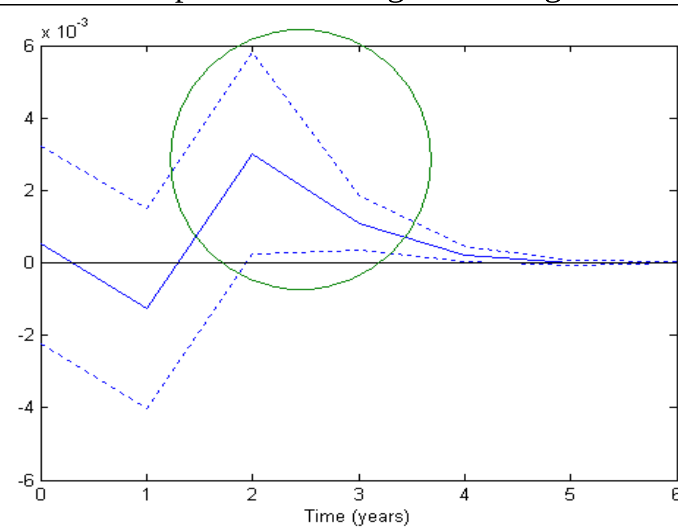
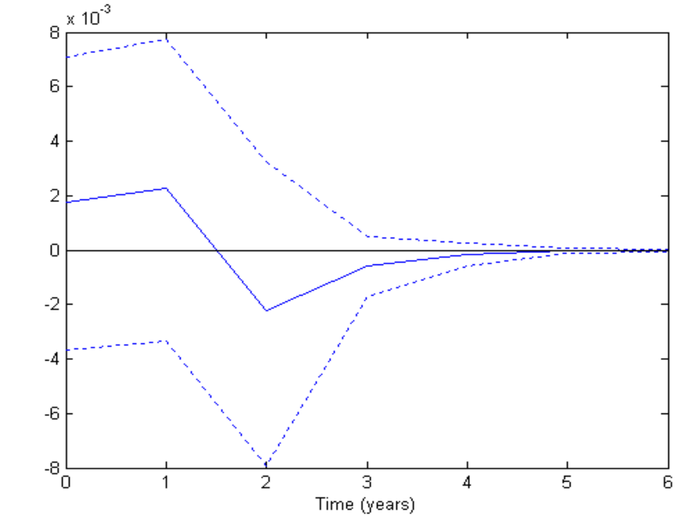
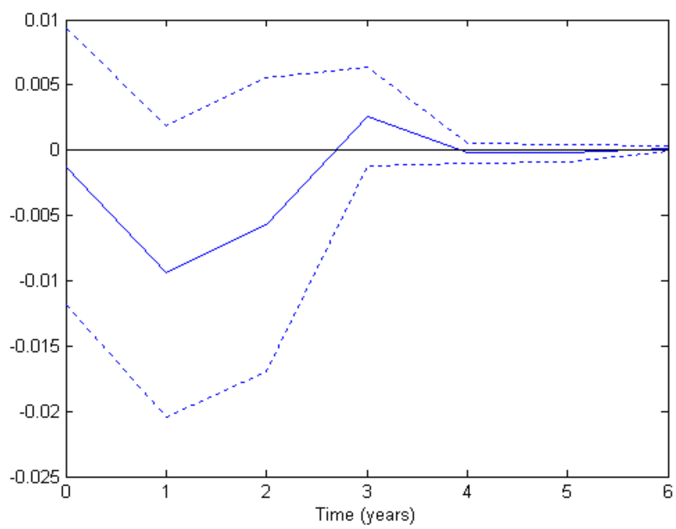


Figure IV.3: Response to Earthquake Shock

Mean response of GDP growth



Mean response of agricultural growth



Mean response of non-agricultural growth

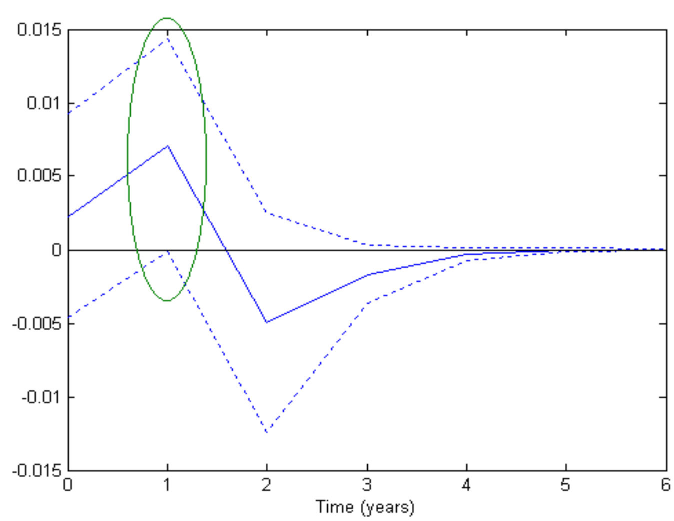
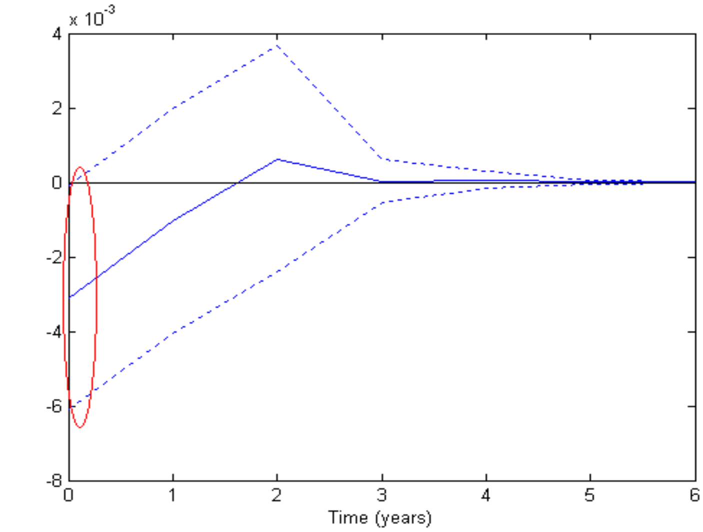
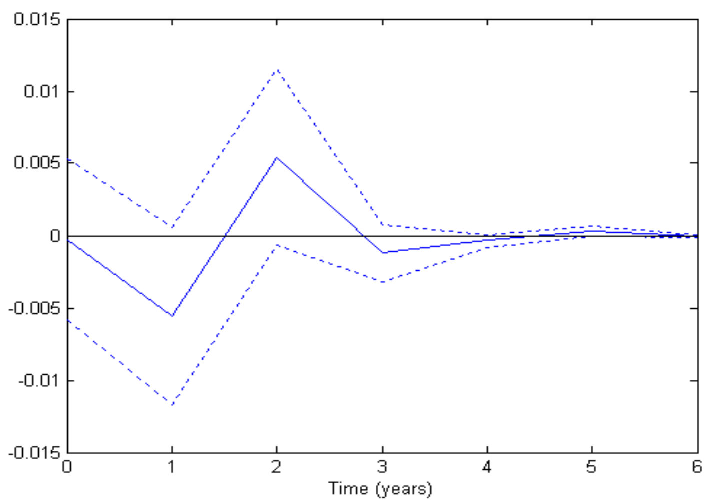


Figure IV.4: Response to Storm Shock

Mean response of GDP growth



Mean response of agricultural growth



Mean response of non-agricultural growth

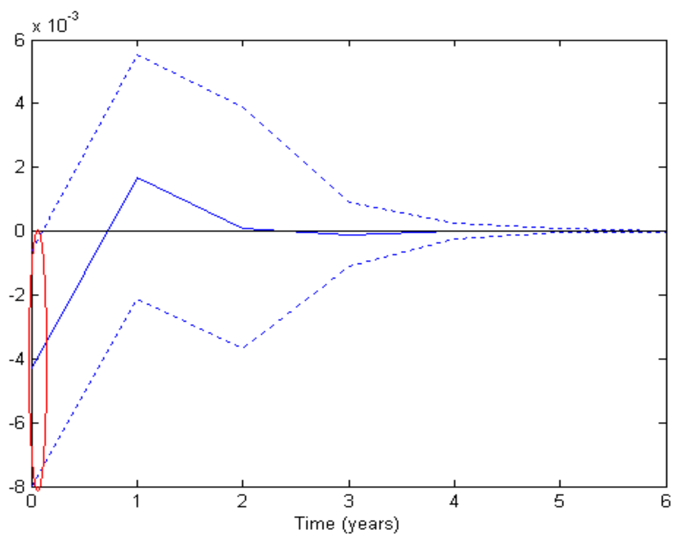


Table A.1
Mean responses of the growth rates of each sector to natural disaster shocks (with $p = q = 1$)
Sample: Developing countries

		Mean responses of					
		GDP growth		Agr. growth		Non-agr. Growth	
AIC		-14.5606		-12.7264		-14.4661	
SBC		-14.5103		-12.6694		-14.4085	
Droughts	Year 0	-0.013799	**	-0.031014	**	-0.0053130	*
	Year 1	0.0013177		0.022584	**	-0.0010444	
	Year 2	-0.0000049136		-0.006832	**	-0.00047764	
	Year 3	0.0000089841		0.0019891	**	-0.000090109	
	Cumulative effect	-0.012477	**	-0.013273	**	-0.0069251	
Floods	Year 0	0.00156690		0.00133190		0.00074075	
	Year 1	0.00018370		0.00501190	*	-0.00094847	
	Year 2	0.0001215		-0.0013814	*	-0.000070547	
	Year 3	0.0000047314		0.00039035		-0.000028721	
	Cumulative effect	0.0018768		0.0053528	**	-0.0003070	
Earthquakes	Year 0	0.001798		-0.00020651		0.0024988	
	Year 1	0.0027774		-0.0086748		0.0073422	*
	Year 2	-0.00027501		0.0021892		0.0011007	
	Year 3	0.0000114		-0.00059905		0.00030342	
	Cumulative effect	0.0043118		-0.0072912		0.011245	
Storms	Year 0	-0.0028280		0.00041656		-0.0040363	*
	Year 1	-0.00071057		-0.0058776		0.0015851	
	Year 2	-0.00035935		0.0015246		0.000018088	
	Year 3	-0.000015152		-0.00042154		0.000033405	
	Cumulative effect	-0.0039131		-0.0043580		-0.0023997	

** (**) denotes statistical significance at one-tail 10 (5) percent level.*

Table A.2

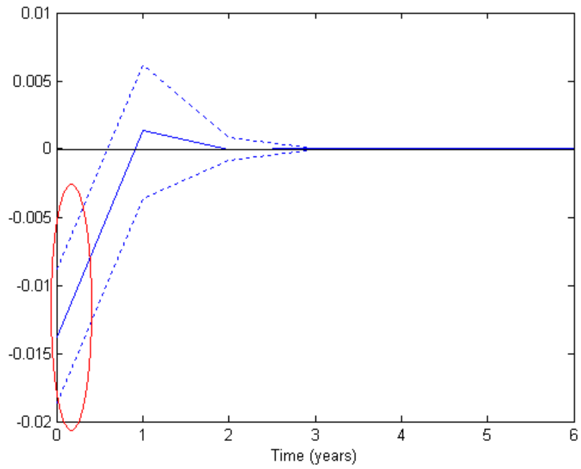
Mean responses of the growth rates of each sector to moderate/severe natural disaster shocks (with $p = q = 1$)

Sample: Developing countries ** (**) denotes statistical significance at one-tail 10 (5) percent level.*

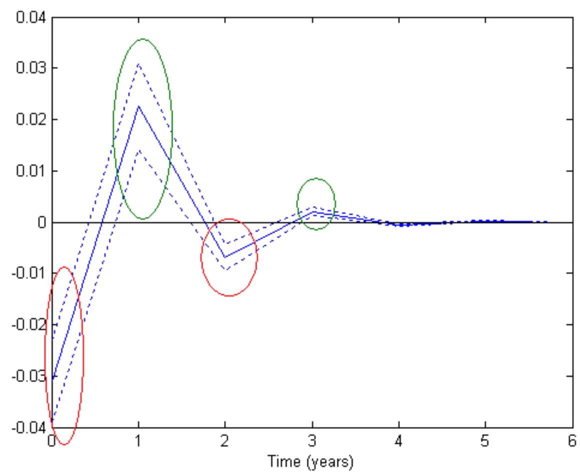
		Mean responses of					
		GDP growth		Agr. growth		Non-agr. Growth	
		Moderate	Severe	Moderate	Severe	Moderate	Severe
AIC		-14.5435		-12.7126		-14.4412	
SBC		-14.453		-12.61		-14.3375	
Droughts	Year 0	-0.0079178 *	-0.018701 **	-0.011129	-0.046391 **	-0.0026107	-0.0077559 *
	Year 1	-0.0053518	0.0062294 *	0.0027189	0.037006 **	-0.0052728	0.0021805
	Year 2	-0.00087276	0.00055808	-0.0010556	-0.01101 **	-0.0015441	0.00021606
	Year 3	-0.00006324	0.000060463	0.00032598	0.0031707 **	-0.00032876	0.000074007
	Cumulative effect	-0.014206 *	-0.011853 *	-0.0091397	-0.017224 **	-0.0097564	-0.0052853
Floods	Year 0	0.0011946	0.0027187	0.00051129	0.0082707	0.00074202	-0.0013555
	Year 1	0.0010416	-0.006966	0.0061001 **	-0.00087786	-0.00043716	-0.0052264
	Year 2	0.00014743	0.000099217	-0.0017522 *	0.0010216	-0.000046472	-0.000079873
	Year 3	0.000011664	-0.000046840	0.00049898 *	-0.00036199	-0.0000153	-0.00011316
	Cumulative effect	0.0023953	-0.0041949	0.0053582 *	0.0080525	0.00024309	-0.0067749
Earthquakes	Year 0	0.0016463	0.0037947	0.0022036	-0.010158	0.0022439	0.0035697
	Year 1	0.0029503	0.00079829	-0.0077088	-0.021632	0.0084635 *	0.00076896
	Year 2	-0.00020976	-0.00066901	0.0018478	0.0061573	0.001313	-0.000080931
	Year 3	0.000015021	-0.000013519	-0.00049239	-0.0017483	0.00035681	0.000003059
	Cumulative effect	0.0044019	0.0039105	-0.0041498	-0.027381	0.012377	0.0042608
Storms	Year 0	-0.0028685	-0.0053638	-0.00022475	-0.00014246	-0.0043831 *	-0.0013487
	Year 1	-0.00026787	-0.0053952	-0.0062769 *	-0.00062212	0.0019576	-0.0040608
	Year 2	-0.00044568	0.00029306	0.0015361	0.00078555	-0.00002783	-0.00010281
	Year 3	-0.00001471	-0.000030068	-0.00041283	-0.00027976	0.000033918	-0.000093899
	Cumulative effect	-0.0035968	-0.010496	-0.0053784	-0.00025879	-0.0024194	-0.0056062

Figure A.1: Response to Drought Shock (with $p = q = 1$)

Mean response of GDP growth



Mean response of Agricultural growth



Mean response of Non-agricultural growth

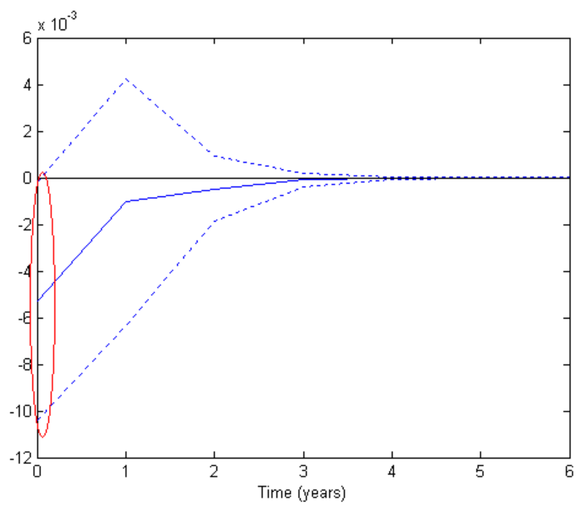
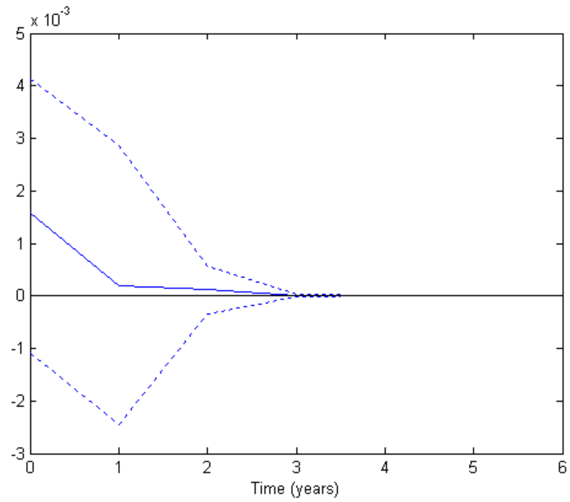
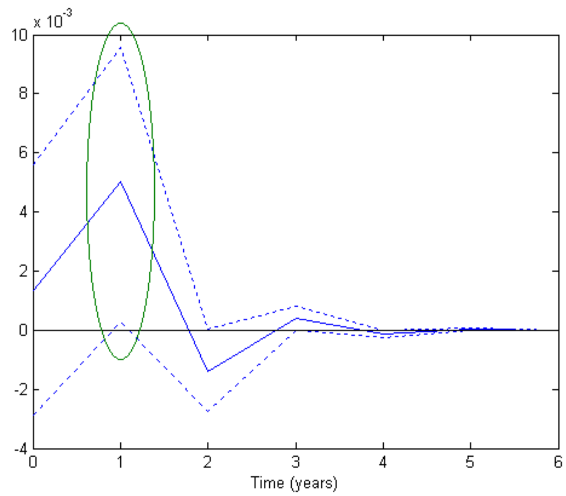


Figure A.2: Response to Flood Shock (with $p = q = 1$)

Mean response of GDP growth



Mean response of Agricultural growth



Mean response of Non-agricultural growth

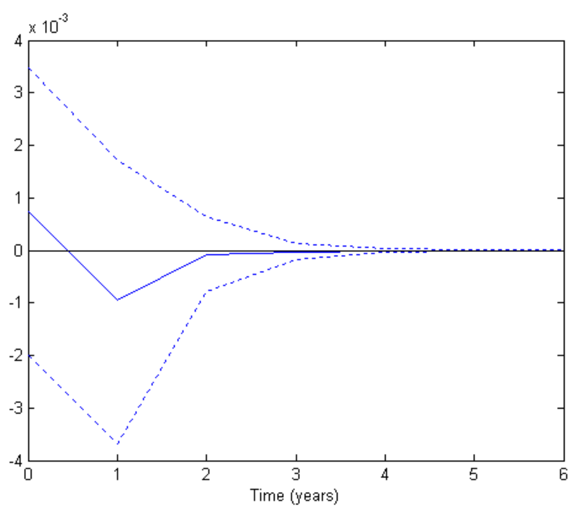
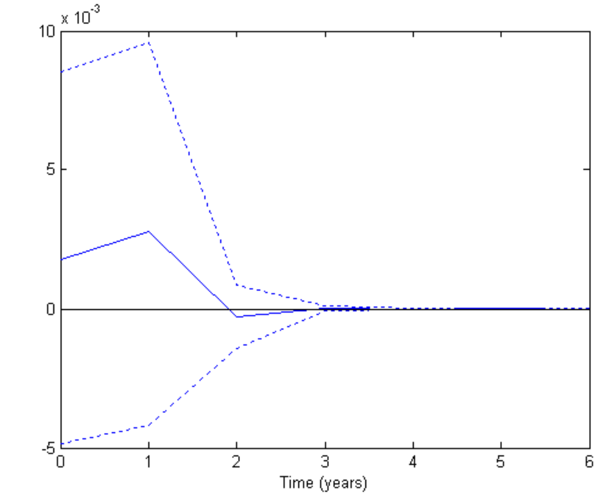
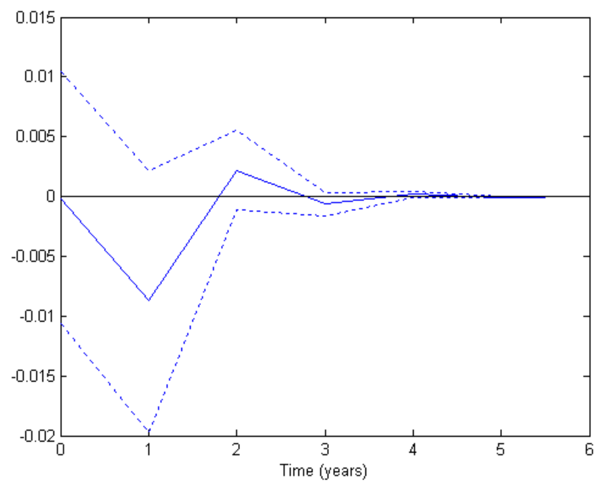


Figure A.3: Response to Earthquake Shock (with $p = q = 1$)

Mean response of GDP growth



Mean response of Agricultural growth



Mean response of Non-agricultural growth

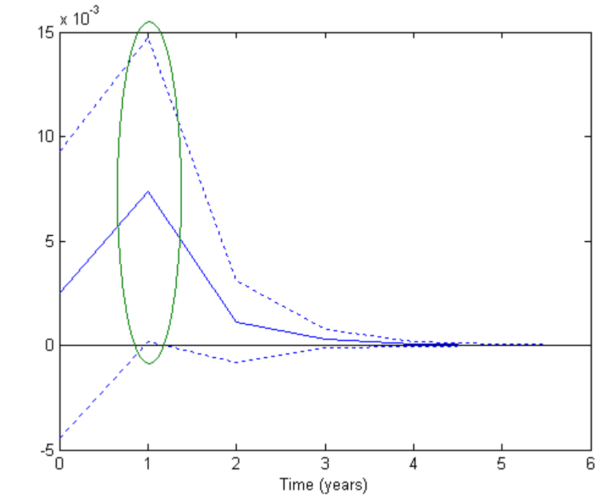
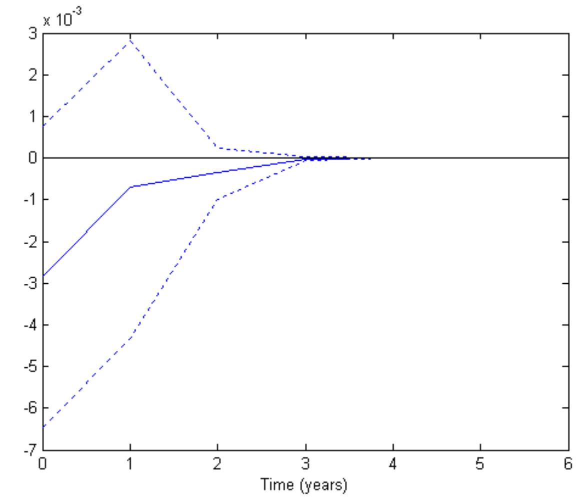
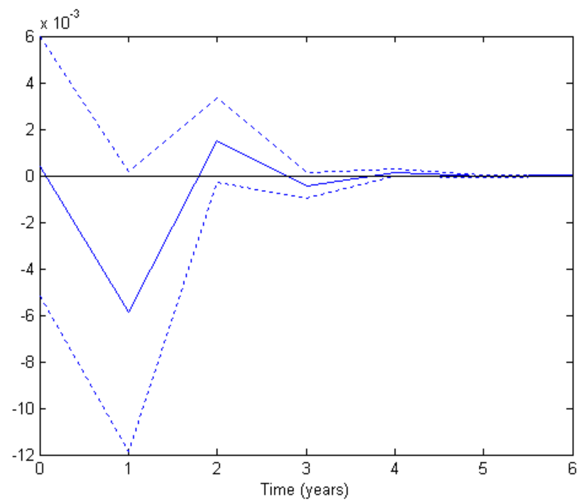


Figure A.4: Response to Storm Shock (with $p = q = 1$)

Mean response of GDP growth



Mean response of Agricultural growth



Mean response of Non-agricultural growth