# Essays on Dynamic Macroeconomics

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**Essays on Dynamic Macroeconomics**

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Abstract

The significant increase in income inequality in the United States over the last 30 years is an issue of great interest. Chapter 2 is intended to analyze the welfare effects of the rise in cross-sectional wage inequality. Under the standard Mirrleesian framework in which risk sharing is limited by the presence of private information, we first consider a simple static model that allows us to analytically investigate the welfare implication of the change in wage dispersion. Our analysis reveals that the impact of the change crucially depends on the initial degree of the dispersion. We then develop a dynamic Mirrlees model and verify whether the results obtained with the simple model can be generalized to the model with relaxed assumptions. Finally we evaluate the welfare implication of the recent increase in wage inequality using the most preferred model within our framework and find that the welfare effects associated with the change can be positive. Chapter 3 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 response of gross domestic product (GDP) growth—both aggregated and disaggregated into its agricultural and non-agricultural components—to four types of natural disasters: droughts, floods, earthquakes, and storms. We use a methodological approach based on pooling the experiences of various countries over time. It consists of vector autoregressions 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 on developing than on advanced countries. Second, not all natural disasters are alike in terms of the growth response they induce, and some can even have positive effects on economic growth. Third, the timing of the growth response varies with both the type of natural disaster and the sector of economic activity.

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[3]This chapter is forthcoming in Journal of Applied Econometrics.

# Dedication

This dissertation is dedicated to my family and friends,
for their love and support throughout my life.

## Acknowledgments

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# Chapter 1

## Introduction

This dissertation consists of two essays on dynamic macroeconomics; the first essay is on the welfare implications of the rise in wage inequality in the United States over the last three decades, and the second essay is on the dynamic growth effects of natural disasters which occurred during the last half a century. While the first essay mostly considers the distribution of wealfare among heterogeneous agents, the second essay focuses on the aggregate and sectoral economic growth.

On the topic of wage inequality, Chapter 2 characterizes the welfare implication of the rise in wage inequality using the model which connects changes in wage dispersion to those in the dispersion of consumption and hours worked. In this essay we develop a class of heterogeneous-agent economies with private information. Specifically, we consider an environment in which each worker has private information on his labor productivity shocks and chooses labor supply based on the information. With this framework we study the welfare effects of a change in wage dispersion through associated changes in the informationally-constrained efficient allocation of consumption and hours worked.

Chapter 2 is intended to address the following two questions: what are the welfare effects of a change in wage dispersion given the presence of private information, and what are the welfare costs of the informational friction at each level of wage dispersion? For the first question we set the optimal consumption and labor supply under no wage dispersion as the base and compute the costs and benefits of an increase in wage dispersion in units of the equivalent compensating variation in the base consumption, as Lucas (1987) measures the welfare cost of the business cycle. With regard to the second question, we compare the benchmark economy with two extreme cases: an economy with full ex-ante insurance and autarky, and discuss how the welfare level under the benchmark economy is different from that under different market structures and how the differences change as the wage variance increases.

In the first part of the essay we present a simple static Mirrleesian model that allows us to analytically characterize the constrained efficient allocation and the utilitarian social welfare at optimum. With quasi-linear preferences and two types of shocks, we can obtain a closed form expression for the social welfare and study the properties of the welfare function with respect to the degree of wage dispersion. In the following section we develop a dynamic Mirrleesian framework with more relaxed assumptions, such as non-quasi-linear preferences and more than two types of shocks.

For the first welfare question, the static model finds that the impact of a change in wage inequality crucially depends on the initial degree of dispersion. With both quasi-linear preferences and standard CRRA preferences, the social welfare function is U-shaped; a rise in inequality has a negative impact on the welfare if the initial wage dispersion is relatively low, while it has a positive impact if wages are highly dispersed before the change. With the same preferences, this property is preserved in the dynamic model with three periods, which is our benchmark model. In the model with longer periods, however, the property no longer holds; the welfare function is monotonically increasing in the degree of wage dispersion. This result suggests that the social planner is able to provide more insurance as the number of periods in the model increases.

As to the second welfare question, both the static and dynamic models show that the value and slope of the welfare function with respect to the variance of wage rates are close to those under autarky when the variance is small, and gradually approach to those of full insurance as the variance increases. For quasi-linear preferences with CRRA function over consumption, the slope of the welfare function under the benchmark economy is equal to zero, the same as that of autarky, when there is no wage inequality, while the slope under full insurance is positive at the same point.

On the topic of natural disasters, Chapter 3, which is a joint work with Thomas Fomby and Norman Loayza, 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, Jaramillo (2007) and Loayza et al. (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 essay 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.

Second, the essay 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 of the present study 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 84 countries representing all major regions of the world and 48 years covering the period 1960-2007.

A methodological contribution of Chapter 3 is the application of a re-sampling estimator to control for unobserved fixed effects in the context of a dynamic panel data model. As pointed out by Nickell (1981), the within or least-squares dummy variable (LSDV) estimator is inconsistent in dynamic panels when the time series dimension is small, even if the number of cross-sectional units (countries, in our case) goes to infinity. In order to obtain a bias correction of the LSDV estimator, we use a bootstrap algorithm, originally proposed by Pesaran and Zhao (1999) and Everaert and Pozzi (2007). In order to apply their bootstrap correction to the VARX model with unbalanced panel, we implement some necessary modifications.

Third, this study 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 randomly heterogeneous either. Especially, Rasmussen (2004), Toya and Skidmore (2007), and Noy (2009) document that 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 separately for developing countries (60) and advanced countries (24).

# Chapter 2

# The Welfare Effects of the Rise in Wage Dispersion with Private Information

## 2.1 Introduction

The dramatic increase in wage inequality in the United States over the last 30 years is an issue of great interest.[1] Over the same period, however, the cross-sectional variation in consumption has increased only moderately and the dispersion in hours worked showed no significant change.[2] The objective of this paper is to characterize the welfare implication of the rise in wage inequality using the model which connects changes in wage dispersion to those in the dispersion of consumption and hours worked.

In this paper we develop a class of heterogeneous-agent economies with private information. Specifically, we consider an environment in which each worker has private information on his labor productivity shocks and chooses labor supply based on the information. With this framework we study the welfare effects of a change in wage dispersion through associated changes in the informationally-constrained efficient allocation of consumption and hours worked.

This paper is intended to address the following two questions: what are the welfare effects of a change in wage dispersion given the presence of private information, and what are the welfare costs of the informational friction at each level of wage dispersion?

[1] See, e.g., Katz and Autor (1999) and Acemoglu (2002).

[2] See Cutler and Katz (1991) and Krueger and Perri (2006) for consumption inequality, and Heathcote et al. (2010) for dispersion in hours worked.

For the first question we set the optimal consumption and labor supply under no wage dispersion as the base and compute the costs and benefits of an increase in wage dispersion in units of the equivalent compensating variation in the base consumption, as Lucas (1987) measures the welfare cost of the business cycle. With regard to the second question, we compare the benchmark economy with two extreme cases: an economy with full ex-ante insurance and autarky, and discuss how the welfare level under the benchmark economy is different from that under different market structures and how the differences change as the wage variance increases.

In the first part of the paper we present a simple static Mirrleesian model that allows us to analytically characterize the constrained efficient allocation and the utilitarian social welfare at optimum. With quasi-linear preferences and two types of shocks, we can obtain a closed form expression for the social welfare and study the properties of the welfare function with respect to the degree of wage dispersion. In the following section we develop a dynamic Mirrleesian framework with more relaxed assumptions, such as non-quasi-linear preferences and more than two types of shocks.

Regarding the first welfare question, the static model finds that the impact of a change in wage inequality crucially depends on the initial degree of dispersion. With both quasi-linear preferences and standard CRRA preferences, the social welfare function is U-shaped; a rise in inequality has a negative impact on the welfare if the initial wage dispersion is relatively low, while it has a positive impact if wages are highly dispersed before the change. With the same preferences, this property is preserved in the dynamic model with three periods, which is our benchmark model. In the model with longer periods, however, the property no longer holds; the welfare function is monotonically increasing in the degree of wage dispersion. This result suggests that the social planner is able to provide more insurance as the number of periods in the model increases.

As to the second welfare question, the static model shows that the value and slope of the welfare function with respect to the variance of wage rates are close to those under autarky when the variance is small, and gradually approach to those of full insurance as the variance increases. For quasi-linear preferences with CRRA function over consumption, the slope of the welfare function under the benchmark economy is equal to zero, the same as that of autarky, when there is no wage inequality, while the slope under full insurance is positive at the same point.

For the further understanding of these results, it is instructive to draw attention to two offsetting forces which affect the change in social welfare: the level effect and the uncertainty effect.[3] The former captures an opportunity for the planner to increase the size of economic pie by allocating more labor to the most productive agents as the wage inequality grows. The latter describes the cost involved in the change in the sense that the more wage inequality, the greater risk people are exposed to. Assuming the utility function is concave in consumption and leisure, the uncertainty effect must be always negative and decreasing. We study the change in relative magnitude of these two effects as the wage dispersion increases.

We use the model in which risk sharing is limited by private information for two reasons. First, we need to use a model which is able to capture market incompleteness. Many empirical studies have shown that the assumption of complete markets is incompatible with the data (e.g., Cochrane 1991, Townsend 1994, Attanasio and Davis 1996). Following the failure of the complete consumption insurance hypothesis, the permanent income hypothesis approach has been extensively used to study the dynamics of consumption and income allocation under market incompleteness. In between these two frameworks, there is a class of models in which the degree of risk sharing is determined endogenously, subject to the presence of incentive con-

[3] See Flodén (2001), Bénabou (2002), and Heathcote et al. (2008) for further discussions.

straints that prevent full insurance, imposed by imperfect ability to enforce contracts or private information.

The main difference between the permanent income hypothesis approach and the incentive-constrained economy approach is that while the degree of risk sharing is determined exogenously in the former approach by specifying the financial market structure, in the latter approach it is endogenously derived by specifying the sources of friction. In the class of models used in the current study, the source of friction is the presence of private information and risk sharing responds to changes in the environment, such as a change in wage dispersion. On the other hand, we should note that it is not necessarily clear how constrained efficient allocations are implemented, while the decentralized equilibrium in the permanent hypothesis approach is presented directly.

Second, the optimal social welfare achieved in the current study can be interpreted as the upper limit of welfare which could be delivered by the government through nonlinear income taxation. The difficulty of providing insurance against labor income risks is commonly recognized, since they are largely affected by an individual's choice of unobserved efforts. Given the presence of the asymmetric information, the optimal expected lifetime utility delivered by the planner can be a measure of the level of social welfare the government can provide at most through refining its income taxation system.

The approach we adopt in the current study builds on the literature on the dynamics of the constrained efficient allocation where risk sharing is endogenously limited by private information. Some examples in the literature include, among others, Green (1987), Spear and Srivastava (1987), Thomas and Worrall (1990), Atkeson and Lucas (1992), Phelan (1994), and Albanesi and Sleet (2006). Since our interest is in characterizing the welfare effects of a change in wage dispersion, we focus on an environment where workers have private information about their productivities or wage rates, as in Mirrlees (1971) and Golosov, Kocherlakota, and Tsyvinski (2003).

The paper closest in spirit to ours is Heathcote et al. (2008). They provide an analytical characterization of the welfare effects from an increase in wage dispersion. The key difference between their paper and the current study is that we focus on a Mirrlees environment which generates endogenous market incompleteness, while they study a model in which markets are exogenously incomplete, which enables analytical characterization of equilibrium allocations. Two other works closely related to ours are Ales and Maziero (2008) and Huggett and Parra (2010). The first estimates a dynamic Mirrleesian economy numerically and shows that the U.S. household data can be rationalized as the outcome of their model. The second paper studies how well the stylized version of the U.S. social insurance system provides insurance by contrasting it with the level of insurance provided in the constrained planner's problem with private information.

The rest of the paper is organized as follows. Section 2.2 presents the simple static model, Section 2.3 lays out the dynamic version of the model and discuss the results. Section 2.4 concludes.

## 2.2 The Static Model

### 2.2.1 The Framework

There are $N$ individuals in the economy, indexed by $i = 1, ..., N$, according to their labor productivity. The economy has a constant-returns-to-scale technology and the labor market is perfectly competitive, so differences in the labor productivity are reflected in the fixed wage rates $w_i$. Types are ordered such that $0 < w_1 < ... < w_N$.

A type $i$ individual's before-tax income is

$$y_i = w_i h_i, \tag{2.1}$$

where $h_i$ denotes his labor supply or hours worked.

The government chooses a tax schedule without the ability to observe individual skill types $w_i$ or labor supply $h_i$, while it can observe before-tax income $y_i$ and knows the distribution of skills. The government is able to set any tax schedule using income as the tax base. Without loss of generality, we can assume that the price of the consumption good is equal to 1, so a type $i$ individual's consumption $c_i$ is his after-tax income. Suppose that individuals have preferences represented by a common utility function $U : \mathbb{R}_+ \times \mathbb{R}_+ \to \mathbb{R}$, which is defined in terms of consumption $c_i$ and labor supply $h_i$; both variables are constrained to be non-negative. We assume that $U$ is continuously differentiable and strictly concave on $\mathbb{R}^2_{++}$, strictly increasing in $c_i$, strictly decreasing in $h_i$, $U_c$ is nondecreasing in $w_i$, $\lim_{c \to 0} U_c = \infty$ , and $\lim_{c \to \infty} U_c = 0$. Substituting (2.1) into $U(c_i, h_i)$ yields a type-specific utility function $U^i : \mathbb{R}_+ \times \mathbb{R}_+ \to \mathbb{R}$, which is defined in terms of consumption $c_i$ and before-tax income $y_i$, as $U^i(c_i, y_i) = U\left(c_i, \frac{y_i}{w_i}\right)$.

An allocation is a vector $a = (c, y)$ where $c = (c_1, ..., c_N)$ is a consumption vector and $y = (y_1, ..., y_N)$ is an income vector. The government chooses an allocation to maximize the social welfare function

$$W = \frac{1}{N} \sum_{i=1}^{N} U^i(c_i, y_i). \tag{2.2}$$

A feasible allocation must satisfy the production constraint

$$\sum_{i=1}^{N} c_i \leq \sum_{i=1}^{N} y_i. \tag{2.3}$$

Also, any candidate for the optimal allocation must satisfy the incentive compatibility constraints

$$U^i(c_i, y_i) \geq U^i(c_j, y_j),\ \forall i, j. \tag{2.4}$$

Since people are privately informed about their skills and can always pretend to have skills other than what they actually have, the constraints (2.4) are necessary for an allocation to be achievable.

The optimal nonlinear income tax problem can be summarized as follows.

**Problem 1** *Choose an allocation $a = (c, y) \in \mathbb{R}^N_+ \times \mathbb{R}^N_+$ to maximize the social welfare function (2.2) subject to the allocation satisfying the feasibility constraint (2.3) and the incentive compatibility constraints (2.4).*

### 2.2.2 Existing Analysis

A number of studies explore the implications of the incentive compatibility constraints. Lemma 1 states that with the incentive compatibility constraints, consumption and income must be nondecreasing in the skill level, shown by Cooper (1984) and others.

**Lemma 2.2.1** *(Cooper (1984)) A necessary condition for an allocation $a = (c, y) \in \mathbb{R}^N_+ \times \mathbb{R}^N_+$ to satisfy the incentive compatibility constraints (2.4) is*

$$(c_1, y_1) \leq \cdots \leq (c_N, y_N)$$

*with*

$$(c_{i-1}, y_{i-1}) \ll (c_i, y_i) \text{ if } (c_{i-1}, y_{i-1}) \neq (c_i, y_i),\ i = 2, ..., N.$$

Guesnerie and Seade (1982) establish the following two results. The first lemma states that production efficiency is necessary for optimality.

**Lemma 2.2.2** *(Guesnerie and Seade (1982)) If* $a^* = (a_1^*, ..., a_N^*)$ *solves Problem 1, then* $a^*$ *satisfies the production constraint (2.3) with equality.*

**Lemma 2.2.3** *(Guesnerie and Seade (1982)) If the social weights* $\mu_i$ *are positive and nonincreasing in the wage rates, the incentive compatibility constraints form a simple monotonic chain to the left in the optimum. That is,* $U^i(c_i, y_i) = U^i(c_{i-1}, y_{i-1}),\ i = 2, ..., N.$

With a simple monotonic chain to the left, a type $i$ individual ($i \geq 2$) is indifferent between the bundle of his type and that of the next lower type. The assumption on $\mu_i$ implies that the social planner weakly prefers to redistribute from higher to lower wage individuals. Obviously, the utilitarian welfare function is an example of functions whose weights satisfy this assumption. In the rest of Section 2.1, we keep the assumption.

### 2.2.3 Analytical Solution

#### 2.2.3.1 Quasilinearlity Assumption

So far we have just assumed that the utility function $U^i$ satisfies standard properties of a utility function. In order to further investigate qualitative properties of the optimal allocation, however, we need to consider more restrictive forms of preferences. Assuming quasi-linear preferences enables us to obtain a closed-form solution for the optimal allocation. There are indeed a number of studies that apply this type of preferences. Lollivier and Rochet (1983) and Weymark (1987) derive several comparative static results for the case of preferences that are quasi-linear in leisure, the former for a continuous population and the latter for a finite population, respectively. In his seminal study on the shapes of the marginal tax rates, Diamond (1998) employs quasi-linear-in-consumption preferences. In this section, we shall confine our attention to quasi-linear-in-leisure preferences. Later we will examine the robustness of the results to alternative functional forms through numerical exercises.

Now we suppose that a type $i$ agent's preference is given by the utility function which is quasi-linear in leisure:

$$U^i(c_i, y_i) = u(c_i) - \psi \frac{y_i}{w_i}, \tag{2.5}$$

where $\psi > 0$, $v$ is continuously differentiable, strictly increasing, strictly concave, $\lim_{c \to 0} u_c = \infty$ , and $\lim_{c \to \infty} u_c = 0$.

As shown by Lemmas 2 and 3, a solution to Problem 1 must be production efficient and form a simple monotonic chain to the left. That is,

$$\sum_{i=1}^{N} c_i = \sum_{i=1}^{N} y_i, \tag{2.6}$$

and

$$u(c_i) - \psi \frac{y_i}{w_i} = u(c_{i-1}) - \psi \frac{y_{i-1}}{w_i},\ i = 2, ..., N. \tag{2.7}$$

These $N$ equations, (2.6) and (2.7), can be solved for the income levels as functions of the consumption levels, as $y^*(c) = (y_1^*(c), ..., y_N^*(c))$. With the results of Lemmas 1 to 3, the optimization problem can be simplified as follows.

**Problem 2** *Choose $c \in \mathbb{R}_+^N$ to maximize the social welfare function*

$$W = \frac{1}{N} \sum_{i=1}^{N} U^i(c_i, y_i^*(c)) \tag{2.8}$$

*subject to*

$$y_i^*(c) \geq 0, \forall i, \tag{2.9}$$

$$0 \leq c_1 \leq ... \leq c_N, \tag{2.10}$$

*where $y^*(c) = (y_1^*(c), ..., y_N^*(c))$ is the solution of the system of equations which consist of the production constraint (2.6) and the $N-1$ incentive compatibility constraints with equality (2.7), given the consumption levels $c$.*

#### 2.2.3.2 CRRA preferences

To investigate analytical characteristics of the optimal allocation, we concentrate on the case in which the utility function for consumption, $u(c)$, exhibits constant relative risk aversion (CRRA),

$$U^i(c_i, y_i) = \frac{c^{1-\gamma}}{1-\gamma} - \psi \frac{y_i}{w_i}, \ \gamma \geq 1, \tag{2.11}$$

with $N = 2$. For notational convenience, let $\sigma \equiv s.d.(w_i) = \sqrt{\sum_i \frac{(w_i - \overline{w})^2}{2}}$, where $\overline{w}$ is the mean value of $w_i$. Let $\sigma^*$ be the smallest $\sigma$ with which the non-negativity constraint on income binds. The derivation of $\sigma^*$ is presented in the Appendix. It is straightforward to verify that the non-negativity constraint never binds for $\sigma \in [0, \sigma^*)$ and always binds for $\sigma \in [\sigma^*, \infty)$. Consequently, the optimal social welfare function has different functional forms in the two regions. $W(\sigma)$ with $\gamma = 1$ (i.e., $u(c) = \log(c)$) is [4]

$$\begin{aligned} W(\sigma) &= W^I(\sigma) \equiv 2\log\left(\frac{\overline{w}+\sigma}{\psi}\right) + \left(\frac{\overline{w}-2\sigma}{\overline{w}-\sigma}\right)\log\left(\frac{\overline{w}-2\sigma}{\overline{w}}\right) - 2, \ \text{for } \sigma \in [0, \sigma^*), \\ &= W^{II}(\sigma) \equiv 2\left[\log\left(\frac{\overline{w}+\sigma}{\psi}\right) + \log\left(\text{Lambert}\left(\frac{1}{e}\right)\right)\right], \ \text{for } \sigma \in [\sigma^*, \infty), \end{aligned} \tag{2.12}$$

[4] The function Lambert(.) is the Lambert W function, that is the inverse function of $f(x) = xe^x$.

and with $\gamma > 1$,

$$\begin{aligned} W(\sigma) &= W^{I}(\sigma) \equiv \frac{\gamma}{1-\gamma}\frac{\overline{w}}{\overline{w}-\sigma}\left(\frac{\overline{w}+\sigma}{\psi}\right)^{\frac{1-\gamma}{\gamma}}\left(1+\left(\frac{\overline{w}-2\sigma}{\overline{w}}\right)^{\frac{1}{\gamma}}\right), \text{ for } \sigma \in [0, \sigma^*) \\ &= W^{II}(\sigma) \equiv \frac{2}{1-\gamma}\left(\frac{\overline{w}+\sigma}{\psi}\right)^{\frac{1-\gamma}{\gamma}}\left(\frac{\overline{w}-2\sigma^*}{\overline{w}}\right)^{\frac{1-\gamma}{\gamma}}, \text{ for } \sigma \in [\sigma^*, \infty). \end{aligned} \tag{2.13}$$

Note that $W(\sigma)$ is continuously differentiable on $\sigma^*$, since $W^I(\sigma^*) = W^{II}(\sigma^*)$ and $\frac{dW^I}{d\sigma}(\sigma^*) = \frac{dW^{II}}{d\sigma}(\sigma^*)$. The shape of the function with $\gamma = 1$ is plotted in Figure 2.1. Explicit expressions for the consumption vector $c$ and the income vector $y$ are given in the Appendix.

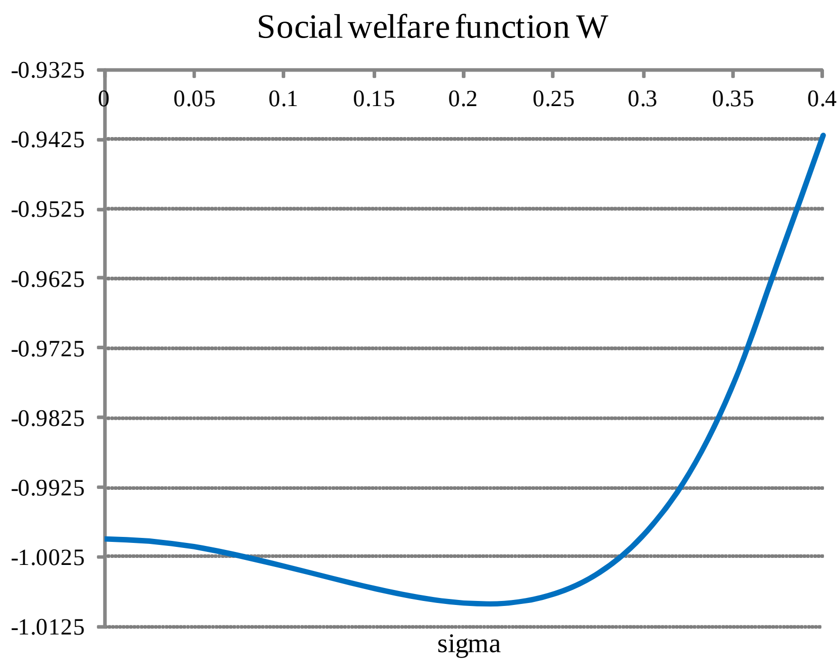



Figure 2.1: The social welfare function $W(\sigma)$ with $u(c) = \log(c)$, $N = 2$, $\underline{\sigma} \approx 0.212$ and $\sigma^* \approx 0.361$.

The social welfare function $W$ exhibits the following properties under certain conditions. The proof is presented in the Appendix.

**Proposition 2.2.4** *Suppose that there are two types of individuals, $N = 2$. If $u(c) = \frac{c^{1-\gamma}}{1-\gamma}$, with $\gamma \in [1, +\infty)$, there exists unique $\underline{\sigma} \in (0, \sigma^*)$ such that (i) the social welfare function $W(\sigma)$ is strictly decreasing for any $\sigma \in (0, \underline{\sigma})$, (ii) $\frac{dW}{d\sigma}(\underline{\sigma}) = 0$, and (iii) $W(\sigma)$ is strictly increasing for any $\sigma > \underline{\sigma}$.*

The proposition simply states that the social welfare function $W(\sigma)$ is a U-shaped curve and reaches the minimum value at the unique point $\underline{\sigma} \in (0, \sigma^*)$. We should notice that $W(\sigma)$ is strictly increasing even on the range $\sigma \in (\underline{\sigma}, \sigma^*)$; it makes clear that $W(\sigma)$ is increasing not only over the range on which the non-negativity constraint is active, i.e., $\sigma \geq \sigma^*$.

The welfare effect of the change in $\sigma$ is also expressed in units of the equivalent compensating variation in consumption with $\sigma = 0$. Let $\alpha(\sigma)$ be such that

$$\frac{1}{N} \sum_{i=1}^{N} \left[ v((1 + \alpha(\sigma)) \, c_i(0)) - \psi h_i(0) \right] = W(\sigma). \qquad (2.14)$$

As discussed in Bénabou (2002) and Flodén (2001), the welfare effect $\alpha(\sigma)$ is affected by two offsetting forces: the level effect $\alpha^{lev}(\sigma)$ and the uncertainty effect $\alpha^{unc}(\sigma)$. These effects are depicted in Figure 2.2.

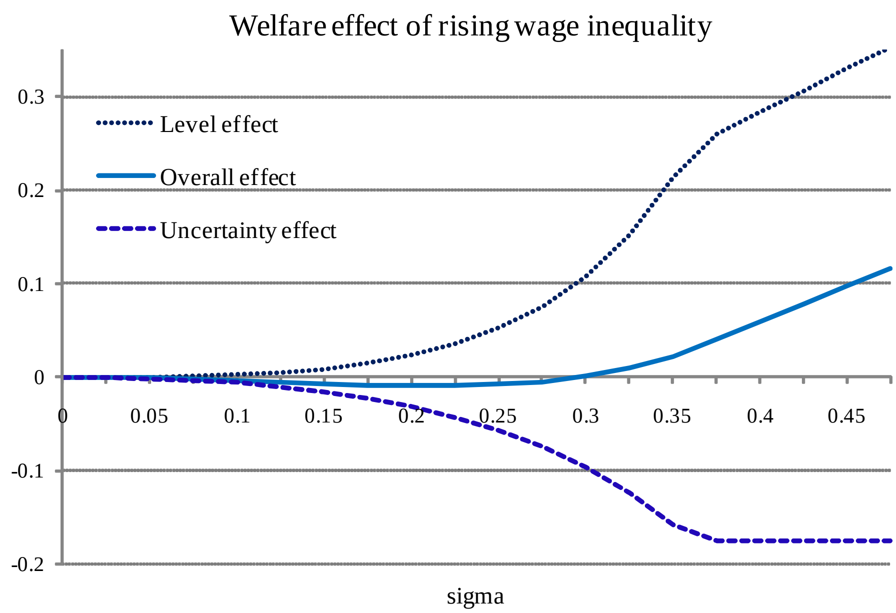



Figure 2.2: The welfare effect $\alpha(\sigma)$, the level effect $\alpha^{lev}(\sigma)$, and the uncertainty effect $\alpha^{unc}(\sigma)$, with $v(c) = \log(c)$, $N = 2$, $\underline{\sigma} \approx 0.212$ and $\sigma^{*} \approx 0.361$.

The level effect captures the welfare change associated with the size of the aggregate production and is defined as the value for $\alpha^{lev}(\sigma)$ that solves

$$U\left(\left(1 + \alpha^{lev}(\sigma)\right)\overline{c}(0), \overline{h}(0)\right) = U\left(\overline{c}(\sigma), \overline{h}(\sigma)\right), \tag{2.15}$$

where $\overline{c}$ and $\overline{h}$ denote the mean consumption level and the mean hours, respectively. Since the social planner can allocate longer hours to the high-skilled worker, provided the incentive compatibility constraints are satisfied, a mean-preserving increase in wage dispersion leads to higher level of aggregate production. In that regard, a rise in $\sigma$ has a positive impact on welfare.

The uncertainty effect represents the welfare change associated with the dispersion of welfare and is defined as the value for $\alpha^{unc}(\sigma)$ that solves

$$U\left((1+\alpha^{unc}(\sigma))\,\overline{c}(\sigma),\overline{h}(\sigma)\right)=W(\sigma). \tag{2.16}$$

The social planner chooses to transfer resources from the high-skilled worker to the low-skilled worker. To prevent the high-skilled worker from pretending to be low-skilled, the planner must award the high-skilled worker sufficiently high level of consumption, and it impedes risk sharing between the two types of agents. Since we assumed strict concavity of $v(c)$, a rise in $\sigma$ has a negative impact on welfare.

Flodén (2001) proves that if the utility function $U(c,h)$ is separable and satisfies $U(kc,h)=f(k)U(c,h)+g(k)$[5], then

$$(1+\alpha(\sigma))=\left(1+\alpha^{lev}(\sigma)\right)(1+\alpha^{unc}(\sigma))\,. \tag{2.17}$$

Within a class of quasilinear preferences, the utility function $U(c,h)=\log(c)+g(l)$ satisfies the condition, for instance.

The relative magnitude of these two effects varies with $\sigma$. When $\sigma$ is small, the uncertainty effect is stronger than the level effect, but as $\sigma$ increases, the level effect outweighs the uncertainty effect even at $\sigma$ lower than $\sigma^*$, i.e., without the effect of the non-negativity constraint. Once the magnitude of the level effect exceeds the uncertainty effect, the dominance never reverses for $\sigma>\underline{\sigma}$. This feature makes the social welfare function U-shaped. Figure 2.3 presents the welfare effects with $\gamma=1$, 1.5, and 2. It shows that the bottom point of the U-curve, $\underline{\sigma}$, is increasing in $\gamma$. That is because the higher the degree of risk aversion, or equivalently the curvature of $u(c)$, the larger the magnitude of the uncertainty effect is.

[5] Even if this condition is not satisfied, $(1+\alpha(\sigma))\approx\left(1+\alpha^{lev}(\sigma)\right)(1+\alpha^{unc}(\sigma))$ when $\alpha(\sigma)$ is small. See next section.

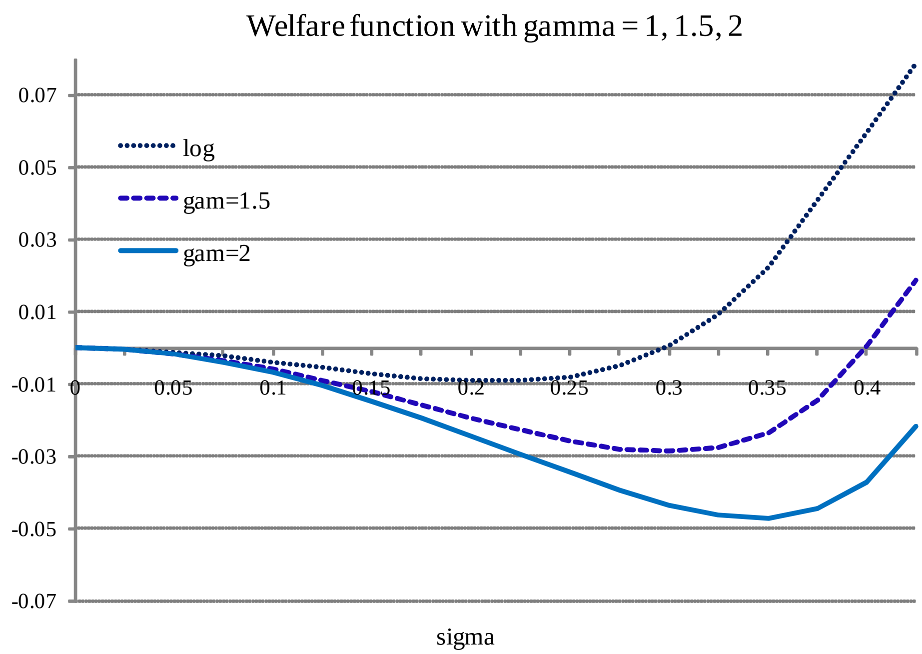



Figure 2.3: The welfare effect $\alpha(\sigma)$ with $u(c) = \frac{c^{-\gamma}}{1-\gamma}$, $\gamma = 1,\ 1.5,\ 2,\ N = 2$.

### 2.2.4 Comparison with Alternative Market Structures

In this subsection, we compare the optimal allocations of the Pareto planning problem under three alternative market structures: the benchmark economy with asymmetric information, autarky, and complete markets economy. The planner's ability to transfer resources between different types of individuals is different in each market structure. We let the function $W^m(\sigma)$ denote the social welfare function under alternative market structures, $m \in \{COM, AUT\}$.

We present the two alternative market structures and the associated budget constraints.

**Complete markets economy:** In this economy the planner is able to transfer resources freely between the different types of individuals. The allocation coincides with the allocation of the aggregate welfare maximization problem:

$$\max_{c_i,y_i} \frac{1}{N}\sum_{i=1}^{N}\left[u(c_i) - \psi\frac{y_i}{w_i}\right] \tag{2.18}$$

subject to the resource constraint

$$\sum_{i=1}^{N} c_i \leq \sum_{i=1}^{N} y_i. \tag{2.19}$$

Solving the problem yields the social welfare function,

$$W^{COM}(\sigma) = \frac{\gamma}{1-\gamma}\left(\frac{\sigma+\overline{w}}{\psi}\right)^{\frac{1-\gamma}{\gamma}}, \tag{2.20}$$

with $u(c) = \frac{c^{1-\gamma}}{1-\gamma}$, $\gamma > 1$, and $N = 2$.

**Autarky:** In this economy the planner is able to transfer resources only between individuals of the same type. The allocation coincides with the allocation of the individual utility maximization problem:

$$\max_{c_i,y_i} u(c_i) - \psi\frac{y_i}{w_i} \tag{2.21}$$

subject to

$$c_i \leq y_i. \tag{2.22}$$

Solving the problem yields the social welfare function,

$$W^{AUT}(\sigma) = \left(\frac{\gamma}{1-\gamma}\right)\left[\left(\frac{\overline{w}-\sigma}{\psi}\right)^{\frac{1-\gamma}{\gamma}} + \left(\frac{\overline{w}+\sigma}{\psi}\right)^{\frac{1-\gamma}{\gamma}}\right], \tag{2.23}$$

with $u(c) = \frac{c^{1-\gamma}}{1-\gamma}$, $\gamma > 1$, and $N = 2$.

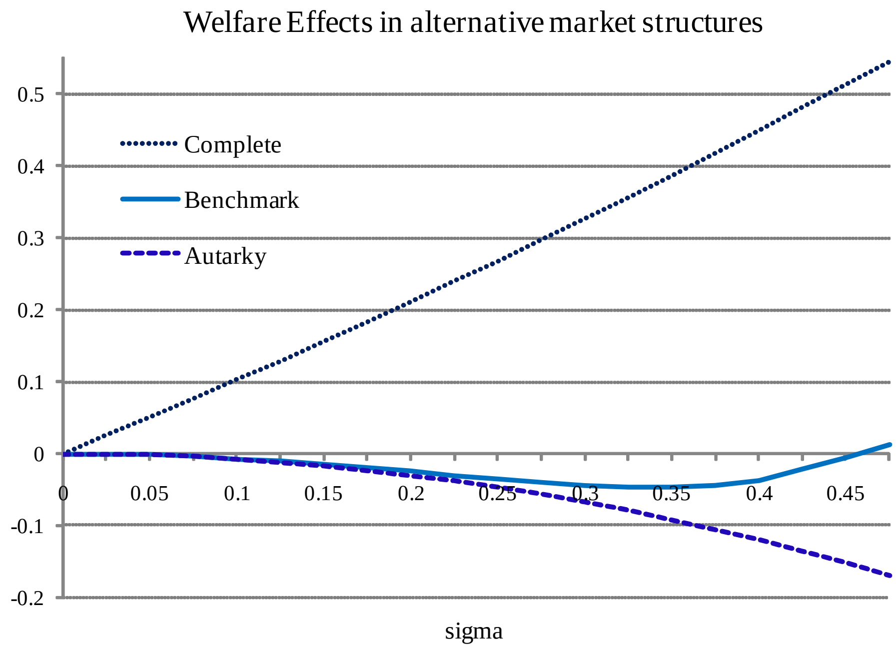



Figure 2.4: The social welfare functions in the benchmark model $W(\sigma)$, in autarky $W^{AUT}(\sigma)$, and in the complete markets economy $W^{COM}(\sigma)$, with $u(c) = \frac{c^{1-\gamma}}{1-\gamma}$, $\gamma = 2$, $N = 2$.

Our findings are summarized in the following lemmas.

**Lemma 2.2.5** *Suppose that there are two types of individuals, $N = 2$. If $u(c) = \frac{c^{1-\gamma}}{1-\gamma}$, $\gamma \in [1, \infty)$,*

$$\frac{dW(0)}{d\sigma} = \frac{dW^{AUT}(0)}{d\sigma} = 0.$$

**Lemma 2.2.6** *Suppose that $N = 2$. If $u(c) = \frac{c^{1-\gamma}}{1-\gamma}$, $\gamma \in [1, \infty)$, then*

$$(i) \quad k\frac{dW(\sigma)}{d\sigma} = \frac{dW^{COM}(\sigma)}{d\sigma}, \ \sigma \geq \sigma^*,$$

*where $k$ is a constant value. If $\sigma = 1$ (i.e., $u(c) = \log(c)$), $k = 1$.*

$$(ii) \quad \lim_{\sigma \to \infty} \frac{dW(\sigma)}{d\sigma} = \lim_{\sigma \to \infty} \frac{dW^{COM}(\sigma)}{d\sigma} = 0.$$

With quasi-linear preferences, when $\sigma$ is very small, the welfare function $W$ of our benchmark economy behaves like the welfare function under autarky $W^{AUT}$; the values and slopes of these two functions are equal at $\sigma = 0$. On the other hand, as $\sigma$ becomes larger, $W$ gradually approaches the welfare function under complete markets $W^{COM}$. When $u(c) = \log(c)$, $W$ and $W^{COM}$ increase parallel to each other, while $W^{AUT}$ monotonically decreases.

## 2.3 The Dynamic Model

### 2.3.1 Environment

In this section we consider a more general form of the model that we discussed in the previous section. There is a unit measure of agents who have preferences of the form

$$\sum_{t=1}^{T} \beta^{t-1} U\left(c_t, h_t\right), \tag{2.24}$$

where agents discount the future at rate $0 < \beta < 1$, and there are $T$ periods in an agent's working life which is finite.

Let $w_t$ be an agent's labor productivity shock in period $t$, which is an element of a constant finite set $\Omega$. We consider that $w_t$ is independently and identically distributed (i.i.d.) across agents and over time. Each agent realizes his own shock at the beginning of each period, and a history of productivity shocks up to period $t$, $w^t = (w_1, w_2, ...., w_t)$, is observed only by the agent. Given $w_t$, the agent can produce $y_t = w_t h_t$ units of consumption good in period $t$, where $h_t$ denotes hours worked.

The planner's problem is to choose an allocation $(c, y) = (c_t, y_t)_{t=1}^{T}$ to maximize the ex-ante lifetime utility,

$$W = \sum_{t=1}^{T} \sum_{w^t \in \Omega^t} \beta^{t-1} \pi\left(w^t\right) U\left(c_t\left(w^t\right), \frac{y_t\left(w^t\right)}{w_t}\right), \tag{2.25}$$

where $\pi\left(w^t\right)$ denotes the probability of a sequence of shocks $w^t$.

An allocation $(c, y)$ is incentive compatible if it satisfies the following constraint:

$$\sum_{t=1}^{T} \sum_{w^t \in \Omega^t} \beta^{t-1} \pi\left(w^t\right) U\left(c_t\left(w^t\right), \frac{y_t\left(w^t\right)}{w_t}\right) \geq \sum_{t=1}^{T} \sum_{w^t \in \Omega^t} \beta^{t-1} \pi\left(w^t\right) U\left(c_t\left(s_t\left(w^t\right)\right), \frac{y_t\left(s_t\left(w^t\right)\right)}{w_t}\right), \tag{2.26}$$

for any $s$, where $s = (s_t)_{t=1}^T$ is a reporting strategy which maps $w^t \in \Omega^t$ into $\Omega$. Because $w^t$ is private information, an achievable allocation must be always incentive compatible. Also, a feasible allocation must satisfy the production constraint:

$$\sum_{t=1}^{T} \sum_{w^t \in \Omega^t} \left(\frac{1}{R}\right)^{t-1} \pi(w^t) \left[y_t\left(w^t\right) - c_t\left(w^t\right)\right] \geq 0, \tag{2.27}$$

where $R$ is the gross interest rate. Throughout this section, we analyze a partial equilibrium model in which the gross interest rate $R$ is exogenous and constant over time.

As discussed in Green (1987) and Spear and Srivastava (1987), we can rewrite the original utility maximization problem as the dual cost minimization problem. Define the function $C(V)$ to be

$$C(V) = \min_{(c,y)} \sum_{t=1}^{T} \left(\frac{1}{R}\right)^{t-1} \pi\left(w^t\right) \left(c_t(w^t) - y_t(w^t)\right), \tag{2.28}$$

subject to

$$\sum_{t=1}^{T} \beta^{t-1} \pi(w^t) U\left(c_t(w^t), \frac{y_t(w^t)}{w_t}\right) = V, \tag{2.29}$$

and

$$\sum_{t=1}^{T} \beta^{t-1} \pi(w^t) U\left(c_t(w^t), \frac{y_t(w^t)}{w_t}\right) \geq \sum_{t=1}^{T} \beta^{t-1} \pi(w^t) U\left(c_t\left(s_t(w^t)\right), \frac{y_t(s_t(w^t))}{w_t}\right), \tag{2.30}$$
$$\forall\ s = (s_t)_{t=1}^T, \text{ where } s_t : \Omega^t \to \Omega.$$

$C(V)$ is the cost that the planner needs to pay to provide the ex-ante lifetime utility $V$.

With finite $T$, restating the problem in a recursive form brings

$$C_T(V) = \min_{(c_T, y_T)} \sum_{w_T \in \Omega} \pi(w_T) \left( c_T(w_T) - y_T(w_T) \right), \tag{2.31}$$

subject to

$$U\left( c_T(w_T), \frac{y_T(w_T)}{w_T} \right) \geq U\left( c_T(\widehat{w_T}), \frac{y_T(\widehat{w_T})}{w_T} \right) \quad \text{for all } w_T, \widehat{w_T} \in \Omega, \tag{2.32}$$

$$\sum_{w_T \in \Omega} \pi(w_T) \left[ U\left( c_T(w_T), \frac{y_T(w_T)}{w_T} \right) \right] = V, \tag{2.33}$$

for the last period $T$ and,

$$C_t(V) = \min_{(c_t, y_t, V_t')} \sum_{w_t \in \Theta} \pi(w_t) \left( c_t(w_t) - y_t(w_t) + \frac{C_{t+1}\left( V_t'(w_t) \right)}{R} \right), \tag{2.34}$$

subject to

$$U\left( c_t(w_t), \frac{y_t(w_t)}{w_t} \right) + \beta V_t'(w_t) \geq U\left( c_t(\widehat{w}_t), \frac{y_t(\widehat{w}_t)}{w_t} \right) + \beta V_t'(\widehat{w}_t) \quad \text{for all } w_t, \widehat{w}_t \in \Omega, \tag{2.35}$$

$$\sum_{w_t \in \Omega} \pi(w_t) \left[ U\left( c_t(w_t), \frac{y_t(w_t)}{w_t} \right) + \beta V_t'(w_t) \right] = V, \tag{2.36}$$

for period $t = 1$ to $T - 1$, where $V_t'(w_t)$ denotes the continuation utility given to an agent who reports type $w_t$ in period $t$. The optimal social welfare attained in this problem is given by $V^*$ which satisfies $C_1(V^*) = 0$.

### 2.3.2 Quantitative Analysis

We quantitatively investigate the implications of the rise in wage inequality in the United States over the last 30 years. Specifically, using the dynamic model described above, we quantify (i) the welfare effects of the rise in wage inequality and (ii) the differences in welfare under the benchmark economy and alternative market structures at each level of wage risk.

#### 2.3.2.1 Parameter Values

We focus on the following period utility function that is additively separable between consumption and hours worked,

$$U\left(c_t, h_t\right) = \frac{c_t^{1-\gamma}}{1-\gamma} - \psi \frac{h_i^{1+\rho}}{1+\rho}, \tag{2.37}$$

where $\gamma = 2$, $\psi = 1$, and $\rho = 2$, which are set equal to the values in Heathcote et al. (2008).

As a benchmark case, we set the number of model periods $T = 3$, and the gross interest rate per period $R = 1.05^{\frac{35}{T}}$.[6] The distribution of shocks is a discrete approximation to a lognormal distribution such as

$$\log(w_t) \sim N\left(-\frac{\sigma^2}{2}, \sigma^2\right). \tag{2.38}$$

Following Tauchen (1986), we approximate the lognormal distribution with five equi-spaced grid points in logs on the interval $\left[-\frac{\sigma^2}{2} - 3\sigma, -\frac{\sigma^2}{2} + 3\sigma\right]$.[7]

#### 2.3.2.2 Welfare Effects

To examine the implications of the rise in wage inequality, we compare the optimal allocations and the social welfare levels in two steady states, given two distinct levels of wage dispersion, before and after the change. Heathcote et al (2008) estimate the variance of log wages using the 1968-1997 waves of the Panel Study of Income Dynamics (PSID) and find that it rose from 0.25 to 0.35 over the time period. We use these numbers as inputs for the model.

[6] Appendix D discusses the selection of $T$ in connection with the persistence of the labor income.

[7] Note that $E[w] = 1$, $\forall\sigma$, given the log normal distribution with its mean (in log), $-\frac{\sigma^2}{2}$. Under the discrete approximation, however, $\sum_{i=1}^{N} \pi(w_i) w_i|_\sigma$ slightly changes as $\sigma$ increases. To prevent the effect of the change on welfare, we standardize $w$ by dividing the mean value so that $\sum_{i=1}^{N} \pi(w_i) w_i|_\sigma = 1$, $\forall\sigma$.

We express the welfare effect of a change in wage dispersion, $\alpha(\sigma)$, in units of the equivalent variation in lifetime consumption under no wage dispersion, such that

$$\sum_{t=1}^{T} \beta^{t-1} U\left(\left(1+\alpha(\sigma)\right) c_t\left(\overline{w}^t\right), h_t\left(\overline{w}^t\right)\right) = W(\sigma), \tag{2.39}$$

where $\overline{w}^t = (\overline{w}, ..., \overline{w})$.

Figure 2.5 displays the welfare effect of the change in the variance of log wages in our benchmark case with $T = 3$. The welfare function is U-shaped and reaches its bottom at a strictly positive variance ($var(\ln(w)) = 0.05$) and the slope turns positive afterwards. This is exactly the same characteristic we have seen in the static part with quasi-linear preferences. When the variance of log wages increases by 0.10, from 0.25 to 0.35, it corresponds to the increasing part of the welfare function and the welfare gain is approximately 1% of lifetime consumption in the economy with no wage dispersion (equation (2.39)).

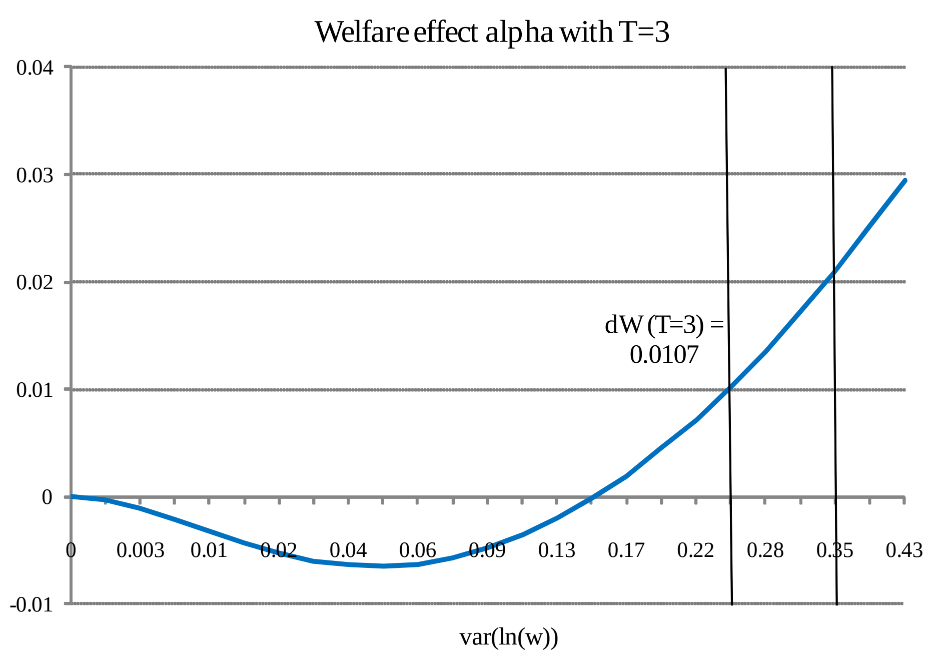



Figure 2.5: The welfare effect $\alpha(\sigma)$ of the change in $var(\ln(w)) : 0.25 \rightarrow 0.35$, $T = 3$ .

To gain a further understanding of the mechanism, it is useful to look at the two effects we introduced in Section 2.2: the level effect and the uncertainty effect. The level effect shows the welfare gain associated with the rise in average (aggregate) labor productivity, and the uncertainty effect captures the cost of uncertainty associated with the increase in wage risk. In the dynamic model, the level effect is defined as the value for $\alpha^{lev}(\sigma)$ that solves,

$$\sum_{t=1}^{T} \beta^{t-1} U\left(\left(1+\alpha^{lev}(\sigma)\right) \overline{c_t}\,(0)\,, \overline{h_t}\,(0)\right) = \sum_{t=1}^{T} \beta^{t-1} U\left(\overline{c_t}\,(\sigma)\,, \overline{h_t}\,(\sigma)\right), \tag{2.40}$$

where the mean consumption $\overline{c_t}(\sigma)$ and hours worked $\overline{h_t}(\sigma)$ in period $t$ are defined as

$$\overline{c_t}\,(\sigma) = \sum_{w^t} \pi(w^t) c_t\left(w^t\right), \tag{2.41}$$

$$\overline{h_t}\,(\sigma) = \sum_{w^t} \pi(w^t) h_t\left(w^t\right). \tag{2.42}$$

The uncertainty effect is defined as $\alpha^{unc}(\sigma)$ that solves,

$$\sum_{t=1}^{T} \beta^{t-1} U\left(\left(1+\alpha^{unc}(\sigma)\right) \overline{c_t}\,(\sigma)\,, \overline{h_t}\,(\sigma)\right) = W(\sigma). \tag{2.43}$$

Although a class of preferences we use in this section does not necessarily allow us to show the welfare effect $\alpha(\sigma)$ as the exact product of these two effects (as in equation 2.17), paying attention to them helps us to understand the two aspects of the effect of the rising wage inequality: the effect on aggregate productivity and the effect on the equity of distribution.

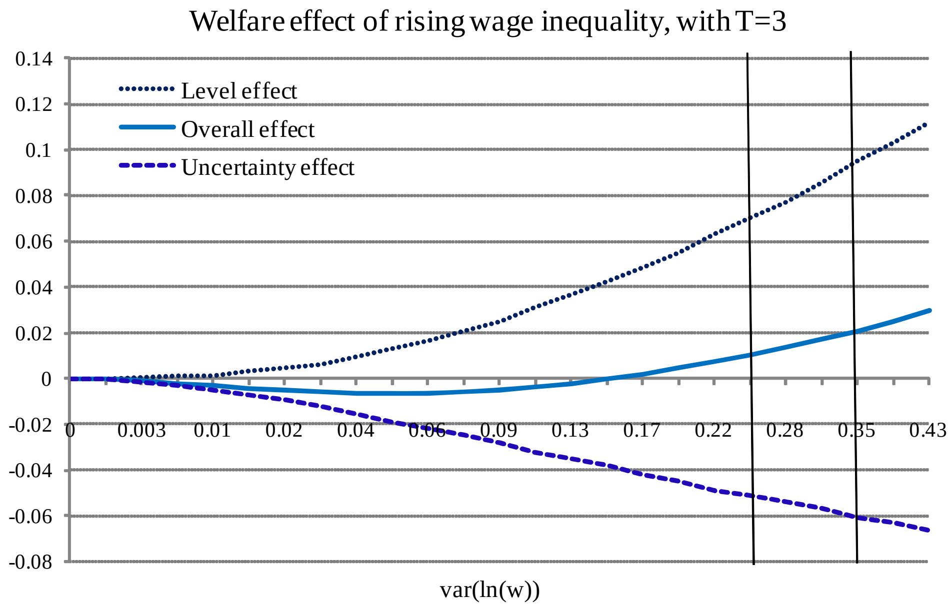



Figure 2.6: The welfare effect in the benchmark model with $T = 3$ : (1) level effect (2) overall effect, and (3) uncertainty effect.

Figure 2.6 displays the two effects along with the overall effect $\alpha(\sigma)$. The results are obtained by drawing 50000 lifetime profiles of labor productivity shocks. As we have seen in the static model, the uncertainty effect outweighs the level effect when wage dispersion is small, but their relative relation is reversed at $var(\ln(w)) \geq 0.13$. The rise in the variance of log wages, from 0.25 to 0.35, pushes up the level effect from 0.07 to 0.10, while it also raises the cost of uncertainty from 0.05 to 0.06. This increase in the size of the economic pie contributes to the overall welfare gain and helps to mitigate the negative impact of increasing risk on the economy.

#### 2.3.2.3 Optimal Allocations of Consumption and Hours

The welfare effects of the rise in wage dispersion reflects the change in optimal allocations of consumption and hours. We now look at the model-implied changes in the cross-sectional variances of hours and consumption and covariance between hours and wages, and compare them with their data counterparts.

Table 2.1 summarizes the changes in the cross-sectional variances of log consumption, log hours, and covariance between log hours and log wages, associated with the rise in wage dispersion, $var(\ln(w))$, from 0.25 to 0.35. The left column shows the changes observed in the data, which are set equal to estimates in Heathcote et al. (2008), and the right column displays the model-implied changes.

In general, the changes in variance of log consumption in the model are slightly underestimated, while the model expects higher increases in covariance between hours and wages than observed in the data. It suggests the possibility that the model tends to overestimate the welfare gain through the rising wage dispersion, if it underestimates the uncertainty effect and overestimates the level effect. This tendency might be true, but there are two things we should note here. First, as shown in Figure 2.5, the bottom of the welfare function is quite far from the range of the wage dispersion values that we are considering, between 0.25 and 0.35. Thus, it is highly possible that the positive effect remains even after we adjust for the estimates. Second, the social welfare and the level of insurance provided in the current study can be interpreted as the upper limit of welfare and insurance which could be delivered by the government.

#### 2.3.2.4 Comparison with Alternative Market Structures

Finally we compare the levels of social welfare under different market structures. In addition to the two market structures introduced in Section 2.2, we also consider the

| | Observed | Model implied ($T=3$) | | |
|---|---|---|---|---|
| | | $t=1$ | $t=2$ | $t=3$ |
| $\Delta var(\ln(c))$ | 0.03 | 0.002 | 0.004 | 0.009 |
| $\Delta var(\ln(h))$ | 0.01 | 0.015 | 0.016 | 0.015 |
| $\Delta cov(\ln(h), \ln(w))$ | 0.017 | 0.036 | 0.035 | 0.033 |

Table 2.1: Changes in the cross-sectional variances of log consumption, log hours, and covariance between log hours and log wages, associated with $var(\ln(w)) : 0.25 \rightarrow 0.35$, with the benchmark model with $T = 3$.

model with private information in which one model period corresponds to one year, that is, $T = 35$.

**Complete markets economy:** In this economy the planner is able to transfer resources freely between the different types of individuals. The allocation coincides with the allocation of the aggregate welfare maximization problem:

$$W^{COM} = \max \mathbb{E}_0 \left[ \sum_{t=1}^{T} \beta^{t-1} U\left(c_t, h_t\right) \right], \tag{2.44}$$

subject to the resource constraint

$$\sum_{t=1}^{T} \sum_{w^t \in \Omega^t} \pi(w^t) \left(\frac{1}{R}\right)^{t-1} \left[y_t\left(w^t\right) - c_t\left(w^t\right)\right] \geq 0. \tag{2.45}$$

**Autarky:** In autarky, consumption must be equal to income every path of history.

$$W^{AUT} = \max \mathbb{E}_0 \left[ \sum_{t=1}^{T} \beta^{t-1} U\left(c_t, h_t\right) \right], \tag{2.46}$$

A feasible allocation $(c, y)$ must satisfy the production constraint:

$$y_t\left(w^t\right) - c_t\left(w^t\right) \geq 0, \ \forall w^t. \tag{2.47}$$

**Incomplete markets economy (T=35):** As discussed in the Appendix, the number of model periods represents the persistence of labor productivity shocks; the less the number of periods is, the more persistent shocks are. In the model with $T = 35$, one model period is one year and it implies that we have less persistent shocks on labor productivity compared to our benchmark case with $T = 3$.

Figure 2.7 summarizes the results. With $T = 35$, the welfare function is monotonically increasing with respect to the degree of wage dispersion. As depicted in the figure, the level of social welfare with $T = 35$ is much closer to that of complete markets economy in comparison with the benchmark case. The welfare function approaches to that of complete markets economy as the number of model periods increases, and it comes closest in the extreme case in which $T$ is infinity. Though the infinite horizon case is different from complete markets economy, the effect of the private information friction is negligible compared to cases with lower number of periods. In this sense, it is important to select a right number of periods to evaluate the effect of the rise in wage inequality with the model with private information.

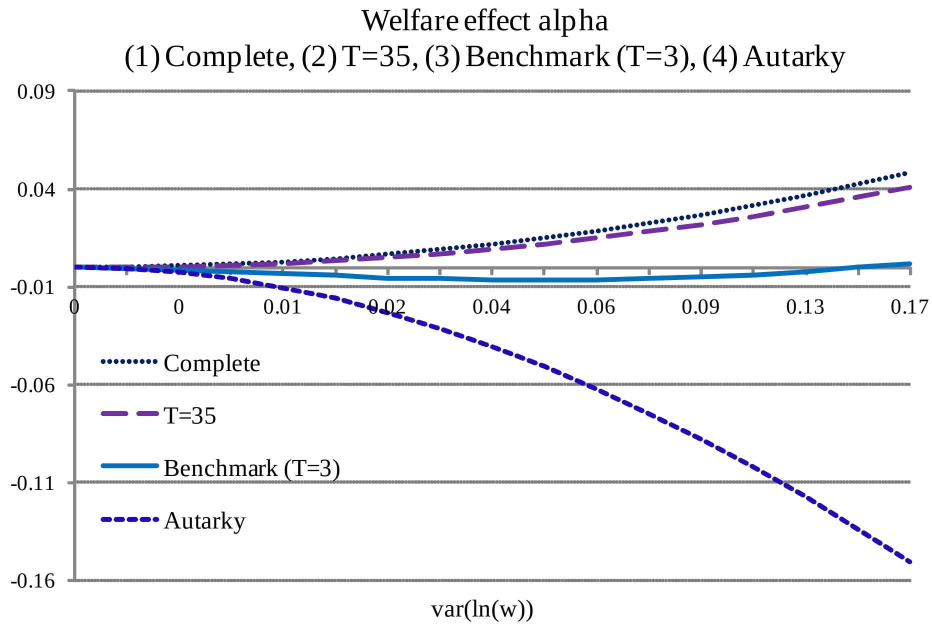



Figure 2.7: Comparison of the welfare effects in (1) complete markets economy, (2) incomplete markets with $T = 35$, (3) benchmark model ($T = 3$), and (4) autarky.

## 2.4 Concluding Remarks

This paper is intended to address the following two questions: what are the welfare effects of a change in wage dispersion given the presence of private information, and what are the welfare costs of the informational friction at each level of wage dispersion. First, the results suggests that the implication really depends on the initial degree of the wage dispersion; an increase in wage inequality has a negative impact on the welfare if the initial dispersion is relatively low, while it has a positive impact if wages are highly dispersed before the change. This characteristic is present in both the static and dynamic models. Second, the welfare function in the benchmark economy is close to that under autarky when $\sigma$ is very small; we find that the slope of these functions are the same at $\sigma = 0$ with the static model. As $\sigma$ becomes larger, however, the function gradually approaches that of complete markets economy. The distance between the welfare functions under incomplete markets with private information and complete markets are greatly affected by the number of periods we introduce in the model. In other words, if labor productivity shocks are less persistent, the planner can provide higher level of insurance which is close to the full insurance provided under complete markets economy.

## 2.A Appendix

### 2.A.1 The Optimal Welfare Functions and Allocations

**Log quasi-linear utility function**

Let $N = 2$. We choose $c \in \mathbb{R}^2_+$ to maximize the social welfare function

$$W = \frac{1}{2} \sum_{i=1}^{2} (\log(c_i) - \psi y_i^*(c)) \tag{2.48}$$

subject to

$$y_i^*(c) \geq 0, \ \forall \ i, \tag{2.49}$$

$$0 \leq c_1 \leq c_2, \tag{2.50}$$

where $y^*(c) = (y_1^*(c), y_2^*(c))$ is the solution of the system of equations which consist of the production constraint (2.6) and the incentive compatibility constraint with equality (2.7), given the consumption levels $c$.

The optimized social welfare function is[8]:

$$
\begin{aligned}
W(\sigma) &= W^{I}(\sigma) \equiv \log\left(\frac{\overline{w}+\sigma}{\psi}\right) + \frac{1}{2}\left(\frac{\overline{w}-2\sigma}{\overline{w}-\sigma}\right)\log\left(\frac{\overline{w}-2\sigma}{\overline{w}}\right) - 1, \text{ for } \sigma \in [0,\sigma^*], \qquad (2.51)\\
&= W^{II}(\sigma) \equiv \log\left(\frac{\overline{w}+\sigma}{\psi}\right) + \log\left(\text{Lambert}\left(\frac{1}{e}\right)\right), \text{ for } \sigma \in [\sigma^*,\infty).
\end{aligned}
$$

The consumption and income vectors are:

$$
\begin{aligned}
(c_1(\sigma), c_2(\sigma)) &= \left(\frac{(\overline{w}+\sigma)(\overline{w}-2\sigma)}{\psi\overline{w}}, \frac{\overline{w}+\sigma}{\psi}\right), \text{ for } \sigma \in [0,\sigma^*], \qquad (2.52)\\
&= \left(\frac{(\overline{w}+\sigma)(\overline{w}-2\sigma^*)}{\psi\overline{w}}, \frac{\overline{w}+\sigma}{\psi}\right), \text{ for } \sigma \in [\sigma^*,\infty),
\end{aligned}
$$

and

$$
\begin{aligned}
y_1(\sigma) &= \frac{\overline{w}+\sigma}{2\psi}\left[\frac{2\overline{w}-2\sigma}{\overline{w}} - \log\left(\frac{\overline{w}}{\overline{w}-2\sigma}\right)\right], \text{ for } \sigma \in [0,\sigma^*], \qquad (2.53)\\
&= 0, \text{ for } \sigma \in [\sigma^*,\infty),\\
y_2(\sigma) &= \frac{\overline{w}+\sigma}{2\psi}\left[\frac{2\overline{w}-2\sigma}{\overline{w}} + \log\left(\frac{\overline{w}}{\overline{w}-2\sigma}\right)\right], \text{ for } \sigma \in [0,\sigma^*], \qquad (2.54)\\
&= \frac{\overline{w}+\sigma}{\psi}\left(1 + \frac{\overline{w}-2\sigma^*}{\overline{w}}\right), \text{ for } \sigma \in [\sigma^*,\infty).
\end{aligned}
$$

### CRRA quasi-linear utility function

Let $N = 2$. We choose $c \in \mathbb{R}^2_+$ to maximize the social welfare function

$$
W = \frac{1}{2}\sum_{i=1}^{2}\left(\frac{c_i^{1-\gamma}}{1-\gamma} - \psi y_i^*(c)\right), \ \gamma > 1, \qquad (2.55)
$$

subject to

$$
y_i^*(c) \geq 0, \forall i, \qquad (2.56)
$$

$$
0 \leq c_1 \leq c_2, \qquad (2.57)
$$

[8]The function Lambert(.) is the Lambert W function, that is the inverse function of $f(x) = xe^x$.

where $y^*(c) = (y_1^*(c), y_2^*(c))$ is the solution of the system of equations which consist of the production constraint (2.6) and the $N-1$ incentive compatibility constraint with equality (2.7), given the consumption levels $c$.

The optimized social welfare function is:

$$\begin{aligned} W(\sigma) &= W^I(\sigma) \equiv \frac{1}{2}\frac{\gamma\overline{w}}{(1-\gamma)(\overline{w}-\sigma)}\left(\frac{\overline{w}+\sigma}{\psi}\right)^{\frac{1-\gamma}{\gamma}}\left[1+\left(\frac{\overline{w}-2\sigma}{\overline{w}}\right)^{\frac{1}{\gamma}}\right], \text{ for } \sigma \in [0,\sigma^*], \quad (2.58)\\ &= W^{II}(\sigma) \equiv \frac{1}{(1-\gamma)}\left(\frac{\overline{w}+\sigma}{\psi}\right)^{\frac{1-\gamma}{\gamma}}\left(\frac{\overline{w}-2\sigma^*}{\overline{w}}\right)^{\frac{1-\gamma}{\gamma}}, \text{ for } \sigma \in [\sigma^*,\infty). \end{aligned}$$

The consumption and income vectors are:

$$\begin{aligned} (c_1(\sigma), c_2(\sigma)) &= \left(\left(\frac{(\overline{w}+\sigma)(\overline{w}-2\sigma)}{\psi\overline{w}}\right)^{\frac{1}{\gamma}}, \left(\frac{\overline{w}+\sigma}{\psi}\right)^{\frac{1}{\gamma}}\right), \text{ for } \sigma \in [0,\sigma^*], \quad (2.59)\\ &= \left(\left(\frac{(\overline{w}+\sigma)(\overline{w}-2\sigma^*)}{\psi\overline{w}}\right)^{\frac{1}{\gamma}}, \left(\frac{\overline{w}+\sigma}{\psi}\right)^{\frac{1}{\gamma}}\right), \text{ for } \sigma \in [\sigma^*,\infty), \end{aligned}$$

and

$$\begin{aligned} y_1(\sigma) &= \frac{1}{2}\left(\frac{\overline{w}+\sigma}{\psi}\right)^{\frac{1}{\gamma}}\left[\left(\frac{\overline{w}-2\sigma}{\overline{w}}\right)^{\frac{1}{\gamma}} + 1 - \frac{\left(1-\left(\frac{\overline{w}-2\sigma}{\overline{w}}\right)^{\frac{1-\gamma}{\gamma}}\right)}{1-\gamma}\right], \text{ for } \sigma \in [0,\sigma^*], \quad (2.60)\\ &= 0, \text{ for } \sigma \in [\sigma^*,\infty),\\ y_2(\sigma) &= \frac{1}{2}\left(\frac{\overline{w}+\sigma}{\psi}\right)^{\frac{1}{\gamma}}\left[\left(\frac{\overline{w}-2\sigma}{\overline{w}}\right)^{\frac{1}{\gamma}} + 1 + \frac{\left(1-\left(\frac{\overline{w}-2\sigma}{\overline{w}}\right)^{\frac{1-\gamma}{\gamma}}\right)}{1-\gamma}\right], \text{ for } \sigma \in [0,\sigma^*], \quad (2.61)\\ &= \left(\frac{\overline{w}+\sigma}{\psi}\right)^{\frac{1}{\gamma}}\left[1+\frac{(\overline{w}-2\sigma^*)^{\frac{1}{\gamma}}}{\overline{w}}\right], \text{ for } \sigma \in [\sigma^*,\infty). \end{aligned}$$

### 2.A.2 Derivation of $\sigma^*$

**Log quasi-linear utility function**

$\sigma^*$ is the unique solution of

$$y_1(\sigma^*) = \frac{\overline{w} + \sigma^*}{2\psi\overline{w}} \left[ \frac{2\overline{w} - 2\sigma^*}{\overline{w}} - \log\left( \frac{\overline{w}}{\overline{w} - 2\sigma^*} \right) \right] = 0, \tag{2.62}$$

or equivalently,

$$\frac{2\overline{w} - 2\sigma^*}{\overline{w}} = \log\left( \frac{\overline{w}}{\overline{w} - 2\sigma^*} \right). \tag{2.63}$$

Taking exponential gives

$$\frac{\overline{w} - 2\sigma^*}{\overline{w}} \exp\left( \frac{\overline{w} - 2\sigma^*}{\overline{w}} \right) = \exp(-1). \tag{2.64}$$

Finally we have the expression for $\sigma^*$, that is,

$$\sigma^* = \frac{\overline{w}}{2}\left( 1 - \text{Lambert}\left( \frac{1}{e} \right) \right). \tag{2.65}$$

**CRRA quasilinear utility function**

$\sigma^*$ is the unique solution of

$$y_1(\sigma^*) = \frac{1}{2}\left( \frac{\overline{w} + \sigma^*}{\psi} \right)^{\frac{1}{\gamma}} \left[ \left( \frac{\overline{w} - 2\sigma^*}{\overline{w}} \right)^{\frac{1}{\gamma}} + 1 - \frac{\left( 1 - \left( \frac{\overline{w} - 2\sigma^*}{\overline{w}} \right)^{\frac{1-\gamma}{\gamma}} \right)}{1 - \gamma} \right] = 0, \tag{2.66}$$

or equivalently,

$$\left( \frac{\overline{w} - 2\sigma^*}{\overline{w}} \right)^{\frac{1}{\gamma}} + 1 = \frac{\left( 1 - \left( \frac{\overline{w} - 2\sigma^*}{\overline{w}} \right)^{\frac{1-\gamma}{\gamma}} \right)}{1 - \gamma}. \tag{2.67}$$

Except for some special cases, it is not easy to derive a closed-form expression of $\sigma^*$. If $\gamma = 2$, for instance, then $\sigma^* = \overline{w}(\sqrt{2} - 1)$. Note that $\sigma^*$ is always less than $\frac{\overline{w}}{2}$.

### 2.A.3 Proof of Proposition 4

The proof consists of three parts: we first verify that $W(\sigma)$ is strictly decreasing when $\sigma$ is small, then we show that $W(\sigma)$ is strictly increasing in the second region, $\sigma \geq \sigma^*$, and we finish by proving that the first derivative of $W(\sigma)$ is 0 only at $\underline{\sigma}$ (except for $\sigma = 0$).

[1] $W(\sigma)$ **is strictly decreasing if** $\sigma$ **is small enough**

**Log quasilinear utility function**

The optimal social welfare function for $\gamma = 1$ is

$$\begin{aligned} W(\sigma) &= W^{I}(\sigma) \equiv \log\left(\frac{\overline{w}+\sigma}{\psi}\right) + \frac{1}{2}\left(\frac{\overline{w}-2\sigma}{\overline{w}-\sigma}\right)\log\left(\frac{\overline{w}-2\sigma}{\overline{w}}\right) - 1, \text{ for } \sigma \in [0, \sigma^*], \\ &= W^{II}(\sigma) \equiv \log\left(\frac{\overline{w}+\sigma}{\psi}\right) + \log\left(\text{Lambert}\left(\frac{1}{e}\right)\right), \text{ for } \sigma \in [\sigma^*, \infty). \end{aligned} \tag{2.68}$$

At $\sigma = 0$,

$$\frac{dW^{I}}{d\sigma}(0) = -\frac{0}{2\overline{w}} = 0, \tag{2.69}$$

and

$$\frac{d^2W^{I}}{d\sigma^2}(0) = -\frac{1}{\overline{w}^2} < 0. \tag{2.70}$$

Thus, when $v(c) = \log(c)$, the social welfare function $W$ is strictly decreasing at $W(\varepsilon)$ if $\varepsilon \in \mathbb{R}_{++}$ is small enough.

**CRRA quasilinear utility function**

Recall that the optimal social welfare function for $\gamma > 1$ is

$$\begin{aligned} W(\sigma) &= W^{I}(\sigma) \equiv \frac{\gamma\overline{w}}{(1-\gamma)(\overline{w}-\sigma)}\left(\frac{\overline{w}+\sigma}{\psi}\right)^{\frac{1-\gamma}{\gamma}}\left[1+\left(\frac{\overline{w}-2\sigma}{\overline{w}}\right)^{\frac{1}{\gamma}}\right], \text{ for } \sigma \in [0, \sigma^*], \\ &= W^{II}(\sigma) \equiv \frac{2}{(1-\gamma)}\left(\frac{\overline{w}+\sigma}{\psi}\right)^{\frac{1-\gamma}{\gamma}}\left(\frac{\overline{w}-2\sigma^*}{\overline{w}}\right)^{\frac{1-\gamma}{\gamma}}, \text{ for } \sigma \in [\sigma^*, \infty). \end{aligned} \tag{2.71}$$

At $\sigma = 0$,

$$\frac{dW^{I}}{d\sigma}(0) = \frac{1}{2}\left(\frac{\gamma}{1-\gamma}\right)\psi^{\frac{\gamma-1}{\gamma}}\overline{w}^{\frac{1-2\gamma}{\gamma}}\left(\frac{2}{\gamma}-\frac{2}{\gamma}\right) = 0, \tag{2.72}$$

and

$$\frac{d^2W^I}{d\sigma^2}(0) = \left(\frac{\gamma}{1-\gamma}\right)\psi^{\frac{\gamma-1}{\gamma}}\overline{w}^{\frac{1-3\gamma}{\gamma}}\left(\frac{1}{\gamma}-2\right)\left(\frac{1}{\gamma}-1\right) < 0, \text{ for any } \gamma > 1. \tag{2.73}$$

Thus, for $\gamma \in (1, +\infty)$, the social welfare function $W$ is strictly decreasing at $W(\varepsilon)$ if $\varepsilon \in \mathbb{R}_{++}$ is small enough.

**[2]** $W(\sigma)$ **is strictly increasing for** $\sigma \geq \sigma^*$

**Log quasilinear utility function**

The first derivative of the optimal welfare function for $\sigma \geq \sigma^*$, $W^{II}(\sigma)$ is

$$\frac{dW^{II}(\sigma)}{d\sigma} = \frac{1}{\overline{w}+\sigma} > 0. \tag{2.74}$$

Thus, $W(\sigma) = W^{II}(\sigma)$ is strictly increasing for any $\sigma \geq \sigma^*$.

**CRRA quasilinear utility function**

Suppose $\gamma > 1$. The first derivative of the optimal welfare function for $\sigma \geq \sigma^*$, $W^{II}(\sigma)$ is

$$\frac{dW^{II}(\sigma)}{d\sigma} = \frac{1}{\gamma}\psi^{\frac{\gamma-1}{\gamma}}(\overline{w}+\sigma)^{\frac{1-2\gamma}{\gamma}}\left(\frac{\overline{w}-2\sigma^*}{\overline{w}}\right)^{\frac{1-\gamma}{\gamma}} > 0. \tag{2.75}$$

Thus, $W(\sigma) = W^{II}(\sigma)$ is strictly increasing for any $\sigma \geq \sigma^*$.

**[3] The first derivative of** $W(\sigma)$ **is negative for** $\sigma \in (0, \underline{\sigma})$, **0 at** $\underline{\sigma}$, **and positive for** $\sigma > \underline{\sigma}$

**Log quasilinear utility function**

The first derivative of $W^I(\sigma)$ for $\sigma \in [0, \sigma^*]$ is

$$\frac{dW^I}{d\sigma}(\sigma) = b\left(f_1 - f_2\right), \tag{2.76}$$

where

$$b = -\frac{1}{2\left(\overline{w}+\sigma\right)}, \tag{2.77}$$

$$f_1 = \frac{4\sigma}{\overline{w}+\sigma}, \tag{2.78}$$

$$f_2 = -\frac{\overline{w}}{\left(\overline{w}-\sigma\right)}\log\left(\frac{\overline{w}-2\sigma}{\overline{w}}\right). \tag{2.79}$$

We show that $W^I(\sigma) = 0$ only at $\sigma = 0$ (as shown in (2.69)) and unique $\underline{\sigma} \in (0, \sigma^*)$.

First,

$$f_1(0) = f_2(0) = 0. \tag{2.80}$$

Secondly, the first derivative of $f_1$ is greater than $f_2$ at 0,

$$\frac{df_1(0)}{d\sigma} - \frac{df_2(0)}{d\sigma} = \frac{2}{\overline{w}} > 0. \tag{2.81}$$

Thirdly, the second derivative of $f_1$ is strictly negative,

$$\frac{d^2 f_1(\sigma)}{d\sigma^2} = -\frac{8\overline{w}}{(\overline{w}+\sigma)^3} < 0, \tag{2.82}$$

and the second derivative of $f_2$ is strictly positive,

$$\frac{d^2 f_2(\sigma)}{d\sigma} = -\frac{2\overline{w}}{(\overline{w}-\sigma)^2}\left[\frac{\log\left(\frac{1-2\sigma}{\overline{w}}\right)}{\overline{w}-\sigma} - \frac{1}{\overline{w}-2\sigma} + \frac{4\sigma-3\overline{w}}{(\overline{w}-2\sigma)^2}\right] > 0, \text{ for } \sigma < \frac{\overline{w}}{2}. \tag{2.83}$$

Lastly,

$$f_1\left(\frac{\overline{w}}{2}\right) = \frac{4}{3}, \text{ and } \lim_{\sigma \to \frac{\overline{w}}{2}} f_2\left(\frac{\overline{w}}{2}\right) = +\infty. \tag{2.84}$$

Thus, $f_1$ and $f_2$ intersect only once between the range $\left(0, \frac{\overline{w}}{2}\right)$ at $\underline{\sigma}$, where $f_1(\underline{\sigma}) = f_2(\underline{\sigma})$, or equivalently, $W^I(\underline{\sigma}) = 0$. As (2.81) to (2.84) show, $W^I(\sigma)$ is strictly decreasing for $\sigma \in (0, \underline{\sigma})$ and strictly increasing for $\sigma > \underline{\sigma}$. Since $W(\sigma^*) > 0$, $\underline{\sigma} < \sigma^* < \frac{\overline{w}}{2}$.

**CRRA quasilinear utility function**

Suppose $\gamma > 1$. The first derivative of $W^I(\sigma)$ for $\sigma \in [0, \sigma^*]$ is

$$\frac{dW^I}{d\sigma}(\sigma) = b\left(f_1 - f_2\right), \tag{2.85}$$

where

$$b = \frac{1}{2}\frac{\gamma\overline{w}}{1-\gamma}\psi^{\frac{\gamma-1}{\gamma}}\frac{\left(\overline{w}+\sigma\right)^{\frac{1-2\gamma}{\gamma}}}{\left(\overline{w}-\sigma\right)^2}, \tag{2.86}$$

$$f_1 = \frac{\frac{\overline{w}}{\gamma} + \left(2 - \frac{1}{\gamma}\right)\sigma}{\overline{w}+\sigma}\left(1 + \left(\frac{\overline{w}-2\sigma}{\overline{w}}\right)^{\frac{1}{\gamma}}\right), \tag{2.87}$$

$$f_2 = \frac{2}{\gamma\overline{w}}\left(\overline{w}-\sigma\right)\left(\frac{\overline{w}-2\sigma}{\overline{w}}\right)^{\frac{1-\gamma}{\gamma}}. \tag{2.88}$$

We show that $W^I(\sigma) = 0$ only at $\sigma = 0$ (as shown in (2.72)) and unique $\underline{\sigma} \in (0, \sigma^*)$. First,

$$f_1(0) = f_2(0) = \frac{2}{\gamma}. \tag{2.89}$$

Secondly, the first derivative of $f_1$ is greater than $f_2$ at 0,

$$\frac{df_1(0)}{d\sigma} - \frac{df_2(0)}{d\sigma} = \frac{2}{\overline{w}}\left(\frac{1}{\gamma} - 2\right)\left(\frac{1}{\gamma} - 1\right) > 0. \tag{2.90}$$

Thirdly, the second derivative of $f_1$ is strictly negative,

$$\frac{d^2 f_1(\sigma)}{d\sigma^2} < 0,^{9} \tag{2.91}$$

---

9 $\frac{d^2 f_1}{d\sigma^2} = a * (A + B - C) - b\left(D + E\right)$, where $a = \frac{\overline{w}}{\phi} + \left(2 - \frac{1}{\phi}\right)\sigma\frac{2}{\phi\overline{w}^2\left(\overline{w}+\sigma\right)^3}$, $b = \frac{2\left(2-\frac{1}{\phi}\right)}{\phi\overline{w}\left(\overline{w}+\sigma\right)^2}$, $A = \phi\overline{w}^2\left(1 + \left(\frac{\overline{w}+2\sigma}{\overline{w}}\right)^{\frac{1}{\phi}}\right)$, $B = 2\overline{w}\left(\overline{w}+\sigma\right)\left(\frac{\overline{w}-2\sigma}{\overline{w}}\right)^{\frac{1-\phi}{\phi}}$, $C = -2\left(\overline{w}+\sigma\right)^2\left(-1 + \frac{1}{\phi}\right)\left(\frac{\overline{w}-2\sigma}{\overline{w}}\right)^{\frac{1-2\phi}{\phi}}$, $D = \phi\overline{w}\left(1 + \left(\frac{\overline{w}-2\sigma}{\overline{w}}\right)^{\frac{1}{\phi}}\right)$, $E = 2\left(\overline{w}+\sigma\right)\left(\frac{\overline{w}-2\sigma}{\overline{w}}\right)^{\frac{1-\phi}{\phi}}$, and all are positve. Since $bD > aA$ and $bE > aB$ for $\phi > 1$, $\frac{d^2 f_1}{d\sigma^2} < -aC < 0$.

and the second derivative of $f_2$ is strictly positive,

$$\frac{d^2 f_2(\sigma)}{d\sigma} => 0, \text{ for } \sigma < \frac{\overline{w}}{2}. \tag{2.92}$$

Lastly,

$$f_1\left(\frac{\overline{w}}{2}\right) = \frac{2}{3}\left(\frac{2\gamma+1}{2\gamma}\right), \text{ and } \lim_{\sigma \to \frac{\overline{w}}{2}} f_2\left(\frac{\overline{w}}{2}\right) = +\infty. \tag{2.93}$$

Thus, $f_1$ and $f_2$ intersect only once between the range $\left(0, \frac{\overline{w}}{2}\right)$ at $\underline{\sigma}$, where $f_1(\sigma) = f_2(\sigma)$, or equivalently, $W^I(\sigma) = 0$. As (2.90) to (2.93) show, $W^I(\sigma)$ is strictly decreasing for $\sigma \in (0, \underline{\sigma})$ and strictly increasing for $\sigma > \underline{\sigma}$. Since $W(\sigma^*) > 0$, $\underline{\sigma} < \sigma^* < \frac{\overline{w}}{2}$.

### 2.A.4 Selection of $T$

The persistence of the individual labor income is well documented in the literature (e.g., Aiyagari 1994; Storesletten, et al. 2004; Guvenen 2007), while in this study we consider the model with only transitory shocks on labor productivity. In order to replicate the persistence of the labor income with a model with i.i.d. shocks, we select the number of years corresponds to one model period so that the model has approximately the same degree of persistence as in a model with persistent shocks.

We first describe a model with persistent shocks. Take the following AR(1) process for earnings:

$$\begin{aligned} y_{i,t} &= \rho y_{i,t-1} + u_{i,t}, \\ & u_{i,t} \sim N(0, \sigma_u^2), \end{aligned} \tag{2.94}$$

where $\rho = 0.9$. Assume that an agent starts the working life at age 25 and retires on his 60th birthday. It implies that $T = 35$, given that one model period corresponds to one year. The annual gross interest rate $R$ is 1.05. Compute the ratio $\Psi$ of (i) the cross-sectional variance of the present value of lifetime earnings $Var\left(\sum_{t=1}^{35} y_{it}/R^{t-1}\right)$

to (ii) the mean of the cross-sectional variance of current earnings $E\left(Var\left(y_{i,t}\right)\right)$. The ratio $\Psi$ can be interpreted as a measure of the persistence of the income process; the more persistent the income process is, the higher the ratio $\Psi$ is. We simulate the $AR(1)$ process using a random number generator and obtain a series of 10000 draws, taking $y_{i,0}$ from the normal distribution $N(0, \sigma_y^2)$ where $\sigma_y^2 = \frac{\sigma_u^2}{1-\rho^2}$.

Now we take a model in which shocks on earnings are i.i.d. across periods:

$$y_{i,t} \sim N(0, \sigma_y^2). \tag{2.95}$$

Assume that the number of model periods is $T$. Thus, each period is $35/T$ years and the gross interest rate per period is $R_{iid} = R^{35/T}$. Compute the same statistic $\Psi$ as described above, with the i.i.d. process. That is,

$$\begin{aligned} \Psi_{iid}(T) &= \frac{Var\left(\sum_t y_{it}/R_{iid}^{t-1}\right)}{E\left(Var(y_{it})\right)} \\ &= \frac{\left(\sum_{t=1}^{T} \frac{1}{R_{iid}^{2(t-1)}}\right)}{\left(\sum_{t=1}^{T} \frac{1}{R_{iid}^{t-1}}\right)^2}. \end{aligned} \tag{2.96}$$

Table 2.2 summarizes the results. The value for $T$ which comes closest to equating the two statistics $\Psi_{AR(1)}$ and $\Psi_{iid}(T)$ is $T = 3$.

| | $AR(1)$ | *i.i.d.* $T=2$ | $T=3$ | $T=4$ |
|---|---|---|---|---|
| $\Psi$ | 0.39 | 0.58 | 0.40 | 0.30 |

Table 2.2: $\Psi$, the ratio of the cross-sectional variance of the present value of lifetime earnings to the cross-sectional variance of current earnings

# Chapter 3

## The Growth Aftermath of Natural Disasters

(with Thomas B. Fomby[1] and Norman V. Loayza[2])[3]

### 3.1 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, Jaramillo (2007) and Loayza et al. (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.[4] For instance,

[1]Southern Methodist University, Dallas, TX, USA

[2]World Bank, Washington, DC, USA

[3]This chapter is forthcoming in Journal of Applied Econometrics.

[4]There are some important studies focusing on the long-run effects of natural disasters. Among others, Skidmore and Toya (2002) investigate the long-term macroeconomic impacts of natural disasters using the average growth rates over 1960-1990.

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.[5]

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 of the present study 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 84 countries representing all major regions of the world and 48 years covering the period 1960-2007.

A methodological contribution of the paper is the application of a re-sampling estimator to control for unobserved fixed effects in the context of a dynamic panel data model. As pointed out by Nickell (1981), the within or least-squares dummy variable (LSDV) estimator is inconsistent in dynamic panels when the time series dimension is small, even if the number of cross-sectional units (countries, in our case) goes to infinity. In order to obtain a bias correction of the LSDV estimator, we use a bootstrap algorithm, originally proposed by Pesaran and Zhao (1999) and Everaert and Pozzi (2007). In order to apply their bootstrap correction to the VARX model with unbalanced panel, we implement some necessary modifications.[6]

Third, the paper considers the difference between advanced and developing countries. Some key papers in this literature have noted that although the impact of

[5] In a methodologically similar exercise, Ramey and Shapiro (1998) estimated the effect of military shocks on macroeconomic variables. However, while they use a univariate autoregressive model to obtain reduced-form effects of shocks, we take into account multiple endogenous variables in a panel-VARX context.

[6] The adapted algorithm is outlined in the Appendix and its MATLAB code is available in the Journal of Applied Econometrics Data Archive.

natural disasters is not the same across countries, it is not randomly heterogeneous either. Especially, Rasmussen (2004), Toya and Skidmore (2007), and Noy (2009) document that 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 separately for developing countries (60) and advanced countries (24).

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, for instance, raising land productivity or inducing capital transformation. However, if the disaster is of such magnitude that it overwhelms public and private responses, its effect is likely to be more detrimental.

There is a robust and growing literature on the economic effects of natural disasters. Three recent papers are, however, the most closely connected with this study. The first is Loayza et al. (2009). That paper is similar to the current one in that both take advantage of disaggregation by type of disaster, sector of economic activity, and level of economic development. 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 (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'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 is 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 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. He also 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.

The outline of the paper is the following. Section 3.2 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. It also introduces the econometric methodology, including an exposition of the VARX method, and corresponding specification tests. Section 3.3 presents the basic results, discussing and contrasting the effects of droughts, floods, earthquakes, and storms, focusing mostly on the sample of developing countries. Section 3.4 offers some concluding remarks.

## 3.2 Data and Methodology

### 3.2.1 Data

We use annual panel data for 84 countries over the period 1960-2007. The panel is unbalanced. We split the panel into two groups: developing countries and developed countries, classifying 60 countries into the first group and the other 24 counties into the second group. Table A-I in the Supplement of the paper (available online at the Journal of Applied Econometrics homepage) gives the list of countries of these groups.

The data on natural disasters are obtained from the Emergency Disasters Database (EM-DAT), maintained by the Centre for Research on the Epidemiology of Disasters (CRED). For a disaster to be entered into EM-DAT, at least one of the following criteria must be fulfilled: 10 or more people reported killed; 100 or more people reported affected; declaration of a state of emergency; and call for international assistance. The database describes the dates and the types of natural disasters (e.g., drought, flood, etc.). For each disaster event, the number of fatalities (persons confirmed as dead, missing, and presumed dead), the number of people injured, needing immediate assistance for shelter (referred to "homeless"), and affected are reported. People affected are those requiring immediate assistance during a period of emergency. For our purposes, people reported injured or homeless are aggregated with those affected to produce the total number of people affected (referred to "total affected").

As mentioned in the introduction, we study four types of natural disasters: droughts, floods, earthquakes, and storms. The measure of the intensity of natural disasters used in the paper, $ND'_{i,t} = (drought_{i,t}, flood_{i,t}, earthquake_{i,t}, storm_{i,t})$, is given by:

$$ND_{i,t}(k) = \sum_{j=1}^{J} intensity_{i,t,j}^{k}, \tag{3.1}$$

where

$$\begin{aligned} intensity_{i,t,j}^{k} &= 1, \text{ if } \frac{fatalities_{i,t,j}^{k} + 0.3 * total\ affected_{i,t,j}^{k}}{population_{i,t}} > 0.0001, \\ &= 0, \text{ otherwise} \end{aligned} \tag{3.2}$$

and $J$ indicates 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 the intensity measure was created. First, for each event of type-$k$ disaster, we create a dummy variable $intensity_{i,t,j}^{k}$ measuring the magnitude of the event relative to the size of the economy such that the variable takes 1 if the sum of the number of fatalities $\left(fatalities_{i,t,j}^{k}\right)$ and 30% of the total number of people affected $\left(total\ affected_{i,t,j}^{k}\right)$ is greater than 0.01% of the population and 0 otherwise (equation 3.2). Then, for each type of disaster, the dummy variables are summed up to obtain the discrete value $ND_{i,t}(k)$ to assess the total magnitude of type-$k$ disasters for country $i$ and year $t$ (equation 3.1). This intensity measure is similar to the one established by the International Monetary Fund (IMF, 2003), and used by Becker and Mauro (2006). In Section 3.3.2, we check for the robustness of the benchmark results with respect to alternative measurements of the intensity of natural disasters.

Many practitioners point out that the impact of moderate disasters and extremely severe disasters on the economic performance differs, not only in their magnitude, but also in their dynamic characteristics. To capture the particular effects of severe disasters, we construct the measure of severity, $sevND_{i,t}^{\prime} = (sev\ drought_{i,t}, sev\ flood_{i,t}, sev\ earthquake_{i,t}, sev\ storm_{i,t})$, as follows:

$$sevND_{i,t}(k) = \sum_{j=1}^{J} sev\ intensity_{i,t,j}^{k} \tag{3.3}$$

where

$$\begin{aligned} sev\ intensity_{i,t,j}^{k} &= 1, \ \text{if}\ \frac{fatalities_{i,t,j}^{k} + 0.3 * total\ affected_{i,t,j}^{k}}{population_{i,t}} > 0.01, \quad (3.4) \\ &= 0, \ \text{otherwise} \end{aligned}$$

Here, for the dummy variable for the intensity of individual severe disaster, , we set the threshold at 1% of the population, while we apply 0.01% for general or moderate disasters. In Section 3.1, the results of two models are presented: (i) the model which includes only the variables measuring the intensity of disasters, $ND_{i,t}$, focusing on the general effects of natural disasters, and (ii) the model which includes variables measuring the severity of disasters, $sev\ ND_{i,t}$, besides the measure of intensity, $ND_{i,t}$, in order to distinguish the effects of moderate and severe disasters.

Data on macroeconomic variables are obtained from the World Development Indicators of the World Bank (2009). The variables and sources are presented in Supplement Table A-II. To capture possible heterogeneous impacts of natural disasters on different sectors of the economy, three types of growth variables are considered as dependent variables: the growth rate of real per capita Gross Domestic Product (GDP), and 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 real output,[7] and per capita output is obtained by dividing the value added of each sector by the total population. Supplement Tables A-III and A-IV summarize the main characteristics of these variables. As described in Supplement Table A-III, the growth performance greatly varies across the sectors. During the period 1960-2007, the non-agricultural sector has had much higher average growth rate (1.8% in developing countries and 2.2% in developed countries) than the agricultural sector (0.4% in developing countries and 0.7% in developed countries). Also, Supplement Table A-IV shows that the correlation between the growth rate of non-agricultural sector and that of agricultural sector is rather low (0.085 in developing countries and 0.060 in developed countries). The considerable disparities among the growth performances suggest the possibility that natural disasters have diverse effects on the different sectors of the economy.

Besides the natural disaster variables, two groups of growth determinants are considered: variables that represent domestic conditions and policies, and variables that proxy the role of external conditions. Similar to the growth specifications by Levine, Loayza, and Beck (2000) and Dollar and Kraay (2002), inflation, trade openness, government consumption, and financial depth are considered as major growth determinants. In addition, the investment rate is included as in Mankiw, Romer, and Weil (1992). The second group of growth determinants represents the role of external conditions that may affect the growth performance across countries; we use shocks to the terms of trade which are measured by the growth rate of export prices relative to import prices, and the growth rate of the world's GDP per capita. The idea is

[7] For the stationarity of these variables, see Section 3.2.3.

to capture interactions among countries, shifts in the world business cycle, and the demand for a country's exports. These variables are assumed to be exogenous.[8]

### 3.2.2 Econometric Methodology

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

$$\mathbf{y}_{i,t} = \boldsymbol{\alpha}_i + \Phi_1\mathbf{y}_{i,t-1} + \Phi_2\mathbf{y}_{i,t-2} + \Theta_0\mathbf{x}_{i,t} + \Theta_1\mathbf{x}_{i,t-1} + \Theta_2\mathbf{x}_{i,t-2} + \boldsymbol{\varepsilon}_{i,t} \tag{3.5}$$

where the country index is i = 1, 2, . . . , $N$, and the time index for country $i$ is $t$ = -1, 0, 1, . . . , $T_i$.[9] The model is applied to two different groups of countries: developing countries and developed countries. The fixed effect for each country is represented by $\alpha_i$. Hereafter, the total number of usable observations in the panel is denoted by $T = \sum_{i=1}^{N} T_i$. The $6 \times 1$ endogenous variables vector $\mathbf{y}_{i,t}$ represents (i) the growth rate of fixed capital formation (as share of GDP), (ii) the consumer price index (CPI) inflation rate, (iii) the growth rate of trade openness, (iv) the growth rate of government consumption expenditure (as share of GDP), (v) the growth rate of financial depth, and (vi) any one of the growth rates of real GDP per capita, real agricultural value added per capita, and real non-agricultural value added per capita, that is,

$$\mathbf{y}_{i,t} = \begin{bmatrix} Capital\ formation_{i,t} \\ Inflation_{i,t} \\ Trade\ openness_{i,t} \\ Government\ consumption_{i,t} \\ Financial\ depth_{i,t} \\ GDP/Agr./Non\text{-}agr.growth_{i,t} \end{bmatrix}.$$

[8]For the exogeneity of the regressors, see Section 3.3.2.

[9]For the lag structure of the model, see Section 3.2.3.

The $6 \times 1$ exogenous variables vector $\mathbf{x}_{i,t}$ denotes (i) – (iv) the four types of disaster variables, respectively, drought, flood, earthquake, and storm, defined in the previous sub-section, (v) the growth rate of terms of trade index, and (vi) the growth rate of the world's real GDP per capita, that is,

$$\mathbf{x}_{i,t} = \begin{bmatrix} Drought_{i,t} \\ Flood_{i,t} \\ Earthquake_{i,t} \\ Storm_{i,t} \\ TOT_{i,t} \\ World\ growth_{i,t} \end{bmatrix}.$$

In equation (3.5) we assume a homogenous error structure $E(\boldsymbol{\varepsilon}_{i,t}\boldsymbol{\varepsilon}_{i,t}^{'}) = \Omega$ for all $i$ and $t$ where is the vector of errors of the system. Furthermore, we assume independence of the errors within equations, $E(\boldsymbol{\varepsilon}_{i,s}\boldsymbol{\varepsilon}_{i,t}^{'}) = 0$, $s \neq t$, and across equations, $E(\boldsymbol{\varepsilon}_{i,s}\boldsymbol{\varepsilon}_{j,t}^{'}) = 0$, for any $s$ and $t$ where $i \neq j$.

As mentioned above, the dependent variables on which we focus our attention are output growth rates. These are likely to be affected not only by domestic conditions and natural disasters but also by global factors. In turn, since global factors can also affect the other endogenous variables (such as investment and inflation) omitting them can lead to serious estimation bias (see Forni and Reichlin 1998). To control for the effect of global shocks, we include World GDP growth and TOT growth in the set of exogenous explanatory variables. The first is common across countries, and it is assumed to affect all countries homogeneously. By itself, this does not eliminate the bias if there is more than one global factor or its effect is heterogeneous across countries (Giannone and Lenza 2010). For this reason, we also include TOT growth as a control variable. This varies from country to country, reflecting how country-specific characteristics (e.g., oil exporter or importer) determine the way global factors (e.g., oil prices) affect domestic economic growth and the other endogenous variables. Naturally, it is still possible that some remaining bias lingers on. However, it would have to be quite strong to affect the coefficients of natural disaster variables, which at least in principle are exogenous.

After controlling for country fixed effects, the multiplier form of the model can be written more compactly by inverting equation (3.5) as follows,

$$\mathbf{y}_{i,t} = \Phi(L)^{-1}\Theta(L)\mathbf{x}_{i,t} + \Phi(L)^{-1}\boldsymbol{\varepsilon}_{i,t} \tag{3.6}$$

where $L$ denotes the usual lag operator.[10] The mean responses from the occurrences of natural disasters are therefore captured by the lag polynomial,

$$\Psi(L) = \Phi(L)^{-1}\Theta(L). \tag{3.7}$$

As pointed out by Nickell (1981), given that the model is dynamic, if $T_i$ is small and fixed, the within (fixed-effects) estimator or least-squares dummy variable (LSDV) estimator is inconsistent, even if the number of countries, N, goes to infinity. (The bias, however, decreases as $T_i$ grows.) In order to obtain a bias correction of the LSDV estimator, we use a bootstrap algorithm, which is proposed by Pesaran and Zhao (1999) and Everaert and Pozzi (2007).[11] In order to apply their bootstrap correction in simulations to the VARX model with unbalanced panel, some modifications are required. The procedure of obtaining the bootstrap bias-corrected (BSBC) estimator is outlined in the Appendix.

[10] To ensure that (3.6) produces a steady state, we require that all of the roots of the determinant equation $|\Phi(L)| = \left|(\mathbf{I}-\Phi_1 L-\Phi_2 L^2)\right| = 0$ lie outside the unit circle. This is indeed the case.

[11] Pesaran and Zhao (1999) point out that the bias of the LSDV estimator of the mean responses is generally smaller than that of the underlying short-run coefficients $(\Phi(L), \Theta(L)$ in our model).

The use of the bootstrap is appealing compared to analytical bias corrections in several respects. First, models are not constrained by theoretical assumptions. Especially in higher order dynamic models like ours, a bootstrap approach is easier than deriving an analytical correction. Second, the bias correction of the mean responses, which is our main focus, can be obtained in a more direct way with a bootstrap approach compared to the analytical correction based on the bias-corrected estimators of the short-run coefficients.[12]

### 3.2.3 Diagnostic Tests

#### 3.2.3.1 Individual and panel unit root tests

The VARX model presented in the previous sub-section is dependent on the assumption of stationarity of the variables. Before we can proceed to estimate a VARX panel model for analyzing the effects of natural disasters on the growth variables, we need to determine the stationary forms of the variables we are going to be using in our analysis. In this study we choose as the variables of interest: (i) real GDP per capita, (ii) real agricultural value added per capita, (iii) real non-agricultural value added per capita, (iv) fixed capital formation (as share of GDP), (v) consumer price index (CPI), (vi) trade openness, (vii) government consumption expenditure (as share of GDP), (viii) financial depth, (ix) terms of trade index, and (x) the world's real GDP per capita. We use the log transformation of these 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 straightforward interpretation of the differenced data, namely percentage change or growth rate.

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

We proceed to pursue unit root testing in two ways. First we conduct series-by-series unit root tests; the augmented Dickey-Fuller (ADF) test and the Phillips-Perron (PP) test are of this form. Then the panel unit root tests with individual country effects are implemented, as in the Levin-Lin-Chu (2002) and Im-Pesaran-Shin (2003) panel unit root testing frameworks. These unit root tests are dependent on the specification of the deterministic parts of the unit root test equations. 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 test the significance of the trend in the above ten series by testing the significance of the intercept in the following AR(2) equation of the variable in question, country-by-country:

$$\Delta z_{i,t} = \alpha_i + \phi_i z_{i,t-1} + \beta_i \Delta z_{i,t-1} + \varepsilon_{i,t}. \tag{3.8}$$

In equation (3.8) $z_{i,t}$ represents a particular country's logged variable in question and $\Delta$ represents the first-difference operator. We specify 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 would be appropriate for testing for the presence or absence of trend. In the case that the null hypothesis $H_0 : \alpha_i = 0$ is supported, we conclude that the data does not have a time trend. As shown in Table 3.1, with respect to the log of fixed capital formation, the log of CPI, and the log of government consumption expenditure, the preponderance of tests indicates that a trend is present. Also for the log of the world's real GDP per capita, the null hypothesis is rejected. Thus, for the production run of unit root tests, we treat the series of these four variables as having trends. In contrast, for the rest of the variables, the preponderance of tests indicates that a trend is absent, so we treat them accordingly. Consistent with these tests we use an intercept and deterministic trend for the series with trends in the series-by-series tests, while we use only an intercept for the series without trends.

**Table 3.1: Unit root tests**

| With coutnry-specific intercept | GDP | Agr. | Non-agr. | Trade openness | Financial depth | TOT |
|---|---|---|---|---|---|---|
| **Fraction of countries w/o significant trend**[*1] | | | | | | |
| | 45/78 | 40/76 | 42/76 | 48/78 | 53/78 | 72/78 |
| **A. Tests for Series in levels** | | | | | | |
| I. Fraction of countries that reject UR in ADF test | | | | | | |
| | 5/78 | 4/76 | 6/76 | 8/78 | 3/78 | 14/78 |
| II. Fraction of countries that reject UR in PP test | | | | | | |
| | 8/78 | 14/76 | 10/76 | 10/78 | 8/78 | 17/78 |
| III. P-values of Levin-Lin-Chu test | | | | | | |
| | 0.0040 | 0.0096 | 0.1552 | 0.6260 | 0.3938 | 0.0858 |
| IV. P-values of Im-Pesaran-Shin test | | | | | | |
| | 0.9999 | 0.9379 | 1.0000 | 0.9728 | 0.9996 | 0.0341 |
| **B. Tests for Series in Differences** | | | | | | |
| I. Fraction of countries that reject UR in ADF test | | | | | | |
| | 37/78 | 45/76 | 38/76 | 57/78 | 51/78 | 61/78 |
| II. Fraction of countries that reject UR in PP test | | | | | | |
| | 75/78 | 76/76 | 70/76 | 78/78 | 78/78 | 78/78 |
| III. P-values of Levin-Lin-Chu test | | | | | | |
| | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |

| With coutnry-specific intercept and country-specific trend | Capital formation | CPI | Gov't consump. | World GDP |
|---|---|---|---|---|
| **Fraction of countries with significant trend**[*1] | | | | |
| | 61/78 | 55/78 | 53/78 | 1/1 |
| **A. Tests for Series in levels** | | | | |
| I. Fraction of countries that reject UR in ADF test | | | | I. P-value of ADF test |
| | 4/78 | 6/78 | 10/78 | 0.0995 |
| II. Fraction of countries that reject UR in PP test | | | | II. P-value of PP test |
| | 7/78 | 3/78 | 14/78 | 0.1263 |
| III. P-values of Levin-Lin-Chu test | | | | |
| | 1.0000 | 0.0006 | 0.0125 | |
| IV. P-values of Im-Pesaran-Shin test | | | | |
| | 0.8740 | 0.9989 | 0.5316 | |
| **B. Tests for Series in Differences** | | | | |
| I. Fraction of countries that reject UR in ADF test | | | | I. P-value of ADF test |
| | 65/78 | 24/78 | 70/78 | 0.0037 |
| II. Fraction of countries that reject UR in PP test | | | | II. P-value of PP test |
| | 76/78 | 38/78 | 78/78 | 0.0055 |
| III. P-values of Levin-Lin-Chu test | | | | |
| | 0.0000 | 0.0000 | 0.0000 | |
| IV. P-values of Im-Pesaran-Shin test | | | | |
| | 0.0000 | 0.0000 | 0.0000 | |

*Note*: Countries with observations more than or equal to 20 are counted.
[*1] the significance level is at 10 percent.

In contrast to the individual 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. Consider the basic ADF specification:

$$\Delta z_{i,t} = \alpha_i + \phi_i z_{i,t-1} + \sum_{j=1}^{p_i} \beta_{i,j} \Delta z_{i,t-j} + \varepsilon_{i,t}. \tag{3.9}$$

Both in the Levin-Lin-Chu (LLC) test and in the Im-Pesaran-Shin (IPS) test, the null hypothesis states that all series have a unit root:

$$H_0 : \phi_i = 0, \text{ for all } i.$$

The LLC test assumes that there is a common unit root process identical across countries, thus the alternative hypothesis can be written as

$$H_1 : \phi_i = \phi < 0. \tag{3.10}$$

For the IPS test a more general alternative is used, which allows individual unit root processes $\phi_i$ to vary across countries, i.e.,

$$H_1 : \phi_i < 0, \text{ for at least one country } i. \tag{3.11}$$

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 ten series are summarized in Table 3.1.[13] The left half of the table pertains to unit root tests of the non-trending series while the right half of the table pertains to the unit root tests of the trending series. 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.[14]

The results reported in Table 3.1 are summarized as follows:

[13] All of the results reported in Table 3.1 were produced by EViews 5.0.

[14] Note that, in the case of the first difference of the non-trending data, the Im-Pesaran-Shin test is not reported as EViews 5.0 does not accomodate the zero mean case.

- Log of real non-agricultural value added per capita, trade openness, financial depth, capital formation, the world's real GDP per capita: The preponderance of the individual unit root tests of these variables indicates the presence of unit roots. The panel unit root tests likewise indicate the presence of unit roots. After first differencing the series seem to be stationary.

- Log of real GDP per capita, real agricultural value added per capita, CPI, government consumption expenditure: The preponderance of the individual unit root tests of these variables indicates the presence of unit roots. Regarding the panel unit root tests, the LLC test rejects the null hypothesis of a unit root. In contrast, the IPS test clearly fails to reject the null. Considering these results together, unit roots seem to be present in these series. The first differenced series appear to be stationary.

- Log of Terms of Trade: The results for this series are similar to those of the previous series. In this case, however, the IPS test rejects the null hypothesis of a unit root, while the LLC test indicates a unit root at the 5% level. As it shows, the log of terms of trade is "near" stationary. Despite this split decision on the existence of a unit root we decide to treat this series as having a unit root and to model its differences as being stationary.

In summary, the test results of Table 3.1 indicate that, when building meaningful VARX panel models to examine the impacts of various natural disasters, the growth rate forms of the variables should be used.

#### 3.2.3.2 Lag Structure

Before estimating the panel VARX model, we need one more crucial piece of information. That is the number of lags to include for each variable in the model. To identify the lag structure, we employ two well-known criteria: Akaike's information criterion (AIC) and Schwarz's Bayesian information criterion (SBC).

Table 3.2 shows the AIC and SBC statistics for the benchmark models with three different growth variables (GDP growth, agricultural growth, and non-agricultural growth) and two different groups of countries (developing countries and developed 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 $p = q = 3$, and one result suggests $p = q = 2$. 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, taking the middle between the AIC and SBC statistics. On the one hand, it is desirable to have a parsimonious model to keep the size of the matrix manageable for the bootstrap procedure. On the other hand, the higher lag length provides 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, we believe that it is reasonable to select the lag length 2. We apply this lag structure to all of our models homogenously to simplify the interpretation.

**Table 3.2: Lag structure selection**

| | | Number of lags | | |
|---|---|---|---|---|
| | | $p = q = 1$ | $p = q = 2$ | $p = q = 3$ |
| **Developing countries** | | | | |
| GDP growth | AIC | -10.1693 | -10.2231 | **-10.2521** |
| | SBC | **-9.8491** | -9.6895 | -9.5051 |
| Agr. growth | AIC | -9.2183 | **-9.2935** | -9.2738 |
| | SBC | **-8.8633** | -8.7017 | -8.4453 |
| Non-agr. growth | AIC | -10.4316 | -10.5031 | **-10.5191** |
| | SBC | **-10.0750** | -9.9087 | -9.6869 |
| **Developed countries** | | | | |
| GDP growth | AIC | -21.6669 | -21.7556 | **-21.8074** |
| | SBC | **-21.0185** | -20.6749 | -20.2944 |
| Agr. growth | AIC | -18.7248 | -18.7506 | **-18.7957** |
| | SBC | **-17.9940** | -17.5326 | -17.0906 |
| Non-agr. growth | AIC | -21.6535 | -21.7171 | **-21.8170** |
| | SBC | **-20.9227** | -20.4991 | -20.1118 |

*Note*: Bold figures indicate the minimum AIC / SBC.

## 3.3 Results

### 3.3.1 Benchmark 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 dynamic effects on GDP per capita growth and its major components, agricultural and non-agricultural per capita value-added growth. We estimate these effects separately for the samples of developed and developing countries. Then, we focus on the sample of developing countries (for which the effects are stronger), considering the differing impact of moderate and severe natural disasters and various robustness checks.

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. As explained in the methodological section, these mean responses result from combining the conditional effects of natural disaster on growth with growth's own autoregressive process (see equation 3.6). Since the effects are small and non-significant a few years after the event, in the tables 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 procedure 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 Tables 3.3 - 3.5. 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 3.1-3.4). They show the mean responses for a more extended period of time, from years 0 to 6 of the aftermath of the event. As a complement, in Supplement Figures C-1 to C-4 we present the cumulative mean responses, and corresponding confidence bands, per type of disaster and production level.

#### 3.3.1.1 Droughts

In developing countries, droughts have an overall negative effect on economic growth (see Table 3.3, first panel, and Figure 3.1). The effect is significantly negative for aggregate GDP growth as well as for both types of sectoral growth, with stronger effects for agricultural than for non-agricultural growth on the year of the drought. Specifically, the mean response of agricultural growth to droughts is deeply negative on the year of the event, but a significant recovery occurs on the following year. The cumulative effect, nonetheless, remains significantly negative (see also Supplement Figure C-1).

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 this case, there is no sign of recovery but a build-up of negative responses. In the sample of developing countries, the cumulative negative response to droughts is about 2 percentage points for GDP growth and slightly less for each agricultural and non-agricultural growth.

In advanced countries, there is also a significantly negative response on the year of the drought but it only applies to agricultural growth (see Table 3.4, first panel). Furthermore, in the subsequent years agricultural growth fluctuates and recovers so substantially that the cumulative effect of droughts for advanced countries is essentially zero.

Let's turn to the analysis of severe vs. moderate cases (see Table 3.5, first panel). On the year of the event, the mean response of GDP, agricultural, and non-agricultural growth to severe droughts is significantly more negative than the response to moderate droughts. In fact, in year 0 severe droughts have twice the negative impact on GDP growth and more than three times the impact on agricultural growth than moderate droughts do. Furthermore, severe droughts induce larger volatility of growth: while they produce a larger drop the year of the event, they also induce 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 less negative than that of moderate droughts, although not significantly. In the case of agricultural growth, the recovery is insufficient and concentrated only on the year after the drought; so that the cumulative impact of severe droughts is more negative than that of moderate ones, albeit not statistically significantly. For non-agricultural growth, severe droughts do not appear to have different effects than moderate droughts do.

**Table 3.3: Mean responses of the growth rates of each sector to natural disaster shocks [BSBC estimator]**

Sample: Developing countries

| *Endogenous variables* | *Exogenous variables* |
|---|---|
| Capital formation | 4 natural disaster variables |
| Inflation | Terms of trade |
| Trade openness | World growth |
| Government consumption | |
| Financial depth | |

| | | Mean responses of | | |
|---|---|---|---|---|
| | | GDP growth | Agr. growth | Non-agr. growth |
| | Year 0 | -0.0160 ** | -0.0349 ** | -0.0076 ** |
| Droughts | Year 1 | -0.0009 | 0.0214 ** | -0.0043 |
| | Year 2 | -0.0034 | -0.0050 | -0.0055 * |
| | Year 3 | -0.0012 | -0.0008 | -0.0024 * |
| | Cumulative effect | -0.0214 ** | -0.0192 ** | -0.0198 ** |
| | Year 0 | 0.0017 | 0.0033 | 0.0008 |
| Floods | Year 1 | 0.0012 | 0.0064 * | 0.0001 |
| | Year 2 | 0.0029 * | -0.0002 | 0.0040 * |
| | Year 3 | 0.0004 | -0.0006 | 0.0012 * |
| | Cumulative effect | 0.0062 * | 0.0090 ** | 0.0061 * |
| | Year 0 | 0.0046 | -0.0008 | 0.0046 |
| Earthquakes | Year 1 | 0.0049 | -0.0020 | 0.0071 * |
| | Year 2 | -0.0038 | -0.0072 | -0.0054 |
| | Year 3 | 0.0011 | 0.0026 | -0.0009 |
| | Cumulative effect | 0.0067 | -0.0074 | 0.0054 |
| | Year 0 | -0.0028 | 0.0021 | -0.0038 |
| Storms | Year 1 | -0.0009 | -0.0048 | 0.0021 |
| | Year 2 | 0.0011 | 0.0062 | 0.0004 |
| | Year 3 | 0.0006 | -0.0008 | 0.0008 |
| | Cumulative effect | -0.0020 | 0.0026 | -0.0005 |
| | Number olf countries | 60 | 60 | 60 |
| | Sample period | 1960-2007 | 1960-2007 | 1960-2007 |
| | Number of observation: | 2097 | 1878 | 1863 |

*Note* : Asterisks (*) indicate statistical significance at the one-tail 10 percent level and (**) 5 percent level.

**Table 3.4: Mean responses of the growth rates of each sector to natural disaster shocks [BSBC estimator]**

Sample: Developed countries

| *Endogenous variables* | *Exogenous variables* |
|---|---|
| Capital formation | 4 natural disaster variables |
| Inflation | Terms of trade |
| Trade openness | World growth |
| Government consumption | |
| Financial depth | |

| | | Mean responses of | | |
|---|---|---|---|---|
| | | GDP growth | Agr. growth | Non-agr. growth |
| Droughts | Year 0 | 0.0102 | -0.0626 ** | 0.0087 |
| | Year 1 | -0.0028 | -0.0151 | -0.0038 |
| | Year 2 | 0.0034 | 0.1035 ** | -0.0025 |
| | Year 3 | 0.0022 | -0.0261 ** | -0.0004 |
| | Cumulative effect | 0.0129 | -0.0004 | 0.0020 |
| Floods | Year 0 | 0.0018 | 0.0056 | 0.0017 |
| | Year 1 | 0.0015 | 0.0074 | 0.0016 |
| | Year 2 | 0.0024 | 0.0121 | -0.0008 |
| | Year 3 | 0.0012 | -0.0037 | 0.0005 |
| | Cumulative effect | 0.0069 | 0.0214 ** | 0.0030 |
| Earthquakes | Year 0 | 0.0003 | 0.0054 | -0.0001 |
| | Year 1 | -0.0044 | -0.0109 | -0.0057 |
| | Year 2 | 0.0030 | 0.0017 | -0.0002 |
| | Year 3 | 0.0024 | 0.0042 | 0.0014 |
| | Cumulative effect | 0.0013 | 0.0004 | -0.0047 |
| Storms | Year 0 | 0.0000 | -0.0044 | 0.0010 |
| | Year 1 | -0.0002 | 0.0093 | -0.0018 |
| | Year 2 | 0.0014 | -0.0150 | 0.0004 |
| | Year 3 | -0.0004 | 0.0024 | -0.0007 |
| | Cumulative effect | 0.0008 | -0.0077 | -0.0011 |
| | Number olf countries | 24 | 24 | 24 |
| | Sample period | 1960-2007 | 1960-2007 | 1960-2007 |
| | Number of observation | 853 | 740 | 740 |

*Note*: Asterisks (*) indicate statistical significance at the one-tail 10 percent level and (**) 5 percent level.

#### 3.3.1.2 Floods

In contrast to droughts, floods tend to have a positive effect on economic growth in developing countries (see Table 3.3, second panel, and Figure 3.2). The response of agricultural growth is significantly positive in year 1 but not the same year of the event. This may indicate that the potentially beneficial impact of floods on land productivity emerges in the subsequent harvesting cycle.

The mean response of GDP growth is significantly positive one year later than for agricultural growth, in year 2 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 manufacturing (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). Regarding the cumulative mean response to floods (see also Supplement Figure C-2), it is fifty percent larger for agricultural growth (0.9 percentage points) than for either GDP or non-agricultural growth (0.6 pp).

For developed countries, only agricultural growth is significantly affected by floods (see Table 3.4, second panel). This positive effect is not statistically significant in any specific year but builds over time in the aftermath of the flood. The mean responses in years 0 to 2 are consistently positive and sufficiently large to render a statistically significant cumulative effect of floods on agricultural growth.

Regarding the comparison between moderate and severe floods (see Table 3.5, second panel), the annual mean responses indicate that the significantly positive effects observed above come mainly from moderate floods. Severe floods do not add to the positive effect of moderate ones. On the contrary, although the difference in mean responses between moderate and severe floods is not statistically significant, the additional impact of severe floods is sufficiently noisy to render them statistically ineffectual for GDP, agricultural and non-agricultural growth. This is always the case for the annual mean responses in the aftermath of floods and also true for the cumulative impacts, with the exception of agricultural growth.

**Table 3.5: Mean responses of the growth rates to moderate/severe natural disaster shocks [BSBC estimator]**

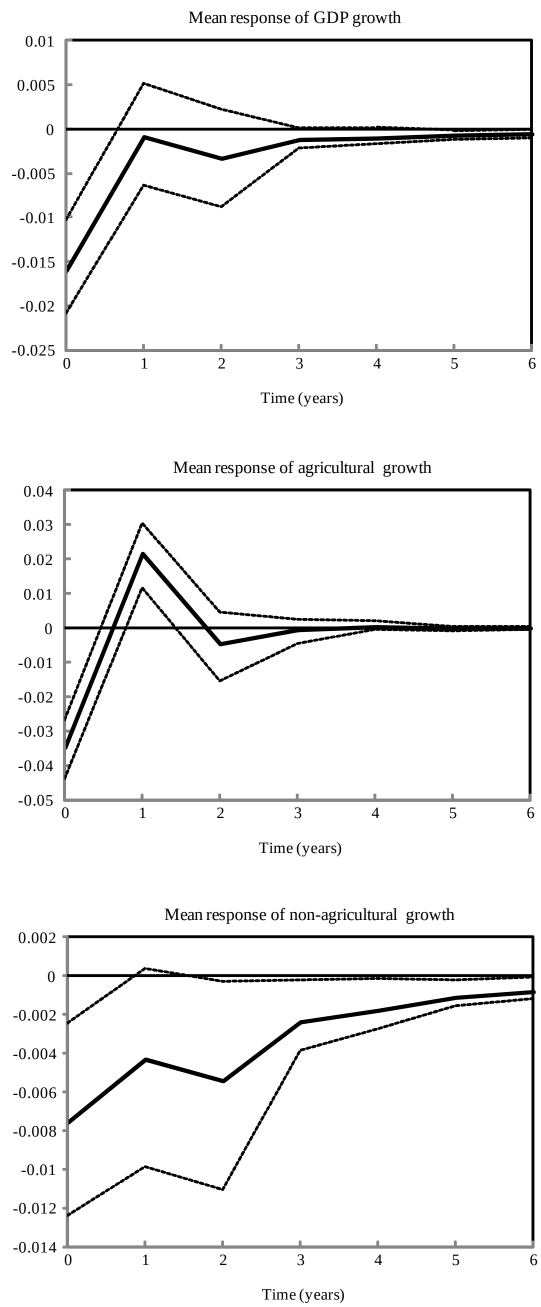
Sample: Developing countries

| *Endogenous variables* | *Exogenous variables* |
|---|---|
| Capital formation | 4 natural disaster variables |
| Inflation | 4 severe natural disaster variables |
| Trade openness | Terms of trade |
| Government consumption | World growth |
| Financial depth | |

| | | Mean responses of | | | | | |
|---|---|---|---|---|---|---|---|
| | | GDP growth | | Agricultural growth | | Non-agricultural growth | |
| | | moderate | severe | moderate | severe | moderate | severe |
| Droughts | Year 0 | -0.0092 * | -0.0225 ** | -0.0159 * | -0.0538 ** | -0.0051 | -0.0106 ** |
| | Year 1 | -0.0086 * | 0.0054 | -0.0003 | 0.0415 ** | -0.0079 * | -0.0013 |
| | Year 2 | -0.0070 | 0.0001 | 0.0009 | -0.0080 | -0.0062 | -0.0044 |
| | Year 3 | -0.0019 | -0.0007 | -0.0007 | -0.0019 | -0.0029 * | -0.0018 |
| | Cumulative effect | -0.0266 ** | -0.0177 * | -0.0159 * | -0.0222 ** | -0.0220 ** | -0.0180 * |
| Floods | Year 0 | 0.0013 | -0.0011 | 0.0031 | 0.0045 | 0.0009 | -0.0019 |
| | Year 1 | 0.0017 | -0.0027 | 0.0064 ** | 0.0055 | 0.0003 | -0.0014 |
| | Year 2 | 0.0029 * | 0.0035 | -0.0009 | 0.0080 | 0.0042 ** | 0.0022 |
| | Year 3 | 0.0003 | 0.0013 | -0.0004 | -0.0023 | 0.0011 * | 0.0017 |
| | Cumulative effect | 0.0062 * | 0.0011 | 0.0082 ** | 0.0157 * | 0.0065 * | 0.0006 |
| Earthquakes | Year 0 | 0.0048 | 0.0060 | 0.0025 | -0.0120 | 0.0045 | 0.0016 |
| | Year 1 | 0.0064 | -0.0009 | 0.0024 | -0.0334 * | 0.0097 * | -0.0037 |
| | Year 2 | -0.0049 | 0.0010 | -0.0052 | -0.0275 | -0.0069 | 0.0042 |
| | Year 3 | 0.0011 | -0.0003 | 0.0015 | 0.0116 * | -0.0002 | -0.0044 |
| | Cumulative effect | 0.0074 | 0.0057 | 0.0012 | -0.0613 ** | 0.0071 | -0.0024 |
| Storms | Year 0 | -0.0026 | -0.0069 | 0.0019 | -0.0030 | -0.0031 | -0.0060 |
| | Year 1 | -0.0007 | -0.0055 | -0.0059 | 0.0015 | 0.0028 | -0.0050 |
| | Year 2 | 0.0020 | -0.0085 | 0.0073 * | -0.0055 | 0.0014 | -0.0099 |
| | Year 3 | 0.0009 * | -0.0024 | -0.0010 | 0.0022 | 0.0011 | -0.0019 |
| | Cumulative effect | -0.0005 | -0.0233 | 0.0023 | -0.0049 | 0.0022 | -0.0228 |
| | Number olf countries | 60 | | 60 | | 60 | |
| | Sample period | 1960-2007 | | 1960-2007 | | 1960-2007 | |
| | Number of observation: | 2097 | | 1878 | | 1863 | |

*Note*: Asterisks (*) indicate statistical significance at the one-tail 10 percent level and (**) 5 percent level.

**Figure 3.1: Response to drought shock**



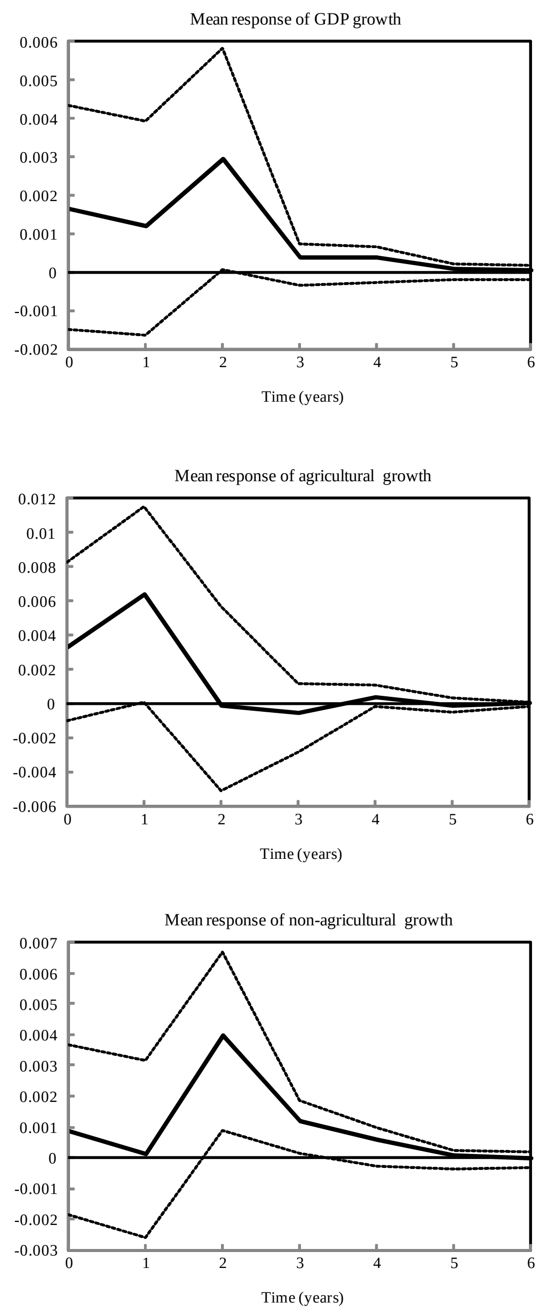
#### 3.3.1.3 Earthquakes

In developing countries, the results on the mean response of growth to earthquakes are weaker in terms of statistical significance than in the case of droughts and floods (see Table 3.3, third panel, and Figure 3.3). The mean responses of growth in developed countries are even weaker than in the developing country sample (see Table 3.4, third panel).

Let us focus on developing countries. Although earthquakes do not seem to have a significant effect on aggregate GDP growth, there are some noteworthy results regarding sectoral growth. Earthquakes appear to have a negative but not statistically significant impact on agricultural growth. In contrast, earthquakes bring about 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 but delayed effect is consistent with the reconstruction activity that follows an earthquake in residential housing, public infrastructure, and production plants.

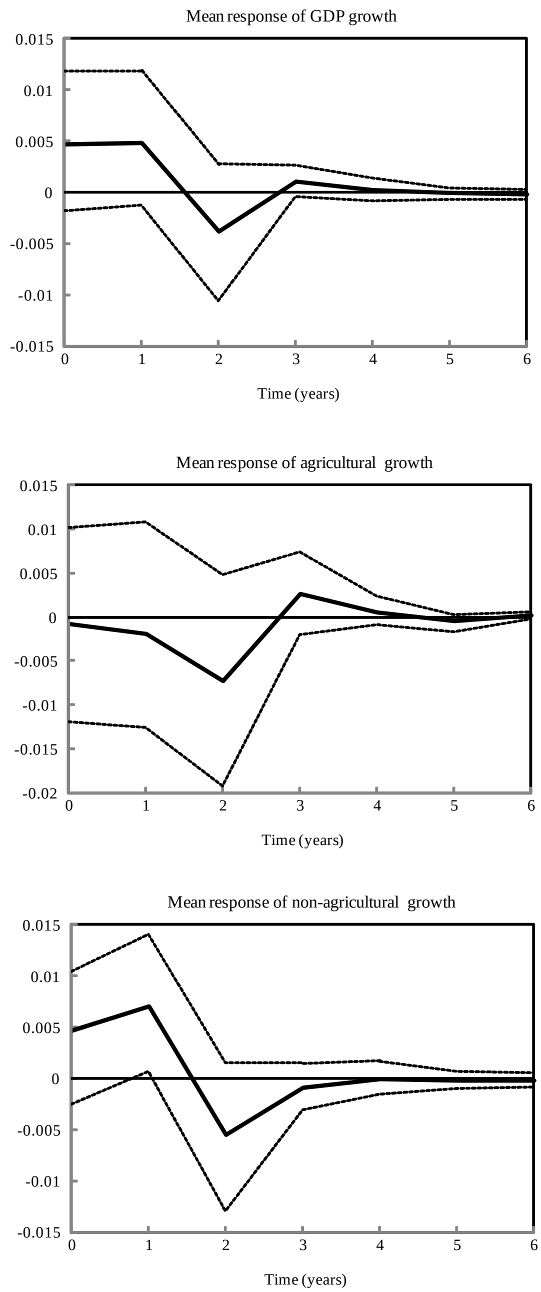
These results are further clarified when considering the effect of moderate vs. severe natural disasters (see Table 3.5, third panel). The negative impact of earthquakes on non-agricultural growth occurs with larger strength and significance for severe earthquakes, especially regarding the cumulative effect. Severe earthquakes produce a total decrease in agricultural growth of 6 pp over the first years after the event. The fact that this effect is not due to a single response in any given year but, rather, to the buildup 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.

**Figure 3.2: Response to flood shock**



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. It seems that 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. The significant difference in the effects of moderate and severe earthquakes, not just in magnitude but also in sign, explains in part why the basic results discussed above were so imprecise.

**Figure 3.3: Response to earthquake shock**

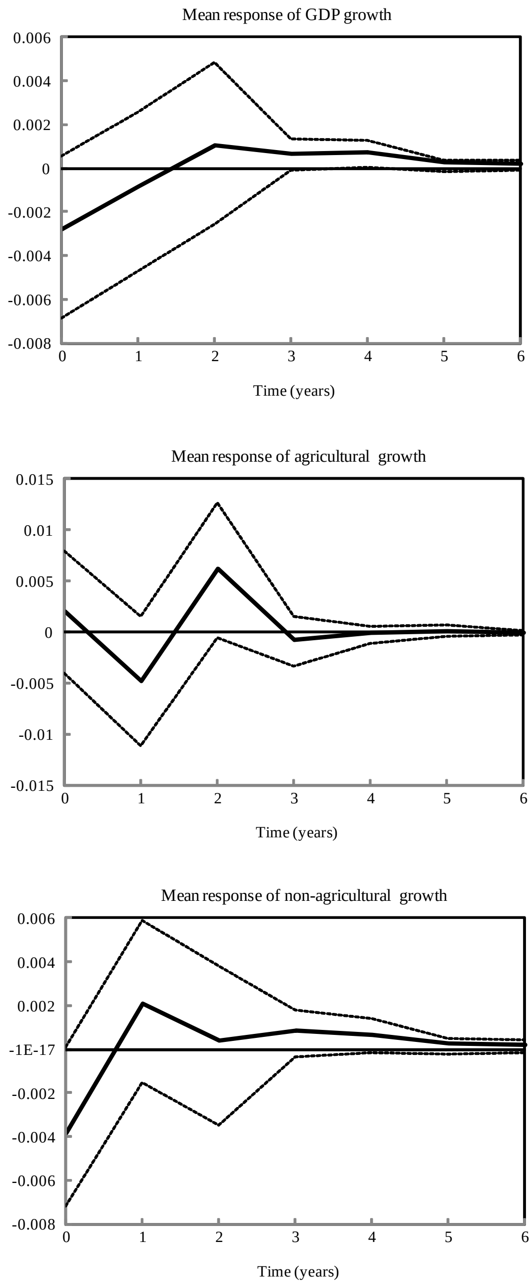


#### 3.3.1.4 Storms

As in the case of earthquakes, the mean responses of growth to storms are weaker in statistical significance than those of droughts and floods. For the sample of developed countries, the effect of storms is minimal (see Table 3.4, fourth panel). Nonetheless, for the sample of developing countries, some results do emerge from the data (see Table 3.3, fourth panel). Storms appear to have a negative effect on GDP growth and non-agricultural growth, but only at levels of significance slightly higher than 10% (Figure 3.4 is useful to appreciate this point). In the following years, particularly for non-agricultural growth, there is a growth rebound representing most likely reconstruction efforts. In the basic model, the mean response of agricultural growth to storms is not significant.

As in previous cases, the comparison between moderate and severe storms sheds some light on the results (see Table 3.5, fourth panel). The first point to observe is that, once severe storms are controlled for, moderate storms may bring about a positive and significant growth response. This is the case for agricultural growth in year 2 after the event and for GDP growth in year 3. The delayed effect suggests a supply-chain mechanism similar to that of floods –higher provision of water and improved soil quality leads to higher agricultural output in future harvest cycles and this in turn benefits the overall economy in subsequent years. The second point is that the mean response of growth is more negative for severe than for moderate storms. Although the estimated difference does not reach levels of conventional significance, it nearly does, especially for GDP and non-agricultural growth.

**Figure 3.4: Response to storm shock**



### 3.3.2 Robustness Check

This sub-section considers a number of alternative specifications to explore the robustness of the benchmark results presented above. First, we consider the results obtained under the simpler least squares dummy variable (LSDV) estimator for fixed effects models. Second, we analyze the sensitivity of the results to changes in the measure of intensity of natural disasters. And, third, we assess the robustness of the results to the assumption of exogeneity of terms of trade shocks and the world's GDP growth.

We first examine how similar are the results obtained under LSDV, the standard estimator to control for fixed effects. As discussed in the methodological section, LSDV renders inconsistent results if the time dimension of the data is not sufficiently large. The results are presented in Supplement Table B-I. They are indeed quite similar in sign, significance, and size with respect to those obtained under the consistent BSBC estimator. The only difference is that under LSDV, the mean response of non-agricultural growth to storms becomes statistically significant, remaining of the same sign and size as in the benchmark case. The similarity between the BSBC and LSDV results indicates that for the time dimension of our sample, 35 years in average per country, the simpler method is a good approximation.

We now examine two alternative measures of natural disasters. The first, , is a binary variable similar to the original measure except that all people affected (fatalities and others) are given the same weight.[15] The second one, , is a continuous variable that consists of (the log of) the share of total population affected by a given type of disaster.[16] The results obtained with the first and second alternative measures are

[15] That is, $ND^{a}_{i,t}(k) = \sum_{j=1}^{J} intensity2^{k}_{i,t,j}$, where $intensity2^{k}_{i,t,j} = 1$, if $\frac{fatalities^{k}_{i,t,j} + total\ affected^{k}_{i,t,j}}{population_{i,t}} > 0.0001$, $intensity2^{k}_{i,t,j} = 0$, otherwise.

[16] That is, $ND^{b}_{i,t}(k) = \log\left[\sum_{j=1}^{J} \frac{fatalities^{k}_{i,t,j} + 0.3 * total\ affected^{k}_{i,t,j}}{population_{i,t}} + \varepsilon\right]$, where $\varepsilon$ is a sufficiently small positive number.

summarized in Supplement Tables B-II and B-III, respectively. For both of them, we find that most of the significant results in the benchmark case are retained for droughts and floods, especially concerning the cumulative effects. For earthquakes, the positive effect on non-agricultural growth in year 1 remains when using the first alternative measure, but not the second one. For storms, the first alternative measure reveals a statistically significant negative impact on non-agricultural growth on the year of the event, which was already near significance in the benchmark case.

Finally, to examine the importance of the assumption of exogeneity of the terms of trade shocks and the world's GDP growth, we set up an alternative model where those two variables are included in the set of endogenous variables and where the set of exogenous variables consists only of the natural disaster variables. We then proceed to estimate the mean responses of growth to natural disasters under the alternative framework. The results with the new specification are presented in Supplement Table B-IV. Again, the majority of significant results for droughts and floods remain the same in terms of sign and significance, especially for the cumulative effects. The mean response of non-agricultural growth to earthquakes in year 1 also remains basically the same as in the benchmark case. Regarding storms, a significantly negative mean response of non-agricultural growth on the year of the event appears, as in some of the previous robustness cases.

Overall, the results from the robustness checks indicate that the features found in the benchmark results are not idiosyncratic to the original specifications.

## 3.4 Concluding Remarks

This study has analyzed the path of output growth in the aftermath of natural disasters. Applying a VARX methodology on a panel of 84 countries (60 of them developing) and 48 years (1960-2007), the essay has measured and examined the mean response of GDP per capita growth and its major components, agricultural and non-agricultural per capita value-added growth, to four types of natural disasters, namely, droughts, floods, earthquakes, and storms. The study finds heterogeneous effects on a variety of dimensions. First, the effects of natural disasters are stronger, for better or worse, on developing than on advanced countries. Second, not all natural disasters are alike in terms of the sign 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). Third, while the impact of some natural disasters can be beneficial when they are of moderate intensity, severe disasters do never have positive effects. Fourth, the timing of the growth response varies with both the type of natural disaster and the sector of economic activity. Some systematic patterns are, however, present. Negative effects tend to occur close to the time of the disaster's occurrence, while positive effects, if any, occur with some delay. Non-agricultural growth is affected a year or two after a climatic disaster has affected agricultural growth, usually with the same sign.

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. 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 growth effects of earthquakes and storms are weaker in size and statistical significance. Earthquakes do not have a statistically significant effect on aggregate GDP growth. However, they seem to elicit a positive mean response of non-agricultural growth one year after. 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 non-agricultural growth the same year of the event. The effect is short-lived and small, however. In the following years, there is some indication of a growth rebound representing reconstruction efforts.

This essay has contributed to highlighting the heterogeneity in the growth response to natural disasters. It has focused on mean responses, averaging over repeated experiences across countries and over time. The mean, however, can mask important case-specific differences. These may express themselves in our econometric analysis in the form of large standard errors of some estimated responses. In order to understand this latent heterogeneity, further work is needed on the precise mechanisms through which natural disasters affect economic activity. For this purpose, both panel and individual country analysis should prove useful.

## 3.A Appendix: Bootstrap Bias Correction for the LSDV Estimator

The econometric model we adopt is a fixed-effects panel VARX model,

$$\mathbf{y}_{i,t} = \boldsymbol{\alpha}_i + \Phi_1 \mathbf{y}_{i,t-1} + \Phi_2 \mathbf{y}_{i,t-2} + \Theta_0 \mathbf{x}_{i,t} + \Theta_1 \mathbf{x}_{i,t-1} + \Theta_2 \mathbf{x}_{i,t-2} + \boldsymbol{\varepsilon}_{i,t} \tag{3.5}$$

where the country index is $i = 1, 2, ..., N$, and the time index for country $i$ is $t = -1, 0, 1, ..., T_i$. The fixed effect for each country is represented by $\alpha_i$. The total number of usable observations in the panel is denoted by $T = \sum_{i=1}^{N} T_i$. In equation (3.5) we assume the homogenous error structure $E\left(\boldsymbol{\varepsilon}_{i,t}\boldsymbol{\varepsilon}_{i,t}'\right) = \Omega$ for all $i$ and $t$ where $\boldsymbol{\varepsilon}_{i,t}$ is the vector of errors of the system. Furthermore, we assume independence of the errors within equations, $E\left(\boldsymbol{\varepsilon}_{i,s}\boldsymbol{\varepsilon}_{i,t}^{'}\right)=0$, $s\neq t$, and across equations, $E\left(\boldsymbol{\varepsilon}_{i,s}\boldsymbol{\varepsilon}_{j,t}^{'}\right)=0$, for any $s$ and $t$ where $i\neq j$.

Stacking the observations over time and cross sections, we have

$$\begin{aligned}\mathbf{y} &= \mathbf{D}\boldsymbol{\alpha}^{'}+\mathbf{y}_{-1}\Phi_1^{'}+\mathbf{y}_{-2}\Phi_2^{'}+\mathbf{x}\Theta_0^{'}+\mathbf{x}_{-1}\Theta_1^{'}+\mathbf{x}_{-2}\Theta_2^{'}+\boldsymbol{\varepsilon}\\ &= \mathbf{D}\boldsymbol{\alpha}^{'}+\mathbf{Z}\boldsymbol{\delta}^{'}+\boldsymbol{\varepsilon}\end{aligned}$$

where $\mathbf{D}$ is a $T\times N$ matrix such that

$$\begin{aligned}\mathbf{D}_{i,j} &= 1 \text{ if } \left(\sum_{k=1}^{j-1}T_k+1\right)\leq i\leq\left(\sum_{k=1}^{j}T_k\right), \quad \text{with } T_0=0, \text{ for } j=1,2,...,N,\\ \mathbf{D}_{i,j} &= 0 \text{ elsewhere}\end{aligned}$$

$\boldsymbol{\alpha}=(\boldsymbol{\alpha}_1\ \boldsymbol{\alpha}_2\ ...\ \boldsymbol{\alpha}_N)^{'}$, $\mathbf{y}_i=(\mathbf{y}_{i,1}\ \mathbf{y}_{i,2}\ ...\ \mathbf{y}_{i,T_i})^{'}$, $\mathbf{y}_{i(-1)}=(\mathbf{y}_{i,0}\ \mathbf{y}_{i,1}\ ...\ \mathbf{y}_{i,T_i-1})^{'}$, $\mathbf{y}_{i(-2)}=(\mathbf{y}_{i,-1}\ \mathbf{y}_{i,0}\ ...\ \mathbf{y}_{i,T_i-2})^{'}$, $\mathbf{y}=(\mathbf{y}_1^{'}\ \mathbf{y}_2^{'}\ ...\ \mathbf{y}_N^{'})^{'}$, $\mathbf{y}_{-1}=(\mathbf{y}_{1(-1)}^{'}\ \mathbf{y}_{2(-1)}^{'}\ ...\ \mathbf{y}_{N(-1)}^{'})^{'}$, $\mathbf{y}_{-2}=(\mathbf{y}_{1(-2)}^{'}\ \mathbf{y}_{2(-2)}^{'}\ ...\ \mathbf{y}_{N(-2)}^{'})^{'}$, $\mathbf{z}=(\mathbf{y}_{-1}\ \mathbf{y}_{-2}\ \mathbf{x}\ \mathbf{x}_{-1}\ \mathbf{x}_{-2})$, and $\boldsymbol{\delta}=(\Phi_1\ \Phi_2\ \Theta_0\ \Theta_1\ \Theta_2)$.[17]

The within (fixed-effects) estimator or least-squares dummy variable (LSDV) estimator $\widehat{\delta}$ for $\delta$ is

$$\widehat{\delta}=(\mathbf{Z}^{'}\mathbf{A}\mathbf{Z})^{-1}\mathbf{Z}^{'}\mathbf{A}\mathbf{y}$$

where the $T\times T$ matrix $\mathbf{A}$ takes the form

$$\mathbf{A}=\begin{pmatrix}\mathbf{A}_1 & 0 & \cdots & 0\\ 0 & \mathbf{A}_2 & \cdots & \vdots\\ \vdots & 0 & \ddots & 0\\ 0 & 0 & \cdots & \mathbf{A}_N\end{pmatrix}$$

with $\mathbf{A}_i=\mathbf{I}_{T_i}-\frac{1}{T_i}\boldsymbol{\iota}_{T_i}\boldsymbol{\iota}_{T_i}^{'}$ and $\boldsymbol{\iota}_{T_i}=(1,1,...,1)^{'}$ a $T_i\times 1$ vector of 1's. The LSDV estimator for the mean response of $\mathbf{y}$ to $\mathbf{x}$ is captured by the lag polynomial

$$\widehat{\Psi}(L)=\widehat{\Phi}(L)^{-1}\widehat{\Theta}(L).$$

[17] $\mathbf{x}_i$, $\mathbf{x}_{i,-1}$, $\mathbf{x}_{i,-2}$, $\mathbf{x}$, $\mathbf{x}_{-1}$, $\mathbf{x}_{-2}$ are similarly constructed.

To obtain a bias correction of the LSDV estimator, we use a bootstrap algorithm, which is proposed by Pesaran and Zhao (1999), Everaert and Pozzi (2007) and others. The procedure of obtaining the bootstrap bias-corrected (BSBC) estimator is as follows:

(i) Given the LSDV estimator $\widehat{\delta}$, calculate the individual fixed effects $\widehat{\boldsymbol{\alpha}}_i = \frac{1}{T_i}\left(\mathbf{y} - \mathbf{Z}\widehat{\delta}'\right)'\mathbf{D}\mathbf{e}_i$, for $i = 1, 2, ..., N$, where $\mathbf{e}_i = (0, ...., 0, 1, ..., 0)'$ denotes a $N \times 1$ vector with 1 in the $i$th element and 0 elsewhere, and the residuals $\widehat{\boldsymbol{\varepsilon}} = \mathbf{y} - \mathbf{D}\widehat{\boldsymbol{\alpha}}' - \mathbf{Z}\widehat{\delta}'$.

(ii) Following MacKinnon (2002) and Everaert and Pozzi (2007), obtain the rescaled residuals which is derived as

$$\widehat{\varepsilon}^r_{i,t} = \sqrt{\frac{T_i}{T_i - 1}}\left(\frac{\widehat{\varepsilon}_{i,t}}{\sqrt{m_{i,t}}} - \frac{1}{T_i}\sum_{k=1}^{T_i}\frac{\widehat{\varepsilon}_{i,k}}{\sqrt{m_{i,k}}}\right) \quad \text{for } t = -1, 0, 1, ..., T_i,\ i = 1, 2, ..., N$$

where $m_{i,t}$ denotes the $\left(\sum_{k=1}^{i-1} T_k + t\right)$-th element of the projection matrix $\mathbf{M} = (\mathbf{I}_T - \mathbf{A}\mathbf{Z}(\mathbf{Z}'\mathbf{A}\mathbf{Z})^{-1}\mathbf{Z}')\mathbf{A}$ with $T_0 = 0$.

(iii) Obtain a bootstrap sample $\widehat{\varepsilon}^{b(j)}$ by picking $T$ integers between 1 and $T$ at random with equal probability. If the $h$-th integer is equal to $g$, we set $\widehat{\varepsilon}^{b(j)}_h = \widehat{\varepsilon}_g$, for $h, g = 1, ..., T = \sum_{i=1}^{N} T_i$.

(iv) Calculate a bootstrap sample $\mathbf{y}^{b(j)} = \mathbf{D}\widehat{\boldsymbol{\alpha}}' - \mathbf{Z}^{b(j)}\widehat{\delta}' + \widehat{\boldsymbol{\varepsilon}}^{b(j)}$, where $\mathbf{Z}^{b(j)} = (\mathbf{y}^{b(j)}_{-1}\mathbf{y}^{b(j)}_{-2}\mathbf{x}\mathbf{x}_{-1}\mathbf{x}_{-2})$, $\mathbf{y}^{b(j)}_{i,-1} = \mathbf{y}_{i,-1}$, and $\mathbf{y}^{b(j)}_{i,0} = \mathbf{y}_{i,0}$, for $i = 1, ..., N$. Then obtain the LSDV estimator $\widehat{\delta}^{b(j)} = \left(\mathbf{Z}^{b(j)\prime}\mathbf{A}\mathbf{Z}^{\mathbf{b(j)}}\right)^{-1}\mathbf{Z}^{b(j)\prime}\mathbf{A}\mathbf{y}^{b(j)}$, and the mean responses $\widehat{\Psi}^{b(j)}(L) = \left[\widehat{\Phi}^{b(j)}(L)\right]^{-1}\widehat{\Theta}^{b(j)}(L)$.

(v) Repeat step (iii) to (iv) for $B$ times ($j = 1, 2, ..., B$). In this study, we set $B = 1000$. The BSBC estimator $\widetilde{\Psi}_s$ for the $s$-period delay mean responses $\Psi_s$ is obtained as

$$\widetilde{\Psi}_s = 2\widehat{\Psi}_s - \frac{1}{B}\sum_{j=1}^{B}\widehat{\Psi}^{b(j)}_s, \quad \text{for } s = 1, 2, ...$$

where $\widehat{\Psi}_s$ denotes the LSDV estimator for $\Psi_s$.

The small sample distribution of $\widetilde{\Psi}$ is estimated by (i) generating $B$ bootstrapped samples for each of $\widehat{\boldsymbol{\delta}}^{b(j)}$ in the above algorithm and computing the BSBC estimator $\widetilde{\Psi}^{(j)}$ from them, and (ii) repeating this process for $B$ times to obtain $\left\{\widetilde{\Psi}^{(1)}, ..., \widetilde{\Psi}^{(j)}, ..., \widetilde{\Psi}^{(B)}\right\}$. To obtain, for example, the 90% confidence interval for the $(i, k)$ element of the s-period delay mean responses $\widetilde{\Psi}_s$, say $\widetilde{\Psi}_s(i, k)$, we need the 5th percentile $\underline{\widetilde{\Psi}}_s(i, k)$, and the 95th percentile $\overline{\widetilde{\Psi}}_s(i, k)$, from the simulated values of $\widetilde{\Psi}^{s(j)}(i, k)$, $j = 1, ..., B$, resulting in the 90% confidence interval for $\widetilde{\Psi}_s$, namely, $\left(\underline{\widetilde{\Psi}}_s(i, k), \overline{\widetilde{\Psi}}_s(i, k)\right)$. The confidence intervals for the remaining elements of $\widetilde{\Psi}_s$ are similarly constructed.

# Bibliography

[1] Acemoglu, D. (2002), "Technical Change, Inequality and the Labor Market," *Journal of Economic Literature* 40(1), 7-72.

[2] Aiyagari, R. (1994), "Uninsured Idiosyncratic Risk and Aggregate Savings," *Quarterly Journal of Economics* 109(3), 659-684.

[3] Albanesi, S., and C. Sleet (2006), "Dynamic Optimal Taxation with Private Information," *Review of Economic Studies* 73(1), 1-30.

[4] Ales L., and P. Maziero (2009), "Accounting for Private Information," Working Paper, Carnegie Mellon University.

[5] Atkeson, A., and R. E. Lucas Jr. (1992), "On Efficient Distribution with Private Information," *Review of Economic Studies* 59(3), 427-453.

[6] Attanasio, O., and S. Davis (1996), "Relative Wage Movements and the Distribution of Consumption," *Journal of Political Economy* 104(6), 1227-1262.

[7] Attanasio, O., and N. Pavoni (2007), "Risk Sharing in Private Information Models with Asset Accumulation: Explaining the Excess Smoothness of Consumption," *NBER Working Paper* 12994.

[8] Becker, T., and P. Mauro (2006), "Output Drops and the Shocks That Matter," IMF Working Paper WP/06/172.

[9] Bénabou, R. (2002), "Tax and Education Policy in a Heterogeneous Agent Economy: What Levels of Redistribution Maximizes Growth and Efficiency?" *Econometrica* 70(2), 481-517.

[10] Brett, C., and J. A. Weymark (2008), "The Impact of Changing Skill Levels on Optimal Nonlinear Income Taxes," *Journal of Public Economics* 92, 1765-1771.

[11] Cochrane, J. (1991), "A Simple Test of Consumption Insurances," *Journal of Political Economy* 99(5), 957-976.

[12] Cooper, R. (1984), "On Allocative Distortions in Problems of Self-Selection," *Rand Journal of Economics* 15(4), 568-577.

[13] Cutler, D. M., and L. F. Katz (1991) "Macroeconomic Performance and the Disadvantaged," *Brookings Papers on Economic Activity*, Economic Studies Program, The Brookings Institution, vol. 22(2), 1-74.

[14] Diamond, P. A. (1998), "Optimal Income Taxation: An Example with a U-Shaped Pattern of Optimal Marginal Tax Rates," *American Economic Review* 88, 83-95.

[15] Dollar, D., and A. Kraay (2002), "Growth is Good for the Poor," *Journal of Economic Growth* 7, 195-225.

[16] Everaert, G., and L. Pozzi (2007), "Bootstrap-based bias correction for dynamic panels," *Journal of Economic Dynamics & Control* 31(4): 1160-1184.

[17] Flodén, M. (2001), "The Effectiveness of Government Debt and Transfers as Insurance," *Journal of Monetary Economics* 48(1), 81-108.

[18] Forni, M., and L. Reichlin (1998), "Let's Get Real: a Factor Analytic Approach to Business Cycle Dynamics," *Review of Economics and Statistics* 65, 452-473.

[19] Giannone, D., and M. Lenza (2010), "The Feldstein-Horioka Fact," In *NBER International Seminar on Macroeconomics* 2009. L. Reichlin and K. West, organizers, University of Chicago Press.

[20] Golosov, M., N. Kocherlakota, and A. Tsyvinski (2003), "Optimal Indirect and Capital Taxation," *Review of Economic Studies* 70(3), 569-587.

[21] Green, E. J. (1987), "Lending and the Smoothing of Uninsurable Income," In *Contractual Arrangements for Intertemporal Trade*, edited by E. C. Prescott and N. Wallace, Minnesota Studies in Macroeconomics series, vol. 1, 3-25, Minneapolis: University of Minnesota Press.

[22] Guesnerie, R., and J. Seade (1982), "Nonlinear pricing in a finite economy," *Journal of Public Economics* 17(2), 157-179.

[23] Guvenen, F. (2007), "Learning Your Earning: Are Labor Income Shocks Really Very Persistent?" *American Economic Review* 97(3), 687-712.

[24] Hashimzade, N., and G. D. Myles (2007), "Structure of the Optimal Income Tax in the Quasi-Linear Model," *International Journal of Economic Theory* 3, 5-33..

[25] Heathcote J., K. Storesletten, and G. L. Violante (2008), "Insurance and Opportunities: The Welfare Implications of Rising Wage Dispersion," *Journal of Monetary Economics* 55(3), 501-525.

[26] —— (2009), "Quantitative Macroeconomics with Heterogeneous Household," *Annual Review of Economics*, Annual Reviews, 1(1), 319-354.

[27] —— (2010), "The Macroeconomic Implications of Rising Wage Inequality in the United States," *Journal of Political Economy* 118(4), 681-722.

[28] —— (2012), "Consumption and Labor Supply with Partial Insurance: An Analytical Framework," Federal Reserve Bank of Minneapolis Research Department Staff Report 432.

[29] Hochrainer, S. (2009), "Assessing the Macroeconomic Impacts of Natural Disasters: Are There Any?" Policy Research Working Paper No.4968, The World Bank.

[30] Huggett, M., and J. C. Parra (2010), "How Well Does the U.S. Social Insurance System Provide Social Insurance?" *Journal of Political Economy* 118(1), 76-112.

[31] Im, K. S., M. H. Pesaran, and Y. Shin (2003), "Testing for Unit Roots in Heterogeneous Panels," *Journal of Econometrics* 115(1), 53–74.

[32] International Monetary Fund (2003), "Fund Assistance for Countries Facing Exogenous Shocks," *Policy Development and Review Department*, International Monetary Fund.

[33] Jaramillo, H. C. R. (2007), "Natural Disasters and Growth: Evidence Using a Wide Panel of Countries," Documento CEDE 2007-14.

[34] Katz, L. F., and D. H. Autor (1999), "Changes in the Wage Structure and Earnings Inequality," In *Handbook of Labor Economics*, edited by O. Ashenfelter and D. Card, edition 1, vol. 3, chapter 26, 1463-1555, Elsevier.

[35] Kocherlakota, N. R. (2010), *The New Dynamic Public Finance*, New Jersey, Princeton University Press.

[36] Krueger, D., and F. Perri (2006), "Does Income Inequality Lead to Consumption Inequality? Evidence and Theory," *Review of Economic Studies* 73(1), 163-193.

[37] Khan, A., and B. Ravikumar (2001), "Growth and Risk-Sharing with Private Information," *Journal of Monetary Economics* 47(3), 499-521.

[38] Levin. A., C. F. Lin, and C. S. J. Chu (2002), "Unit Root Tests in Panel Data: Asymptotic and Finite-Sample Properties," *Journal of Econometrics* 108(1), 1–24.

[39] Levine, R., N. Loayza, and T. Beck (2000), "Financial Intermediation and Growth: Causality and Causes," *Journal of Monetary Economics* 46(1): 31-77.

[40] Loayza, N., E. Olaberría, J. Rigolini, and L. Christiaensen (2009), "Natural Disasters and Growth: Going Beyond the Averages," Policy Research Working Paper No.4980, The World Bank.

[41] Lollivier, S., and J.-C. Rochet (1983), "Bunching and Second-Order Conditions: A Note on Optimal Tax Theory," *Journal of Economic Theory* 31(2), 392-400.

[42] Lucas, R. E. Jr. (1987), *Models of Business Cycles*, Basil Blackwell: New York.

[43] MacKinnon, J. G. (2002), "Bootstrap Inference in Econometrics," *Canadian Journal of Economics* 35(4), 615-645.

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

[45] Mirrlees, J. A. (1971), "An Exploration in the Theory of Optimal Income Taxation," *Review of Economic Studies* 38(2), 175-208.

[46] Nickell, S. (1981), "Biases in Dynamic Models with Fixed Effects," *Econometrica* 49(6), 1417-1426.

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

[48] Pesaran, M. H., and Z. Zhao (1999), Bias reduction in estimating long-run relationships from dynamic heterogeneous panels. In *Analysis of Panels and Limited Dependent Variable Models*, edited by C. Hsiao, M. H. Pesaran, K. Lahiri, L. F. Lee, Cambridge University Press: Cambridge.

[49] Phelan, C. (1994), "Incentives, Insurance, and the Variability of Consumption and Leisure," *Journal of Economic Dynamics and Control* 18(3-4), 581-599.

[50] Raddatz, C. (2009), "The Wrath of God: Macroeconomic Costs of Natural Disasters," Policy Research Working Paper No.5039. The World Bank.

[51] Ramey V. A., and M. D. Shapiro (1998), "Costly Capital Reallocation and the Effects of Government Spending," *Carnegie-Rochester Conference Series on Public Policy* 48(1), 145-194.

[52] Rasmussen, T. N. (2004), "Macroeconomic Implications of Natural Disasters in the Caribbean," IMF Working Paper WP/04/224.

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

[54] Spear, S., and S. Srivastava (1987), "On Repeated Moral Hazard with Discounting," *Review of Economic Studies* 54(4), 599-617.

[55] Storesletten, K., C. I. Telmer, and A. Yaron (2004), "Consumption and Risk Sharing Over the Life Cycle," *Journal of Monetary Economics* 51(3), 609-633.

[56] Tauchen, G. (1986), "Finite State Markov-Chain Approximations to Univariate and Vector Autoregressions," *Economics Letters* 20(2), 177-181.

[57] Thomas, J., and T. Worrall (1990), "Income Fluctuations and Asymmetric Information: An Example of a Repeated Principal-Agent Problem," *Journal of Economic Theory* 51(2), 357-390.

[58] Townsend, R. (1994), "Risk and Insurance in Village India," *Econometrica* 62(3), 539-591.

[59] Toya H., and M. Skidmore (2007), "Economic Development and the Impacts of Natural Disasters," *Economics Letters* 94(1), 20-25.

[60] Weymark, J. A. (1986a), "A Reduced-Form Optimal Nonlinear Income Tax Problem," *Journal of Public Economics* 30, 199-217.

[61] —— (1986b), "Bunching Properties of Optimal Nonlinear Income Taxes," *Social Choice and Welfare* 3, 213-232.

[62] World Bank (2009), *World Development Indicators*. The World Bank: Washington D.C.

[63] World Bank and United Nations (2010), *Natural Hazards, Unnatural Disasters: the Economics of Effective Prevention*, The World Bank, Washington, D.C.