A simple measure of disaster risk

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Abstract:

This paper proposes a simple measure of disaster risk, and explores certain time series properties of the measure. Drawing upon antecedents in literature, the paper examines disasters as deviations from norm, and risk of disaster as the chance of this deviation. Disaster risk is then formalized as expected absolute deviation from norm, and an empirical application of the proposed measure is illustrated in context risk of flood disasters for agricultural workers in Bangladesh. The paper also examines whether past deviations affect the chance of current deviations, and draws upon longitudinal data on real agricultural wages (1979-2005) across districts of Bangladesh to study "long memory" and other temporal properties of the proposed measure. The empirical results indicate that effects of past deviations continue to endure, and disaster risks realized in distant past reinforce current risks. The effects from past are, however, more persistent in regions that experience recurrent occurrences of natural extremes than in regions that are affected less frequently. In light of the empirical findings, the paper argues that if past shortfalls in income bring about added risks of current shortfalls, then disaster risk may have important implications for poverty dynamics, especially for a population repeatedly exposed to natural extremes.

Key words: Disaster risk; expected absolute deviation from norm; long memory; volatility; agricultural wage in Bangladesh

JEL classifications: O15, J3, Q54

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1. Introduction

The main purpose of this paper is to propose a measure of disaster risk and examine certain time series properties of the measure. The paper invokes an alternative approach of analyzing disaster as deviation from norm, which contrasts with the more conventional notion of disaster as an exogenous shock. Accordingly, risk of disaster is examined as the chance of this deviation, and is formalized as expected absolute deviation from norm. While this deviation can be measured in terms of a number of economic and non-economic variables, the present study focuses on income changes, and evaluates disaster risk in terms of fluctuations in income change patterns for a vulnerable population when an extreme environmental phenomena occurs. The norm, or the benchmark in terms of which the deviation is examined, is defined as income change patterns anticipated under "normal" circumstances, i.e., in absence of environmental extremes. The paper thus steps away from both an expected utility based as well as a non-expected utility based measurement of risk. It does so with the aim of offering an objective approach to measurement of risk, especially for cases when information on subjective preference for risk for the exposed population is not readily available.

The paper posits that the chance of deviation from norm is conditional on factors that antecede the occurrence of natural extremes, together with aleatory factors that trigger sudden violence in nature. The former set of factors give rise to deterministic aspects of disaster risk, while the latter set of factors give rise to unforeseen aspects of risk. Disaster risk is, therefore, to be analyzed in terms of both its determinable and unforeseeable elements. The paper also explores whether the chance of deviation from norm in the current period is affected by past episodes of deviations. Accordingly, it analyzes "long memory" property of risk. To examine more closely how the past effects may linger, the paper explores volatility of a system and studies certain temporal properties of the proposed risk measure. An empirical illustration of the approach is presented in context of risk of flood disasters for agricultural workers in Bangladesh. Disaster risk for this vulnerable group is measured as chance of deviation in real wage change patterns in times of extreme floods, and the "long memory" and volatility properties of risk are examined. In light of the empirical findings, the paper argues that if past shortfalls in income bring about added risks of current shortfalls, then disaster risk may have important implications for poverty dynamics, especially for a population repeatedly exposed to natural extremes.

The paper is organized in following sections: Section 2 draws reference from existing literature to motivate the derivation of the risk measure. Section 3 formalizes the measure, and analyzes disaster risk as a composite of deterministic and unforeseen elements. Section 4 presents an empirical application of the measure using longitudinal data on district-wise monthly real agricultural wages from Bangladesh for the period 1979-2005, and examines the "long memory" and other temporal properties of the measure. Section 5 presents the main conclusions of the paper, and explores their implications for poverty dynamics.

2. Notions of disaster and disaster risk

The conventional approach in economics is to examine disasters as random exogenous shocks, causing unanticipated fluctuations in endogenous variables, including economic variables like output, consumption, investment and employment. Studies that adopt this approach at the macroeconomic level focus on evaluating impacts of disaster shocks on growth, national income and aggregate employment (see, for example Benson, 1997 a, b, and c; Benson and Clay, 1998, 2001; Cuaresma et al, 2008; Leiter et al, 2009; Noy and Vu, 2009; Skidmore and Toya, 2002; Okuyama, 2003, 2009; and Cavallo et al, 2010), or on aggregate consumption expenditure (Mechler, 2009), or on human capital formation (Cuaresma, 2010), savings (Mechler, 2009), or on asset pricing and equity premiums (Barro, 2006, 2007; Barro and Ursúa, 2008; Barro et al, 2009; Gabaix, 2008). Studies that adopt this approach at the microeconomic level focus on analyzing how economic agents take decisions in presence of risk of shocks, and cope with unanticipated fluctuations in welfare, income, expenditure or consumption, either by choosing suitable income-smoothening strategies (see, for example, Jodha, 1978; Binswanger, 1980; Ravallion, 1988; Adams et al, 1998; Moschini and Hennessy, 2001; and Fafchamps, 2003), or by participating in the insurance market (see, for example, Kunreuther 1968, 1974, 2006; Morduch, 1994; Picard, 2008).

There is, however, a second trend, appearing mainly in the writings of anthropologists, geographers and sociologists, and more recently, economists, that examine disasters not as exogenous shocks, but rather, as deviations in the normal organization and functioning of a social system, generated when the social system interacts with certain "trigger events" (Pelling et al, 2002) or "unleashing events"

(Albala-Bertrand, 1993).[1] These trigger events may originate in the natural physical environment or in a social system. Natural triggers may include severe flooding, earthquakes, and other environmental extremes, while social triggers may include technological meltdowns and industrial collapses, wars or epidemics. Most natural triggers ensue when aleatory factors in the natural physical system bring about violent fluctuations in the system. Certain natural triggers may also stem from human interventions (such as environmental degradation, and deteriorations in safety regulations and social protections). A number of trigger events may coincide or overlap. Disasters materialize as a trigger event (or series of events) disrupts the normal activities of the economy, polity and society, such that the disruptions are significant, pervasive, and are clearly distinguishable as departures from normal conditions and functioning of the social system (Cisin and Clark, 1962, Hewitt, 1997).

A major difference in the notion of disaster in the two trends in literature is as follows: Studies that examine disasters as random exogenous shocks identify a disaster with certain violent occurrences in nature (such as an extreme flood or severe earthquake) or in society (such as an oil spill or an epidemic), and therefore, describe disaster as an *agent* causing negative outcomes. In contrast, studies that examine disasters as deviations from norm describe disaster as the negative *outcome* triggered by a violent agent (see, for example, Dynes, 1970; Burton and Kates, 1978, 1993; Rodríguez et al, 2006; Picou and Marshall, 2007; Tierney 2007).[2] This distinction is crucial. The latter group of studies maintain that mere occurrence of a "trigger event" does not necessarily entail a disaster. Disasters materialize only when the events bring about a "disruption of great magnitude" (Fredrick C. Cuny, as quoted in Davis, 1996) in society.

A second important distinction between the two trends is the following: Studies that consider disasters as random exogenous shocks regard disasters either as external impulses (see, for example, Raddatz 2007), or as accidental and arbitrary events (see, for example, Barro, 2006; Barro and Ursúa, 2008), that are realized instantaneously, having no bearing with the internal organization and functioning of a social system that it affects (Yodmani, 2001; Benight and McFarlane, 2007). In

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[1] More recently, this approach to disaster analysis has been adopted by a number of international agencies, including UNDP (2004) and UNISDR (2009).

[2] Dombrowsky (1998, p. 21), for instance, writes: "Disasters do not cause effects. The effects are what we call a disaster". Thus, circumstances that are described as impacts of disaster shocks in more conventional approaches to disaster analyses are identified as the disaster in itself in studies that examine disasters as deviation from norm.

contrast, studies that examine disasters as deviations from norm argue that the likelihood and extent of such disruption is conditional on past conditions that antecede the trigger events and preexisting states of vulnerabilities in a social system (Cutter, 1996, 2008; Quarantelli, 2005; Benight and McFarlane, 2007; Tierney, 2006, 2007). Many of these studies aim at analyzing disasters as social processes that emerge through interactions of deterministic conditions and chance factors over time (Drabeck, 1986; Oliver-Smith, 1996; Renn, 1998).

The present paper is motivated by the second trend in disaster analysis. It accepts the notion that environmental extremes, by themselves, are not disasters, but may lead to disasters if and when they trigger deviations from norm. The paper also accepts the argument that these deviations are not arbitrary, but rather, are contingent occurrences. Disasters occur in context of preexisting exigencies and vulnerabilities. Potential disaster conditions develop over time, either through interactions of systemic forces, or as remnants of past catastrophes, or both. In presence of these vulnerability conditions, trigger events (like environmental extremes) act as catalysts leading to deviations from norm. Thus, "the threat of disaster is as important to the comprehension of disaster as the disaster event itself" (Westgate and O'Keefe, 1976, p. 4). Accordingly, the paper examines the "threat" or risk of disaster as the chance of deviation from norm. To measure this risk in cardinal and objective manner, the paper formalizes risk as expected absolute deviation from norm.

The objective here is, however, not to present a forecasting analysis of risk, but rather, to examine in retrospect the following two issues: First, can risk of disaster be analyzed in terms of its determinable and unforeseeable aspects? And second, what implications do past conditions have for disaster risks? The paper seeks to answer these questions analytically and empirically. Analytically, the issue is addressed by demonstrating that disaster risk is a composite of (a) antecedent elements that precede the current episode of natural extreme, (b) contemporaneous elements generated by current volatility in systemic factors, and (c) and aleatory elements generated through sudden occurrences of trigger events in the current period. The paper posits that while (a) and (b) constitute the determinable aspects of disaster risk, (c) constitutes the unforeseeable aspect. The paper then focuses on (a), and empirically studies the effects of past deviations on current deviations. Towards this, it draws upon the district-wise longitudinal data (over 1978-2005) on real agricultural wage in Bangladesh to examine the "long memory" and other temporal properties of risk.

3. A simple measure of disaster risk

"Trigger events" in nature, such as severe floods or violent storms, may cause variables in a social system to fluctuate in a manner that clearly indicates a deviation from their normal pattern of fluctuations. If one accepts the notion that this deviation indicates occurrence of a disaster, then, risk of disaster may be defined as the chance of deviation from norm. The norm in this case is the fluctuation pattern of the variable expected on the basis of past observations. This notion of disaster risk can be formalized in the following manner: Consider an economic variable "x_t". x_t is systemically determined by market and non-market conditions, and is also affected by chance occurrences of natural extremes. Let $F(x)$ be the distribution function of this variable. Our objective is to derive a measure of risk, $R_t(F)$, associated with this distribution function. Now, deviations from norm may be triggered by natural extremes as well as by other non-related phenomenon. For instance, fluctuations in real wages may be triggered by extreme flooding (as, floods cause decline in labor demand), and/or be caused by price shocks unrelated to flood occurrences. To determine the risk specifically associated with a "trigger event" in nature, let us define a variable "S" indicating the "state of nature". S takes the following values:

$$S = \begin{cases} 1 & \text{if a natural extreme occurs} \\ 0 & \text{if a natural extreme does not occur} \end{cases}$$

The two "states of nature" are clearly distinguishable in terms of non-economic environmental variables, such as hydrological, geological, and/or meteorological conditions of the natural physical system.[3] Let $\boldsymbol{S = 0}$ be defined as the "normal" state of nature. Then, the norm, say "m", is defined as the expected value of x_t such that $S = 0$. Formally,

(1) $$m = \left(E(x_t) \middle| S = 0\right)$$

[3] For example, in Bangladesh, a country experiencing recurrent riverine flooding in monsoons, an extreme flood condition can be identified from a "normal" flood condition in terms of the extent, duration, and depth of inundation, which clearly indicate an aberration from flood conditions normally experienced (Bangladesh Ministry of Irrigation, 1986).

Given m, deviation in x_t can be captured by a class of volatility measures, V_θ, where

(2) $$V_\theta = E\left((|x_t - m|)^\theta\right)$$

V_θ in [2] is a slightly re-formulated version of a limited class of risk measures originally derived axiomatically in Luce (1980, correction in 1981), and later analyzed in Ding et al (1993), Granger and Ding (1995), Granger et al (2000), and Granger (2002).[4] It can be readily seen that V_θ takes different forms depending on the values of θ.[5] For $\theta = 1$, V_θ is the expected absolute deviation in x_t. Among the class of volatility measures given by V_θ, expected absolute deviation is particularly attractive as a measure of risk. On one hand, the measure is stable, and is suitable for analyzing risk using long-tailed time series data.[6] On the other, the measure exhibits longest memory property among all other measures given by V_θ (Ding et al, 1993).[7] Formally, for $\theta = 1$, (2) reduces to:

(3) $$V_\theta = E(|x_t - m|).$$

Let us define $|x_t - m|$ in (3) as "d_t", the absolute value of deviation or shortfall in x_t from the norm m in period t. Thereby, we can formalize the chance of deviation from norm in the event of an environmental extreme (i.e, when the "state of nature" is $\boldsymbol{S = 1}$) in period $\boldsymbol{t}$ as:

(4) $$R_t(F) = E(d_t)\big| S = 1, \text{ where } d_t = |x_t - m|.$$

This paper proposes $R_t(F)$ as a simple measure of disaster risk. Note, the measure is derived in terms of observable and quantifiable variables. In doing so, the paper steps away from both the expected utility based, and the non-expected utility based,

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[4] In the original formulation, m was the unconditional mean $E(x_t)$.

[5] The simplest case is when $F(x)$ is Gaussian with mean zero and variance σ^2. In this case, $\boldsymbol{m = 0}$ (from (1)), $V_\theta = \sigma^\theta$ (from (2)), and risk is captured by standard deviation of x_t when $\boldsymbol{\theta = 1}$ (since, $V_\theta = \sigma$), and by variance of x_t when $\boldsymbol{\theta = 2}$ (since, $V_\theta = \sigma^2$). The derivation is more complicated when $F(x)$ is non-Gaussian. In the latter case no direct relationship can be established between V_θ as a measure of risk and σ, except when $\boldsymbol{\theta = 2}$ (Granger and Ding 1995).

[6] Since variance of absolute deviation of a stochastic variable is simply the variance of the variable, therefore expected absolute deviation is more stable amongst the class of volatility measures given by V_θ. See Granger (2002) for a discussion on this stability property of expected absolute deviation as a measure of risk.

[7] See Granger and Sin (2000) and Granger et al (2000) for detailed discussions.

measurement of risk. It does so with the aim to evaluate risks even in cases when no information is available on subjective preferences for risks for the exposed population.

The measure proposed in (4) can be decomposed to reflect the determinable and unforeseen elements of disaster risk in the following manner: Consider following representation of d_{t+k}

(5) $$d_{t+k} = E(d_{t+k}|I_t) + e_{t,k}^d$$

In (5), I_t is the information set available in period t on $d_t, d_{t-1}, d_{t-2}, ..$ etc. I_t describes the conditions, including market and non-market conditions, which already existed in period t and determined x_t, and affect x_{t+k}. Some of these conditions may have developed historically over the distant past, in periods $t-1$, $t-2$, etc.; while others may have developed in the recent past, in period t. Therefore, the conditional expected deviation term $E(d_{t+k}|I_t)$ in (5) captures that aspect of disaster risk in period $t+k$ which is determined by antecedent conditions already existing in period t. For simplicity, let $E(d_{t+k}|I_t) = \mu_{t,k}^d$. This paper identifies $\mu_{t,k}^d$ as a determinable aspect of disaster risk, which can be identified based on conditions that exist prior to the actual occurrence of the natural extreme in period $t+k$.

The term $e_{t,k}^d$ in (5), on the other hand, captures the unanticipated (or purely uncertain) aspect of the deviation in period $t+k$. This aspect of deviation cannot be known in period t on the basis of I_t, $e_{t,k}^d \sim$ i.i.d. (0, 1), and $E(e_{t,k}^d|I_t) = 0$. This paper identifies $e_{t,k}^d$ as the unforeseen aspect of disaster risk. $e_{t,k}^d$ can further be decomposed as: $e_{t,k}^d = \left(e_{t,k}^d|S=1\right) + \left(e_{t,k}^d|S=0\right)$, where, $\left(e_{t,k}^d|S=1\right)$ is the unexpected deviation triggered by sudden fluctuations in the environmental system, $\left(e_{t,k}^d|S=0\right)$ is due to triggering factors unrelated to the occurrence of natural extremes.

Let us now examine the determinable aspect of deviation more closely. Consider the following representation of x_t:

(6) $$x_t = \sigma_t e_t$$

In (6), σ_t^2 is the unconditional (or observed) variance of x_t in period t, and $E(e_t^2) = 1$. σ_t is a deterministic function of time, while e_t captures any stochastic time series properties of x_t. Accordingly, for any period $t+k$,

(7) $$E(x_{t+k}^2 | I_t) = E(\sigma_{t+k}^2 e_{t+k}^2 | I_t) = \sigma_{t+k}^2$$

Now, by definition: $d_t = |x_t - m|$. Therefore, $x_{t+k} = d_{t+k} + m$, and accordingly,

(8) $$E(x_{t+k}^2 | I_t) = E(d_{t+k}^2 | I_t) + 2mE(d_{t+k} | I_t) + m^2.$$

Rearranging the terms in (8), we have

(9) $$E(d_{t+k} | I_t) = \frac{1}{2m}\left(E(x_{t+k}^2 | I_t) - E(d_{t+k}^2 | I_t) - m^2\right)$$

Using (5) and (7), equation (9) becomes:

(10) $$E(d_{t+k} | I_t) = \frac{1}{2m}\left(\sigma_{t+k}^2 - E\left(\left(\mu_{t,k}^d + e_{t,k}^d\right)^2 \middle| I_t\right) - m^2\right)$$

$$= \frac{1}{2}\left(\frac{\sigma_{t+k}^2}{m} - \frac{\left(\mu_{t,k}^d\right)^2}{m} - \frac{E\left(\left(e_{t,k}^d\right)^2 \middle| I_t\right)}{m} - m\right).$$

In (10), expected deviation in period $t+k$ conditional on I_t (i.e., $E(d_{t+k} | I_t)$) is expressed as a linear function of the following four terms: (1) variance of x_t normalized by m (i.e., $\frac{\sigma_{t+k}^2}{m}$); (2) the squared value of conditional expected deviation, also normalized by m (i.e., $\frac{\left(\mu_{t,k}^d\right)^2}{m}$); (3) the term $E\left(\left(e_{t,k}^d\right)^2 \middle| I_t\right)$ normalized by m (i.e., $\frac{E\left(\left(e_{t,k}^d\right)^2 \middle| I_t\right)}{m}$); and (4) the norm m. One way of interpreting these terms may be as follows: The first term in (10), i.e., σ_{t+k}^2, captures deviations in x_{t+k} due to current systemic conditions in period $t+k$. In the second term, $\mu_{t,k}^d$ captures expected deviations in x_{t+k} based on I_t. In the third term, $E\left(\left(e_{t,k}^d\right)^2 \middle| I_t\right)$ captures the purely uncertain aspects of deviations in x_{t+k}. Finally, the norm m in (10) indicates a central tendency in the longitudinal series on x_{t+k} when the state of the nature is "normal", i.e., when there is no environmental extreme. The term, therefore, may be indicative of long-term trend in the values of the variable x_{t+k}.

Invoking (5) and (10), the risk measure given by (4) can be expressed as:

$$(11) \qquad R_{t,k}(F) = \left[E(d_{t+k} | I_t) + e_{t,k}^d\right] \Big| S=1 = \phi\left(\sigma_{t,k}^2; \left(\mu_{t,k}^d\right)^2; E\left(\left(e_{t,k}^d\right)^2 \Big| I_t\right); m\right)$$

Equation (11) recognizes the implicit role of both deterministic and chance factors in generating disaster risks. From (11), the risk measure introduced in (4) can be induced as:

$$(12) \qquad R_t(F) = \left[E(d_t | S = 1\right] = \left[E(d_t) | I_{t-k} + e_t^d\right] = \phi\left(\sigma_t^2; \left(\mu_{t-k}^d\right)^2; E\left((e_{t-k}^d)^2 \Big| I_t\right); m\right)$$

To summarize, in equation (12), disaster risk in period t, $R_t(F)$, is given as a composite of different elements, including a volatility component (captured by unconditional or observed variance σ_t^2), a pre-existing vulnerability component (indicated by the nonlinear function of μ_{t-k}^d), and an uncertainty component (indicated by the non-linear function $(e_{t-k}^d)^2 | I_t$). The volatility component captures fluctuations in x_t caused by current systemic factors. The vulnerability component captures fluctuations in x_t caused by pre-existing factors, and can be evaluated based on past observations. The uncertainty component is generated through sudden occurrences of "trigger events". Thus, the risk measure $R_t(F)$, proposed in equation (4) and expounded in equation (12), encapsulates disaster risk in terms of its determinable and unforeseeable aspects. The next task for this paper is to present an empirical illustration of this measure, and examine its properties.[8]

4. An empirical application of the risk measure

An application of the proposed risk measure is presented in this section. The analytical exercise in the earlier section indicates that antecedent conditions have important implications for current risks of disaster. This section delves into this issue empirically with the aim to reflect upon how past experiences of a vulnerable group can indicate their current patterns of risk. Disaster risk is measured for agricultural workers in flood-prone Bangladesh. Agricultural workers are exposed to extreme floods that

[8] Empirical estimation of the various components of the proposed risk measure is carried out in a forthcoming article.

periodically occur in the country due to the very nature of their work. This occupation group is also one of the poorest income groups in Bangladesh (ADB, 2006; Hossain and Nargis, 2010). Risk is measured for this group by examining fluctuations in real wages. The norm is identified as the rate of wage change anticipated in absence of environmental extremes. The deviation is measured in terms of fluctuations in this rate when an extreme flood occurs.

Wage change is, however, only one of the many quantifiable variables (including mortality rate and morbidity rate as presented in Frankenberg et al, 2011) in terms of which disaster risk can be measured. The variable is specifically chosen as the measurement unit in the present context for the following reason: Earlier authors, including Ravallion (1988), Morduch (1994) and Fafchamps (2003) have pointed out that vagaries of nature can have critical implications for poverty dynamics, especially in poor agrarian societies. Morduch (1994, p. 221), however, noted: "At a practical level, issues of risk have not been addressed for lack of much longitudinal data on the income and consumption of poor households." The issue is at least partially resolved here by generating a time series on real wages for agricultural workers. Household income and expenditure surveys for Bangladesh show a strong correlation between agricultural wages and rural household income.[9] This paper therefore uses agricultural wage as a proxy for income, and draws out certain inferences about disaster risk and the dynamic nature of income poverty.

The longitudinal data on real agricultural wage is generated by pooling together the district-wise monthly observations for the period January 1979 to December 2005, for the 21 "greater districts" (or regions) in Bangladesh. The series has 5090 observations. From this data, a continuous series on real wage index, $w_{t,j}$ ("t" indicating the month-year, and "j" indicating the district), is generated by normalizing each monthly district-wise real wage observation by the corresponding annual average observation. From this series, a series on change in real wage index, $x_{t,j} = \frac{w_{t,j} - w_{t-1,j}}{w_{t-1,j}}$, is obtained. This is a main series of interest for the present study. In the appendix a more detailed discussion on how the three series, namely, real wage level, real wage index ($w_{t,j}$), and change in real wage index ($x_{t,j}$), are

[9] Agricultural wage constitute 33 percent of total household income for rural poor in Bangladesh (BBS, 2003). See ADB (2006) and Hossain and Nargis (2010) for a detailed discussion on agricultural wage as a source of household income in the country.

generated. From the series on $x_{t,j}$, the norm, "m", is calculated as $m = (E(x_{t,j})|S = 0)$ for each month for each district over the period January 1979 to December 2005. Accordingly, deviation from norm, is generated as $d_{t,j} = |x_{t,j} - m|$. This is the other main series of interest for the present study. Table A.1 in the appendix presents the descriptive statistics for $w_{t,j}$, $x_{t,j}$, and $d_{t,j}$.

The series on $d_{t,j}$ is serially correlated, but stationary, as the correlation coefficient $\rho_t = \mathrm{Corr}(d_{0,j}, d_{t,j})$ decays to zero as lag increases ($t = 0, 1, 2, ..$). Thus, auto and cross correlations for the variable can be estimated from the observed series. Also, mean value of $d_{t,j}$ is approximately equal to its standard deviation. Thus, an inference can be drawn that marginal distribution of $d_{t,j}$ is exponential, taking the form $F(d_{t,j}) = \frac{1}{\alpha} e^{-\frac{d_{t,j}}{\alpha}}$, where $\alpha = \text{mean}(d_{t,j}) = \text{s.d.}(d_{t,j})$.

The wage data used in present analysis spans over a relatively long period of time. Over this period there may have been structural and institutional changes in agricultural labor market in Bangladesh, which have possibly affected real agricultural wage formations in the country. In addition, stochastic changes unrelated to natural disaster occurrences may have taken place, affecting real wages, and causing deviations from norm even when $S = 0$. Any analysis of risk based on the data is likely to be affected by these factors. Rather than embracing any theoretical position on these issues for the data, the paper aims to attend to them by following the approach adopted in Granger and Ding (1995). To address the first issue, the series on deviation, $d_{t,j}$, is arbitrarily divided into 10 equal-sized temporal sub-samples, each consisting of approximately 509 observations, and calculations carried for the entire series are repeated for the subgroups. To address the second issue, the series is examined for the presence of outliers. Outliers are identified as any $d_{t,j}$ greater than four standard deviations from the rest of the sample in period t when $S = 0$. An "outlier down-weighted" set is generated from the original data set by putting the outliers at the four standard deviation value. All calculations carried for the entire series are repeated for the outlier down-weighted set. The main empirical results are reported for the different temporal subgroups for each of these two data sets. Table A.2 in the appendix presents the descriptive statistics for the original data and the "outlier down-weighted" data.

The data on flood occurrence in Bangladesh is collected from various national and international agencies that record disaster occurrences in the country. Earlier studies (Banerjee, 2007a and b) indicate that effects of even extreme flood may not be uniform across the country. To examine the spatial distribution of flood risk, districts in Bangladesh are sub-grouped in terms of their relative flood-proneness as "more flood-prone" districts and "less flood prone" districts (henceforth to be identified as "MF" and "LF" districts respectively). Bangladesh Ministry of Irrigation (1986) recognizes more flood-prone districts as the districts with 50 percent or more area vulnerable to inundation in a "normal" year. These districts are also the more frequently flooded districts of the country. All other districts are considered less flood-prone. The summarized information on flood occurrences and relative flood-proneness of districts in Bangladesh are obtained from Banerjee (2007b). Table A.3 in the appendix presents the descriptive statistics for the series on d_j^t separately for the two groups of districts, for "normal" periods (S=0) and for periods of "extreme flood" (S=1).

Drawing upon the series on $x_{t,j}$ and $d_{t,j}$, the empirical analysis is presented in three parts: First, flood risk scores are derived for agricultural workers in Bangladesh. Next, "long memory" property of risk is examined to see if past disasters have any implications for current risks of flood disasters. Finally, to see if past variations in wage changes have any implications for current variations certain other temporal properties of risk are examined.

4.1 Risk scores

The risk measure is now employed to derive disaster risk scores for agricultural workers in Bangladesh. Recall, $R_{t,j}(F)=E(d_{t,j})\big|S=1$ is a measure of risk in period "t" in district "j". Panels (a) and (b) of Table 1 below respectively present the results based on original and "outlier down-weighted" data. The first column of each panel present risk scores for the entire longitudinal data set and for the temporal subgroups. The second and third columns present the risk scores separately for two spatial sub-groups of districts in Bangladesh, identified respectively as MF (i.e., "more flood-prone") districts and LF (i.e., "less flood prone") districts.

Insert Table 1 here

Table 1 shows the following: First, risk score derived for the aggregated data (spanning over 1979-2005) is 0.097 when the original data is examined, and is 0.096 when outlier down-weighted data is examined. Compared to these benchmarks, risk scores for MF districts are higher, and that for the LF districts are lower. This ordinal pattern is observed consistently across all temporal subgroups for both sets of data. Second, cardinal values of risk scores derived in terms of the original data match closely with their counterparts derived in terms of the outlier down-weighted. This result holds across all temporal subgroups. Third, risk scores seem to show an increasing trend over successive temporal subgroups. In other words, flood risks seem to be increasing for agricultural workers in Bangladesh over time.

To examine this third result more closely, risk scores are derived separately for the following three decades: January 1979–December 1988; January 1989–December 1998; January 1999–December 2005, and percentage changes in risk scores across the decades are examined. Panels (a) and (b) of Table 2 below present the results respectively in terms of the original data and the "outlier down-weighted" data.

Insert Table 2 here

Table 2 confirms that flood risk for agricultural workers in Bangladesh has indeed been increasing over decades. The following results are prominent in the table: First, compared to the benchmark of aggregated risk score 0.097 (derived over the span of 1979-2005, using the original data), risk was lower (0.093) in 1979-1988, but higher (0.102) in 1999-2005. This ordinal pattern is observed consistently for risk scores derived separately for each district subgroup. Analogous patterns are observed for the outlier down-weighted data. Second, aggregated risk (all districts considered together) show a 4% (approximately) increase between 1980s and 1990s, and a further 5% (approximately) increase between 1990s and 2000s, when measured in terms of the original data. The percentage increases are slightly different (respectively, by approximately 5% and 4%) when measured in terms of outlier down-weighted data. For the MF districts, risk score has increased by almost 5% between 1980s and 1990s, and by an additional 4% between 1990s and 2000s. The increases are, respectively, by 4.5% and 4.3%, when measured in terms of outlier down-weighted data. For the

LF districts, the increases in risk score are approximately by 5% and 4% respectively between 1980s and 1990s, and between 1990s and 2000s. The percentage changes remain the same when outlier down-weighted data is used.

To summarize, two salient observations can be made on spatial and temporal patterns of disaster risk for agricultural workers in Bangladesh: First, spatially distribution of risk is uneven, with, unsurprisingly, risks being higher for workers in the "more flood-prone" districts than the "less flood-prone districts". Second, temporally, disaster risk is increasing over the decades for this occupation group.

4.2 Long memory of risk

The rising trend in disaster risk scores begets the following question: What implication, if any, do past disasters have for risks in the current period? The issue is examined by exploring "long memory" of risk. The "Long memory" property captures any persistent dependence between the current observation of a stochastic process and the one at a distant past (Giraitis et al, forthcoming). In the present context, if $d_{t,j}$ is a long memory process then deviations from norm that took place during past episodes of extreme flooding will continue to influence the probability and extent of any deviations in the present period if an extreme flood occurs again. To examine whether or not $d_{t,j}$ is indeed a long memory process, this paper follows the specification presented in Taylor (1986).[10] Consider any pair $\{d^{\delta}_{t,j}, d^{\theta}_{s,j}\}$. The correlation coefficient of this pair is $\rho_t(\delta,\theta) = \mathrm{Corr}(d^{\delta}_{t,j}, d^{\theta}_{s,j})$. The stochastic process $d_{t,j}$ has long memory if $\rho_t(1,1) > \rho_t(\delta,\delta)$ for any $\delta \neq 1$, so that $\rho_t(1,1)$ declines slowly. The task is now to examine if indeed $\rho_t(1,1) > \rho_t(\delta,\delta)$ for the current data.

Now, it has already been noted that $d_{t,j}$, derived for the present study in terms of agricultural wage change in Bangladesh, is stationary, and a plausible marginal distribution of the variable is exponential. It, therefore, follows that the distribution for the pair $\{d^{\delta}_{t,j}, d^{\theta}_{s,j}\}$, $t \neq s$, is bivariate exponential, with each marginal

[10] See Granger and Ding (1995) for the detailed expositions in this regard.

having an exponential distribution with mean equal to standard deviation, and pair-wise correlation coefficient $\rho_t(1,1) = \rho$.[11] We know that for any such distribution,

$$\rho_t(\delta,\theta) = \mathrm{Corr}(d_{t,j}^{\delta}, d_{s,j}^{\theta}) = \frac{\mathrm{Cov}(d_{t,j}^{\delta}, d_{s,j}^{\theta})}{\sqrt{\mathrm{var}(d_{t,j}^{\delta})\mathrm{var}(d_{s,j}^{\theta})}}$$

and, $\rho_t(2,2) = \rho - \frac{1}{5}\rho(1-\rho)$ when $\delta = \theta = 2$; and $\rho_t(3,3) = \rho - \frac{1}{19}\rho(1-\rho)(10+\rho)$, when $\delta = \theta = 3$.

On examining the data on $d_{t,j}$ it is found that ρ is 0.299 when the original data is considered, and is 0.302 when the "outlier down-weighted" data is considered; $\rho_t(2,2)$ is 0.249 for the original data, and as 0.251 for the "outlier down-weighted" data; and $\rho_t(3,3)$ as 0.173 for the original data, and as 0.181 for the "outlier down-weighted" data. Accordingly, we have $\rho_t(1,1) > \rho_t(2,2) > \rho_t(3,3)$. Thus, following the Taylor specification, $d_{t,j}$ is indeed a long memory process when derived in terms of changes in real agricultural wage in Bangladesh. Accordingly, the risk measure derived in terms of $d_{t,j}$ has "long memory" property, and effects of deviations from norm in distant past persist in the present period. In summary, disasters, defined as deviations from norm, endure, and risks realized in the past reinforce current risks. This result may have serious implications for impoverished households who were exposed to risky situations in past, since, the households now bear greater risks of income shortfalls if extreme floods occur again.

4.3 Other temporal properties of the risk measure

If past risks affect current risks, then of immediate concern is how do the past effects continue? This question is examined by exploring the effects of past fluctuations in real wages on current fluctuations in terms of the following simple temporal model:

(13) $$E(|x_{t,j}| \,|I_{t-k,j}) = \gamma_0 + \gamma_1 |x_{t-k,j}| + \gamma_3 x_{t-k,j}^2 + u_{t-k,j}$$

[11] Nagao and Kadoya (1971) explains that such a distribution can be formalized as:

$$p(d_1,d_2) = \frac{1}{\alpha^2(1-\rho)} e^{\frac{d_1+d_2}{\alpha(1-\rho)}} I_0\left(\frac{2\sqrt{\rho}}{\alpha(1-\rho)}\sqrt{d_1 d_2}\right) \text{ with } I_0(z) \text{ being } \sum_{n=0}^{\infty} \frac{z^{2n}}{2^{2n}(n!)^2}.$$

In (13), expected change in real wage (absolute value) in current period (t) in district j is explained in terms of past linear changes (absolute value) and quadratic changes in period $t-k$, (k=1,2,..). The term $E(|x_{t,j}| \mid I_{t,j})$ has the following additional interpretation. Recall, $E(d_{t,j} \mid I_{t-k,j})$ is the determinable aspect of disaster risk in period "t", and is conditional on factors that already realized in period $\boldsymbol{t-k}$. The information set $I_{t-k,j}$ contains information on $d_{t,j}, d_{t-1,j}, d_{t-2,j},..$ etc. Thus, $E(|x_{t,j}| \mid I_{t,j})$ in equation (12) may be interpreted to capture determinable aspect of disaster risk when $m = \left(E(x_t) \mid S = 0\right) = 0$.

Estimations for the model given by (13) are run for $\boldsymbol{k}$ =1, 2, 5, 10, 20, 30, 40, 50, and 100 for the longitudinal data. Table 3 below presents the results using the aggregated data. Table A.4 in appendix presents the estimates for different temporal sub-groups. Table 4 below focuses on spatial sub-groups, and presents the estimates separately for MF (i.e., "more flood-prone") districts and LF (i.e., "less flood prone"). Estimation results are presented separately for the original data and the "outlier down-weighted" data respectively in panels (a) and (b) in each of these three tables.

Insert Table 3 here

Insert Table 4 here

The following results are notable in Table 3: First, estimated values of γ_0 for the original and the outlier down-weighted data are comparable for all ks, but that of γ_1 and γ_2 are not. Summary statistics (correlation coefficient R^2 and Durbin-Watson statistics) for different ks are, however, comparable for the two data sets, with R^2 values being consistently higher for the outlier down-weighted data than the original data. Second, estimated values of γ_0 are highly statically significant for all ks. Estimated values of γ_1 and γ_2 are statistically significant at 95% level or higher for k=1, 2, 5, 10, 20, 30, 40; at 90% level or higher for k=50; and at less than 90% level for k=100. Third, estimated values of γ_1 are always positive in sign. Thus, higher magnitude of wage fluctuations in past bring about higher fluctuations in wages in the present. Fourth, Durbin-Watson test statistics generated for either data sets is greater than 2 for k=1; and is less than 2 (but greater than 1) for all other ks. Thus, there is evidence of positive serial correlation in the data, and it can be inferred that past fluctuations (or, positive errors) in real wages increase the chances of subsequent fluctuations (or positive errors). While positive serial correlation in the data makes forecasting and predictive analysis tenuous, it does not affect the consistency of estimated regression coefficients (Bhargava et al, 1982). In summary, the estimation results in Table 3 indicate that past changes in real wages have significant impact on current changes in real wages. The magnitude of impact however decline with time (i.e., with increase in the time lag k).

While Table 3 presents estimation results for the aggregated data, Table 4 presents the disaggregated results for "more" and "less" flood-prone districts. The following results are notable in Table 4: For "more" flood-prone districts, estimated values of γ_1 are statistically significant at 90% level or higher for $k \leq 40$; and that of γ_2 are statistically significant at 90% level or higher for $k \leq 10$. For "less" flood-prone districts, estimated values of γ_1 are statistically significant at 90% level or higher for $k \leq 20$; and that for γ_2 are statistically significant at 90% level or higher for $k \leq 5$. Thus, effects of distant past on current changes.in real wages declines faster in the case of "less" flood-prone districts than in the case of "more" flood-prone districts.

Note, in Tables 3 and 4, values of R^2 are low (column 5 in panels (a) and (b) of the tables), suggesting that the temporal model given by (12) is underspecified. Evidently, there are other important determinants of expected (absolute) change in real wages, apart from past linear (absolute) and past quadratic changes, that are not identified in the model.[12] Nevertheless, the relevance of this simple model is in highlighting that past fluctuations in wages have important role in determining current fluctuations. The effects of past fluctuations, however, gradually decline as we go back in time. Declining values of R^2 as k increases from 1 to 2 to 100 indicates this.

The above results imply that volatility in income change patterns in past for a population group is likely to bring about volatility in present. Though the effects of distant past is gradually dampened, the process is slower if the population group is more frequently exposed to natural extremes.

[12] Difficulties in obtaining longitudinal data on other determinants of wage changes, including changing market and nonmarket conditions that determine demand and supply of labor, prevent a more complete empirical analysis. To address the issue, cross-sectional analysis and analysis in terms of panel data are carried out in two forthcoming articles.

5. Conclusion

The main argument in this paper has been the following: If disaster is perceived as deviation from norm, then the risk of disaster, construed as chance of this deviation, can be formalized as expected absolute deviation from norm. This risk is not entirely accidental or arbitrary. Rather, it is a composite of deterministic elements that may either have developed from past events or may ensue from current systemic conditions or both, and an unforeseeable element generated by "trigger events" in nature. This approach to disaster risk is then applied to examine the conditions of agricultural workers in disaster-prone Bangladesh. The empirical results indicate that spatial distribution of flood disaster risk is uneven, with workers in "more flood-prone" districts bearing higher risks than workers in "less flood-prone districts". Irrespective of their location, however, flood disaster risk is increasing for this occupation group over the decades.

Analysis of the particular case of agricultural workers in Bangladesh helps to draw out certain general conclusions about temporal properties of the proposed risk measure. It is found that disaster risk has "long memory". In other words, past deviations from norm have significant effects on chances of current deviations. Thus, if a population group has experienced disaster in past, their risk of current disaster increases if a natural trigger occurs again. The paper then attempts to identify the process through which the effects of past deviations persist. It finds that, unsurprisingly, memory of past deviations decay slowly in a more volatile system. In the case of Bangladesh, for example, this is observed in regions that experience repeated occurrences of extreme floods (i.e., the "more flood-prone" or MF districts), especially when their case is compared with regions that are less frequently flooded (i.e., the "less flood-prone" or LF districts). Disaster risk, measured cardinally as expected absolute deviations in income change patterns from the norm, is higher for the MF districts, and the fluctuations in this income change pattern, once triggered by a extreme flood, take a longer period of time to decay than the LF districts.

Based on the above results, additional inferences can be drawn regarding disaster risk and poverty dynamics for an impoverished population recurrently exposed to environmental extremes. It is well established that environmental risks have significant negative implications for welfare, material and otherwise. Among those who are exposed to natural extremes, the population group with income level close to poverty line faces the threat of being dropped below the threshold, while those who have been poor a good deal longer face the threat of deepening of poverty with additional depletion of income level. If, further, the natural extreme poses threat to the rate of change in income, the recovery process may be long drawn for the transitional poor, and poverty traps may be generated for the chronically poor. The reason is the following: With volatile income change patterns, any projection and planning strategies to ward off the next episode of crisis may turn elusive. While this condition is detrimental to the wellbeing of any group, it is especially so for those who are already deprived and lead a precarious existence. This group may thus be forced to exist in a constant state of flux. Failure to plan ahead to smoothen future streams of income (or consumption or any other indicators of economic wellbeing) imply that support must be obtained immediately when a violent event occurs in nature, otherwise the likelihood of persistent poverty increases. In absence of supports, either from the state or from the community or garnered from the market, immediate responses at the individual level invariably involve either reduction of consumption expenditure leading to a further deepened state of impoverishment in the short run, or depletion of assets which may compromise long term prospects of prosperity, or both. For a resource-strapped society, impromptu and provisional supports in times of disaster may be inadequate, and may additionally involve reallocation of funds away from other needs. This may generate endemic poverty in the region. The present analysis indicates that this risk is higher for those who had already experienced an earlier episode of disaster. For these individuals, whose circumstances have already been reduced, adoption of adequate disaster mitigation strategies for future may be difficult. If risk of disaster additionally generates risks of poverty, and this risk cannot be mitigated at an individual level, then disaster planning at the supra-individual level cannot be ad hoc or be disassociated from larger concerns of poverty reduction.

Appendix

A.1 Derivation of the wage series ($w_{t,j}$), 1979–2005

Data on average daily nominal wage for male agricultural workers (without food) is obtained for each month, for each of the "greater" districts in Bangladesh, for the period January 1979–December 2005.[13] The nominal wage series is then deflated by rural CPI to generate a district-wise monthly series on real wage.[14] The real wage series thus obtained is used to generate a series on monthly wage indices, $w_{t,j}$, where

$w_{t,j} = \frac{v_{t,j}}{\underline{v}_{t,j}}$ is the real agricultural wage index in district "j" in month-year "t" is $w_{t,j}$,

where j=Bandarban, Barisal, .. , Tangail; and t=January 1979, February 1979,.. , December 2005; $v_{t,j}$ is real agricultural wage rate in district "j" in month-year "t"; and $\underline{v}_{t,j}$ is the relevant annual average real agricultural wage rate in district "j", the average being taken over the months. The district-wise monthly wage index data is then pooled together by applying the least-squares-with-dummy-variables (LSDV) method to generate a continuous series on real wage for the period January 1979–December 2005.[15] The pooled series has 5090 observations. The present series is a

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[13] Source: BBS[a], [b] and [c], various years. The data is available for the period 1979-2005. The nominal wage series has missing data for January 1990-November 1990 and for January 1991-June 1992. The "greater districts" or "regions" of Bangladesh considered for the present study are Bandarban, Barisal, Bogra, Chittagong, Chittagong Hill Tracts, Comilla, Dhaka, Dinajpur, Faridpur, Jamalpur, Jessore, Khulna, Kushtia, Mymensingh, Noakhali, Pabna, Patuakhali, Rajshahi, Rangpur, Sylhet, and Tangail.

[14] Source: (1) BBS[c], various years; (2) BBS[b], various years. Data on CPI for agricultural workers are not available for Bangladesh. Therefore rural CPI is used as a proxy. The data on rural CPI is available for four Divisions: Dhaka, Chittagong, Khulna and Rajshahi. The series is available from July 1978, and has missing data for December 1987–October 1988.

[15] The cross-sectional and time-series observations are pooled together to generate a continuous series on real agricultural wages in the following manner: Defining $A_{t,j}$ as the vector of explanatory variables in district 'j' in month-year 't' that explain wage rate, the following separate regressions are postulated for each district 'j': $w_{t,j} = \alpha_j + A_{t,j}\beta_j + u_{t,j}$. Next, the hypothesis H1 is tested, where H1 : $\beta_1 = \beta_2 = .. = \beta_{20} = \beta$, and the following common regression equation is estimated: $w_{t,j} = \alpha_j + A_{t,j}\beta + u_{t,j}$. The F ratio (p<0.01) is not significant, and we fail to reject the hypothesis. As there are no significant differences in the coefficients in the district-

temporal extension of an original series (that covered the period January 1979–December 2000) generated for another study (Banerjee, 2007b). From this series, a series on change in real wage index, $x_{t,j} = \frac{w_{t,j} - w_{t-1,j}}{w_{t-1,j}}$, is obtained.

Insert Table A.1 here

Insert Table A.2 here

The districts in Bangladesh are classified according to their relative flood-proneness in the following manner (Bangladesh Ministry of Irrigation, 1986): "More flood-prone" ("MF") districts are: Bogra, Comilla, Dhaka, Faridpur, Jessore, Mymensingh, Pabna, Sylhet, and Tangail. 50 percent or more area of these districts is vulnerable to inundation of flood depth 90cm or more in a "normal" year. All other districts are considered "less flood-prone" ("LF"). The "less flood prone" districts are Bandarban, Barisal, Chittagong, Chittagong Hill Tracts, Dinajpur, Khulna, Kushtia, Noakhali, Patuakhali, Rajshahi, and Rangpur. In a "normal" year, 12% of net cultivated area of Bangladesh (constituting almost 19% of the total area) experiences 'deep' floods (of depth over 180cm), 16% experiences 'moderate' floods (of depth 90-180cm), 35% experiences 'shallow' floods (of depth 30-90cm), and the remaining 37% is not affected by floods (Bangladesh Ministry of Irrigation, 1986). In years of extreme floods 35% or more of total area of the country (constituting 55% or more of the total area) experience 'moderate' to 'deep' flooding (of flood-depth 90cm or more). Over the period 1979–2005, extreme flood occurred in Bangladesh in the following years in the monsoon months (June–September) of 1984, 1987, 1988, 1998, and 2004 (Banerjee, 2007b; DHA, various years). For the present analysis, we consider $S = 1$ for these month-years.

Insert Table A.3 here

Insert Table A.4 here

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wise regression equations, the data is pooled together. See Maddala (1977) for detail discussion on this methodology.

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Tables to be inserted in the main body of the text

Table 1
Disaster risk scores ($R_{t,j}$) for agricultural workers,
Bangladesh, and "more flood-prone" (MF) and "less flood-prone" (LF) districts
Temporal sub-samples, original and outlier down-weighted data, 1979-2005[a]

	Panel (a) Original data			Panel (b) Outlier down-weighted data		
	$R_{t,j}$, All districts *(s.d.)*	$R_{t,j}$, MF districts *(s.d.)*	$R_{t,j}$, LF districts *(s.d.)*	$R_{t,j}$, All districts *(s.d.)*	$R_{t,j}$, MF districts *(s.d.)*	$R_{t,j}$, LF districts *(s.d.)*
Across all period, 1979-2005	0.097 *(0.099)*	0.100 *(0.107)*	0.093 *(0.088)*	0.096 *(0.097)*	0.098 *(0.105)*	0.091 *(0.086)*
Sub-sample 1	0.081 *(0.086)*	0.083 *(0.078)*	0.077 *(0.069)*	0.079 *(0.084)*	0.082 *(0.076)*	0.075 *(0.067)*
2	0.087 *(0.091)*	0.090 *(0.103)*	0.083 *(0.106)*	0.086 *(0.089)*	0.089 *(0.100)*	0.082 *(0.103)*
3	0.092 *(0.088)*	0.094 *(0.080)*	0.087 *(0.065)*	0.091 *(0.085)*	0.092 *(0.078)*	0.086 *(0.064)*
4	0.104 *(0.110)*	0.107 *(0.097)*	0.099 *(0.094)*	0.102 *(0.107)*	0.105 *(0.095)*	0.097 *(0.092)*
5	0.105 *(0.110)*	0.108 *(0.145)*	0.100 *(0.112)*	0.103 *(0.107)*	0.107 *(0.141)*	0.098 *(0.109)*
6	0.091 *(0.081)*	0.094 *(0.156)*	0.087 *(0.101)*	0.090 *(0.079)*	0.093 *(0.152)*	0.085 *(0.099)*
7	0.107 *(0.091)*	0.110 *(0.128)*	0.102 *(0.080)*	0.105 *(0.089)*	0.108 *(0.125)*	0.101 *(0.078)*
8	0.111 *(0.133)*	0.114 *(0.105)*	0.106 *(0.081)*	0.108 *(0.130)*	0.112 *(0.102)*	0.86 *(0.079)*
9	0.091 *(0.098)*	0.094 *(0.092)*	0.087 *(0.082)*	0.090 *(0.096)*	0.093 *(0.090)*	0.034 *(0.080)*
10	0.104 *(0.099)*	0.107 *(0.096)*	0.099 *(0.085)*	0.102 *(0.097)*	0.106 *(0.094)*	0.097 *(0.082)*

[a] Standard deviations (*s.d.*) in the parenthesis

Table 2
Disaster risk scores ($R_{t,j}$) and changes in risk ($\nabla R_{t,j}$) for agricultural workers,
Bangladesh, and "more flood-prone" (MF) and "less flood-prone" (LF) districts
Across decades (1979-1988, 1989-1998, and 1999-2005), original and outlier down-weighted data[a]

	Panel (a) Original data						Panel (b) Outlier down-weighted data					
	$R_{t,j}$, All districts *(s.d.)*	$\nabla R_{t,j}$, (in %) All districts	$R_{t,j}$, MF districts *(s.d.)*	$\nabla R_{t,j}$, (in %) MF districts	$R_{t,j}$, LF districts *(s.d.)*	$\nabla R_{t,j}$, (in %) LF districts	$R_{t,j}$, All districts *(s.d.)*	$\nabla R_{t,j}$, (in %) All districts	$R_{t,j}$, MF districts *(s.d.)*	$\nabla R_{t,j}$, (in %) MF districts	$R_{t,j}$, LF districts *(s.d.)*	$\nabla R_{t,j}$, (in %) LF districts
1979-2005	0.097 *(0.099)*	—	0.100 *(0.107)*	—	0.093 *(0.088)*	—	0.096 *(0.096)*	—	0.098 *(0.105)*	—	0.091 *(0.086)*	—
1979–1988	0.093 *(0.093)*	—	0.096 *(0.110)*	—	0.089 *(0.091)*	—	0.092 *(0.090)*	—	0.094 *(0.107)*	—	0.087 *(0.089)*	—
1989–1998	0.097 *(0.096)*	0.039%	0.101 *(0.118)*	0.048%	0.093 *(0.101)*	0.049%	0.096 *(0.093)*	0.047%	0.099 *(0.115)*	0.045%	0.092 *(0.91)*	0.049%
1999–2005	0.102 *(0.106)*	0.052%	0.105 *(0.120)*	0.040%	0.097 *(0.090)*	0.039%	0.100 *(0.098)*	0.039%	0.103 *(0.117)*	0.043%	0.095 *(0.088)*	0.039%

[a] Standard deviations (*s.d.*) in the parenthesis

Table 3
Effects of past wage changes on current wage changes for agricultural workers in Bangladesh:
Summary of regression model (12) for original and outlier down-weighted longitudinal data, 1979-2005[a]

	Panel (a) Original data					Panel (b) Outlier down-weighted data				
	γ_0 (*t*)	γ_1 (*t*)	γ_2 (*t*)	R^2	D-W	γ_0 (*t*)	γ_1 (*t*)	γ_2 (*t*)	R^2	D-W
k=1	0.057 *(8.83)****	0.536 *(3.21)****	-1.339 *(-2.95)****	0.111	2.09	0.063 *(8.86)****	0.631 *(3.24)****	-1.244 *(-2.98)****	0.148	2.10
2	0.067 *(9.48)****	0.238 *(2.49)***	-1.290 *(-3.78)****	0.105	1.67	0.072 *(9.51)****	0.243 *(2.46)****	1.386 *(3.76)****	0.142	1.68
5	0.066 *(8.95)****	0.159 *(2.58)****	-0.508 *(-3.42)****	0.102	1.53	0.072 *(8.99)****	0.254 *(2.62)****	-0.413 *(-3.44)****	0.139	1.54
10	0.074 *(10.54)****	0.156 *(3.17)****	0.045 *(2.03)***	0.101	1.52	0.075 *(10.57)****	0.060 *(3.13)****	0.140 *(2.01)***	0.138	1.53
20	0.072 *(9.43)****	0.023 *(2.16)***	0.056 *(2.15)***	0.100	1.50	0.078 *(9.47)****	0.072 *(2.12)***	0.151 *(2.13)***	0.137	1.51
30	0.073 *(8.73)****	0.025 *(2.14)***	0.058 *(3.12)****	0.099	1.47	0.079 *(8.77)****	0.120 *(2.17)***	0.154 *(3.10)****	0.136	1.48
40	0.070 *(7.70)****	0.293 *(2.99)****	-0.822 *(-3.51)****	0.096	1.46	0.080 *(7.74)****	0.388 *(3.02)****	-0.727 *(-3.53)****	0.133	1.47
50	0.044 *(7.67)****	0.263 *(1.96)***	-0.852 *(-1.78)**	0.066	1.43	0.044 *(7.67)****	0.263 *(1.96)***	0.050 *(1.71)**	0.103	1.44
100	0.014 *(7.64)****	0.23 *(0.93)*	-0.882 *(-0.05)*	0.036	1.40	0.014 *(7.64)****	0.233 *(0.93)*	0.020 *(0.68)*	0.073	1.41

[a] t statistics in the parenthesis
*** Significant at 1%
** Significant at 5%
*Significant at 10%

Table 4
Effects of past wage changes on current wage changes for agricultural workers in Bangladesh:
Summary of regression model (12) for "more flood-prone" (MF) and "less flood-prone" (LF) districts, for original and outlier down-weighted data, 1979-2005[a]

Panel (a)
Original data

	"More flood-prone" (MF) districts					"Less flood-prone" (LF) districts				
	γ_0 (t)	γ_1 (t)	γ_2 (t)	R^2	D-W	γ_0 (t)	γ_1 (t)	γ_2 (t)	R^2	D-W
k=1	0.071 *(5.97)****	0.216 *(2.95)****	-0.427 *(-3.72)****	0.109	2.09	0.050 *(5.61)****	0.188 *(3.08)****	-0.253 *(-3.60)****	0.089	2.08
2	0.078 *(6.88)****	0.339 *(3.69)****	1.652 *(2.94)****	0.104	2.03	0.054 *(6.15)****	0.060 *(3.30***)*	0.667 *(2.06)***	0.088	2.40
5	0.066 *(5.46)****	0.555 *(2.57)***	-1.509 *(-2.53)***	0.109	1.97	0.054 *(5.95)****	0.073 *(3.17)****	-0.003 *(-2.01)***	0.090	2.41
10	0.081 *(5.91)****	0.305 *(2.45)***	0.857 *(1.70)**	0.115	1.90	0.064 *(6.76)****	0.030 *(2.62)***	0.163 *(1.65)**	0.091	2.37
20	0.087 *(6.65)****	0.110 *(2.41**)*	0.462 *(0.73)*	0.113	1.95	0.061 *(6.48)****	0.111 *(2.35)***	0.461 *(1.37)*	0.092	2.31
30	0.085 *(6.12)****	0.352 *(2.19)***	1.176 *(1.62)*	0.117	1.59	0.073 *(6.31)****	0.409 *(2.59)***	1.736 *(1.31)*	0.097	1.71
40	0.101 *(6.94)****	0.091 *(2.18)***	-0.022 *(-0.04)*	0.122	1.56	0.084 *(5.81)****	0.606 *(2.42)***	-1.325 *(1.33)*	0.098	1.66
50	0.057 *(6.91)****	0.121 *(0.30)*	-0.008 *(-1.56)*	0.092	1.53	0.031 *(5.78)****	0.636 *(1.61)*	1.295 *(1.56)*	0.068	1.63
100	0.027 *(6.88)****	0.151 *(0.73)*	-0.038 *(-0.18)*	0.062	1.50	0.0401 *(5.75)****	0.666 *(1.31)*	1.265 *(0.17)*	0.038	1.60

Table 4 continued

Panel (b)
Outlier down-weighted data

	MF districts					LF districts				
	γ_0 (*t*)	γ_1 (*t*)	γ_2 (*t*)	R^2	D-W	γ_0 (*t*)	γ_1 (*t*)	γ_2 (*t*)	R^2	D-W
k=1	0.076 *(6.00)****	0.311 *(2.98)*	-0.331 *(-0.75)*	0.146	2.10	0.056 *(5.64)****	0.284 *(3.12)****	-0.158 *(-3.62)****	0.126	2.09
2	0.084 *(6.91)****	0.244 *(2.92)****	1.747 *(-1.53)*	0.141	2.04	0.060 *(6.18)****	0.036 *(2.31)***	0.762 *(1.58)*	0.125	2.41
5	0.072 *(5.50)****	0.651 *(2.45)***	-1.414 *(-2.56)***	0.146	1.98	0.060 *(5.99)****	0.168 *(1.45)*	-0.099 *(-1.98)***	0.127	2.42
10	0.086 *(5.94)****	0.400 *(2.22)***	0.761 *(1.33)*	0.152	1.91	0.070 *(6.79)****	0.065 *(3.13)****	-0.067 *(-1.40)*	0.129	2.32
20	0.093 *(6.68)****	0.206 *(2.48)***	0.367 *(0.76)*	0.150	1.96	0.066 *(6.52)****	0.015 *(1.99)***	0.556 *(1.04)*	0.128	2.38
30	0.091 *(6.15)****	0.448 *(1.23)*	1.081 *(1.64)*	0.154	1.60	0.079 *(6.34)****	0.314 *(1.46)*	1.831 *(1.29)*	0.134	1.72
40	0.107 *(6.97)****	0.004 *(1.30)*	-0.118 *(-0.07)*	0.159	1.57	0.090 *(5.84)****	0.510 *(1.25)*	-1.421 *(-1.27)*	0.135	1.67
50	0.059 *(6.940)****	0.026 *(1.33)*	-0.088 *(-1.57)*	0.129	1.54	0.060 *(5.81)****	0.540 *(1.45)*	1.391 (1.55)	0.105	1.64
100	0.031 *(6.91)****	0.056 *(1.360)*	-0.058 *(-0.19)*	0.099	1.51	0.030 *(5.78)****	0.570 *(1.30)*	1.361 *(0.16)*	0.075	1.61

[a] t statistics in the parenthesis
*** Significant at 1%
** Significant at 5%
*Significant at 10%

Tables to be inserted in the Appendix

Table A.1
Descriptive statistics: Real agricultural wage index ($w_{t,j}$), change ($x_{t,j}$), and deviation ($d_{t,j}$), Bangladesh, original data, 1979-2005

	Maximum	Minimum	Mean	Standard Deviation	Skewness	Kurtosis
$w_{t,j}$	1.610	0.515	1.000	0.095	0.145	6.573
$x_{t,j}$	0.799	-1.000	0.005	0.110	1.143	9.899
$d_{t,j}$	1.007	0.000	0.091	0.091	3.060	12.531

Table A.2
Descriptive statistics: Real agricultural wage deviation ($d_{t,j}$), Bangladesh
Temporal sub-samples, original and outlier down-weighted data, 1979-2005

	Panel (a) Original data				Panel (b) Outlier down-weighted data			
	Mean	Standard Deviation	Skewness	Kurtosis	Mean	Standard Deviation	Skewness	Kurtosis
Across all period, 1979-2005	0.091	0.091	3.060	12.531	0.088	0.087	2.900	12.371
Sub-sample 1	0.076	0.078	3.781	19.661	0.073	0.074	3.621	19.501
2	0.082	0.085	2.593	8.120	0.079	0.081	2.433	7.960
3	0.086	0.083	2.571	7.972	0.083	0.079	2.411	7.812
4	0.097	0.095	2.791	9.079	0.094	0.091	2.631	8.919
5	0.099	0.095	2.723	2.723	0.096	0.091	2.563	2.563
6	0.086	0.081	3.504	17.539	0.083	0.077	3.344	17.379
7	0.100	0.102	2.375	6.824	0.097	0.098	2.215	6.664
8	0.104	0.106	2.680	9.027	0.101	0.102	2.520	8.867
9	0.086	0.088	3.252	15.317	0.083	0.084	3.092	15.157
10	0.098	0.100	2.550	7.372	0.095	0.096	2.390	7.212

Table A.3
Descriptive statistics: Real agricultural wage deviation ($d_{t,j}$),
Bangladesh, and "more flood-prone" (MF) and "less flood-prone" (LF) districts
"Normal" periods (S=0) and "extreme flood" periods (S=1), 1979-2005

	Maximum	Minimum	Mean	Standard Deviation	Skewness	Kurtosis
Across all period, 1979-2005; all districts	1.007	0.000	0.091	0.091	3.060	12.531
For periods S=0; all districts	1.007	0.000	0.081	0.083	3.135	13.316
For periods S=1; all districts	0.613	0.000	0.097	0.099	2.299	5.489
Across all period, 1979-2005; "More flood-prone" (MF) districts	1.007	0.013	0.090	0.103	0.398	-1.558
For periods S=0; "More flood-prone" (MF) districts	1.007	0.013	0.083	0.078	1.327	1.535
For periods S=0; "More flood-prone" (MF) districts	0.515	0.000	0.100	0.107	1.884	2.882
Across all period, 1979-2005; "Less flood-prone" (LF) districts	0.613	0.000	0.087	0.101	1.408	1.162
For periods S=0; "Less flood-prone" (LF) districts	0.386	0.004	0.068	0.071	3.910	21.835
For periods S=0; "Less flood-prone" (LF) districts	0.749	0.000	0.093	0.088	2.921	10.690

Table A.4

Effects of past wage changes on current wage changes for agricultural workers in Bangladesh:

Summary of regression model (12) for original and outlier down-weighted data, and temporal sub-samples, 1979-2005

	Panel (a)								Panel (b)							
	Original data								Outlier down-weighted data							
	γ_0	t	γ_1	t	γ_2	t	R^2	D-W	γ_0	t	γ_1	t	γ_2	t	R^2	D-W
k=1																
Across all period, 1979-2005	0.057	8.83	0.536	3.21	-1.339	-2.95	0.111	2.091	0.063	8.86	0.631	3.24	-1.24	-2.98	0.148	2.10
Sub-sample 1	0.049	8.82	0.528	3.20	-1.347	-2.96	0.103	2.083	0.055	8.86	0.623	3.23	-1.25	-2.99	0.140	2.093
2	0.044	8.82	0.523	3.19	-1.352	-2.97	0.098	2.078	0.050	8.85	0.618	3.23	-1.26	-2.99	0.135	2.088
3	0.050	8.82	0.529	3.20	-1.346	-2.96	0.104	2.083	0.056	8.86	0.624	3.23	-1.25	-2.98	0.141	2.093
4	0.058	8.83	0.537	3.21	-1.338	-2.95	0.112	2.092	0.064	8.86	0.632	3.24	-1.24	-2.98	0.149	2.102
5	0.064	8.84	0.543	3.21	-1.332	-2.95	0.118	2.098	0.070	8.87	0.639	3.25	-1.24	-2.97	0.155	2.108
6	0.058	8.83	0.537	3.21	-1.338	-2.95	0.112	2.092	0.064	8.86	0.632	3.24	-1.24	-2.98	0.149	2.102
7	0.059	8.83	0.538	3.21	-1.337	-2.95	0.113	2.093	0.065	8.87	0.633	3.24	-1.24	-2.98	0.150	2.103
8	0.069	8.84	0.548	3.22	-1.327	-2.94	0.123	2.102	0.074	8.87	0.643	3.25	-1.23	-2.97	0.160	2.112
9	0.061	8.83	0.540	3.21	-1.335	-2.95	0.115	2.095	0.067	8.87	0.635	3.24	-1.24	-2.97	0.152	2.105
10	0.058	8.83	0.537	3.21	-1.338	-2.95	0.112	2.091	0.064	8.86	0.632	3.24	-1.24	-2.98	0.149	2.101
k=2																
Across all period, 1979-2005	0.067	9.48	-0.238	-2.49	1.290	3.78	0.105	1.672	0.072	9.51	-0.143	-2.46	1.386	3.76	0.142	1.68
Sub-sample 1	0.058	9.47	-0.247	-2.50	1.282	3.77	0.097	1.664	0.064	9.50	-0.151	-2.46	1.378	3.75	0.134	1.674
2	0.102	9.51	-0.203	-2.45	1.326	3.82	0.141	1.707	0.108	9.55	-0.108	-2.42	1.421	3.79	0.178	1.717
3	0.108	9.52	-0.197	-2.45	1.332	3.82	0.146	1.713	0.114	9.55	-0.102	-2.41	1.427	3.80	0.183	1.723
4	0.116	9.53	-0.189	-2.44	1.340	3.83	0.155	1.721	0.122	9.56	-0.093	-2.41	1.435	3.81	0.192	1.731
5	0.122	9.53	-0.183	-2.43	1.346	3.84	0.161	1.728	0.128	9.57	-0.087	-2.40	1.442	3.81	0.198	1.738
6	0.116	9.53	-0.189	-2.44	1.340	3.83	0.155	1.721	0.122	9.56	-0.093	-2.41	1.435	3.81	0.192	1.731
7	0.117	9.53	-0.188	-2.44	1.341	3.83	0.156	1.722	0.123	9.56	-0.092	-2.41	1.436	3.81	0.193	1.732
8	0.127	9.54	-0.178	-2.43	1.351	3.84	0.165	1.732	0.133	9.57	-0.083	-2.40	1.446	3.82	0.202	1.742
9	0.119	9.53	-0.186	-2.44	1.343	3.83	0.157	1.724	0.125	9.56	-0.091	-2.40	1.438	3.81	0.194	1.734
10	0.116	9.53	-0.189	-2.44	1.340	3.83	0.154	1.721	0.122	9.56	-0.094	-2.41	1.435	3.81	0.191	1.731
k=5																
Across all period, 1979-2005	0.066	8.95	0.159	2.58	-0.508	-3.42	0.102	1.527	0.072	8.99	0.254	2.62	-0.41	-3.44	0.139	3.72
Sub-sample 1	0.058	8.95	0.150	2.57	-0.516	-3.43	0.094	1.519	0.064	8.98	0.246	2.61	-0.42	-3.45	0.131	3.715
2	0.102	8.99	0.194	2.62	-0.473	-3.39	0.137	1.562	0.107	9.02	0.289	2.65	-0.38	-3.41	0.174	3.758
3	0.107	9.00	0.200	2.62	-0.467	-3.38	0.143	1.568	0.113	9.03	0.295	2.66	-0.37	-3.40	0.180	3.764
4	0.116	9.00	0.208	2.63	-0.459	-3.37	0.152	1.576	0.121	9.04	0.303	2.67	-0.36	-3.40	0.189	3.772
5	0.122	9.01	0.214	2.64	-0.452	-3.37	0.158	1.582	0.128	9.04	0.310	2.67	-0.36	-3.39	0.195	3.779
6	0.116	9.00	0.208	2.63	-0.459	-3.37	0.152	1.576	0.121	9.04	0.303	2.67	-0.36	-3.40	0.189	3.772
7	0.117	9.00	0.209	2.63	-0.458	-3.37	0.153	1.577	0.122	9.04	0.304	2.67	-0.36	-3.39	0.190	3.773
8	0.126	9.01	0.219	2.64	-0.448	-3.36	0.162	1.587	0.132	9.05	0.314	2.68	-0.35	-3.38	0.199	3.783
9	0.118	9.01	0.211	2.63	-0.456	-3.37	0.154	1.579	0.124	9.04	0.306	2.67	-0.36	-3.39	0.191	3.775
10	0.115	9.00	0.208	2.63	-0.459	-3.37	0.151	1.576	0.121	9.04	0.303	2.67	-0.36	-3.40	0.188	3.772

k=10																
Across all period, 1979-2005	0.074	10.54	-0.156	-3.17	0.045	2.03	0.101	1.517	0.075	10.57	-0.060	-3.13	0.140	2.01	0.138	1.53
Sub-sample 1	0.066	10.53	-0.164	-3.18	0.037	2.02	0.092	1.509	0.067	10.56	-0.069	-3.14	0.132	2.00	0.129	1.519
2	0.109	10.57	-0.121	-3.13	0.080	2.06	0.136	1.552	0.111	10.61	-0.025	-3.10	0.176	2.04	0.173	1.562
3	0.115	10.58	-0.115	-3.13	0.086	2.07	0.142	1.558	0.117	10.61	-0.019	-3.09	0.182	2.05	0.179	1.568
4	0.123	10.59	-0.106	-3.12	0.095	2.08	0.150	1.567	0.125	10.62	-0.011	-3.08	0.190	2.06	0.187	1.577
5	0.130	10.59	-0.100	-3.11	0.101	2.09	0.156	1.573	0.131	10.63	-0.005	-3.08	0.196	2.06	0.193	1.583
6	0.123	10.59	-0.106	-3.12	0.095	2.08	0.150	1.567	0.125	10.62	-0.011	-3.08	0.190	2.06	0.187	1.577
7	0.124	10.59	-0.105	-3.12	0.096	2.08	0.151	1.568	0.126	10.62	-0.010	-3.08	0.191	2.06	0.188	1.578
8	0.134	10.60	-0.096	-3.11	0.105	2.09	0.161	1.577	0.135	10.63	0.000	-3.07	0.201	2.07	0.198	1.587
9	0.126	10.59	-0.104	-3.12	0.097	2.08	0.153	1.569	0.128	10.62	-0.008	-3.08	0.193	2.06	0.190	1.579
10	0.123	10.59	-0.107	-3.12	0.094	2.08	0.150	1.566	0.125	10.62	-0.011	-3.08	0.190	2.06	0.187	1.576
k=20																
Across all period, 1979-2005	0.072	9.43	-0.023	-2.16	0.056	2.15	0.100	1.496	0.078	9.47	0.072	-2.12	0.151	2.13	0.137	1.51
Sub-sample 1	0.064	9.42	-0.031	-2.17	0.047	2.14	0.092	1.488	0.070	9.46	0.064	-2.13	0.143	2.12	0.129	1.498
2	0.108	9.47	0.012	-2.12	0.091	2.19	0.136	1.531	0.113	9.50	0.108	-2.09	0.186	2.16	0.173	1.541
3	0.114	9.47	0.018	-2.12	0.097	2.19	0.141	1.537	0.119	9.51	0.113	-2.08	0.192	2.17	0.178	1.547
4	0.122	9.48	0.026	-2.11	0.105	2.20	0.150	1.546	0.127	9.52	0.122	-2.08	0.201	2.18	0.187	1.556
5	0.128	9.49	0.033	-2.10	0.111	2.21	0.156	1.552	0.134	9.52	0.128	-2.07	0.207	2.18	0.193	1.562
6	0.122	9.48	0.026	-2.11	0.105	2.20	0.150	1.546	0.127	9.52	0.122	-2.08	0.201	2.18	0.187	1.556
7	0.123	9.48	0.027	-2.11	0.106	2.20	0.151	1.547	0.129	9.52	0.123	-2.07	0.202	2.18	0.188	1.557
8	0.132	9.49	0.037	-2.10	0.116	2.21	0.160	1.556	0.138	9.53	0.132	-2.06	0.211	2.19	0.197	1.566
9	0.125	9.48	0.029	-2.11	0.108	2.20	0.153	1.548	0.130	9.52	0.125	-2.07	0.203	2.18	0.190	1.558
10	0.122	9.48	0.026	-2.11	0.105	2.20	0.149	1.545	0.127	9.52	0.121	-2.08	0.200	2.18	0.186	1.555
k=30																
Across all period, 1979-2005	0.073	8.73	0.025	2.14	0.058	3.12	0.099	1.469	0.079	8.77	0.120	2.17	0.154	3.10	0.136	1.48
Sub-sample 1	0.065	8.72	0.017	2.13	0.050	3.11	0.091	1.461	0.071	8.76	0.112	2.16	0.146	3.09	0.128	1.471
2	0.108	8.77	0.060	2.17	0.094	3.16	0.134	1.504	0.114	8.80	0.156	2.21	0.189	3.13	0.171	1.514
3	0.114	8.77	0.066	2.18	0.100	3.16	0.140	1.510	0.120	8.81	0.161	2.21	0.195	3.14	0.177	1.520
4	0.122	8.78	0.074	2.19	0.108	3.17	0.148	1.519	0.128	8.82	0.170	2.22	0.203	3.15	0.185	1.529
5	0.129	8.79	0.081	2.19	0.114	3.18	0.155	1.525	0.135	8.82	0.176	2.23	0.210	3.15	0.192	1.535
6	0.122	8.78	0.074	2.19	0.108	3.17	0.148	1.519	0.128	8.82	0.170	2.22	0.203	3.15	0.185	1.529
7	0.124	8.78	0.075	2.19	0.109	3.17	0.149	1.520	0.129	8.82	0.171	2.22	0.204	3.15	0.186	1.530
8	0.133	8.79	0.085	2.20	0.119	3.18	0.159	1.529	0.139	8.83	0.180	2.23	0.214	3.16	0.196	1.539
9	0.125	8.78	0.077	2.19	0.111	3.17	0.151	1.521	0.131	8.82	0.173	2.23	0.206	3.15	0.188	1.531
10	0.122	8.78	0.074	2.19	0.108	3.17	0.148	1.518	0.128	8.81	0.169	2.22	0.203	3.15	0.185	1.528
k=40																
Across all period, 1979-2005	0.070	7.70	0.293	2.99	-0.822	-3.51	0.096	1.460	0.080	7.74	0.388	3.02	-0.727	-3.53	0.133	1.470
Sub-sample 1	0.067	7.70	0.290	2.99	-0.825	-3.51	0.093	1.458	0.077	7.73	0.385	3.02	-0.729	-3.53	0.130	1.468
2	0.072	7.70	0.295	2.99	-0.819	-3.50	0.098	1.463	0.082	7.74	0.391	3.03	-0.724	-3.53	0.135	1.473
3	0.073	7.71	0.296	2.99	-0.818	-3.50	0.099	1.464	0.083	7.74	0.392	3.03	-0.723	-3.53	0.136	1.474
4	0.068	7.70	0.291	2.99	-0.824	-3.51	0.094	1.458	0.078	7.73	0.386	3.02	-0.728	-3.53	0.131	1.468
5	0.071	8.02	-0.098	0.14	0.489	-0.14	0.089	1.247	0.081	8.06	-0.003	0.17	0.584	-0.17	0.126	1.257
6	0.071	8.34	-0.490	-2.71	1.799	3.22	0.081	1.033	0.081	8.37	-0.394	-2.68	1.895	3.20	0.118	1.043
7	0.089	8.36	-0.472	-2.70	1.817	3.24	0.099	1.051	0.099	8.39	-0.377	-2.66	1.912	3.21	0.136	1.061
8	0.113	8.38	-0.447	-2.67	1.842	3.26	0.124	1.076	0.123	8.42	-0.352	-2.64	1.937	3.24	0.161	1.086
9	0.120	8.39	-0.440	-2.66	1.849	3.27	0.131	1.083	0.130	8.42	-0.345	-2.63	1.944	3.25	0.168	1.093
10	0.128	8.40	-0.433	-2.66	1.856	3.28	0.138	1.090	0.138	8.43	-0.338	-2.62	1.951	3.25	0.175	1.100

k=50																
Across all period, 1979-2005	0.044	7.67	0.263	1.96	-0.852	-1.78	0.066	1.430	0.050	7.71	0.358	1.39	-0.757	-1.50	0.103	1.44
Sub-sample 1	0.041	7.67	0.260	1.96	-0.855	-1.78	0.063	1.428	0.047	7.70	0.355	1.39	-0.759	-1.50	0.100	1.438
2	0.047	7.67	0.265	1.96	-0.849	-1.77	0.068	1.433	0.052	7.71	0.361	1.40	-0.754	-1.50	0.105	1.443
3	0.047	7.68	0.266	1.96	-0.848	-1.77	0.069	1.434	0.053	7.71	0.362	1.40	-0.753	-1.50	0.106	1.444
4	0.042	7.67	0.261	1.96	-0.854	-1.78	0.064	1.428	0.048	7.70	0.356	1.39	-0.758	-1.50	0.101	1.438
5	0.016	7.38	0.433	4.47	-1.779	-5.41	0.036	1.330	0.021	7.42	0.528	3.90	-1.684	-5.13	0.073	2.433
6	-0.013	7.09	0.603	6.98	-2.707	-9.03	0.006	1.228	-0.008	7.13	0.698	6.41	-2.612	-8.76	0.043	3.424
7	0.004	7.11	0.620	6.99	-2.690	-9.02	0.024	1.246	0.010	7.14	0.716	6.43	-2.594	-8.74	0.061	3.442
8	0.029	7.14	0.645	7.02	-2.665	-8.99	0.048	1.271	0.035	7.17	0.741	6.45	-2.569	-8.72	0.085	3.467
9	0.036	7.14	0.652	7.02	-2.658	-8.99	0.055	1.278	0.042	7.18	0.748	6.46	-2.562	-8.71	0.092	3.474
10	0.043	7.15	0.660	7.03	-2.651	-8.98	0.063	1.285	0.049	7.18	0.755	6.47	-2.555	-8.70	0.100	3.481
k=100																
Across all period, 1979-2005	0.014	7.64	0.233	0.93	-0.882	-0.05	0.036	1.400	0.020	7.68	0.328	-0.24	-0.787	-0.53	0.073	1.41
Sub-sample 1	0.011	7.64	0.230	0.93	-0.885	-0.05	0.033	1.398	0.017	7.67	0.325	-0.24	-0.789	-0.53	0.070	1.408
2	0.017	7.64	0.235	0.93	-0.879	-0.04	0.038	1.403	0.022	7.68	0.331	-0.23	-0.784	-0.53	0.075	1.413
3	0.017	7.65	0.236	0.93	-0.878	-0.04	0.039	1.404	0.023	7.68	0.332	-0.23	-0.783	-0.53	0.076	1.414
4	0.012	7.64	0.231	0.93	-0.884	-0.05	0.034	1.398	0.018	7.67	0.326	-0.24	-0.788	-0.53	0.071	1.408
5	-0.010	8.40	0.047	-1.97	-0.634	2.65	0.007	1.367	-0.007	8.44	0.143	-3.14	-0.538	2.17	0.044	0.284
6	-0.035	9.17	-0.138	-4.88	-0.386	5.35	-0.022	1.334	-0.034	9.20	-0.043	-6.04	-0.290	4.86	0.015	-0.842
7	-0.017	9.18	-0.121	-4.86	-0.368	5.37	-0.005	1.351	-0.016	9.22	-0.025	-6.02	-0.273	4.88	0.032	-0.825
8	0.007	9.21	-0.096	-4.83	-0.343	5.39	0.020	1.376	0.009	9.24	-0.001	-6.00	-0.248	4.91	0.057	-0.800
9	0.014	9.22	-0.089	-4.83	-0.336	5.40	0.027	1.383	0.016	9.25	0.006	-5.99	-0.241	4.91	0.064	-0.793
10	0.022	9.22	-0.082	-4.82	-0.329	5.40	0.034	1.391	0.023	9.26	0.014	-5.99	-0.234	4.92	0.071	-0.786